The Relationship Between Technological Progress and Human Capital Development: Regional Comparison in China

Zong Rundong*, Doris Padmini S Selvaratnam

Faculty of Economics and Management, Universiti Kebangsaan Malaysia

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ABSTRACT

The education expansion efforts have shown positive developments in China, nevertheless, the increasing disparities among the eastern, central, western, and northeastern regions pose the concern whether technological advancements support the development of human capital. This paper utilized unbalanced panel data from China's 262 prefecture-level cities between the years 2010 and 2023 to explore the association between TIC and Human Capital, and to build an econometric model for the empirical test: the econometric model mainly applies the two-way fixed effects model to deal with the influences of the intercity heterogeneity and time trends.

The results of the correlation analysis matrix show that the correlation between variables is, in general, remarkable and wide-ranging, reflecting the essential issues that are influential to the capacities of urban innovation and the intrinsic relationship between them. The results suggest that policies promoting innovation are likely to be more effective when coordinated with urban development and education-related conditions that jointly shape human capital accumulation.

Keywords*:* technological progress, human capital development, regional comparison, China

INTODUCTION

Technological progress and human capital have been identified as the twin pillars of sustained national competitiveness in the 21st century (World Economic Forum, 2020). As the largest developing country in the world, China has addressed its agenda for changing from an investment-based economy to an innovation-based economy (World Bank & Development Research Center of the State Council, 2019).

In a global context, this link has also become more apparent as the global economic focus shifts toward a knowledge-based approach to economic growth that sees increases in productivity also linked to innovation capacity or the supply of skilled labor. With amplified focus on digitization as a general-purpose technology, international competition in the supply of skilled labor will continue, as will the value placed on skills and constant learning. In this context, regional heterogeneity in translating technological growth with human capital accumulation has become a major driver of economic growth and resilience.

While education expansion efforts have shown positive developments (NBS, 2021; MOE, 2024), the increasing disparities among the eastern, central, western, and northeastern regions pose the concern whether technological advancements support the development of human capital.

From a theoretical point of view, human capital theory relates education to productivity (Becker, 1993), while endogenous growth theory focuses on complementarity between technology innovation and human capital, in that technology improvement generates a demand for skilled workforce and a more educated workforce drives technology innovation (Romer, 1990). The policy priorities in China's agenda, such as National Innovation-Driven Development Strategy Outline (2016) and 14th Five-Year Plans (2021-2025), emphasize integration of science, education, and industry as well as regional innovation (State Council, 2016, 2021).

However, this also indicates a potential scenario in which different results in terms of human capital can emerge from a singularly implemented technology innovation policy due to heterogeneity in regional circumstances.

In this paper, technological progress is represented by technological innovation capacity (TIC) measured as a proportion of science and technology expenditure to local government budget expenditure for the city as a whole (Dai, Gao & Chen, 2025; Wang, 2023). Human capital, embodied in education, skills, and knowledge, is measured as the proportion of students enrolled in regular higher education institutions relative to the resident population, consistent with the city-level empirical design (Jing, 2025).

Previous studies (Shao, 2025; Xu et al., 2024) indicated some factors relating to innovation could positively promote human capital accumulation. However, the regional heterogeneity and interaction between various factors may not be fully interpreted, as well as some single-factor results failing to consider the combined effects of important city characteristics. This motivates a regional comparison within a consistent city-level framework.

Accordingly, this paper uses unbalanced panel data for 262 prefecture-level cities in China (2010–2023) to examine the relationship between TIC and human capital. The analysis controls for population size, economic development level, financial development level, level of openness to the outside world, industrial structure, education expenditure level, and urbanization level, enabling systematic comparison across China's major regions. The study provides policy-relevant evidence for coordinated regional strategies that link innovation support with human capital development.

LITERATURE REVIEW

A large body of theory views technological progress and human capital as mutually reinforcing forces behind long-run growth. Human capital theory treats education and skill accumulation as productivity-enhancing investments that support economic development (Becker, 1993).

Endogenous growth theory further argues that technological innovation is generated by purposeful investment and that a more educated workforce both accelerates innovation and improves a region's ability to absorb new knowledge; meanwhile, technological progress raises the demand for skilled labor and the returns to education, creating complementarity between innovation and human capital (Romer, 1990).

These frameworks imply that the effect of technological progress on human capital may be strong on average, but heterogeneous across places depending on development conditions and institutional contexts.

