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Research Paper

Human Capital and Innovation Nexus in India: Evidence from Simultaneous Equation Modelling

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ABSTRACT

Using a simultaneous equation model, the present study attempts to empirically, investigate the interrelationship between human capital and innovation in Indian context. The study is conducted by taking all the 36 Indian states and Union territories into consideration from a regional perspective, focusing mainly on the quantification of the factors used. Since the simultaneous equation model is often subject to the problem of simultaneous bias and endogeneity, instrumental variable method using Two Stage Least Squares (2SLS) has been utilised to overcome the issue. In fact, the 2SLS provides the evidence of bidirectional spatial causality between human capital and innovation for Indian states, which holds significant policy implications for the country. Given a large demographic dividend in the form of highest working age population in the world, India could reap its benefits by promoting investments in the soft infrastructure such as health, education, and labour skills. This could help to boost its economic growth in the long run.

HIGHLIGHTS

- This study constructs human capital index and innovation index for 36 Indian states and union territories using principal component analysis.
- Using a simultaneous equation model, the study investigated the inter-relationship between human capital and innovation for Indian states.
- This study provides empirical evidence of a two-way relationship between human capital and innovation for Indian states
- Empirical findings of the study emphasize that countries like India, which has the largest working-age population in the world, can reap the full benefits of the demographic dividend by promoting investments in soft infrastructure such as health, education, and labor skills.

Keywords: Labour Productivity, Economic growth, Simultaneous equation model, Instrumental Variable Regression, Two Stage Least Squares

The classical theory of economic growth had considered labour productivity, as an exogenous variable, which in turn depends upon ratio between the work force and physical capital. Although this theory considered other factors like technical progress for instance, it completely ignored the role of the key variables like education and their possible beneficial effects on total productivity growth. However, the theories of economic growth that emerged in the decade of 1980s attempted to fill this gap, by laying larger emphasis on the elements of human capital like health and education in the context of long run economic growth. On the other hand, the theory of market value and the studies related to it, found the increasing evidence of the market value of companies being influenced by the

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intangible assets like patents, intellectual property rights, research, and development. Gradually the consensus emerged that, innovation , is as a key factor that promotes economic growth at the macro level and has a significant role in increasing the profits and market share of business firms at the micro level (Aghion & Howitt, 1992; Dakhli & De Clercq, 2004; Grossman & Helpman, 1991; Hasan & Tucci, 2010; Lucas, 1988; Pathak *et al.* 2016; Romer, 1986; Schultz, 1961; Schumpeter, 1934; Solow, 1956; van Uden *et al.* 2017).

Productivity is boosted by innovative output and for this to happen, it is prerequisite for a country's human capital to possess enough skills to translate the research and development initiatives into innovative output. Thus, the key characteristic of human capital includes the skills, knowledge and experience of the workforce (Kale & Rath, 2019; Kathuria, n.d.; Mariz-Pérez, Teijeiro-Álvarez, & García-Álvarez, 2012; NITI Aayog, 2019; Uden *et al.* 2014; WIPO, INSEAD, & Bussiness, 2021). In fact several studies (Capozza & Divella, 2019; D'Amore, Iorio, & Lubrano Lavedera, 2017; Diebolt & Hippe, 2019; Faggian & McCann, 2009; Fonseca *et al.* 2019; NITI Aayog, 2019; OECD/Eurostat, 2018; Schoellman, 2012; Uden *et al.* 2014; Ugalde-Binda *et al.* 2014; WIPO *et al.* 2021) strongly argued that, that human capital strengthens nation's productive capacity to absorb and develop new knowledge and is an important part of catch-up innovations. Even when a country adapts technologies and products that are already available elsewhere, it still requires a workforce that possesses appropriate skills and technical know-how, to work with the adapted technology. Thus, the innovation potential of a country largely depends on the intangible assets and knowledge its work force possesses, and the ability to use the knowledge at hand. It is these intangible assets otherwise called as intellectual capital, that forms a major part of human capital.

