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Specific Human Capital and Skills in Indian Manufacturing: Observed Wage and Tenure Relationships from a Worker Survey

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Abstract
Successive Indian governments have attempted to increase the growth in employment alongside encouraging skill enhancement. Against this background, we empirically explore issues surrounding the investment in specific capital by workers. In particular, we try to discern the presence of specific human capital investment by investigating whether there is a link between tenure and wages and find that there is indeed such a link evident in India. This allows us to infer that it is valuable to have long-term relations between employers and their workers and therefore labour market institutions that support long-term employer–employee relationship need to be encouraged.

Keywords Specific human capital · Indian labour market policy · Skills · Wage and tenure relationship

JEL Classification J24 · J83 · J41

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1 Introduction

Unfortunately, it is an overarching and persistent fact that job creation in the Indian manufacturing sector has fallen short of the growth in the workforce. Among the many attempts to increase employment, the current NDA government has pushed the *Make in India* policy—Starting in 2014, the critical components of this approach were to increase the growth of the manufacturing sector so that both employment in the sector and share of the sector in the national income goes up substantially. This has not quite fructified along envisioned lines with the growth of manufacturing averaging around 6.9% between 2014–2015 and 2019–2020 (as against the objective of 12 to 14% per annum), and the share of manufacturing dropped from 16.3% of GDP in 2014–2015 to 15.1% in 2019–2020 (as against an objective of 25% of GDP by 2022).[1] The changes in employment are equally dismal with sectoral contribution to total employment being constant around 12% and fall in manufacturing employment by 9 million between 2011–2012 and 2017–2018 (Mehrotra and Parida 2019). Be this as may, as an essential component of the job creation policy, the NDA government has attempted a series of programs aimed at skill formation to enhance the quality of employment—a vital input into the *Make in India* endeavour so as "to transform India into a global design and manufacturing hub".[2] In the face of the COVID-19 pandemic, the NDA government finds itself now speaking about Atmanirbhar Bharat Abhiyan, which aims to build capacities across sectors and promote local products, with the role of skill formation continuing to be a central concern.

In pursuance of this overall agenda of skill enhancement, starting in 2015 a series of policy moves were made.[3] The spirit behind these programs is to encourage public–private partnerships in the area of skilling, where the government funds entrepreneurs, who in turn skill workers in collaboration with employers and are refunded by the government based on their performance. This strategy to enhance

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[1] See key macroeconomic-indicators published by National Statistical Office, Ministry of Statistics and Programme Implementation (https://eaindustry.nic.in/Key_Economic_Indicators/Key_Macro_Economic_Indicators.pdf, last accessed 17th July 2020) and M. Suresh Babu, "Why 'Make in India' has failed". The Hindu. (https://www.thehindu.com/opinion/op-ed/why-make-in-india-has-failed/article30601269.ece, last accessed on 23rd July 2020).

[2] See About Make in India (https://www.makeinindia.com/about,last accessed on 23rd July 2020).

[3] One of the first steps in this regard was to marginally refurbish the Apprentice Act, 1961, the law which makes it obligatory for a set of employers to engage apprentices in designated trades and contribute towards setting up training institutes—Industrial Training Institutes (ITIs) and Industrial Training Centers. Those trained in these institutes are employed for a short duration by employers who participate in the apprenticeship endeavour. It needs to be noted that this arrangement is quite far removed from standard systems of apprenticeship (such as in Germany) where apprentices can look forward to long-term relationships with employers. In addition to this, a National Policy on Skill Development and Entrepreneurship was also declared in 2015, resulting in a new ministry, the Ministry for Skill Development and Entrepreneurship that is dedicated to various programs to skill the Indian workforce. Prominent among these are schemes such as the Pradhan Mantri Kaushal Vikas Yojana (PMKVY) along with other schemes like Deen Dayal Upadhyay Gramin Kaushalya Yojana (DDUGKY) and more recently the project associated with Skills Acquisition and Knowledge Awareness for Livelihood Promotion (SANKALP).

skills does not attempt to strengthen labour market institutions that can guarantee long-term employment and real wage stability—instead as time has gone by, the labour protection regime has only been weakened, culminating with the NDA ruled states effectively suspending protective labour laws during a raging pandemic,[4] and subsequently, rendering such changes more permanent by providing the legislative basis to strengthen moves by individual states to enact competitively weaker labour laws.[5] The absence of any thinking in this regard implies that the policymakers have ignored a crucial point made by Becker in his seminal work on human capital—the distinction between general human capital and specific human capital (Becker 1975). General human capital is productive across employers, while specific human capital is associated with increased productivity of the worker only to a particular employer/firm or employee-job match. Specific investments are more valuable if the match continues, than if it is truncated. If employers have invested in specific skills, they will want workers to continue, and to the extent, workers have invested in gaining the specific skills they will want to ensure returns to their investment with wage stability and long-term employment. If workers feel that the employment opportunities associated with the specific skills that they have invested in will evaporate soon, they will be reluctant to invest in these specific skills. This becomes a problem, particularly if employers need these specific skills to compete in the international market (Estevez-Abe et al. 2001). Without some guarantee of long-term employment and real wage stability, these specific skills will be undersupplied. This is indeed an important concern in a labour abundant country seeking to gain a comparative advantage by becoming skill abundant. There is, by now, a good deal of empirical support for the proposition that labour market institutions affect workers incentives to acquire firm-specific skills on the job and thereby shape the export patterns of countries (Tang 2012). While the Make in India policy seems to aspire "to transform India into a global design and manufacturing hub", the skilling policy is devoid of any recognition of specific skills. In this context there is no real attempt to check for the presence of patterns of specific human capital in India—typically a discussion of human capital in the Indian context is confined to broad general human capital concerns [See (Singh et al. 2020; Sharma 2019; Chakravarty and Bedi 2019; Mitra and Verick 2013; Mehrotra et al. 2013; Kumar et al., 2013; Dev and Venkatanarayana 2011)].