Guided by this literature, the present study defines the dependent variable human capital in a way that is consistent with prefecture-level city panel research and yearbook-based data availability. Beyond commonly used attainment measures (e.g., average years of schooling), recent city-level studies in China operationalize human capital using higher-education participation intensity. For example, Jing (2025) measures the human capital level by the ratio of students enrolled in regular higher education institutions to the total population at the prefecture-level city scale, supporting the use of an enrollment–population ratio as a practical proxy in urban panel settings.

Following this empirical practice, this paper measures human capital as the proportion of students enrolled in regular higher education institutions relative to the resident population, capturing a city's higher-education participation intensity and thus its education-related human capital accumulation.

For technological progress, empirical studies typically distinguish between output-based indicators (e.g., patents) and input-based indicators (e.g., R&D or fiscal science-and-technology spending). When the focus is on policy-driven innovation support and the role of local government, studies often proxy innovation effort using the fiscal share devoted to science and technology.

Dai et al. (2025), for instance, define fiscal appropriation intensity as the ratio of fiscal science and technology expenditure to fiscal general budget expenditure, and related empirical work also uses "science and technology expenditure as a percentage of general public budgetary expenditure" at the city level to represent technological support intensity. Consistent with this line of measurement, this paper captures technological progress via technological innovation capability (TIC), measured as the ratio of science and technology expenditure to local government general budget expenditures.

The literature also suggests that the TIC–human capital relationship can be confounded or conditioned by city fundamentals and structural characteristics, so a standard approach is to include controls that capture scale, development capacity, financing, openness, upgrading, public education inputs, and urban development.

In this study, population size is measured as the logarithm of the year-end resident population, while economic development level is measured as the logarithm of per capita GDP—an approach commonly used in panel specifications to reflect development level and reduce skewness. For financial development level, city studies frequently use the ratio of deposit and loan balances to GDP as a measure of financial depth. For level of openness to the outside world, empirical work often measures openness by the ratio of actual utilization of foreign direct investment to GDP.

Industrial structure is captured by the share of tertiary industry value added in GDP, reflecting structural upgrading toward services and knowledge-intensive activities. education expenditure level is defined as education expenditure as a share of total public budget expenditures, reflecting local fiscal priority for education. Finally, given China's hukou-based statistical system, urbanization level can be measured by the ratio of non-agricultural population to total registered population, a definition explicitly used in empirical work on China's registered-population urbanization.

Overall, prior theory and measurement traditions support a city-level framework in which technological innovation capability (TIC) is expected to be positively associated with human capital, while the magnitude of this relationship may vary across regions due to differences in economic foundations, factor mobility, and development stages. This motivates the present paper's regional comparison design using consistent variable definitions and a comprehensive set of controls to evaluate how technological progress relates to human capital development across China's major regions.

METHODOLOGY

This study aims to explore the relationship between technological progress and human capital development, and constructs an econometric model based on data from prefecture-level cities in China for empirical testing. The model specification primarily employs a two-way fixed-effects panel model to control for the impact of individual city heterogeneity and time trends. The baseline regression model is specified as follows:

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$$Human_{Capital_{it}} = \alpha_0 + \beta_1 TIC_{it} + \sum \beta_j Controls_{it}^{j} + \mu_i + \rho_t + \varepsilon_{it}$$

Among these, $Human\_Capital_{it}$ denotes the human capital level of city i in year t. The core explanatory variable TIC_{it} represents the technological innovation capability of city i in year t. variables, this includes population size, economic development level, financial development level, level of openness to the outside world, industrial structure, education expenditure level, and urbanization level. μ_i and ρ_t denote city fixed effects and year fixed effects, respectively, capturing city-specific characteristics and macro-level temporal trends that do not vary over time. ε_{it} represents the random error term. Robust standard errors are employed in model estimation to mitigate heteroskedasticity issues.

Regarding variable definitions, the dependent variable (human capital level) is measured by the proportion of students enrolled in regular higher education institutions relative to the resident population. The core independent variable (technological innovation capability) is proxied by the ratio of science and technology expenditure to local government general budget expenditures.

For controls, population size is the logarithm of year-end resident population; economic development level is the logarithm of per capita GDP; financial development level is the ratio of financial institutions' deposit and loan balances to GDP; level of openness to the outside world is the share of actual foreign direct investment utilization in GDP; industrial structure is the share of tertiary industry value-added in GDP; education expenditure level is the proportion of education spending in fiscal expenditures; and urbanization level is the ratio of non-agricultural population to registered population.

