Skill and Wage-Earning Potential: Evidence from Indian Labour Market

Sonu Madan[1] | *Indira Gandhi University, Meerpur, Rewari, India*
Surender Mor | *B. P. S. Women University, Khanpur Kalan, Sonipat, India*

Abstract

The focus of paper is on explaining variations in wage earning potential of regular wage earners caused by varying skill levels. Further, the paper attempts to analyse the conditional causal effect for a broad range of occupational groups to infuse external validity during estimation process which helps to explore how universal is the causal effect. The study brought out the fact that skill level of workers affects the wage-earning potential of workers significantly. However, different skill requirements to perform a range of tasks & operations, along with associated complexity, moderates the strength of causal linear relationship and the resultant slope indicating relationship between skill level of workers and their wage-earning potential varies significantly across occupational groups. Thus, conceptualization of task-content based approach of occupations determines wage-earning potential of workers and hereby is a promising boulevard for future research. The study recommends in job training courses along with introduction of intra-occupational diversified range of tasks & operations to secure incremental wage.

Keywords

Skill, regular wage earners, wage-earning potential, occupational groups, conditional effect

JEL code

J01, J21, J31

INTRODUCTION

Globalization has contributed towards integration of labor markets and has enhanced the mobility of labour leading to reduced wage-gap, among workers in both developed and developing countries due to technological development and transmission. Developing countries has experienced increased efficiency owing to more openness, especially in trade. Increasing economic activities across the globe has given rise to the relative demand for unskilled workers resulted in narrowing the gap in wages between unskilled and skilled workers (Wood, 1995).The reduction in wage inequality due to increasing liberalization and globalization in developing countries rests on the fact that the supply of unskilled labor, relative to the skilled labor, is larger in developing in compared to developed countries (Wood, 1994). Simultaneous, technological advancements have raised the demand for skilled workers to meet specific industrial requirements giving way to wage inequality substantially (Vashisht and Dubey, 2018). The wage differentials of skilled and non-skilled workershave enhanced intra-country higher wage differentials

[1] Assistant Professor, Department of Economics, Indira Gandhi University, Meerpur, Rewari, Haryana, 123035, India. Corresponding author: e-mail: sonumadan15@gmail.com, phone: (+91)8685911117.

besides exhibiting a strong tendency for alternative work for higher wages besides willingness to travel more miles to find alternative employment with higher wages (Mor and Mor, 2011).

Wage earning potential depends on skill of a person, which indicates the ability of a person to perform his/her duties, is associated with a given job. Skill is a measure of workers' expertise, specialization, and supervisory capacity and skilled workers are considered more trained than unskilled workers and are paid higher for more responsible position at workplace. Wage earned by workers has its demand side linkages with the economy and hereby serve as control phenomenon for the economy in broader sense (Madan, 2019a). An occupation is a set of tasks & duties performed in a job, which are characterized by high degree of similar work types. A set of tasks to be performed requires specific type of skill for operational efficiency (Annex 1). Tasks performed by workers at their work place can be divided into two categories i.e. routine tasks, which can be easily performed using machines & can be codified, and non-routine tasks, which cannot be mechanized easily and require cognitive skills or non-routine manual tasks (Vashisht and Dubey, 2018).

Digitization of technology and de-routinised the nature of work in various occupations has substantially affected the wage-earning potential of workers. The occupational diversity has contributed a lot in this phenomenon of wage differential because different occupations require different set of skills (Annex 1), depending upon the range& complexity of tasks to be performed. Occupations are central to the economic diversification and are accounted for the growth of long run wage inequality (Madan, 2019b). Task dimension of occupations is one of the key reasons for variance in occupational mean wage because of differentiated risk & skill requirements in accordance with occupational structure (Liu and Grusky, 2013; Williams and Bol, 2018). Skill requirements, job content, occupational descriptions, among others, are considerations for wage differential among workers (Madan and Goyal, 2019).

The Indian labour market, with 500 million adults, is the second largest economy in terms of labour force, where around 90 percent of workforce is employed in the informal economy (Mor et al., 2020). Recently, Government of India (2020) has tasked numerous steps for employment generation coupled with improving employability such as Prime Minister's Employment Generation Programme (PMEGP), Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS), Pt. Deen Dayal Upadhyaya Grameen Kaushalya Yojana (DDU-GKY) and Deendayal Antodaya Yojana-National Urban Livelihoods Mission (DAY-NULM) etc. Moreover, owing to various initiative to formalize the economy like introduction of GST, digitization of payments, direct benefit transfer of subsidies/scholarships/wages & salaries to bank accounts, opening of Jan-Dhan accounts, extending social security coverage to more workers. The measures also have increased the demand for skilled labourers to be placed at different positions in accordance with their capabilities leading to wage differentials. Moreover, formal employment in the economy increased from 8 per cent in 2011–12 to 9.98 per cent in 2017–18 and number of workers who receive predetermined wages/salary on regular basis increased from 88 million in 2011–12 to 115 million in 2017–18 (Government of India, 2020).

Surely, a significant part of variation in wage differential is explained by the differences in educational attainments, occupational differences and work experience gained with age, among others. The interaction between technology and tasks, at various levels of educational attainments of workers, to be performed has categorized the employment structure as low and high wage occupational structure. This paper is an attempt to overcome the challenges that have emerged from changing demand of work force leading to diversified wage-earning potential of workers. Considering the polarization of work opportunities in the light of skill oriented de-routinization, years spent to acquire formal education may be considered as a proxy for skill level of workers, which in turn may be an enabling factor to make a choice of occupation as different occupations require different skill levels. In this backdrop, education can be considered not only a factor responsible for wage differentials as there is remarkable difference in the wage earning of workers with same educational attainments.

1 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

1.1 Skill and wages

The human capital revolution and increased availability of information on earnings and individual skills have shifted the weight of education, age, and experience towards differences in earnings. The difference in wages is determined by competitive factors like costs of training, probability of success, steadiness of work, workplace amenities, differences in individual inborn abilities, institutional factors such as regulation of wages, restricted labor mobility, and barriers to entry. Human capital in terms of schooling and training explains the differences in the structure of wage earnings across the globe resembling higher earnings for more educated/skilled workers (Willis, 1986; Becker, 1993). Labor market integration, coupled with migration in response to wage differentials, changes the wage structures and per capita GDP provide stimulus to skilled formation in both host and home countries (Behrens and Sato, 2006). Skill dynamics may result in a sub-optimal situation of an under-education trap due to a lack of human capital at stationary state. The public sector can play an important role in the skills development process by incentivizing parents and employers in early level of schooling (Cunningham and Villasenor, 2016). Contrary to this, Mason (2008) pointed in his study that enhancing workforce skills may not enhance the relative productivity of a worker. Expansions of educational institutions have accelerated the growth in the supply of qualified workers to outstrip the growth in demand resulting in a substantial decline in the wage premium to white collar jobs. These educational attainments need to fulfill the requirement of employer to be utilised effectively within firms and other organisations. Employers value all skill sets including socio-emotional skills, cognitive skills and technical skills and are valued differently in the labor market across region, industry, occupation, and education level.