However, despite the key role played by the human capital in a country's economic growth, it is in the last two decades of 21st century, witnessed a significant growth in the body of literature on the issue of the role of human capital in innovations and its impact on the Total Factor Productivity (TFP) growth (Alawamleh *et al.* 2019; Benhabib & Spiegel, 1994; Diebolt & Hippe, 2019; Lucas, 1988; Maudos *et al.* 1999; McGuirk *et al.* 2015; Miller & Upadhyay, 2002; Romer, 1990). While these studies enhanced the literature in this area of research, most of them have been conducted from a country perspective, thus leaving a lacuna in the literature that focuses on the role of human capital on innovation from a regional perspective. It would be more interesting in Indian context, given the largely diverse socio, economic backgrounds of each state and union territory.

In this context, the present study attempts to fill this gap and aims at exploring the link between human capital and innovation at the state level in India. A human capital and innovation index for 36 Indian states has been developed separately. The Human Capital Index (HCI) is created using three relevant proxies such as survival rate, health index and educational index. Similarly, the state wise innovation index is constructed by taking a combination of various relevant proxies such as number of patents, number of articles published, number of article citations, number of new designs and geographical indicators. Subsequently, using these two indices indicating the progress of human capital and innovation respectively, the present study aims at exploring the interrelationship between human capital and innovation in India. As there is a possibility that the use of Ordinary Least Square (OLS) method may result in biased results due to problem of endogeneity, the present study uses Simultaneous Equation Modelling (SEM) to avoid such issues.

This study is divided into four sections. While the first section provides introduction to the study, the second section discusses the underlying data and econometric tools employed for the purpose. Third section is devoted to discussion on the empirical results on relationship between human capital and innovations, followed by the conclusion, which is made in the fourth section.

DATA AND METHODOLOGY

The present study constricted a composite index of Human capital (HCI) and Innovation (SII) for 36 Indian States and Union Territories separately.

HCI is a combination of three sub-indices which includes survival index, health index and education index. Survival index is measured as complement of under-five mortality rate. Data on under-five mortality rate is taken from NFHS-4 state fact sheets. Health index is created using nine proxies which include Infant mortality rate (IMR), Total fertility rate (TFR), Immunization (Imz), Average out of pocket expenditure for healthcare (AOPEH), Institutional deliveries (ID), stunting, wasting, Underweight (UW) and Life Expectancy. The data on IMR, TEF, Imz, ID, Stunting, wasting and UW were collected from state wise reports of NFHS-4. Similarly, the data on AOPEH and life expectancy were collected from Health Care Financing Division (2014) and Office of the Registrar General and Census Commissioner of India respectively. As the data on life expectancy for smaller states and UTs were not available, the same has been generated using the regression analysis suggested by Swanson (1989), which uses population (65+) and Crude Death Rate (CDR) as input variable. Data for every variable is, further, scaled between 0 and 1 based on its impact on both health and human capital using equations below:

$$\text{Case of positive effect} = S_{ij} = \frac{V_{ij} - Min\left(V_{ij}\right)}{Max\left(V_{ij}\right) - Min\left(V_{ij}\right)}$$

$$\text{Case of Negative effect} = S_{ij} = \frac{Max\left(V_{ij}\right) - V_{ij}}{Max\left(V_{ij}\right) - Min\left(V_{ij}\right)}$$

Finally, the health index is constructed using PCA technique. As the KMO values for AOPEH and wasting were observed to be less than 0.5, which indicate inadequate sampling, they have been dropped from the index creation and the final composite health index is constructed as below—

$$Health\ Index = b_1\ IMR + b_2\ TFR + b_3\ Imz + b_4\ ID + b_5\ Stunting + b_6\ UW + b_7\ LE \quad \ldots(1)$$

Where, $b_0, b_1 \ldots b_7$ are weights of the variables given by principal component analysis.