In terms of data sources, this study uses an unbalanced panel dataset of 262 prefecture-level cities in China from 2010 to 2023. The raw data are drawn from the China City Statistical Yearbook, the China Regional Economic Statistical Yearbook, and statistical yearbooks of individual provinces and cities. To eliminate the effects of price fluctuations, all economic variables are deflated using 2010 as the base year.

Regarding sample selection, cities with substantial missing data are excluded, while those with only partial missing values are retained, resulting in an unbalanced panel. In addition, to verify the robustness of the findings, the study conducts sensitivity tests by excluding the pandemic years and excluding municipalities directly under the central government, ensuring that the estimation results are not driven by special factors.

Empirical Results and Analysis

Descriptive Statistics

The sample includes 2,976 observations of prefecture-level cities in China, and descriptive statistics show significant regional differences in core variables. Human Capital and Technological Innovation Capability (TIC) have similar means (1.428 and 1.421) but large standard deviations (1.463 and 1.454) and maxima far above the means, indicating that talent and innovation are concentrated in a few cities, consistent with their clustering in developed eastern regions and provincial capitals (e.g., Beijing, Shenzhen, and Shanghai), while many small and medium-sized cities show weaker momentum.

Population size (People) and economic development level (Economic) display relatively small dispersion (0.665 and 0.657), whereas financial development level (Finance) has a pronounced upper tail (maximum 14.42 vs. mean 2.381), implying some cities may serve as regional financial centers. The level of openness (Open) remains very low on average (0.002) with limited variation, though some port or foreign trade hub cities are higher; industry structure (Industry) and education expenditure (Education) average 0.410 and 0.177 with small standard

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deviations; and urbanization (Urban) averages 0.363 but ranges widely (0.075–1), reflecting different urbanization stages and continued improvement potential in some cities, in line with research on regional urbanization gaps and human capital structure optimization.

Table 1 Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Human Capital	2976	1.428	1.463	0.0100	11.98
TIC	2976	1.421	1.454	-0.00700	16.27
People	2976	5.868	0.665	2.996	7.380
Economic	2976	10.62	0.657	8.555	13.09
Finance	2976	2.381	1.067	0.588	14.42
Open	2976	0.00200	0.00300	0	0.0290
Industry	2976	0.410	0.0940	0.0980	0.766
Education	2976	0.177	0.0400	0.0440	0.356
Urban	2976	0.363	0.195	0.0750	1

Correlation Analysis

Based on the correlation analysis matrix results in Table 2, broad and significant correlations exist among the variables, revealing the key factors influencing urban innovation capabilities and their intrinsic connections. A high positive correlation exists between human capital level and technological innovation capability, with a correlation coefficient of 0.621, significant at the 1% level, indicating that the concentration of highly skilled talent plays a core driving role in technological innovation. The correlation between economic development level and technological innovation capability is even stronger, reaching a coefficient of 0.550, suggesting that economically developed regions are more likely to form innovation ecosystems. Meanwhile, the level of financial development and industrial structure show a significant positive correlation, with a coefficient of 0.605, reflecting the high dependence of high-end industries on financial resources.

Table 2 Correlation Analysis Matrix

	Human Capital	TIC	people	economic	finance	open	Industry	education	Urban
Human Capital	1								
TIC	0.621***	1							
People	0.197***	0.193***	1						

Economic	0.500***	0.550***	-0.173***	1					
Finance	0.500***	0.170***	-0.054***	0.239***	1				
Open	0.256***	0.468***	0.125***	0.236***	-0.0160	1			
Industry	0.431***	0.275***	0.142***	0.312***	0.605***	0.037**	1		
Education	-0.192***	-0.00600	0.454***	-0.238***	-0.265***	-0.091***	-0.139***	1	
Urban	0.386***	0.254***	-0.231***	0.528***	0.327***	0.124***	0.253***	-0.321***	1

Multicollinearity Test

From the results presented in Table 3 above, the variance inflation factor (VIF) values obtained after performing the multicollinearity test are all very low and less than the critical value of 10. The values are as follows: the maximum value is 2.05 for the economic level variable, the lowest value is 1.34 for the openness level variable, and the overall values have an average of 1.68. These suggest that the values are all within acceptable limits and indicate that the relationships are only linear and have a minimal effect on the results. The values are all within the acceptable limit of 10 and can be regarded as rational and very appropriate.