Thus, over this paper, we are motivated to explore issues surrounding the investment in specific capital by workers, attempting to assess empirical patterns of specific human capital investment. In particular, we hope to discern basic displays of specific human capital investment by crucially investigating whether there is a link between tenure and wages—this has come to be an important investigation all over

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[4] Uttar Pradesh, Madhya Pradesh, Gujarat, Rajasthan and Himachal Pradesh have initiated steps, details regarding which can be found at https://www.mondaq.com/india/employment-and-workforce-wellbeing/935398/suspension-of-labour-laws-amidst-covid-19.

[5] See Somesh Jha Codes give more power to states to be flexible on labour laws Business Standard September 4 2020 https://www.business-standard.com/article/printer-friendly-version?article_id=120092401255_1

the world, typically undertaken to signify the presence of a specific capital investment in the employment relation. We go on to raise cognate questions as to what are the motivations for workers to gain skills by training themselves and if tenure is taken as an important incentive for worker investment in the job, what factors influence such tenure. These questions are important to ask, but often enough, this type of inquiry has been absent in India, mainly on account of the lack of data (as discussed later in the paper). In the face of this, we seek to use data from a special worker-oriented survey conducted in 2017. While this was a small sample cross-section survey, it is nevertheless very valuable in helping us open up some questions concerning the Indian labour market.

We begin with Section 2, where we discuss the background literature related to specific human capital investment, providing an overall basis of our study. Next in Section 3 after a brief discussion on the lacunae in Indian labour data, we provide details regarding the survey, the type of information gathered and followed this by tabulating some noticeable patterns evident from the data. In Section 4, we describe the models we seek to estimate and define the variables used in the estimation. This is followed by Section 5, which presents the results of the estimations, and we conclude in Section 6.

2 Background and Empirical Context

The key analytical point associated with specific human capital is that it involves a series of ex-ante investment decisions by both employers and employees, which are subject to an ex-post risk of quasi-rent appropriation (Klein et al. 1978). When employers invest in specific human capital, workers can quit, putting to waste the fruits of training and recruitment costs incurred by the employer. At the other end of the relationship, there are concerns of the appropriation of quasi-rent as well, because workers who have invested in specific human capital on the job can be fired by opportunistic employers near retirement, disabusing them from enjoying the returns to investing in the job. Clearly, this leads up to hold up in investment, with both or one of the parties underinvesting. Such hold up can, of course, be mitigated by writing contingent contracts but it has been widely held that this is impossible–the incomplete contract argument. Since efficient contracts that condition relation-specific investment cannot be written, hold-up problems in human capital investment end up being governed by the legal/institutional regime, within which the relationships are embedded. A variety of theoretical discussions have discussed various responses including long-term contracts, wage rigidities, fixed-wage contracts and renegotiation [See (Hashimoto and Yu 1980; Macleod and Malcomson 1993; Grout 1984; Grossman and Hart 1986; Hart and Moore 1988 and Hermalin and Katz 1993)]. The empirical literature has also grown looking for turnover costs, forms of employment contracts and wage characteristics that are consistent with hold-up theories. Particularly prominent is the positive relationship between wage and tenure—the pioneering work of Becker, Mincer and Schultz [(Becker 1975), (Mincer 1962), Schultz (1961)] suggested that to avoid inefficient separations, costs and returns would be shared by both employer and worker and since on

the job training increases with tenure, we should also see a rise in wages alongside tenure. To explore the veracity of this proposition, a series of studies were undertaken (mainly in the late 1980s and early 1990s) using panel data in the USA—some finding a more definite positive relation between wage and tenure than others [See (Altonji and Shakotko 1987; Brown 1989 and Topel 1991)]. Since then, empirical studies investigating this relationship can be found all over the world—for example, the presence of a positive wage tenure has been noted in Germany (Dustmaan and Meghir 2005), Italy (Sulis 2014) and China (Qu and Wang 2019), among others. Given the multiple Indian endeavours to impart skills to workers, it is crucial to get a sense of how skills improve on the job and whether such skills are transferable and more importantly what are the returns to experience and seniority in this context. Unfortunately, such questions are hard to pursue because of the lack of substantial data in this regard. However, nevertheless, we have relied on a small survey to initiate an inquiry into this genre of questions in the Indian context.

3 Survey Description

3.1 Labour Data in India

Data pertaining to labour in India is strangely plentiful and simultaneously very scarce. There are several agencies and mechanisms involved in the collection of the data (Papola 2014). Labour laws produce a good bulk of the data—in a sense several labour laws decree that establishments covered by the law have to furnish returns providing information about the establishment. For example, the Annual Survey of Industries (ASI) used by scholars all over the world as the principal source of industrial statistics of India is produced by the combined requirements of the Collection of Statistics Act 1953 and the Factories Act, 1948. As per the Factories Act enterprises employing more than a certain threshold of workers (i.e. those factories employing ten or more workers using power; and those employing 20 or more workers without using power) have to submit details about their establishments, which form the basis for the data. This data and a good deal of other data associated with labour is typically gathered from the employer—and provides information only on a few labour characteristics—say, numbers employed and wages paid but little or no information on the many other worker characteristics such as educational attainment, skills, tenure or tasks undertaken in the workplace. Some of this lacuna was overcome by the data generated from surveys conducted by the National Sample Survey Office (NSSO).

The NSSO carried out quinquennial surveys on employment and unemployment with the aim to capture the many associated characteristics that include age, education, gender, social group, level of living, industry and occupational category and ends up facilitating the creation of valuations for labour force participation rate, worker population ratio, unemployment rate, industry and occupational distribution of workers, the extent of underemployment, wages of employees to name just a few of the useful indices available to us on account of this data. In the 2004 (NSSO 60th Round) some data was collected on vocational training in the 66th Round

details on education, and many aspects of work training were included. This was followed by the NSSO 68th Round undertaken in 2011–2012 where we again get some information on training and skill formation. While useful in giving us snapshots of the education and training currently gathered by sampled workers, this data tells us very little about the changes that take place over the lifespan of a worker. Furthermore, since the data is available only once in five years, one cannot do any in-depth analysis regarding trends or demand for skills. Thus, many questions asked of human capital accumulation cannot be asked in the Indian context because there is limited data. Recently the Employment and Unemployment Survey by NSSO has been replaced by the Periodic Labour Force Survey (PLFS), and this is now the primary source of labour market data at both the National and State level. The survey is oriented mainly towards collecting data on the employment status of workers but also includes questions that collection information on training. Seeking information on type of training, source of funding, duration of training and whether any training was undertaken over the last 365 days.