Lastly, the education index is constructed using three indicators namely expected years of schooling (EYS), quality of education in schools, and returns to education. The expected years of schooling (EYS) is measured based on age-wise enrolment rates and adjust it for quality using NAS score. The expected years of schooling are calculated as the sum of age-specific enrolment rates for the age group 6-17 years.

$$EYS = \sum_{k=6}^{17} ENR_k$$

Where ENR_k is age-specific enrolment rate for children age k. Data is not available for each age but in cohorts like 6-10, 11-13, 14-15, and 16-17. The expected years of schooling are adjusted for quality using NAS score, where class 3, 5, 8 and 10 given equal weights which is further divided into subjects like maths, language, etc. If the data is not available for any class for a given state, weights of that class distributed into other classes for which NAS score is available. NAS score is scaled between 0 and 1 and then averaged for each state. This NAS score is divided by the best-performing state to get single NAS score (Filmer *et al.* 2018). Quality-adjusted expected years of schooling (QAEYS) is obtained by multiplying single NAS score and EYS for each state.

$$QAEYS = single\ NAS\ score \times EYS$$

Education index, which shows returns to education of a student, who is part of Human Capital, is calculated as returns to education times QAEYS.

$$Education\ Index = returns\ to\ education \times QAEYS$$

State innovation index (SII) is created using different proxies such as number of patents, new designs, Geographical Indications (GIs), Articles published, and citations by employing PCA technique. Each of these proxies considered to create composite index of innovation is measured for per lakh population. Again, the data is scaled down between 0 and 1 using same method as done in case of health index. Construction of SII is expressed as under—

$$SII = c_1\ Patents + c_2\ Designs + c_3\ GIs + c_4\ Articles + c_5\ Citations$$

Where, $c_0, c_1 \ldots c_5$ are weights of the respective variable produced by PCA.

Human Capital and Innovation – Analytical framework

The empirical model on interrelationship between Human Capital and innovation consists of two structural equations, one equation for innovation determination and other one for human capital determination.

The proposed two models, in this regard, are specified as under

$$Innovation = \alpha_0 + \alpha_1\ Human\ Capital + u_1 \quad \text{...Eq. 1}$$

$$Human\ Capital = \beta_0 + \beta_1\ Innovation + u_2 \quad \text{...Eq. 2}$$

There is simultaneous bias due to correlation between human capital and. To prove this, we substitute Eq. 1 into Eq. 2. We get—

$$Human\ Capital = \beta_0 + \beta_1\ (\alpha_0 + \alpha_1\ Human\ Capital + u_1) + u_2$$

$$Human\ Capital = \beta_0 + \beta_1\ \alpha_0 + \beta_1\ \alpha_1\ Human\ Capital + \beta_1\ u_1 + u_2$$

$$Human\ Capital - \beta_1\ \alpha_1\ Human\ Capital = \beta_0 + \beta_1\ \alpha_0 + \beta_1\ u_1 + u_2$$

$$Human\ Capital = \frac{\beta_0}{1-\beta_1\alpha_1} + \frac{\beta_1\alpha_0}{1-\beta_1\alpha_1} + \frac{\beta_1 u_1 + u_2}{1-\beta_1\alpha_1}$$

$$E\ (Human\ Capital) = \frac{\beta_0}{1-\beta_1\alpha_1} + \frac{\beta_1\alpha_0}{1-\beta_1\alpha_1}$$

$$Human\ Capital - E(Human\ Capital) = \frac{\beta_1 u_1 + u_2}{1-\beta_1\alpha_1}$$

Also $u_1 - E(u_1) = u_1$

$$Cov(Human\ Capital,\ u_1) = E[Human\ Capital - E(Human\ Capital)]\ [u_1 - E(u_1)]$$

$$= \frac{E(\beta_1 u_1^2) + E(u_2)}{1-\beta_1\alpha_1}$$

$$= \frac{E(\beta_1 u_1^2)}{1-\beta_1\alpha_1} \quad \text{as } E(u_2) = 0$$

$$= \frac{\beta_1 E(u_1^2)}{1-\beta_1\alpha_1}$$

$$= \frac{\beta_1}{1-\beta_1\alpha_1}\sigma^2$$

Since σ^2 is positive by assumption, the covariance between Human Capital and u_1 is bound to be different from zero. As a result of this, Simultaneous bias may occur due to a strong correlation between human capital and error term (u_1). This seems to violate the assumptions of the classical linear regression model. As a result, OLS may produce biased and inconsistent results for the above two equations. Before proceeding further, it is necessary to check whether these equations are identified.