Table 3 Multicollinearity Test

Variable	VIF	1/VIF
economic	2.050	0.489
TIC	1.960	0.511
Industry	1.800	0.557
finance	1.740	0.575
Urban	1.550	0.646
people	1.530	0.652
education	1.450	0.689
open	1.340	0.744
Mean VIF	1.680	-

Benchmark Regression

From the Figure 1 in the scatter plot graph, we can clearly derive the relationship of positive correlation between human capital and technological innovation capability. Keeping the level of TIC consistent, the curve of human capital exhibits an upward relationship. The gray 95% confidence interval remains relatively narrow and stable across the TIC range (0–20), suggesting good predictive stability and reliable estimation. Overall, the figure visually supports the previously reported significant positive correlation (0.621) between the two variables, indicating that at the prefecture-level city level in China, higher technological innovation capability is closely associated with greater human capital accumulation.

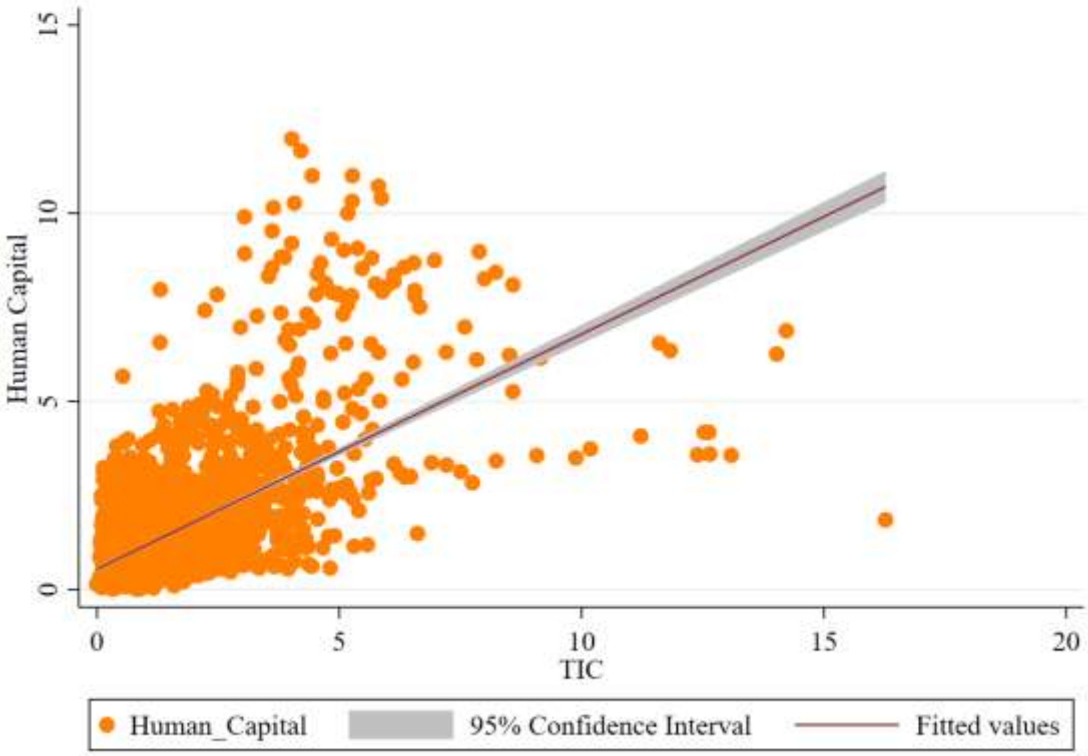

Figure 1. Scatter plot

Table 4 reports the benchmark regressions examining the effects of technological innovation capability (TIC) and controls on human capital in Chinese prefecture-level cities, with city and year fixed effects added stepwise to strengthen robustness. TIC is significantly positive at the 1% level in all models (1–4), but its coefficient declines from 0.143 in Model 1 (city fixed effects only) to 0.044 in Model 4 (city and year fixed effects), suggesting the positive effect remains robust but may be overstated when time factors are not controlled. While controls are added, economic development and financial development are significantly positive in Model 3 but become insignificant in Model 4 after adding year fixed effects, which suggests that their effects might be absorbed by the macro level time trend. The coefficient for the level of urbanization (Urban) was still highly and consistently significant at 0.890 and 0.522 for Models 3 and 4, respectively. It thus confirms the continued contribution to human capital accumulation.

The effects of the population size (People), openness to the outside world (Open), industrial structure (Industry), and education expenditure (Education) were not statistically significant in Model 4. It is thus implied that after accounting for regional and year heterogeneity, their contribution is small.

Overall, the method reduces the effects of missing variable bias and is consistent with the broader context and process of development experienced in China, whereby technological innovations and urbanization underpin development and contribute to accumulation in human capital, and more temporal drivers and dynamics influence regions.