Thus, some additional information on skill training is becoming available, but again information on many important characteristics of workers and the jobs they do, such as the length of tenure is still missing in PLFS. Furthermore, the institution of this new survey is not without criticism—some severe lacunae have been pointed out by scholars working on labour issues in India (Kapoor 2019). All this effectively means that it is fortuitous that we could work to manage a small survey which provides some vital information that allows us to empirically explore some of the specific human capital issues on hand.

3.2 Survey Details

Our specially commissioned survey was conducted over April–June 2017, supported by a World Bank-funded project 'Jobs and Development' 2014–2016 and undertaken by the Indian Council for Research on International Economic Relations (ICRIER). This survey is linked to an earlier survey supported by the same program of the World Bank, that aimed to look at issues associated with the employment of contract workers in the Indian manufacturing sector. The earlier survey gathered data from 500 firms, with these firms being chosen using a larger ASI frame set for the year 2013–2014 and was located in five states, namely Haryana, Tamil Nadu, Maharashtra, Gujarat and Karnataka. The survey covered eight industry divisions, viz. Manufacture of Food Products; Manufacture of Textiles; Manufacture of Wearing Apparel; Manufacture of Leather and Leather Products; Manufacture of Computer, Electronic and Optical Products; Manufacture of Electrical Equipment; Manufacture of Motor Vehicles, Trailers and Semi-Trailers; and Manufacture of Other Transport Equipment. Further details regarding the survey can be gathered from our work that used data from the survey to investigate the employment of contract labour, one study covering the entire sample (Singh et al. 2019a), and another a sub-sample confined to the state of Haryana (Singh et al. 2017), as well as a study looking at union activity in the manufacturing sector (Singh et al. 2019b).

Table 1 Industry groups covered.

| NIC-2008 (2 Digit)	Industry group (NIC-08)	Industry group (Survey)
10	Manufacture of food products	Food processing
13 + 14	Manufacture of Textiles + Manufacture of Wearing Apparel	Textile and garments
15	Manufacture of Leather and Related Products	Leather and leather Products
26 + 27	Manufacture of Computer, Electronic and Optical products + Manufacture of Electrical Equipment	Electronics and computer equipment
29 + 30	Manufacture of Motor vehicles, trailers and semi-trailers + Manufacture of Other Transport Equipment	Auto products

(*Source: Authors own compilation*)

The worker-oriented study survey used in this paper aimed to ask questions regarding human capital accumulation from workers instead of employers, covering workers from the same set of industry groups covered in the earlier employer-oriented survey. The five industry groups located in districts of the State of Haryana, neighbouring Delhi, are Food Processing, Textile and Garments, Leather and Leather Products, Electronics and Computer Equipment and Auto Products, which can be mapped to eight Industry groups as per NIC-08 Classification as shown in Table 1 below.

Haryana is a state located in the northern part of India which contributed 3.63% to India's GDP in 2017–2018. The Industrial sector contributed 32% towards state's GSVA in 2017–2018 at constant (2011–2012) prices, and the industry has grown at a CAGR of 7.50% between 2011–2012 and 2017–2018. The total number of people engaged in organised manufacturing during 2017–2018 was 8.42 lakh, which is approximately 6% of the All-India total.

Unlike other industrial states such as Tamil Nadu, Gujarat, and Maharashtra, the state has no coastal border or any major port to facilitate trade through the sea. The state is a leading state in terms of production and exports of automobile products such as passenger cars, two-wheelers, mobile cranes & tractors. Maruti Udyog Ltd., Hero MotoCorp Ltd, Yamaha Motor Pvt Ltd. and Escorts Group are some of the leading automobile companies based in Haryana. The Gurgaon–Manesar–Bawal belt is the auto hub of India. Apart from automobiles, the other major industry in the state is the textile and wearing apparel industry employing around 1.77 lakh people. Districts such as Panipat, Gurugram, Faridabad, Hisar and Sonipat are the textile centers in Haryana and engage in production and exports of primarily the cotton readymade garments.

In Haryana, the proportion of workers employed as contract workers is one of the highest among the Indian states. In 2013–2014, out of every 10-worker engaged in manufacturing, about 5 of them were on a contract job. The two charts below provide trend and contrast Haryana with All India in terms of worker engagement. The state has witnessed significant worker unrest as well

Panel A: Harayana   Panel B: All-India
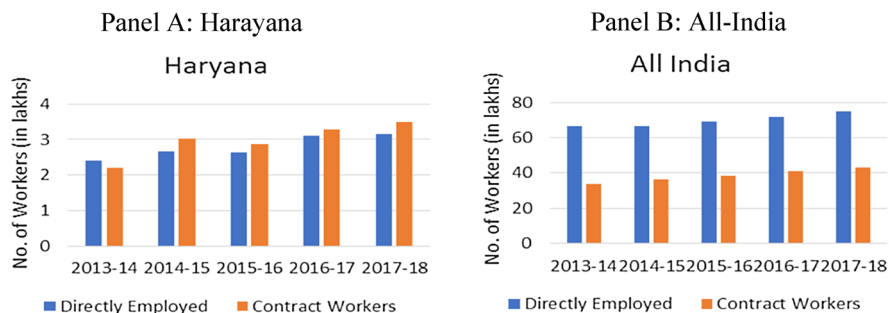
Fig. 1 Directly Employed v/s Contract Workers in Manufacturing: Haryana and All-India. Panel A: Harayana, Panel B: All-India. (*Source: Various Issues, Annual Survey of Industries, Ministry of Statistics and Programme Implementation, Govt. of India.*)

owing to this practice, the 2012 violence incidence at Maruti Suzuki factory in Manesar was one such event. Given the industrial nature and practice of employing workers on contract, Haryana is the ideal state in the northern region of India to study the issue of relationship-specific investment in India (Fig. 1).