Horvath (2014) highlighted that skill-biased technological change lead to increasing inequality in wages and employment opportunities between high school and college graduates. The output per capita as well as wage equality can be enhanced effectively by a minimum wage or a redistribution policy. Wage policies of organisations and individual skill differences are the key noted pattern of inter-industry wage differentials. Linkages between technological development and access to education lead towards an increase in the demand for more educated labour which is responsible for different wage structures. The increased participation between secondary and tertiary sector, routed through secondary & technically education, is crucial for improved skilled development (Onsomu et al., 2010). Further, skills equipment reduces the fear of failing (Mor, Madan, Chhikara, 2020). There may be a positive relationship between skill level and wage earnings. Higher the skill, a worker/employee possess, more the chances of fetching higher wages/salaries. Hence, testing of the following hypothesis is of immense importance:

H_{01}: Skill, education and experience do not affect the wage earnings.

1.2 Wage income and occupational structure

The wage rates/salaries differ in accordance with different structure of occupation's as some highly technical or risky occupation may offer higher wages/salaries as compared less risky and non-technical types of jobs/activities. Autor and Dron (2013) in their pioneering work have attributed towards exploring changes in the task content of works associated with different occupation structure in the light of changes in technology. The study reported a negative association between the use of information and communications technologies (ICT) and task contents which are routine manual & routine cognitive, while it was positively associated with non-routine cognitive task contents in USA during 1960 and 1980. These results are in line with for selected OECD countries (Michaels, Natraj, Van Reenen, 2014; De La Rica and Gortaazar, 2016). De-routinisation of jobs, has also been confirmed by Salvatori (2015) while examining the employment structure in the United Kingdom between 1979 and 2012 due to a sharp decline in supply of non-graduate workers rather than technology. These results coincide with the research findings of Hardy, Keister, Lewandowski (2015, 2016) for central and East European countries. However, structural changes have been found an important reason for divergence of work opportunities in US started in the early 1950s (Barany and Siegel, 2018).

Wage inequality began to rise in the early 1980s, just a few years after the invention of microcomputers and this burst of new technology caused a rise in the demand for highly skilled workers, which in turn led to a rise in earnings inequality (Card and Dinaro, 2002). The relative demand for highly skilled workers increased in the 1980s, causing earnings inequality to increase (Johnson, 1997). The demand for skilled labour increases as the pool of skills increased in OECD countries but innovation has been found threatening the interests of workers with demand for high skills. In view of this, the following hypothesis will be tested:

H_{02}: Wage earnings are independent of occupation structure.

1.3 Occupation and skills

Different occupations require different kind of skills to perform the tasks of different level of activities. Skills play an important role in labour market disparities because labor mobility reduces differences in regional unemployment rates while migration of high-skilled labourers tends to reinforce disparities in labour market (Granato et al., 2014). Skill requirements vary across occupations and certain job-specific tools (skills), specifically required for an occupation, and are associated with higher pay whereas non-specific tools correlate to lower-paying sales, service, and administrative occupations (Cunningham and Mohr, 2019). Moreover, occupations that require high skills need costly investment in human capital (Conley, Onder, Torgler, 2012). The quality of employment and the technological knowledge base have different impact on the location of knowledge-intensive and on low-cost labour-intensive manufacturing sectors (Amoroso et al., 2015). The access and use of ICT has not been equal for the different groups of our societies, and Europe witnessed an emergence of social cleavages due to skills and occupational differences. Skilled immigrants and natives are imperfect substitutes in some occupations but are complements in others which resemble that even large inflows of foreign skilled workers have limited impacts on domestic workers (Ma, 2020). There exist wage differentials in public and private sectors occupations where public sector premiums at the bottom of the wage distribution reflecting that low skill workers are overpaid (Siminski, 2012) and degrees holder workers possess more substantial advantages than certificates in the labor market (Bailey and Belfield, 2019). Hence, the under-mentioned hypothesis intends to be tested.

H_{03}: Occupation and skills are independent of each other.

2 METHODOLOGY

2.1 Database and sampling

Periodic Labour Force Survey (PLFS) provides statistics on labour force specific indicators in cross classification of education, industry, occupation, wages and various demographic characteristics such as age, marital status, region based on the data collected during July 2017 to June 2018. PLFS covered 102 113 households and have enumerated 433 339 persons in numbers. A sample of 42 417 regular wage earners engaged in various occupational groups to perform economic activities are considered purposefully to analyze thewage-earning potential of workers at various skill levelsmoderated for classified occupational groups. For the purpose, regular wage earners from nine broad group of occupations, corresponding to their skill level, as per International Standard Classification of Occupations-08, (ILO, 2012) are selected. The details on occupational groups along with number of workers selected thereof is given in the Annex 2.

2.2 Specification of variables, moderator, and covariate

Wage earning is a randomized continuous variable. To meet the assumption of normality in the distribution of residuals, natural log (Ln) of wage is considered. Years of formal education has been considered as a proxy to capture skill level of workers and hereby is a continuous variable. Occupational category of workers influences, significantly, the nature of relationship between skill level of workers and their wage-earning potential. Hereby, seven dummies (number of occupational groupsless one) are used to compute the individual interaction lines (Annex 2). The age of employees, a continuous variable, has been used as a covariate to neutralize the effect of experience gained with age on the stated relationship. The interaction effect of skill and occupation on wage reveals that age has been an important factor to affect the relationship. Research on labour forces in Israel confirm that unemployment rate of young people can be attributed more towards characteristics of the labour market, whereas for elder employment aspirants it is more a function of their age (Axelrad, Malul, Luski, 2018). Though, gender of workforce is also an important factor of concern, but the present study is confined in exploration of varying earning potential of all workers in different occupation and hereby occupational diversity has been considered as moderator instead of gender.

2.3 Model specification and estimation techniques

2.3.1 Main effect and interaction effects

A linear causal relationship between *skill level of workers (X) and their wage earning (Y)* is presumed to measure the main/direct effect of variations in *X* on *Y*. The main effect is measured by regression coefficient *bi* (Formula (1)). However, the strength of this relationship alters with *occupations* wherein a worker is employed. Different occupations require different skill level depending upon the range of tasks & operations to be performed along with their complexity, and so we would say that *occupation (M)* moderates the causal linear relationship between *X* and *Y*. Though, regression coefficients measure the strength of relationship persisting between variables, but at the same time the relationship may not be same for all categories of moderated variable (Bauer and Curran, 2005; Preacher et al., 2006; Hayes and Matthes, 2009). A moderator can reverse or intensify a relationship (Judd and Kenny, 2010). The slope of relationship between response variable and predictor varies across groups represented by categorical moderator variable. A moderation analysis infuses external validity during estimation process which helps to explore how universal is the causal effect. It's is customary to indicate the effect of moderator by the *interaction* of *X* and *M (XM)* while explaining *Y*. Interaction term is to estimate the expected difference in the effect of an additional year of formal education for workers engaged in different occupational structure (Figure 1). However, experience gained with age *(A)* is in question to affect the stated relationship and hereby need to be controlled to neutralize its effect while measuring the impact of *X* on *Y*. At this backdrop, the following multiple regression equation is estimated:

$$Ln\ (Y_i) = \alpha + b_1X_i + \sum_{j=2}^{k} bjMi + \sum_{\lambda=k+1}^{2k-1} b\lambda XiMi + C_1A_i + e_{Yi}. \tag{1}$$