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Table 4: Benchmark Regression

	(1)	(2)	(3)	(4)
VARIABLES	Human Capital	Human Capital	Human Capital	Human Capital
TIC	0.143***	0.043***	0.054***	0.044***
	(0.028)	(0.015)	(0.017)	(0.015)
people			0.311	0.177
			(0.229)	(0.207)
economic			0.393***	-0.054
			(0.038)	(0.070)
finance			0.116***	-0.005
			(0.030)	(0.019)
open			-9.832*	0.829
			(5.932)	(5.506)
Industry			0.545**	0.041
			(0.243)	(0.248)
education			-0.235	0.006
			(0.439)	(0.447)
Urban			0.890***	0.522*
			(0.300)	(0.295)
Constant	1.217***	1.359***	-5.408***	0.692
	(0.040)	(0.021)	(1.425)	(1.630)
Observations	2,967	2,967	2,967	2,967
R-squared	0.950	0.975	0.969	0.975
City FE	YES	YES	YES	YES
Year FE	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Robustness Tests

Excluding Pandemic Years

Table 5 reports robustness tests that exclude pandemic-year observations to assess whether the benchmark results are sensitive to exceptional periods. Across Models (1)–(4), the coefficient on technological innovation capability (TIC) remains statistically significant and close in magnitude to the benchmark estimates, indicating that TIC continues to exert a robust positive effect on human capital even after removing external-shock interference. This is consistent with the robustness-testing logic in related studies and suggests that the relationship between technological progress and human capital is resilient across sample periods, strengthening the generalizability of the conclusions.

Table 5 Robustness Test 1

	(1)	(2)	(3)	(4)
VARIABLES	Human Capital	Human Capital	Human Capital	Human Capital
TIC	0.124***	0.043**	0.052***	0.039**
	(0.032)	(0.017)	(0.020)	(0.017)
people			0.263	0.135
			(0.216)	(0.200)
economic			0.354***	0.007
			(0.041)	(0.066)
finance			0.084***	-0.013
			(0.024)	(0.016)
open			-3.590	3.378
			(4.784)	(4.519)
Industry			0.586***	0.082
			(0.222)	(0.235)
education			-0.286	-0.015
			(0.378)	(0.388)
Urban			0.897***	0.542*
			(0.320)	(0.309)
Constant	1.159***	1.267***	-4.695***	0.201
	(0.043)	(0.023)	(1.335)	(1.561)
Observations	2,368	2,368	2,368	2,368
R-squared	0.956	0.976	0.971	0.977
City FE	YES	YES	YES	YES
Year FE	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Exclude Municipalities Directly Under the Central Government

Table 6 reports a second robustness test that excludes municipal-level samples. The coefficient of the core variable—technological innovation capability (TIC)—remains statistically significant at the 1% level across Models (1)–(4), with magnitudes close to the benchmark results (0.146 in Model 1; 0.048 in Model 4).

This indicates that the positive effect of technological progress on human capital accumulation is robust even after removing the influence of municipalities' special administrative status and concentrated policy resources. Overall, the findings strengthen the universality of the benchmark conclusion, suggesting that the positive relationship between technological progress and human capital is not driven by a few resource-rich municipalities but is widely present across China's prefecture-level cities, providing more reliable empirical evidence for regional human capital development strategies.

Table 6 Robustness Test 2

	(1)	(2)	(3)	(4)
VARIABLES	Human Capital	Human Capital	Human Capital	Human Capital
TIC	0.146***	0.046***	0.058***	0.048***
	(0.029)	(0.015)	(0.018)	(0.016)
people			0.227	0.107
			(0.235)	(0.206)
economic			0.393***	-0.054
			(0.038)	(0.070)
finance			0.111***	-0.008
			(0.029)	(0.019)
open			-9.197	1.457
			(5.934)	(5.572)
Industry			0.557**	0.028
			(0.240)	(0.248)
education			-0.308	-0.016
			(0.437)	(0.451)
Urban			0.883***	0.518*
			(0.303)	(0.297)
Constant	1.190***	1.329***	-4.915***	1.090
	(0.040)	(0.021)	(1.449)	(1.610)

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Observations	2,944	2,944	2,944	2,944
R-squared	0.948	0.974	0.968	0.974
City FE	YES	YES	YES	YES
Year FE	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Heterogeneity Analysis

Four Major Geographic Regions

According to the heterogeneity test in Table 7, the test based on data from the four main geographic areas presents significant regional differences in the impact of technology innovation capability (TIC) on human capital.