The Identification Problem

The study obtains parameter of equations from reduced form of coefficients to identify the equations. The rule of law says that: (1) the equation is exactly identified when the unique values are obtained for every parameter, (2) the equation is over identified when more than one values are obtained for any parameter, and (3) the equation is under identified when the given equation cannot be solved. Present study uses post-estimation tests[1] of instrumental variable regression (ivreg2 in Stata) for identification of equations.

Instrumental Variable Method

Instrumental variable (IV) is chosen in such a way to reduce correlation between endogenous variable and random error term. The IV must satisfy two conditions for being appropriate: (i) it must be highly correlated with endogenous variable; (ii) it must not be correlated with error term.

After adding IVs and Exogenous variables, the model of equations changed as below

$$Innovation = \alpha_0 + \alpha_1\ Human\ Capital + \alpha_2\ IV_1 + \alpha_3\ HEIperkm + u_1 \quad \text{...Eq. 1}$$

$$Human\ Capital = \beta_0 + \beta_1\ Innovation + \beta_2\ IV_2 + \beta_3\ IV_3 + \beta_4\ PTR\_S + u_2 \quad \text{...Eq. 2}$$

As shown in Eq.1, literacy rate (LR) and enrolment per lakh in schools were used as Instrument variables (IV_2 and IV_3) and the pupil teacher ratio for school (PTR_S) is usedas exogenous variable for Human Capital. Similarly, as reported in Eq.2, gross enrolment ratio (IV_2) and the higher educational instruments per km (HEIperkm) were used as instrument and exogenous variables, respectively, for innovation.

[1] *These tests include LM version of the Anderson canonical correlations test, Cragg-Donald Wald F-Test, and Sargan-Hansen test)*

Two Stage Least Squares (2SLS)

The study employed Two Stage Least Square method to solve the simultaneous equation model. In the Stage I, endogenous variable is regressed on all the exogenous variables using OLS and obtained its predicted value. In stage II, endogenous variable is again regressed on that predicted value and all the exogenous variables. The study used ivreg2 in Stata to compute the 2SLS. Before estimating, both the equations (Eq.1 and Eq.2) were checked for identification. Due to endogeneity problem, as discussed above, if simple OLS is used to solve these two equations, the estimated values for α_1 and β_1 would appear to be biased and inconsistent.

Both Eq.1 and Eq.2 were solved one at a time for estimation under the 2SLS procedure. In the stage 1 regression, for Eq.1, the study Obtain $\widehat{Endogenous\ Varible}$ by estimating OLS against all exogenous variables, including all the instrument variables.

The model for Human Capital, in stage one regression, is specified as under

$$Human\ Capital = \gamma_0 + \gamma_1\ IV_1 + \gamma_2\ HEIperkm + \gamma_3\ IV_2 + \gamma_4\ IV_3 + \in_1 \qquad \ldots Eq.\ 3$$

Where, IV_2 and IV_3 are instrumental variables. The Eq.3 states that: (1) these instrument variables are highly correlated with Human Capital, (2) they do affect innovation indirectly through Human Capital, and (3) they are considered as exogenous to the equation (Corr (IV_2, $\in_1$) = 0) and (Corr (IV_3, $\in_1$) = 0). The study further regress Eq. 3 using OLS and obtain the estimated value of coefficients and generated equation with predicted coefficients as under—

$$\widehat{\text{Human Capital}} = \hat{\gamma}_0 + \hat{\gamma}_1 IV_1 + \hat{\gamma}_2 HEIperkm + \hat{\gamma}_3 IV_2 + \hat{\gamma}_4 IV_3$$