The survey collected information on skills, tenure and wages of workers from a sample of 100 workers engaged in the organised sector. Ideally, we would have liked to work with a larger sample, but resources limited us to canvass a small sample. We were confronted with two questions—one, how many workers need to be surveyed from each industry and two, how to choose the worker to be interviewed? To keep some parity with the earlier employer-oriented survey, we used the ASI frame 2013–2014. We computed the total number of persons engaged in each of the Industry Groups as a ratio to the total number of persons employed across all five Industry Groups. This share then allowed us to decide how many workers to allocate to out of 100 to each industry group. (For example, the Food Processing Industry Group engaged 52,816 persons, which was about 8% of the total number of persons employed across all Industry Groups, which meant that eight workers belonging to the Food Processing Industry Group were canvassed during the survey.) To choose the specific worker, each worker employed in the industry was given a random number and five times the number of workers chosen to represent the industry were chosen randomly and located by identifying the firm employing them as per the ASI frame 2013–2014. We proceeded to interview the stipulated number of workers for each industry working down the list. (For example, in the Food Processing Industry we worked with a pool of 40 workers each associated with an identifiable firm, and out of this pool eight workers were interviewed working down the list—if a worker from a firm could not be found we moved to the next worker on the list.)

Turning to a description of the questions canvassed—workers were asked to identify their status as a regular, contract or casual labour, wage levels, education details, how long they have been in the current job and other details regarding their past experience, details and attitudes regarding skilling and training as well as their views on links between skills learnt and job regularisation.

4 Models and Explanatory Variables

Our primary target over this paper is to see if we can detect some basic configurations of specific human capital investment, using the data we have on hand. Thus, we aim to see whether there is a link between tenure and wages, if tenure is taken as an important incentive for worker investment in the job what factors influence such tenure, and what are the motivations for workers to train or invest in skilling on the job. This is attempted by looking at three sets of relationships – (i) Wage–Tenure Relationship (ii) Determinants of Tenure (iii) Drivers of Worker Training. We proceed below to describe the empirical models that we use to look at these relationships.

4.1 Wage–Tenure Relationship

In the first exercise, we attempt to look at the wage–tenure relationship, suggesting that the underlying relationship, following the specifications in much of the literature, can be captured by

$$W_i = f(X_i, T_i, V_i) \tag{1}$$

where W_i is the wage of worker i; the coefficient of X_i is the return to general human capital, gathered by gaining experience and captured empirically as the total market experience; T_i represents job-specific capital, empirically measured as the tenure with the employer; and V_i includes other characteristics, which may be person-specific or industry-specific. We include three variables as components of V_i in our empirical model, the Skill level of the worker, the nature of job—regular or contract worker and to capture the role of industry-specific factors in wage determination, the industry in which the worker is employed. To be able to adapt this model to the data on hand we have to, among other things, represent wages in a limited dependent variable format because the data on wages was collected in wage bands. Thus, the empirical model that was estimated is of the form[6]

$$
\begin{aligned}
W_i^* &= \beta_1 X_i + \beta_2 T_i + \beta_3 S_i + \beta_4 R_i + \beta_5 I_i + \varepsilon_i \\
W &= 0 (W* < 6000) \\
W &= 0 (W* < 6000) \\
W &= 1 (6000 < W* < 9000) \\
W &= 2 (9000 < W* < 12000) \\
W &= 3 (12000 < W* < 15000) \\
W &= 4 (15000 < W*)
\end{aligned}
\tag{2}
$$

where W_i^* and W_i are the latent and observed variables relating to wages received by worker i, respectively, and are believed to depend on X_i the general human capital

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6 The numbers are in Indian Rupees and the intervals the ones used in the survey.

of the worker (measured as the age of worker), T_i the specific human capital of the worker (measured as the years spent in the current job), S_i the skill level of the worker, R_i whether the worker is a regular or contract worker and I_i the industry in which the worker is employed. The term ε_i is an error term and we assume that it is normally distributed—this assumption allows us to estimate the model as an Ordered Probit Model and we estimate the parameters of the model $\beta_1 \ldots \beta_5$ using the Maximum Likelihood method.

4.2 Determinants of Tenure

As a follow-up from the previous model, it was thought it would be useful to see if we can identify some factors that may be influencing the tenure of workers. Thus, the equation we estimate is

$$T_i = g_0 + g_1 F_i + g_2 E_i + g_3 S_i + g_4 R_i + g_5 ET_i + g_6 H_i + g_7 X_i + g_8 SBR_i + e_i \quad (3)$$

where T_i is the tenure, dependent variable and the independent variables include worker related characteristics such as whether the worker stays with family (F_i), education levels of the worker (E_i), the skill level of the worker (S_i), whether the worker is a regular or contract worker (R_i), whether the employer-provided training or not (ET_i), hours worked by the worker (H_i), age of the worker (X_i) and the job regularisation policy of the employer was contingent on skills (SBR_i). We assume the error term is independently, identically and normally distributed and we use the method of Ordinary Least Squares to estimate the parameters of the equation $\gamma_0 \ldots \gamma_8$.

4.3 Worker Training or Propensity to Train

In pursuit of our attempts to see whether our data provides some evidence about the training of workers as a firm-specific human capital investment, we look at the factors that affect the propensity of workers to be trained. It is impossible from the data to look into the psychological profile of workers. However, we can infer inclinations from observed actions of reported participation in training endeavours—the fact that a worker reports training reflects his inclination. Thus, we look at factors that may be influencing the propensity of workers to undergo training on the job. The model characterising the propensity to be trained as follows:

$$\begin{aligned}
Y*_i &= \eta_0 + \eta_1 E_i + \eta_2 T_i + \eta_3 X_i + \eta_4 S_i + \eta_5 PT_i + \eta_6 R_i + \eta_7 L_i + u_i \\
Y_i &= (Y_i^* > 0) \\
Y_i &= 0 (Y_i^* = 0)
\end{aligned} \quad (4)$$

where Y_i^* and Y_i are the latent and observed variables related to the propensity to be trained. Here the observed variable takes note if the worker reported any training on the job whatsoever. The independent variables include E_i which represents

the education level of the worker, T_i the tenure or the number of years the worker has worked in her current job, X_i the age of the worker, S_i skills of the worker, PT_i whether the worker says he would pay to be trained, R_i captures the type of worker-contract or regular and L_i represents the nature of the industry in which the worker is employed-labour intensive or capital intensive. The error term u_i is assumed to be normally distributed, and the parameters of the model $\eta_0 \ldots \eta_7$ are estimated as a probit model using the Maximum Likelihood method.