For the sample as a whole, the coefficient is not significant, except that it is significant at a 5% test value (0.045) in the Central Region, but it is not significant in the Eastern, Western, and Northeastern Regions, and the coefficient is somewhat negative in the Eastern and Northeastern Regions.

The human capital conversion capability from technology innovation is much stronger in the Central Region due to the bridge position and the fairly well-balanced structure.

Moreover, urbanization level (Urban) is significantly positive in the eastern region (1.115), highlighting agglomeration effects under high urbanization, while economic development level (economic) is significantly negative in the central region (-0.682), possibly reflecting structural transformation pressures that limit the translation of economic output into human capital gains.

Population size (people) and financial development level (finance) are not consistently significant across regions, further suggesting that regional characteristics moderate these relationships.

Overall, the results imply that the technological progress–human capital relationship is shaped by regional geography, economic foundations, and development stages, supporting differentiated regional policies.

Table 7 Regional Comparison: Four Major Geographic Divisions

	(1)	(2)	(3)	(4)
	East	Central	West	Northeast
VARIABLES	Human Capital	Human Capital	Human Capital	Human Capital
TIC	-0.014	0.045**	0.052	-0.012
	(0.057)	(0.018)	(0.042)	(0.049)
people	-0.351	-0.745*	0.083	-0.524

	(0.475)	(0.434)	(0.520)	(0.562)
economic	-0.348	-0.682***	-0.076	-0.006
	(0.213)	(0.234)	(0.124)	(0.215)
finance	-0.045	0.017	0.032	0.003
	(0.054)	(0.032)	(0.048)	(0.042)
open	-16.982	-22.923	29.639	-6.501
	(11.407)	(14.952)	(24.153)	(5.102)
Industry	-1.209	0.557	-0.378	-0.282
	(0.738)	(0.550)	(0.324)	(0.544)
education	-0.290	-0.398	0.212	0.392
	(1.061)	(0.921)	(0.681)	(0.874)
Urban	1.115**	0.696	-0.114	-0.210
	(0.434)	(0.523)	(0.615)	(0.468)
Constant	7.932	12.935***	1.403	4.328
	(4.771)	(4.439)	(3.907)	(4.476)
Observations	739	898	928	377
R-squared	0.977	0.984	0.955	0.969
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

CONCLUSION

This paper investigates the connection between the technological advancement and the growth of human capital based on unbalanced panel data of 262 Chinese cities at prefecture level between 2010-2023. Technological innovation capability (TIC) defines technological advancement in that the ratio of science and technology spending plus expenditures on local government general budgets is taken, and human capital is defined as the number of students enrolled in regular higher education institutions divided by the number of residents. A fixed effects model of relevancy that is two sided and incorporates the necessary controls is used to evaluate the net effect and its heterogeneity.

According to the benchmark results, TIC is positively correlated with the human capital, significantly across common specifications. Though inclusion of year fixed effects lowers the TIC coefficient indicating that the common time trends could be overstated the effect, the positive association is strong. Control factors with a relatively steady positive effect are urbanization level (Urban), which is rather high, and the level of population, the openness to the outside world, the industrial structure, and the level of education expenditure are not significant when full fixed effects are taken into consideration.

The resilience tests ensure the validity of the key results. Even after dropping the years during the pandemic and eliminating municipalities under the absolute authority of the central government, TIC is still significant with coefficients that are near the benchmarks, which means that it is not the occasional shocks that are at work, nor is it that the handful of cities with enough resources.

It is also found that heterogeneity analyses show that there are high levels of regional and scale differences. TIC is important only in the Central Region and not in the Eastern, Western, and Northeastern regions (negative coefficients in the Eastern and Northeastern subsamples), which suggests that the transformation of the input of innovation into human capital is a regional phenomenon. The effect of TIC in promoting is focused in the non-large and medium-sized cities, and not in big cities and middle-sized cities, whereas Urban is more dominant in big cities, which is Bearing in mind that agglomeration effect is stronger.

On the whole, the results require that human capital policies based on innovation should be separated. The smaller cities as well as the Central Region should enhance the connection between investment in innovation and the development of talents whereas the large cities and the regions in which TIC is not significant must raise the absorption capacity by enhancing industrial upgrading, the quality of education, and urban functions. Further studies can take on more robust identification methods and include a more in-depth challenge of innovation and human capital to understand the processes that never beheld the heterogeneity.

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