From the above specification, it may be said that $\widehat{Human\ Capital}$ would not be influenced by error term, $\in_1$, which means it shall not be influenced by any source of endogeneity. Similarly, based on Eq.2, the model for Innovation, in stage one regression, is specified as under—

$$Innovation = \delta_0 + \delta_1\ IV_1 + \delta_2\ IV_2 + \delta_3\ IV_3 + \delta_4\ PTR\_S + \in_2 \qquad \ldots Eq.\ 4$$

Where, IV_1 is an instrumental variable. The Eq.4 states that: (1) this instrument variable is highly correlated with Innovation, (2) It does affect human capital indirectly through innovation, and (3) it is not considered as exogenous to the equation (Corr (Corr (IV_1,$\in_2$) = 0)). The study further regress Eq. 4 using OLS and obtain the estimated value of coefficients and generated equation with predicted coefficients.

$$\widehat{Innovation} = \hat{\delta}_0 + \hat{\delta}_1 IV_1 + \hat{\delta}_2 IV_2 + \hat{\delta}_3 IV_3 + \hat{\delta}_4 PTR\_S$$

Above equation implies that $\widehat{Innovation}$ shall not be influenced by error term, $\in_2$.

In the stage 2 regression, the values of $\widehat{Human\ Capital}$ is used in place of Human Capital. Subsequently, second endogenous variable (Innovation) is, further, regressed against $\widehat{Human\ Capital}$ and other exogenous independent variables excluding instruments. Hence, for Eq. 1—

$$Human\ Capital = \widehat{Human\ Capital} + \in_1 \qquad \ldots Eq.\ 5$$

Substituting the value of $\widehat{Human\ Capital}$ obtained through Eq.5 for Human Capital in Eq. 1, we get,

$$Innovation = \alpha_0 + \alpha_1\ \widehat{Human\ Capital} + \alpha_1 \in_1 + \alpha_2\ IV_1 + \alpha_3\ HEIperkm + u_1$$

$$Innovation = \alpha_0 + \alpha_1\ \widehat{Human\ Capital} + \alpha_1 \in_1 + \alpha_2\ IV_1 + \alpha_3\ HEIperkm + u_1$$

$$Innovation = \alpha_0 + \alpha_1\ \widehat{Human\ Capital} + \alpha_2\ IV_1 + \alpha_3\ HEIperkm + (\alpha_1 \in_1 + u_1)$$

$$Innovation = \alpha_0 + \alpha_1\ \widehat{Human\ Capital} + \alpha_2\ IV_1 + \alpha_3\ HEIperkm + u_1{}^* \qquad Eq.\ 1^*$$

Similarly for Eq. 2, $\widehat{Innovation}$ is used in place of Innovation and second endogenous variable (Human Capital) is, further, regressed against $\widehat{Innovation}$ and all exogenous independent variables excluding instruments again. Thus, for Eq. 2

$$Innovation = \widehat{Innovation} + \in_2 \qquad \ldots Eq.\ 6$$

Substituting the value of $\widehat{Innovation}$ obtained through Eq.6 for Innovation in Eq. 2, we get,

$$Human\ Capital = \beta_0 + \beta_1 (\widehat{Innovation} + \in_2) + \beta_2\ IV_2 + \beta_3\ IV_3 + \beta_4\ PTR\_S + u_2$$

$$Human\ Capital = \beta_0 + \beta_1\ \widehat{Innovation} + \beta_1 \in_2 + \beta_2\, IV_2 + \beta_3\, IV_3 + \beta_4\, PTR_S + u_2$$

$$Human\ Capital = \beta_0 + \beta_1\ \widehat{Innovation} + \beta_2\, IV_2 + \beta_3\, IV_3 + \beta_4\, PTR_S + (\beta_1 \in_2 + u_2)$$

$$Human\ Capital = \beta_0 + \beta_1\ \widehat{Innovation} + \beta_2\, IV_2 + \beta_3\, IV_3 + \beta_4\, PTR_S + u_2^* \qquad \text{Eq. 2*}$$

It is worth noting that Eq.1* and Eq.2* can also be derived by substituting the predicted value of $\widehat{Human\ Capital}$ and $\widehat{Innovation}$ in equation Eq.1 and Eq.2 respectively. Thestudy, finally, estimate the modified equations Eq. 1* and Eq. 2* using OLS. The estimated parameters $\hat{\alpha}_1$ and $\hat{\beta}_1$ are consistent.