4.4 Description of Variables

The empirical estimates of models described above involve a number of variables, and we proceed to describe the content of these variables.

Age Worker (X_i) This variable consists of the reported age of the worker. Since we do not have any information regarding the number of years the worker has worked, which is the usual measure for general human capital, we use the age of the worker as a proxy for general human capital.

Industry (I_i) This variable captures the industry in which the worker is employed viz. *Auto Components, Food Processing, Electronic Appliances, Garments and Leather*: As noted earlier, the survey covered workers working in five industries groups located in the State of Haryana namely Food Processing, Textile and Garments, Leather and Leather Products, Electronics and Computer Equipment and Auto Products. While estimating parameters of models that we have specified, these industries appear as dummy explanatory variables.

Labour Intensive (L_i) In the estimation of Eq. (4) that looks at the propensity of workers to train, we collapse the five industries mentioned above into labour-intensive industries (Garments, Leather, Food Processing) and capital-intensive industries (Auto Products and Electronics). This division is made based on the capital-labour ratio value of these industries between 2009 and 2014. The industries which have a capital-labour ratio value higher than the average value of the five industries combined are taken as capital-intensive industries, whereas the industries, having a lower average capital-labour ratio value than the overall average is taken as labour-intensive industries.

Education Worker (E_i) The workers reported their level of education in the survey. Given the small size of the sample, it is difficult to use the information in a finely portioned manner, so education appears in the equations as a dummy variable taking the value of unity if the worker's education level lies between passing 10th Class and being a college graduate and taking the value zero if illiterate or passed a class till the 8th Standard.

Hours Worked (H_i) The surveyed workers were asked whether they worked 8-h, 10-h or 12-h shifts and based on this information we construct a binary variable which takes the value of one if the worker works an eight-hour shift and zero if they work 'ten hours' or 'twelve-hour' shifts.

Employed Present firm (T_i) We asked the workers surveyed, how long they had been working in the establishment where they were currently employed. This

variable is taken as our measure of tenure and is our measure of specific human capital.

Employer Training (ET$_i$): We asked the workers, whether they were trained by their employers or not and based on this information the variable takes the value unity if the answer was in the affirmative otherwise it takes the value zero.

Job training (Y$_i$) The survey questioned workers, whether they received any training, whether initiated by the employer or otherwise, forming a broader set than the previous variable. We use this information to construct a binary dependent variable (Model 3) which captures the effects of a latent propensity to train by workers which can't be observed directly.

NSQF (S$_i$) This is an attempt to measure the skill of a worker using information reported in the survey as to the tasks performed by the worker. Recently the Indian government has identified a National Skill Qualification Framework (NSQF), which categorises tasks/jobs based on complexity on an ascending scale of 1–10. We took the tasks reported by workers in our sample and slotted them in the categories put out by the NSQF. Our sample showed a range between 2 and 5, and we decided that we would label workers with a score of 4 & 5 as being more skilled than those with a score of 2 and 3. This is an interesting index to use because it captures the complexity of tasks performed by a worker and which is reflective of the innate ability of the worker and an overall association with investment in human capital linked to the worker. While estimating parameters, these skill levels appear as dummy explanatory variables.

Paid Training (PT$_i$) Questioning the workers expressing the willingness to train, whether they would pay for training, and some said they would while others said they would not. We use this information to create a binary variable which takes the value of unity if the worker says he will pay for training and zero otherwise.

Skill Based Regularisation (SBR$_i$) We questioned the workers if their employer had a regularisation policy. For those that said "Yes" (see the discussion on *Patterns Evident from the survey* above) were asked whether the skills learnt formed the basis on which their employer gives them a 'permanent' job and if they said 'Yes' the variable takes the value of the unit or zero otherwise.

Worker Family (F$_i$) Over the survey, the workers were asked whether the worker stays with his family or not. This variable takes the value of unity if he stays with his family and a value of zero if he does not. This variable attempt to measure job-specific investment by the worker—if he lives with his family, then he has invested in establishing a home nearby.

Worker Type (R$_i$) This variable takes the value unity if the worker reports that he has a regular job and zero if he said that he worked as a contract worker, giving us a sense as to which segment of the labour market he belongs.

Wage Category (W$_i$) The workers surveyed were asked information about their monthly pay by identifying in which of the five categories listed in the survey questionnaire, their pay could be placed. These categories (Rupees per month) included (a) less than 6000, (b) 6000–9000, (c) 9000–12,000, (d) 12,000–15,000 and (e) more than 15,000. The collection of wage information in wage bands was done purposely since obtaining point estimates for wages could have induced measurement bias on account of reluctance in reporting precise amounts.

Table 2 Regression Summary Statistics.

Variable	Mean	No of observations	Standard deviation	Min.	Max.
Age worker (X_i)	29.20	96	7.01	19	52
Auto components (I_i)	0.31	96	0.47	0	1
Wage category (W_i)	0.62	95	0.73	0	3
Education worker (E_i)	0.76	95	0.43	0	1
Hours worked (H_i)	0.11	96	0.32	0	1
Electronic appliances (I_i)	0.06	96	0.24	0	1
Employed present firm (T_i)	3.00	96	3.05	0.08	16
Employer training (ET_i)	0.28	96	0.45	0	1
Food processing (I_i)	0.08	96	0.28	0	1
Garments (I_i)	0.48	96	0.50	0	1
Job training (Y_i)	0.29	93	0.46	0	1
Labour intensive (L_i)	0.63	96	0.49	0	1
Leather (I_i)	0.06	96	0.24	0	1
NSQF (S_i)	0.68	96	0.47	0	1
Paid training (PT_i)	0.33	95	0.47	0	1
Skill Based Regularisation (SBR_i)	0.77	94	0.43	0	1
Worker Family (F_i)	0.52	96	0.50	0	1
Worker Type (R_i)	0.40	96	0.49	0	1

(*Source*: ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

Table 3 Maximum Likelihood Estimates of the Ordered Probit Model Wage– Tenure Relationship.