Re-arranging terms in Formula (1), such that:

$$Ln\ (Y_i) = (\alpha + \sum_{j=2}^{k} bjMi) + (b_1 + \sum_{\lambda=k+1}^{2k-1} b\lambda Mi)Xi + C_1A_i + e_{Yi}, \tag{2}$$

here:

Ln (Yi) is the natural logarithm of monthly wage/salary of i^{th} regular worker employed in any broad occupational group,

X_i (I = 0,1, ……N) is years of formal education to acquire skill level required for any occupation;

M_i (I = 0, 1) is the dummy assigned to i^{th} worker belong to a specified occupational group (1) or not (0)

to indicate its effect over reference category occupation,
b_j is the vector of coefficients associated with occupational categories dummies (b_j = 2… k). Herein,
b_λ is the vector of coefficients associated with interaction of years of education & occupational (b_λ = k + 1… 2k − 1). The corresponding values obtained from $b_1 + \sum_{\lambda=k+1}^{2k-1} b\lambda Mi$ is the conditional effect of X (workers' skill) on Y (wage earning potential), given specified M (specified occupational group) and may be referred to as simple slope; and
C_1 (C_1 = 1,…N) is the covariate for age measured in years to adjust moderated causal relationship between X & Y for age.

The sign and magnitude of regression coefficients will be estimated by econometric methods. As all the variables are non-arbitrary, the *b's* are fixed unstandardized model parameters to be estimated. The coefficients b_1 measures the direct effect of X on Y (b_1 = 0,…N) in the absence of any moderator (M_i) (Figure 1).

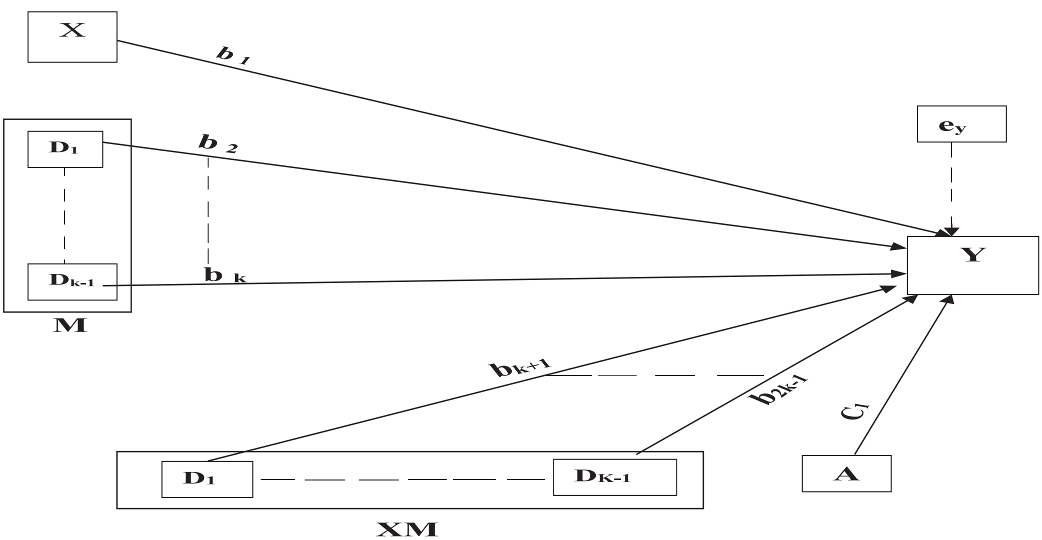
In this study, a log-linear regression model with dummy variables is applied. In the case of dummy variables, the following formula is used to estimate variation in monthly wages:

$$[100(e^b - 1)]. \tag{3}$$

In this model, b_λ is the primary parameter of interest, if non-zero, implies that the linear relationship between workers' skill and wage varies linearly with occupation structure wherein the worker is employed (Aiken and West, 1991; Cohen et al., 2003; Dawson, 2014; Hayes, 2013; Bodner, 2016). The model attempts to capture *conditional effect of X on Y* in the under mentioned form:

$$Ln\ (Y_i) = \alpha + b_{k+1} D_1 + \dots + b_{2k-1} D_{k-1}\ . \tag{4}$$

Figure 1 Model estimation



Source: Graphical presentation of model estimation technique explained in Section 2.3.1

2.3.2 Interaction lines, significance of slope, effect size and power analysis

To capture the causal relationship between the dependent and independent variables for each category of moderator controlled for covariate, separate regressions equations are estimated to provide interaction effect in accordance. Significance of slope of each interaction line is measured at 5 percent levels of significance. Effect size of moderators' effects is measured using f square (f2) to estimate the magnitude of the combined impact of independent variable on the dependent variable. By convention, effect sizes of 0.02, 0.15, and 0.35 are considered small, medium, and large, respectively following Aguinis et al. (2005).

2.3.3 Compilation of output

The output is compiled using Windows software programme namely "Interaction" version 1.7.2211, designed by Danial, S. Soper, especially to analyze and draw statistical interactions.[2] The elementary occupation (group 8) has been considered as reference category.

3 RESULTS

The study utilizes statistics on educational attainments, occupational structure, age, and wage level of 42 417 regular workers obtained from Periodic Labour Force Survey (PLFS) conducted during July 2017 to June 2018. Workers' working in other's farm or non-farm enterprises (both household and non-household) and receiving salary or wages on regular basis (and not based on daily or periodic renewal of work contract) in return are regular wage/salaried workers. This category not only includes persons getting time wage but also persons receiving piece wage or salary and paid apprentices, both full time and part-time. Table 1 shows that the mean monthly Ln wage of regular workers is Ln 9.383 (INR 11 884). The minimum and maximum Ln wage for all workers, irrespective of their occupational group, is witnessed to be Ln 4.605 i.e. INR 100 and Ln 13.459 i.e. INR 700 115. The mean education of regular workers is found to be 11 years of formal education with variation of illiterate, with no formal education, to 21 years of formal education. On an average, the age of workers is 37 years. The statutory working age of India is 15–64 years, but a meager proportion of workforce is found to be working in all ages. Though, the minimum and maximum age of workers is found to be 10 years and 78 years (Table 1), but only a meager percentage is found to be working in the age group below 15 years (0.08 percent) and above 65 years of age (0.51 percent) for their livelihood, so far as PLFS, 2017–18 is concerned. The persons working beyond statutory working age are mainly engaged in informal sector.