RESULTS AND DISCUSSION

In the present study, simultaneous equation modelling is used to estimate the interrelationship between human capital and innovation for the Indian States. Since simultaneous equation modelling is often prone to simultaneity bias and problem of endogeneity; to resolve these issues, we move forward to find a suitable simultaneous equations model, then solve it by instrumental variable method using two stage least squares (2SLS). While selecting instrument variable, the study taken care of two essential conditions which includes high correlation between instrument variable and endogenous variable, and no correlation with residual and other exogenous variables by employing Wu-Hausman F test and Durbin-Wu-Hausman chi-square tests and Pearson Correlation method respectively.

As shown in Table 1, for the first equation, where human capital is checked for endogeneity, Durbin's Chi-square and Wu–Hausman's F-statistic value of both equations is found to be significant at 95% confidence interval. Hence, we reject the null hypothesis of a given variable (human capital) is exogenous and confirm that the human capital is endogenous for innovation. Similarly, for the second equation, where innovation is tested for endogeneity, Durbin's Chi-square, and Wu–Hausman's F-statistic value of both equations is found to be significant at 99% confidence interval (see Table 1). Therefore, we reject the null hypothesis of a given variable is exogenous, which means innovation is found to be endogenous for human capital. Further, the study also verifies whether the equations are identified or not using the under-identification test, weak instrument test, and over identification test of all the instruments.

Since there is problem of endogeneity in both equations, instrumental variable method is exercised to solve the simultaneous equations. The results on selection of instrument variables for both equations presented in Table 2 indicate that, for the first equation, there is high correlation between instrumental variables Enrolment per lakh and LR and endogenous variable human capital. On the other hand, Enrolment per lakh and LR has no correlations with residual u1, and exogenous variables GER, and HEI per km.

For the second equation, the results confirm that there is high correlation between instrumental variables GER and endogenous variable innovation. On the other hand, GER has no correlations with residual u_2, and exogenous variables Enrolment per lakh, LR, and PTR_S. After selecting instrumental variables, simultaneous equations are checked for identification and quality of instrumental variables using the under-identification test, week instrument test, and over identification test of all the instruments.

The under-identification test was used to check if both the equations were identified or if the selected instrument variables in each equation were relevant using LM version of the Anderson

Table 1: Test of Endogeneity

Sl. No.	Equation	Durbin-Wu-Hausman chi-sq test	Wu-Hausman F test	Decision
1	Innovation = (Human Capital = Enrolment) HEIperkm GER	4.67 (p = 0.03)	4.62 (p = 0.04)	Reject null hypothesis
2	Human Capital = (Innovation = GER) Enrolment LR PTR_S	13.10983 (p = 0.00)	17.18182 (p = 0.00)	Reject null hypothesis

Ho: Regressor is exogenous.

Table 2: Pearson Correlations

	HCI	SII	GER	PTR_S	HEI (per km)	Enrolment (per lakh)	LR 5	u_1	u_2
HCI	1	.488**	.529**	-.464**	.291	-.469**	.463**	.000	.704**
SII	.488**	1	.725**	-.310	.768**	-.185	.391*	.519**	.000
GER	.529**	.725**	1	-.275	.566**	.002	.117	.000	.369*
PTR_S	-.464**	-.310	-.275	1	.037	.156	-.608**	-.315	.000
HEI (per km)	.291	.768**	.566**	.037	1	-.206	.200	.000	-.052
Enrolment (per lakh)	-.469**	-.185	.002	.156	-.206	1	-.022	-.012	.000
LR	.463**	.391*	.117	-.608**	.200	-.022	1	.338*	.000
u_1	.000	.519**	.000	-.315	.000	-.012	.338*	1	-.399*
u_2	.704**	.000	.369*	.000	-.052	.000	.000	-.399*	1

*u_1 and u_2 are residuals of Eq-1 and Eq-2, respectively; **. Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed).*

Table 3: Under identification Test

Sl. No.	Equation	Anderson canon. corr. LM statistic	Decision
1	Innovation = (Human Capital=Enrolment, LR) HEIperkm GER	20.72 (p = 0.00)	Reject null hypothesis
2	Human Capital = (Innovation = GER) EnrolmentLR PTR_S	21.338 (p = 0.00)	Reject null hypothesis

Ho: Equation is under identified.