Dependent variables: wages	
Explanatory variable	Coefficients
Age Worker (general K) (X_i)	0.044** (0.020)
Employed present firm (specific K) (T_i)	0.135** (0.058)
NSQF (S_i)	1.348*** (0.413)
Garments (I_i)	2.081** (0.965)
Auto components (I_i)	1.804* (0.923)
Electronic appliances (I_i)	2.739*** (1.043)
Food processing (I_i)	2.698** (1.106)
Worker type (R_i)	0.540* (0.321)
Log-likelihood	−68.561
Pseudo R2	0.279

(*Source:* ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

***Significant at 1% level, **Significant at 5% level *Significant at 10% level

Values in parenthesis represent Standard Errors

Most of the above 14 variables are dummy variables except for the variables capturing the age and tenure of workers. The summary statistics of the variables can be seen in the accompanying Table 2. The overall sample comprised 96 workers as 4 of them had to be dropped due to reporting issues.

5 Empirical Results

Over this section, we present the results from our estimations of Eqs. (2), (3) and (4) described in Sect. 4—reflecting the wage–tenure relationship, the determinants of tenure and the propensity of workers to train, respectively. The results appear statistically robust and prima facie indicate support for the view that specific human capital is quite important in the Indian manufacturing sector.

5.1 Estimates of the Wage–Tenure Relationship

The maximum likelihood estimates of the model endeavouring to capture the wage–tenure relationship can be seen in Table 3. As mentioned earlier, the age of the worker stands in as a measure of general human capital since the data was not able to give us a figure for the total work experience of the worker. The number of years that the worker had worked in the place of current employment is our measure of the specific human capital. The NSQF classification is a measure of the type of job pursued by the worker while simultaneously measuring skill. We also include the type of worker—whether hired as a regular worker or contract worker to see if there is a link between such categorisation and wages. Apart from this, the next set of variables seek to capture industry-level effects. This is captured by setting up dummy variables in relation to the leather industry, depending on whether the worker worked in the Garment, Auto Components, Electronic Appliances or Food Processing industries. By including these other variables, we have attempted to minimise problems of misspecification as can be seen in Table 6 displaying the diagnostic tests associated with the estimated model that the results of the link test in STATA indicate that there is no misspecification and other diagnostic values are well within reasonable bounds.

The results show that all the variables are significant and have a positive sign. Thus, the variables of interest namely the age of the worker—reflecting a dimension of general human capital and the number of years employed in the current firm—reflecting human capital specific to the job are positively and significantly related to wage levels. The positive and significant relationship with the NSQF further links specific human capital (the more skilled/complex job) with wages. The dimensions of the wage tenure relationship are explicitly evident when viewed graphically, as shown in Fig. 2. Here we see that the predicted probability of drawing a worker with a long tenure declines if she is in the lowest wage bracket (Rupees 6000 to Rupees 9000). In the next wage bracket (Rupees 9000–12,000) the probability rises, hitting a maximum of around 10 years but then tapers down. Over the next two higher wage brackets (Rupees 12,000–15,000 and More than Rupees 15,000) the probability of
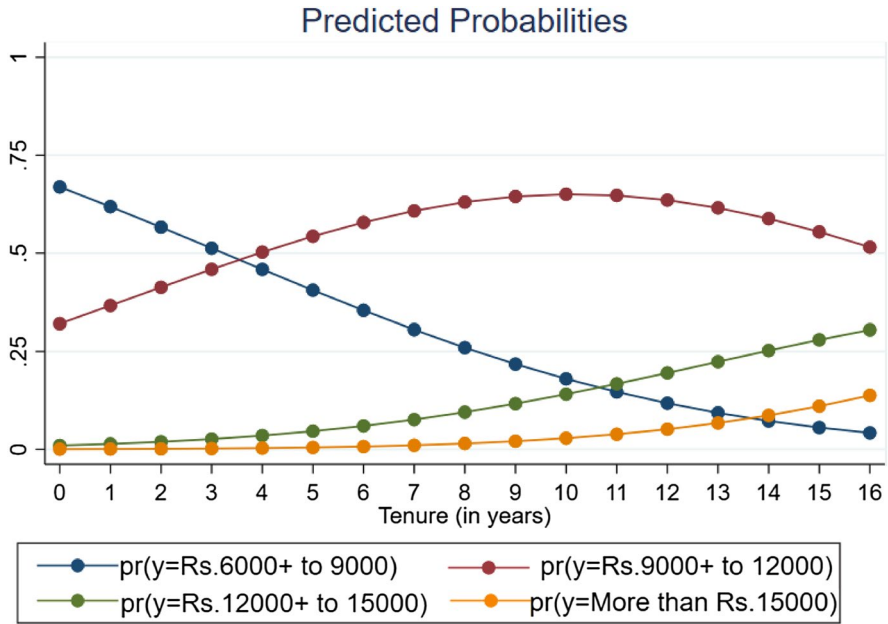
Fig. 2 Tenure and Wages: Predicted Probabilities. (*Source*: Authors' computation based on ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

drawing a worker with long tenure is not as high as the previous bracket but nevertheless is increasing.

While this model only uses a cross-section data where typically large extensive long-term data sets are used, it nevertheless provides reasonable and robust support for the proposition that there is a wage tenure relationship present in the Indian manufacturing sector. This in turn gives us attendant support that specific human capital is present and important in the Indian manufacturing sector.

5.2 Determinants of Tenure: Estimates of the Model

Given the information available within our data set, it is important to see if we can identify some of the factors that might be influencing the tenure of workers. In other words, we try to see if we can identify some of the characteristics of workers that have been with a firm for a relatively long time. Of course, the wage paid is not included due to obvious endogeneity problems. We linked tenure (as dependent variable) with whether the worker stayed with his/her family, education levels, the NSQF value of the job, whether the worker had a regular job or was a contract worker, whether trained by the employer, whether the worker worked an eight-hour shift or longer, the age of the worker and whether the worker reported skill-based regularisation by their employer.