Table 1 Descriptive statistics of Indian labour market

Variables	Mean	SD	Minimum	Maximum	N
Ln (Wage)	9.383	0.816	4.605	13.459	42 417
Formal Education (in Years)	11.023	4.626	0.000	21.000	
Age	37.113	11.274	10.000	78.000	

Source: Author's calculations based on data extracted from PLFS, NSO (2019)

It is clear from Table 2 and 3 that the model is a good fit as it has been able to explain a major portion of variation in the wage level of regular workers as indicated from R^2 = 34.5 (Table 3), $F_{16,\,42\,400}$ = 1 394.92, $p < .001$ (Table 2). The predictive power of model is good enough as it can explain 35 percent variations in the wage level. The value of f square (f^2) effect size (0.526) indicates large effect size, revealing that the magnitude of the combined impact of the skill levelsof workers in various occupations. The value of Beta (type II error rate) is too small (0.0001) indicated negligible probability of committing type II error while making decision on rejection of null hypothesis. Similarly, the

[2] <*https://www.danielsoper.com/Interaction/free.aspx*>.

observed power of the model is greater than 0.80 indicating that the probability of rejecting null hypothesis when it false, is high enough for making a right decision in this regard. The predictive power of the model is estimated to be 34 percent.

Table 2 Model summary: fitting of regression model for Indian labour market

	Sum of square	D.O.F	Mean square	F	Sig
Regression	9 757.798	16	609.862	1 394.924	0.001
Residual	18 537.329	42 400	0.437		
Total	28 295.128	42 416			

Source: Author's calculations based on data extracted from PLFS, NSO (2019)

Table 3 Model summary and power analysis for Indian labour market

Effect size (f^2)	Noncentrality parameter (Lambda)	Critical F	Noncentral F	Beta (Type II error rate)	Observed power	R^2
0.526	22 327.733	4.732	140.736	0.000	1.000	0.345

Source: Author's calculations based on data extracted from PLFS, NSO (2019)

3.1 Main effect

So far as the effect of skill level of worker is concerned (X), workers with higher education can get higher wage. An additional year spent on education leads to raise 7 percent increase inwage as indicated from value of regression coefficient associated with X_1. It indicates that the prompt return for an additional year of education is 6.9 percent and the compounded return is 7.1 percent $[100(e^{0.069} - 1 = 0.071)]$, controlling the effect of age which is found to be a significant positive factor effecting mean wage level due to experience gained with age (Table4, Figure 2). In the light of significant value of parameter estimate, our 1st upheld hypothesis of no effect of skill level obtained from educational attainments on wage earning of workers has been rejected.

Table 4 Parameter estimates of main effect, moderation and interaction

Variables/Interactions	B	Std error	T	Sig
Constant	7.60*	0.02	368.638	0.001
X	0.069*[7.1]	0.001	34.685	0.001
D1	–0.206* [–18.62]	0.073	–2.837	0.004
D2	–0.276* [–24.11]	0.048	–5.729	0.001
D3	–0.184* [-16.81]	0.041	–4.484	0.001
D4	0.551*[73.50]	0.048	11.390	0.001
D5	0.006 [0.60]	0.025	0.230	0.817
D6	0.373* [45.20]	0.027	13.627	0.001
D7	0.510* [66.53]	0.029	17.437	0.001
ID1 (D1X)	0.060*	0.005	11.522	0.001
ID2 (D2X)	0.046*	0.003	12.957	0.001
ID3 (D3X)	0.030*	0.003	9.305	0.001

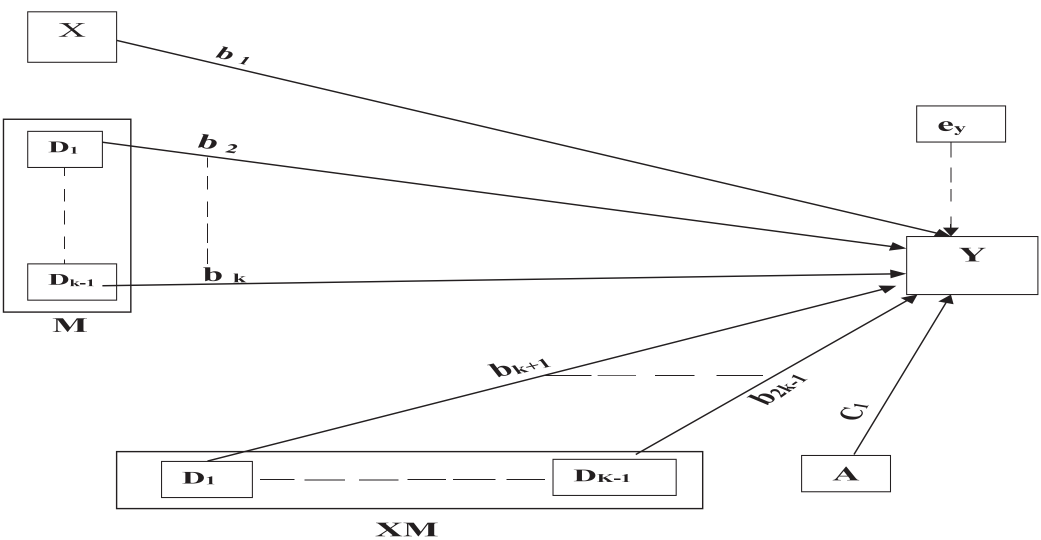
Table 4				(continuation)
Variables/Interactions	B	Std error	T	Sig
ID4 (D4X)	–0.013*	0.004	–3.518	0.001
ID5 (D5X)	0.013*	0.003	5.0423	0.001
ID6 (D6X)	–0.017*	0.003	–5.913	0.001
ID7 (D7X)	–0.024*	0.003	–7.660	0.001
C1 (Age)	0.021*	0.001	71.183	0.001

Notes: (a) The model is estimated in log-linear form. (b) Response variable = Ln (monthly wage). (c) * indicates that the unstandardised coefficient is significant at 1% level of significance. (d) Value of [100(e^b – 1)] is given in square brackets [ ]. (e) D1: Dummy for managers; D2: Dummy for professionals; D3: Dummy for technicians and associate professionals; D4: Dummy for clerical support workers; D5: Dummy for service and sales workers; D6: Dummy for workers skilled in agricultural, forestry, fishery, craft and related trade activities; D7: Dummy for plant & machine operators and assemblers. (f) Reference group: elementary occupation.
Source: Author's calculations based on data extracted from PLFS, NSO (2019)

3.2 Wage earning and occupational structure

Different occupations correspond to different nature of work profiles. Task dimension of occupations is one of the key reasons for variance in occupational mean wage because of differentiated risk & skill requirements in accordance with occupational structure (Liu and Grusky, 2013; Bol and Weeden, 2015; Williams and Bol, 2018). Skill requirement, job content, occupational descriptions, among others, is considerations for wage differential among workers. Table 4 comes out with interesting revealing fact about the differential wage structure for different occupations. So far as mean wage level in different occupations is concerned, it is clear from the value of regression coefficients (Table 4, Figure 1) associated with different occupations that in case of managers (–18.62 percent), professionals (–24.11 percent), technicians and associate professionals (–16.81 percent) the base level mean wage is witnessed to be less than elementary occupations, whereas it begins somehow at high level for other professions. For clerical support workers, the base level mean wage is 73 percent higher than those