Table 4: Weak Instrument Test

Sl. No.	Equation	Stock-Yogo weak ID test critical values				Cragg-Donald Wald F-statistic	Decision
		10%	15%	20%	25%		
1	Innovation = (Human Capital=Enrolment, LR) HEIperkm GER	19.93	11.59	8.75	7.25	21.021 (p = 0.00)	Reject null hypothesis
2	Human Capital = (Innovation = GER) Enrolment LR PTR_S	16.38	8.96	6.66	5.53	45.113 (p = 0.00)	Reject null hypothesis

Ho: equation is weakly identified.

canonical correlations test. The results for the same reported in table 3 indicate that the null hypothesis can be rejected for both the equations. Hence it is confirmed that both the equations are identified, and instrument variables in each equation are relevant.

Similarly, a weak instrument test was used to check whether the instrument variables were actually related to the endogenous variable. The results reported in Table 4 indicates that instrument variables are strongly correlated with endogenous variable as Cragg-Donald Wald F statistic value is greater than the Stock-Yogo weak ID test critical values in both the equations.

Further, we employed Overidentification test to check over-identifying restrictions using Sargan-Hansen test. The results reported in Table 5 shows that the null hypothesis cannot be rejected for the first equation as p value for Sargan Statistic is greater than 0.05, while the second equation is exactly identified so as Sargan Statistic is zero. Hence, it is concluded that instruments are superiorly valid, which means that they are uncorrelated with the error term and the excluded instruments are correctly excluded from the estimated equations. Thus, based on all these econometric specifications it is evidenced that simultaneous equation model is appropriate and correctly specified for estimating the inter-relationship between innovation and human capital. We, further, solve these simultaneous equations by using the instrument variable regression through Two stage least square method (2SLS).

Table 5: Over identification Test

Sl. No.	Equation	Sargan Statistic	Decision
1.	Innovation =(Human Capita l= Enrolment, LR) HEI per km GER	2.108 (p = 0.15)	Do not reject null hypothesis
2.	Human Capital = (Innovation = GER) Enrolment LR PTR_S	0.000 Equation exactly identified	—

Ho: instruments are valid instruments.

Table 6: 2SLS for the first equation

Dependent variable – Innovation			
Independent Variable	**OLS**	**2SLS**	**2SLS (robust)**
HCI	0.13(0.08)	0.28**(0.12)	0.28**(0.13)
GER	0.19**(0.07)	0.13*(0.07)	0.13 (0.09)
HEI perkm	0.97***(0.24)	0.97***(0.20)	0.97***(0.23)
Constant	-0.02(0.04)	-0.062 (0.04)	-0.062 (0.04)
Centered R^2	0.73	0.70	
Tests			
IV heteroskedasticity test(s) using levels of IVs only $^{\varepsilon}$	Pagan-Hall general test statistic		2.83

Note: *1. *, **, *** denotes significant level at 10%, 5%, 1% respectively, 2. Standard error is written is parenthesis. 3. ε: H_0 - Disturbance is homoscedastic.*

Table 7: 2SLS for the second equation

Dependable Variable – Human Capital			
Independent Variable	**OLS**	**2SLS**	**2SLS (robust)**
Innovation	0.32 ** (0.15)	0.78 ***(0.22)	0.78 *** (0.27)
LR	0.004 (0.002)	0.002(0.003)	0.002(0.003)
Enrolment	-0.000*** (0.00)	-0.000** (0.00)	-0.000* (0.00)
PTR_S	-0.003(0.002)	-0.002(0.003)	-0.002(0.003)
Constant	0.36(0.26)	0. .43(0. 29)	0. 43**(0.19)
Centered R^2	0.50	0.38	
Tests			
IV heteroskedasticity test(s) using levels of IVs only $^{\varepsilon}$		Pagan-Hall general test statistic	6.99