Table 4 OLS Estimates-
Determinants of Tenure

| Dependent variable: tenure (experience on the current job)	
Explanatory variable	Coefficient
Worker family (F_i)	−0.0220 (0.706)
Education worker (E_i)	−0.275 (0.881)
NSQF (S_i)	1.099* (0.510)
Worker type (R_i)	1.600*** (0.817)
Employer training (ET_i)	1.675*** (0.634)
Hours worked (H_i)	−2.031** (0.848)
Age worker (X_i)	0.135*** (0.051)
Skill based regularisation (SBR_i)	−0.921 (1.194)
Cons	−1.742 (1.357)
R-squared	0.357***

(*Source*: ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

Values in parenthesis represent Robust Standard Errors

The OLS estimates of the model are shown in Table 4. As can be seen, neither the fact that the worker lives with his family nor education levels is significant. Apart from perhaps reflecting the point that the education variable is not very finely partitioned and that this may be contributing to the insignificant result, it could also suggest the fact that much of the specific capital associated with the job is learned on the job rather than through education. This is evident from the significance of the variable capturing whether an employer imparts training—this perhaps reflects the idea that the employer (and the worker) are investing in a long-term relationship. This is no doubt reflected in the strong significance of the relationship between tenure and whether the worker has been employed on regular terms or a contract worker. The higher complexity/skill of the job is also associated significantly (albeit at the 10% level of significance) with tenure. The fact that the relationship between those who report working more than the reasonable eight hours and tenure is negative indicates that vulnerable low skilled workers are pushed to short tenures. The variable asking workers their subjective opinion as to whether skills they have learnt enable more permanent jobs was not significant in explaining tenure.

As part of diagnostics, the Ramsey Reset Test has been undertaken, with P-value of 0.491 the null hypothesis of No Omitted variable bias is accepted. The mean VIF for the model estimated is 1.27, ruling out multicollinearity. Overall, the significant correlates with tenure support the view that longer tenure is associated with situations where specific capital is important—where the nature and complexity of the job demand it, and the employer sees virtue in training the worker on the job.

Table 5 Maximum Likelihood Estimates of the Probit Model-Worker Training

Dependent variable: the propensity to skill	
Explanatory variable	Coefficient
Education worker (E_i)	1.084* (0.595)
Employed present firm (T_i)	0.164**(0.074)
Age worker (X_i)	−0.016 (0.027)
NSQF (S_i)	0.487 (0.394)
Paid training (PT_i)	−0.579 (0.379)
Worker type (R_i)	1.208*** (0.384)
Labour intensive (L_i)	−0.869** (0.394)
Cons	−1.748*(1.034)
Log-likelihood	−38.322
Pseudo R2	0.307

(*Source:* ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

Values in parenthesis represent Standard Errors

Table 6 Regression Diagnostics and Goodness of Fit (*Source*: Authors' computation based on ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

Measures	Wage tenure model	Propensity to skill model
Log-likelihood: model	−68.563	−38.322
Log-likelihood: intercept-only	−95.175	−55.332
Chi-square: deviance	137.125 (df = 84)	76.645 (df = 83)
Chi-square: LR	53.225 (df = 8)	34.019 (df = 7)
Chi-square: p-value	0.000	0.016
R-square: McFadden	0.280	0.307
R-square: McFadden(adjusted)	0.164	0.163
R-square: McKelvey & Zavoina	0.547	0.551
R-square: Cox-Snell/ML	0.429	0.312
R-square: Cragg-Uhler/Nagelkerke	0.496	0.443
R-square: Count	0.653	0.802
R-square: count(adjusted)	0.298	0.333
Information criterion: AIC	159.125	92.645
AIC divided by N	1.675	1.018
Information criterion: BIC	187.218	112.732
Variance: e	1	1
Variance: y-star	2.209	2.228
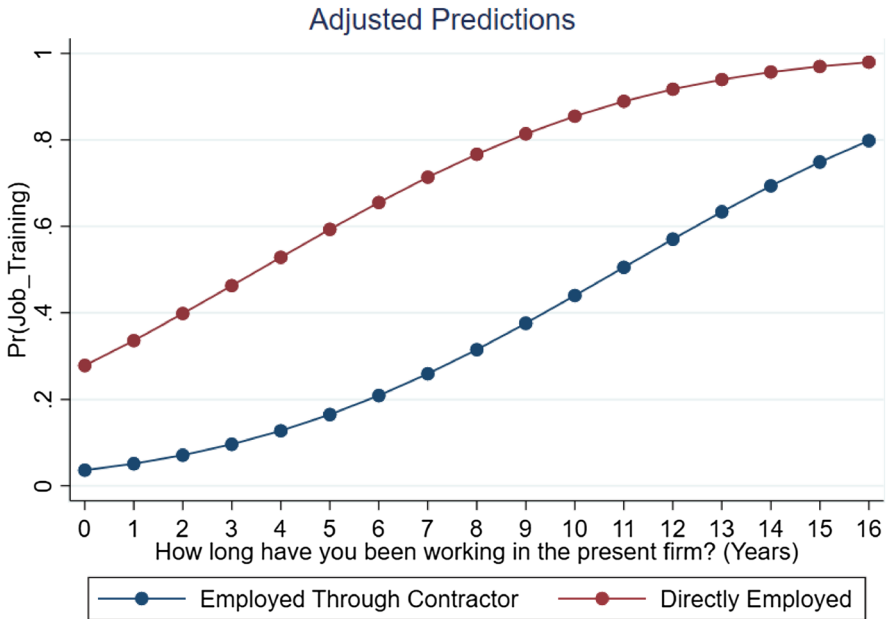
Fig. 3 Job Training and Tenure: Predicted Probabilities (*Source*: Authors' computation based on ICRIER Worker Survey on Labour issues in Indian Manufacturing sector 2017)

5.3 Worker Training: Estimates of the Model

The last model in this study attempts to capture the factors that influence the propensity of workers to train or in other words, gain specific human capital. While we cannot observe the latent variable namely the inclination of workers to train, but only observe as to whether they were trained or not, our model aims at a maximum likelihood estimate of a Probit model. Thus, in Table 5, we see the coefficients associated with a series of variables with respect to whether training is imparted to a worker or not. These variables include worker education levels, tenure, age, NSQF levels, whether the worker has a regular job or is a contract worker whether the worker is willing to pay for training or not and whether the worker works in a labour-intensive industry. The measures of goodness fit for the model are presented in Table 6.