Figure 2 Estimation of regression coefficients



Source: Graphical presentation of Table 4 working in elementary occupations. Similarly, for workers skilled in agricultural, forestry, fishery, craft, and related trade activities and for plant & machine operators and assemblers, the base mean wage is higher by 45 percent and 66 percent than elementary occupations. These findings drive out an interesting fact that managers, professionals & technicians & associate professionals have only required qualification at entry levels which can be replaced easily by other aspirants for work as they lack specified operational skills. At the same time, workers skilled in agricultural, forestry, fishery, craft and related trade activities and for plant & machine operators, assemblers and clerical support workers possess technical expertise to accomplish specified tasks which compels recruiters to offer higher mean wages at the entry level. Hereby, it is evident that wage level of workers at entry levels varies with occupation structure, which provide reason to reject the 2nd maintained hypothesis of independence of wage earning and occupation structure.

3.3 Interaction effect

The presence of a significant interaction of years of formal education and occupation (XM) indicates that the effect of increase in additional one year of education on natural log of mean wage is different for different occupations. It is interesting to note that though the base level mean wage of managers, professionals & technicians & associate professionals is less than elementary workers but the interaction effect is strong enough to give raise to their wage-earning potentials with upgradation in their skill levels. Every one-year increase in formal education, leads to wage hike of managers, professionals & technicians & associate professionals by 6 percentage points, 4.6 percentage points & 3 percentage points respectively over & above to those in elementary occupations. This reveals out the fact that with increased years of education, the workers in these occupations acquire non manual cognitive skills with professional efficiency and cannot be replaced easily given the scarcity of workers with similar skill, efficiency level & managerial capabilities. Though, the base line mean wage in clerical support workers, ignoring the effect of workers' skill level, is witnessed to be 75 percentage points higher than elementary occupations, but skill enhancement provides less monetary benefits by 1.3 percentage points than elementary workers. Similarly, in comparison to elementary workers, workers in occupational group 6 & 7 also get less monetary rewards towards upgraded skill levels (Table 3). Workers belonging to these occupations mostly continue to perform similar type of tasks even after spending more years on skill upgradation making recruiters to provide less increment for additional skill upgradation. This indicates that monetary reward for work is not same for all workers even in same occupation. This correspond to the study of Ma (2019) in United States, which point out that the rewards for skilled labourers from science and engineering background are 2 percent higher as compared to other.

Table 5 brought up the base line mean wage and incremental effect of skill upgradation in different occupations. The base line mean wage is observed to be lowest for professionals (Ln 7.323, i.e. INR 1 515) preceding to managers (Ln 7.393, i.e. INR 1 625), elementary workers (Ln 7.600, i.e. INR 1 999), service and sales workers (Ln 7.606, i.e. INR 2 010), and workers skilled in agricultural, forestry, fishery, craft and related trade activities respectively (Ln 7.974, i.e. INR 2 905). It is found to be highest for clerical support workers (Ln 8.152, i.e. INR 3 470) followed by plant & machine operators and assemblers (Ln 8.110, i.e. INR 3 228). The less base wage for managers and professionals at entry levels indicates that in the initial years of their work, they possess only required qualification and lack cognitive & specialized operational skills in the relevant areas. Moreover, their work profile in the early years can be replaced easily by other aspirants for work.

So far as the incremental effect of skill upgradation on wage earning potential of workers corresponding to different occupations is concerned, it is observed to be highest for managers (12.9 percent) followed by professionals (11.5 percent), technicians and associate professionals (9.9 percent), service and sales workers (8.2 percent), elementary workers (6.8 percent), clerical support workers (5.5 percent), workers

Table 5 Conditional effect of formal education on Ln wage for each group of occupation

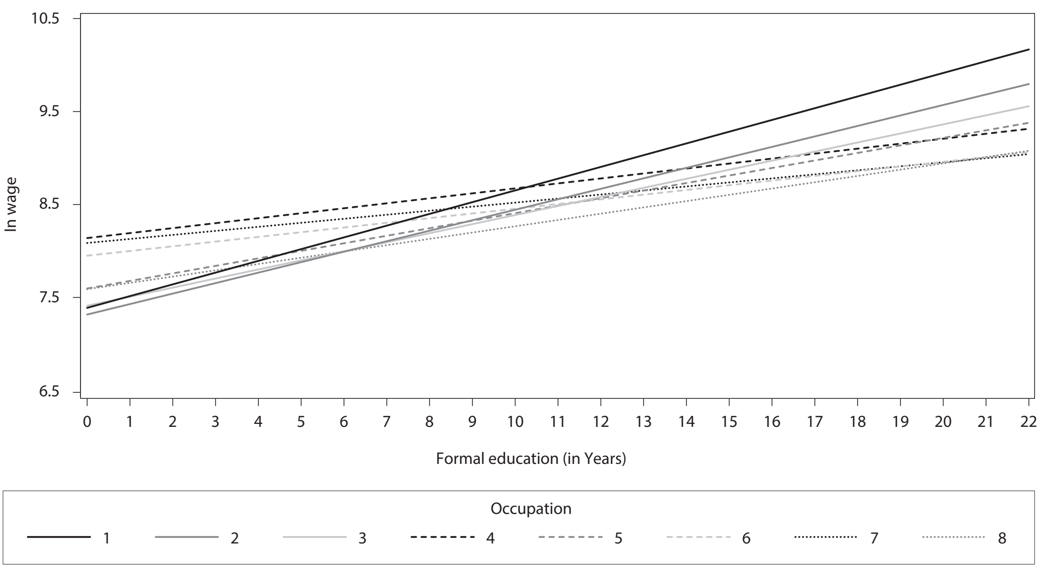
Occupation	Intercept	Coefficient	SE	T	P
1	7.393	0.129*	0.005	26.653	0.001
2	7.323	0.115*	0.003	38.781	0.001
3	7.416	0.099*	0.002	37.393	0.001
4	8.152	0.055*	0.003	16.038	0.001
5	7.606	0.082*	0.002	44.756	0.001
6	7.974	0.051*	0.002	22.597	0.001
7	8.110	0.044*	0.002	17.540	0.001
8	7.600	0.068*	0.002	34.685	0.001

Notes: (a) The model is estimated in log-linear form. (b) Response variable = Ln (monthly wage). (c) * indicates that the unstandardized coefficient is significant at 1% level of significance. (d) Occupational group-1 denotes managers; Occupational group-2 is for professionals; Occupational group-3 denotes technicians and associate professionals; Occupational group-4 denotes clerical support workers; Occupational group-5 denotes service and sales workers; Occupational group-6 is for workers skilled in agricultural, forestry, fishery, craft and related trade activities; Occupational group-7 denotes plant & machine operators and assemblers and Occupational group-8 refers to Elementary occupation.
Source: Author's calculations based on data extracted from PLFS, NSO (2019)

skilled in agricultural, forestry, fishery, craft and related trade activities (5.1 percent) and is minimum for machine operators and assemblers (4.4 percent) in response to increase in every one year of formal education.