Note: *1. *, **, *** denotes significant level at 10%, 5%, 1% respectively. 2. Standard error is written is parenthesis. 3. ε: H_0 - Disturbance is homoscedastic.*

Instrumental Variable (2SLS) Regression

The estimated result of instrumental variables regression (2SLS) for first equation, reported in Table 6, show that the net marginal impact of human capital, after controlling the other exogenous variables, is seems to be significant at 5 % level. Moreover, the results indicated that the process of innovation is positively significant, which implies that 1% increase in human capital leads to enlarge innovative performance in India at state level by 0.29 %. We further provide evidence of simultaneous bias in case of OLS, due to which the value of coefficient for endogenous variable is, seems to be insignificant, while it is significant and relatively high in case of 2SLS. Our empirical evidence suggests that human capital may play an important role in the generation of innovative activities in Indian states. This evidence is also consistent with the notion that basic education and health play a primary role in promoting economic activity through both the direct production channel and the indirect innovation channel.

Similarly, the estimated results, presented in Table 7, on equation two, where human capital is taken as dependent variable, also shows that innovation, after controlling all other instrument variables, seems to be positive and statistically significant at 1% level. Furthermore, the results indicate that 1 % increase in innovations lead to uplift human capital by 0.79 %. Like in the first equation, the results of 2SLS obtained from second equation also seem to be more significant and relatively at higher side than that of OLS, indicating simultaneous bias in the latter case.

After estimating both equations and substituting coefficient values, we have:

$$SII = 0.2852 * HCI + 0.1336\ GER + 0.9752 * HEIperkm$$

$$HCI = 0..7861 * SII - 0.0000 * Enrolment$$

The estimated two equations reported above prove that there is a bidirectional relationship between human capital and innovations, as both are influencing each other. The estimated results, further, demonstrate that increase in human capital leads to an increase in innovation and vice - versa.

CONCLUSION

The present study aims at understanding the interrelationship between human capital and innovation in the Indian context. To realize this objective, the summary measures of human capital and innovation, separately, for 36 Indian states and Union Territories has been created using factor analysis. Subsequently, using these two indices, the interrelationship between human capital and innovation was examined through simultaneous equation model. Since the simultaneous equation model is often subject to the problem of simultaneous bias and endogeneity, the study solved this issue with the help of instrumental variable method using Two Stage Least Squares (2SLS). Instrumental variables regression for first equation, where innovation index taken as dependant variable, show that the net marginal impact of human capital, after controlling the other exogenous variables, seems to be positive and significant at 5 % level. Similarly, the estimated results on equation two, where human capital is taken as dependent variable, also suggests that innovation, after controlling all other instrument variables, seems to be positive and statistically significant at 1% level.

Thus, the study provides the evidence of bidirectional impact between human capital and innovation for Indian states. The presence of bidirectional causality has important policy implications. Given the huge demographic dividend in the form of a billion plus population with a median age of 23 years, India has all the potential to achieve sustainable economic growth and also contribute to global economic growth, with right policy choices related to human capital. With 13 million youngsters joining the country's work force every year, it is imperative of the policy makers to design policies in such a way that this huge work force is qualitative and meet the global standards. It emphasizes the need for joint policy interventions by the Union and the state governments to promote hands on educational learning and internships and promote soft skill development, right from the school level. When these students graduate, they turn into a human capital with higher economic value in the market. Given the rising demand for the skilled work force, it is pertinent to make large scale investments on human capital in India that enables them to be more innovative and productive. An institutional mechanism in place, to monitor the developments on the front of human capital and to provide policy guidance could further makes the task at hand easier. In fact, these policy options, if implemented, have the potential to go a long way in achieving sustainable rates of economic growth.

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