The age of the worker is insignificant, and so is the variable where workers state whether they are willing to pay for training or not. The NSQF value of the job is also insignificant, most probably reflecting the point that workers who perform already skilled tasks are not trained further. Turning to other variables, the propensity to train is significantly linked to education levels and so is the tenure level, both along expected lines. Also, significant but with a negative sign, it appears that workers associated with labour-intensive industries have less of a propensity to train than those in capital intensive industries. The most interesting and significant result is associated with the variable that captures whether the worker is a regular worker or a contract worker. This result tells us that regular workers have a propensity to get

trained, but contract workers do not—in other words, contract workers may not have an incentive to invest in the job. This is indicative of the enormous segmentation in the Indian labour market and is very well illustrated in Fig. 3. Using the underlying estimates of parameters of the model it plots the probability of two types of workers–regular and contract, who has been employed for varying years in the present firm, of undergoing training. As can be seen, workers who are directly employed have a greater chance of undergoing training than their counterpart who is employed through a contractor.

5.4 Summing up over the three models

The predominant finding of our empirical investigation is that there is a reasonably strong link between wages and tenure, allowing us to infer that a value can be ascribed to the continuation of relations between employers and their workers rather than truncating the relationship. In other words, with due admission that we are working with a small sample, we have reasonably robust support to acknowledge the presence of relationship-specific human capital in the Indian manufacturing sector. As we turn to the linkages between tenure and the characteristics of workers—it appears that longer tenure is the device through which both employers and workers seem to overcome hold-up problems, evident in our findings that employers pay for training workers who have a longer tenure and that more skilled workers have longer tenures than those who are less skilled. However, the most interesting finding of our empirical investigation has been to see the link between tenure and the type of worker—clearly being a regular worker with more substantial labour rights gets her a longer tenure than a contract worker. In this the patterns that we gathered from the more subjective inputs of our survey showing that contract workers wait with some expectation to become regular workers may condition some of the learning on the job—but till this is fructified, such workers are probably not investing in the job on hand. To the extent we can see the propensity to train as a proxy for expressing a desire to invest in skilling for the job, our results show that regular workers have a greater propensity to train and gain skills rather than contract workers. It can be effectively gathered from this—since a good amount of employment in the manufacturing sector is in the form of contract employment (36% of the workers in the manufacturing sector are contract workers[7])–there is a loss of specific human capital. The large-scale advent of contract labour in the Indian manufacturing sector can be traced to a Supreme Court of India judgment—after the Steel Authority judgment,[8] Indian employers have been able to hire workers through labour contractors, paying such workers lower wages and effectively denying them any long-term claims on their job (Das et al. 2017). Several studies have made it apparent that contract labour allows employers to use the segmented labour market to bargain lower wages for regular workers [See (Singh et al. (2019a, b), (Kapoor and Krishnapriya 2019), (Sen

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[7] Based on estimates from Annual Survey of Industries (ASI) 2017–2018 report (http://www.csoisw.gov.in/CMS/UploadedFiles/VolumeI_2017_2018.pdf, last accessed on 23rd July 2020).

[8] Steel Authority of India v. National Union Water Front Workers AIR 2001 SC 3527.

and Maiti 2013)]. This benefit comes at a cost and a good portion of this cost comprises of the inadequate specific human capital gained by contract workers. In the new *Code on Industrial Relations* enacted recently to replace existing labour laws,[9] it appears that contract labour may gain some rights but regular workers will lose many existing rights—thus, prima facie it looks like it that the effects of the new law on the formation of specific human capital are not very promising.

6 Concluding Comments

Invoking a much larger data source than we have used, estimates from 2017 to 2018 PLFS report show that nearly 90% of the population in the age group 15–59 years have not received any vocational training. Out of the remaining 10% who have received the training, only 2% point has received through the formal channel which is associated with a structured educational institution resulting in diploma/certificates and qualifications. The three industries that account for 40% of those receiving the formal training are Electrical, Power and Electronics, IT/ITes and Textiles and Handlooms Apparels. In terms of employment outcomes, 12.4% of those who were formally trained were unemployed. Most importantly it turns out that non-formal sources of training which include hereditary, self-learning, learning on the job and other non-formal training are the most prominent methods of skilling. Among these the learning on the job is the most popular source of non-formal skill formation. It is against this background that as we noted in the introduction, the Indian state is desirous of skilling workers sufficiently so that Indian manufacturing output and exports compete in the international market. This cannot be done without enhancing both general and specific human capital—without expanding both categories of human capital, it is hard to imagine up a sizeable skilled workforce. However, for investment in specific human capital to go up, the inherent hold-up problems must be mitigated, and that means having labour institutions in place that can prevent hold-ups on the part of the worker, which in turn implies more secure worker rights. While pre-existing laws may need reform but the current move in the face of the COVID 19 pandemic to suspend labour laws, followed by the enactment of new labour laws that weaken labour rights, counters the aspiration to have a skilled workforce. It is indeed challenging to think how the current Atmanirbhar Bharat Abhiyan policy of the Indian Government will fructify.

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[9] See Somesh Jha 'How 3 labour codes aim to reform employment contract, lay-off, work safety' *Business Standard* September 09 2020 https://www.business-standard.com/article/printer-friendly-version?article_id=120090900775_1.

impossible to write were it not for Prof Deb Kusum Das, our co-author, who unfortunately passed away well before his time.

Declarations

Conflict of interest Opinions and recommendations in the paper are exclusive of the author(s) and not of any other individual or institution to which authors are associated. The authors declare that they have no relevant material or financial interests related to the research presented in this paper.

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