This indicates that increase in wage not only requires work experience but also scope of expertise services within the job profile of a worker. The scope of operational activities performed by managers, professionals, technicians & associate professionals, service & sales workers become wider enabling them

Figure 3 Conditional interaction effect of education on Ln wage with covariate age



Note: Group-8 (elementary occupation) is reference category.
Source: Graphical presentation of Table 5

to perform complex nature of work with expertise. This enables them to earn more from their work/profession with time. Therefore, our 3rd hypothesis stating that occupation and skills are independent of each other has also been rejected.

4 DISCUSSION

Occupations are central to the economic diversification and are accounted for the growth of long-run wage inequality. The study highlights the impact of skill on wage, in different occupations and justifies the consideration of task dimension of occupations as one of the key reasons for variance in occupational mean wage. The study established that wage earnings depend on the skill of a person. It is interesting to note that the base level mean wage of managers, professionals and technicians & associate professionals is less than elementary workers. The observed reason for the same is the lack of specified operational skills for better outcomes in the absence of professional training. Similar inferences have been drawn by Cunningham and Mohr (2019) wherein the numbers of job-specific tools are found highly relevant to perform a range of tasks at different occupation levels. American Community Survey (2010) also observed that the ability to utilize tools is associated with higher wages. The verdicts further suggest that the base mean wage of clerical support workers, workers skilled in agricultural, forestry, fishery, craft and related trade activities, plant & machine operators and assemblers is much higher than elementary occupations as workers in these occupations possess the technical expertise to accomplish specified tasks which compels recruiters to offer higher mean wages at the entry-level.

The addition of the study in the existing research is the minuscule examination of interaction effect of occupational structure and skill up gradation of sampled occupations, which depicts that every one-year increase in formal education, leads to give more rise to workers associated with some specified occupations than in others. The scope of operational activities performed by managers, professionals, technicians & associate professionals, service & sales workers with increasing years of training become wider. At the same time possession of non-manual cognitive & analytical skills enable them to perform complex nature of work with expertise. This indicates that an increase in wage not only requires years of experience but also the scope of expert services within the job profile of a worker enabling them to earn more from their work/profession with time. These findings correspond to the study of Ma (2019) in the United States, which point out that the rewards for skilled labourers from science and engineering background are 2 percent higher as compared to other.

The study further reveals that the task contents of occupations requiring moderate skill- such as elementary workers, clerical support workers are structured, exact, and repetitive in nature to perform routine tasks. Workers employed in agricultural, forestry, fishery, craft and related trade activities, plant & machine operators and assemblers do not depend on computers and are mostly manual in nature and continue to work in the same line and thereby experience less increment in their mean wage structure in spite of high comparative wage-earning without any skill than workers in other occupations. This finding is consistent with the research study of Mason (2008) pointing on the fact that enhancing workforce skills may not enhance the relative productivity performance of a worker as the expansion of educational institutions have accelerated the growth in the supply of qualified workers to outstrip the growth in demand resulting in a substantial decline in the wage premium to white-collar jobs. The similar research undertaken by Shi et al. (2018), for analysis of recruitment process in the German-speaking part of Switzerland, brought out the fact that it is the skill acquired vide academic standard matters to provide employment at the entry-level, not the personal characteristics of employment aspirant.

The findings of the study seem relevant in a larger perspective when compared with research undertaken across the globe. For instance, the study pinpoints that though wage-earning potential of workers and skill acquired by education are associated but the resultant wage premium for every additional year of education is not the same across different occupation. Some occupations require complex operational

& cognitive skills and have diverse job profiles accordingly and have resulted in differentiated wage-earning potential. Similar researches in this line also have shown that wage premium of the tertiary education is found to be slightly lower across EU-15 countries (Obiols-Homs and Sánchez-Marcos, 2015), skill up-gradation of workers results in polarization of workers against mid-skilled jobs taken by graduates (Brekelmans and Petropoulos, 2020) and labour earning penalty is not same for all workers rather differ significantly with their occupation in Brazil (Reis, 2018). The study on skilled labour mobility on ASEAN member economies establishes the advantages of the mobility of skilled labour force in reducing the wage differentials (Corong and Aguiar, 2019).

CONCLUSION

The study measured the impact of workers' skill on their wage-earning potential in consideration of the occupational structure of the workplace, adjusted for age of workers and revealed out skill requirements in different occupations while considering age as a covariate so that the effect of age on the stated relationship can be neutralized. The verdict infers that every additional year of formal schooling is associated with an increase of 7 percent in wages on an average. These dividends of an additional year of education vary across occupations, i.e. managers (6 percent), professionals (4.6 percent), & technicians & associate professionals (4.3 percent), over & above to those in elementary occupations. Furthermore, that managerial, professionals, technical and associate professionals' occupation, without relevant education, lack specified operational skills and can be replaced easily by other aspirants for work resulted in low wage. So far as other occupations are concerned, though their mean wage at the beginning year of education, is found to be higher than workers elementary occupations, the wage increments with due course of time are less as the nature of work performed remains more or less the same.

The present research contributes to the existing body of knowledge by underlying the interaction effect of skill on wage-earning potential of workers in accordance with their job profile in various occupations. So far as other occupations are concerned, though their mean wage at the beginning year of education, is found to be higher than workers elementary occupations, the wage increments with due course of time is less as the nature of work performed remains more or less the same. In the course, the study reported the incremental effect of education (skill) on wage in different occupations besides reporting that the incremental effect of skill up-gradation on wage-earning potential of workers in stated occupations is observed to be highest as they develop complex operational & cognitive skills leading to change in their job profile. Incremental wage differential among occupational structure closely linked to a shift in employment from one occupation to another. Hereby, it is a need of time to mandate in job training courses to increase the labour productivity over time and reduce job polarization caused by intra-occupation migration of workforce.

References

AGUINIS, H., BEATY, J., BOIK, R., PIERCE, C. Effect Size and Power in Assessing Moderating Effects of Categorical Variables using Multiple Regression: a 30-year Review. *J. Appl. Psychol*, 2005, 90, pp. 94–107. DOI: 10.1037/0021-9010.90.1.94

AIKEN, L. AND WEST, S. *Multiple Regression: Testing and Interpreting Interactions.* Newbury Park, CA: Sage, 1991.

AMOROSO, S., DOSSO, M., MONCADA-PATERNO-CASTELLO, P. The Impact of Skill Endowments and Collective Bargaining on Knowledge-Intensive Greenfield FDI. *IPTS Working Papers on Corporate R&D and Innovation*, No 8/2015. DOI: 10.2139/ssrn.2658036

AUTOR, D. H. AND DRON, D. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 2013, 103(5), pp. 1553–1597.

AXELRAD, H., MALUL, M., LUSKI, I. Unemployment among Younger and Older Individuals: Does Conventional Data about Unemployment Tell us the Whole Story? [online]. *Journal of Labour Market Research*, 2018, 52(3), pp. 1–12. <https://doi.org/10.1186/s12651-018-0237-9>.

BAILEY, T. AND BELFIELD, C. The False Dichotomy between Academic Learning & Occupational Skill. *Daedalus*, 2019, 148(4), pp. 164–178. DOI: 10.1162/daed_a_01765

BARANY, Z. L. AND SIEGEL, C. Job Polarisation and Structural Changes. *American Economic Journal: Macroeconomics*, American Economic Association, 2018, 10(1), pp. 57–89. DOI: 10.1257/mac.20150258

BAUER, D. AND CURRAN, P. Probing Interactions in Fixed and Multilevel Regression: Inferential and Graphing Techniques. *Multivariate Behav. Res.*, 2005, 40, pp. 373–400. DOI: 10.1207/s15327906mbr4003_5

BECKER, G. S. *Human Capital.* 3rd Ed. Chicago, IL: University of Chicago Press, 1993.

BEHRENS, K. AND SATO, Y. Labor Market Integration and Migration: Impacts on Skill Formation and the Wage Structure [online]. *CORE Discussion Paper*, No. 2006/1, February 2006. <https://ssrn.com/abstract=912668>. <http://dx.doi.org/10.2139/ssrn.912668>.

BODNER, T. Tumble Graphs: Avoiding Misleading End Point Extrapolation when Graphing Interactions from a Moderated Multiple Regression Analysis. *J. Educ. Behav. Stat.*, 2016, 41, pp. 593–604. DOI: 10.3102/1076998616657080

BOL, T. AND WEEDEN, K. A. Occupational Closure and Wage Inequality in Germany and the United Kingdom. *European Sociological Review*, 2015, 31(3), pp. 354–369. DOI: 10.1093/esr/jcu095

BREKELMANS, S. AND PETROPOULOS, G. *Occupational Change, Artificial Intelligence and the Geography of EU Labour Markets.* Working Paper 03/2020, Bruegel.

CARD, D. AND DINARDO, J. Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics*, 2002, 20, pp. 733–783.

COHEN, J., COHEN, P., WEST, S., AIKEN, L. Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences. 3rd Ed. New York: Routledge, 2003. DOI: 10.4324/9780203774441

CONLEY, J., ONDER, A., TORGLER, B. Are All High-Skilled Cohorts Created Equal? Unemployment, Gender, and Research Productivity [online]. *FEEM Working Paper No. 86/2012*, December 2012. <https://ssrn.com/abstract=2187708>. <http://dx.doi.org/10.2139/ssrn.2187708>.

CORONG, E. AND AGUIAR, A. Economic Impact of Skilled Labor Mobility within the ASEAN Economic Community [online]. In: GENTILE, E. eds. *Skilled Labor Mobility and Migration Challenges and Opportunities for the ASEAN Economic Community*, Edwar Elgar Publishing Online, 2019, pp. 57–88. <https://doi.org/10.4337/9781788116176.00010>.

CUNNINGHAM, C. AND MOHR, R. Using Tools to Distinguish General and Occupation-Specific Skills. *Journal for Labour Market Research*, 2019, 53(6), pp. 1–11. DOI: 10.1186/s12651-019-0256-1

CUNNINGHAM, W. AND VILLASENOR, P. Employer Voices, Employer Demands, and Implications for Public Skills Development Policy Connecting the Labor and Education Sectors. *The World Bank Research Observer*, 2016, 31(1), pp. 102–134. DOI: 10.1093/wbro/lkv019

DAWSON, J. Moderation in Management Research: What, Why, When and How. *J. Busin. Psychol.* I, 2014, 29, pp. 1–19. DOI: 10.1007/s10869-013-9308-7

DE LA RICA, S. AND GORTAZAR L. *Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC.* IZA Discussion Paper No. 9736, 2016.

GOVERNMENT OF INDIA. *Economic Survey, 2019–20.* Department of Economic Affairs, Ministry of Finance, Government of India, 2020, Vol. 2, Chapter 10, pp. 274–301.

GRANATO, N., HAAS, A., HAMANN, S., NIEBUHR, A. The Impact of Skill-Specific Migration on Regional Unemployment Disparities in Germany. *Journal of Regional Science*, 2015, 55(4), pp. 513–539. DOI: 10.1111/jors.12178

HARDY W., KEISTER R., LEWANDOWSKI, P. *Do Entrants Take it All? The Evolution of Task Content of Jobs in Poland.* IBS Working Paper No. 10, 2015.

HARDY W., KEISTER R., LEWANDOWSKI, P. *Technology or Upskilling: Trend in the Task Composition of Jobs in Central and Eastern Europe.* HKUST IEMS Working Paper No. 40, 2016.

HAYES, A. *Introduction to Mediation, Moderation, and Conditional Process Analysis: a Regression-Based Approach.* New York, NY: Guilford, 2013.

HAYES, A. AND MATTHES, J. Computational Procedures for Probing Interactions in OLS and Logistic Regression: SPSS and SAS Implementations. *Behav. Res. Methods*, 2009, 41, pp. 924–936. DOI: 10.3758/BRM.41.3.924

HORVATH, G. Impact of Skill Mismatch on Wage Inequality. *SSRN Electronic Journal*, 2014. DOI: 10.2139/ssrn.2380600

ILO. *International Standard Classification of Occupations.* Geneva, 2012, Vol. 1.

JOHNSON, G. Changes in Earnings Inequality: the Role of Demand Shifts. *Journal of Economic Perspectives*, 1997, 11(2), pp. 41–54.

JUDD, C. M. AND KENNY, D. A. Data analysis. In: GILBERT, D., FISKE, S. T., LINDZEY, G. eds. *The Handbook of Social Psychology*, New York: Wiley, 2010.

LIU, J. AND GRUSKY, D. B. The Payoff to Skill in the third Industrial Revolution. *American Journal of Sociology*, 2013, 118(5), pp. 1330–74. DOI: 10.1086/669498

MA, J. High Skilled Immigration and the Market for Skilled labor: the Role of Occupational Choice [online]. *Labour Economics*, 2020, 63. <https://doi.org/10.1016/j.labeco.2019.101791>.

MADAN, S. AND GOYAL, R. Impact of Location and Type of Enterprise on Extent of Informality in Haryana. *International Journal of Reviews and Research in Social Sciences*, 2019, 7(1), pp. 101–106.

MADAN, S. Outcomes of Labour Market for Informal Workers: an Analysis of Influential Factors in Haryana. *Man and Development*, 2019b, 41(2), pp. 51–70.

MADAN, S. Wage Differentials Among Workers: an Empirical Analysis of the Manufacturing and Service Sectors. *Indian Journal of Labour Economics*, 2019a, 62(4), pp. 731–47.

MASON, G. The Impact of Skills on Relative Productivity Performance at National Level: Exploring Channels of Influence. *Labour, Employment and Work in New Zealand*, 2008, pp. 29–38. DOI: 10.26686/lew. v0i0.1614

MICHAELS, G., NATRAJ, A., VAN REENEN, J. Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *Review of Economics and Statistics*, 2014, 96(1), pp. 60–77.

MOR, S. ET AL. Survival of the Smallest: a Study of Microenterprises in Haryana, India [online]. *Millennial Asia*, 2020, 11(1), pp. 57–78. <https://doi.org/10.1177/0976399619900609>.

MOR, S. AND MOR, N. Worker's Perception and MGNERGA: a Study of Sirsa District of Haryana. *Journal of Engineering Sciences and Management*, 2011, 1(1), pp. 16–21.

MOR, S., MADAN, S., CHHIKARA, R. The Risk-Seeking Propensity of Indian Entrepreneurs: a Study using GEM Data [online]. *Strategic Change*, 2020, 29, pp. 311–329. <https://doi.org/10.1002/jsc.2330>.

NSO. *Periodic Labour Force Survey (PLFS), 2017–18.* Unit level Data, Ministry of Statistics and Programme Implementation, National Statistical Office, Government of India, 2019.

OBIOLS-HOMS, F. AND SÁNCHEZ-MARCOS, V. *Education, Occupation-Mismatch and Unemployment.* Working Papers 807, Barcelona Graduate School of Economics, 2015.

ONSOMU, E. N., NGWARE, M. W., MANDA, D. K. The Impact of Skills Development on Competitiveness: Empirical Evidence from a Cross-Country Analysis. *Education policy analysis archives*, 2010, 18(7), pp. 1–21. DOI: 10.14507/epaa.v18n7.2010

PREACHER, K., CURRAN, P., BAUER, D. Computational Tools for Probing Interaction Effects in Multiple Linear Regression, Multilevel Modeling, and Latent Curve Analysis. J. *Educ. Behav. Stat.*, 2006, 31, pp. 437–448. DOI: 10.3102/10769986031004437

REIS, M. Measuring the mismatch between field of study and occupation using a task-based approach [online]. *Journal of Labour Market Research*, 2018, 52(9), pp. 1–15. <https://doi.org/10.1186/s12651-018-0243-y>.

SALVATORI, A. *The Anatomy of Job Polarization in the UK.* IZA Discussion Papers 9193, 2015.

SHI, L. P., IMDORF, C., SAMUEL, R., SACCHI, S. How Unemployment Scarring affects Skilled Young Workers: Evidence from a Factorial Survey of Swiss recruiters [online]. *Journal of Labour Market Research*, 2018, 52(1), p. 7. <https://doi.org/10.1186/s12651-018-0239-7>.

SIMINSKI, P. Are Low-Skill Public Sector Workers Really Overpaid? A Quasi-Differenced Panel Data Analysis. *Applied Economics-APPL ECON*, 2012, 45, pp. 1–15. DOI: 10.1080/00036846.2011.641928

VASHISHT, P. AND DUBEY, J. D. *Changing Task Content of Jobs in India: Implications and Way Forward.* Indian Council for Research on International Economic Relations, Working Paper No. 355, 2018.

WILLIAMS, M. AND BOL, T. Occupations and the Wage Structure: the Role of Occupational Tasks in Britain. *Research in Social Stratification and Mobility*, 2018, 53, pp. 16–25.

WILLIS, R. J. Wage Determinants: a Survey and Reinterpretation of Human Capital Earnings Functions. In: ASHENFELTER, O. AND LAYARD, R. eds. *Handbook of Labor Economics*, North-Holland, Amsterdam, 1986, Vol. 1.

WOOD, A. How Trade Hurt Unskilled Workers. *Journal of Economic Perspectives*, 1995, 9(3), pp. 57–80.

WOOD, A. *North-South Trade, Employment, and Inequality: Changing Fortunes in a Skill-Driven World.* Oxford: Clarendon Press, 1994.

ANNEX 1

Table A1 Measurement of skill level in related occupations

Skill Level	Nature of work and skill required
I	The ability to perform simple and routine manual or physical tasks, require primary education for basic numeracy, or physical fitness as per the requirement of job.
II	The operational efficiency for operating, maintenance & repair of electrical and mechanical equipment and generally require completion of secondary education for competitive performance.
III	To perform complex technical & practical tasks with technical or procedural knowledge in specialized area.
IV	The creative ability to perform complex problem-solving & decision making and require extended level of literacy and numeric ability along with excellent communication skills. This level involves completion of secondary level of territory education leading to advanced research qualifications. This level of skill level involves on job extensive experience, which in some cases may be replaced for some years of formal education.

Source: ILO (2012)

ANNEX 2

Table A2 The occupational categorization of workers corresponds to their skill level

Group	Occupational group	Occupational functionaries of the group	Sampled observations#	Mean wage (Ln)
1	Managers	Chief executives, senior officials, legislators, administrative & commercial managers, production & specialized services managers, hospitality, retail and other services managers.	2 155 (5.08 percent)	10.087
2	Professionals	Science & engineering professionals, health professionals, Teaching professionals, business & administration professionals, Information & communications technology professionals, legal, social & cultural professionals.	5 631 (13.27 percent)	9.845
3	Technicians and associate professionals	Science & engineering associate professionals; health associate professionals; business and administration associate professionals; legal, social, cultural and related associate professionals; Information and communications technicians.	6 433 (15.17 percent)	9.571
4	Clerical support workers	Occupation as general & keyboard clerks; customer services clerks; numerical & material recording clerks and other clerical support workers.	4 081 (9.62 percent)	9.670
5	Service and sales workers	Personal service workers; sales workers; personal care workers and protective services workers.	8 045 (18.97 percent)	9.150
6	Skilled agricultural, forestry and fishery workers	Market-oriented skilled agricultural workers; market-oriented skilled forestry, fishery and hunting workers; subsistence farmers, fishers, hunters & gatherers.	5 371* (12.66 percent)	9.170
7	Craft and related trade workers	Building and related trades workers, excluding electricians; metal, machinery and related trades workers; handicraft & printing workers; electrical & electronic trades workers; electronics and telecommunications installers and repairers; food processing, wood working, garment and other craft and related trades workers.		
8	Plant & machine operators and assemblers	Stationary plant & machine operators; assemblers; drivers and mobile plant operators.	5 247 (12.37 percent)	9.258
9	Elementary occupations	Cleaners & helpers; agricultural, forestry and fishery labourer; labourer in mining, construction, manufacturing, and transport; food preparation assistants; preparation assistants; street and related sales and service workers; refuse workers and other elementary workers.	5 454 (12.86 percent)	8.870
10	Armed forces occupations	Commissioned armed forces officers; non-commissioned armed forces officers; armed forces occupations, other ranks.	0000 (NA)	NA
Total number of observations			42 417 (100 Percent)	9.383

Notes: # Sampled observations used in the study. * Total from Group 6 and Group 7 together. Figure in parenthesis.
Source: ILO (2012) International Standard Classification on Occupations-08