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Human Capital impact on productivity in Chinese enterprises: analyzing the mediating role of innovation

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Research Article

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Abstract

Human capital can increase productivity by enhancing the innovation, creativity, and technological levels of enterprises. However, it can threaten productivity if inappropriately designed and structured since education and training consume resources like time and finance. This research investigates the impact of human capital on productivity among enterprises in China between 2008 and 2015, using a fixed-effects model. In addition, it measures this impact among enterprises with different levels of productivity levels using the quantile regression technique. Moreover, it examines the moderating role of innovation in this impact by employing the moderating regression method. The results confirm the beneficial impacts of human capital including education, technical skills, and work experience on productivity in Chinese enterprises in the comprehensive analysis. This impact differs in enterprises with various levels of productivity as workers with doctorate and master degrees and middle technical skills indicate higher constructive impacts on productivity. The results of the mediating examination reveal the considerable mediating role of innovation in this impact. These findings highlight the importance of human resource management in enterprises and imply that enterprises with high productivity levels involve complex and advanced systems needing further educated and skillful workers. Therefore, managers should promote investment in human resources and R&D endeavors to escalate productivity, especially in enterprises with higher levels of productivity and technology at the microeconomic level.

1. Introduction

In the 21st century, human capital and productivity play a key role in the welfare and life quality of people around the world. Human capital is among the most influential elements in management and economics (Pham et al., 2020; Tumwine et al., 2014). From the managers' viewpoint, human capital plays one of the most crucial roles in the development of firms. From economists' perspective, it is among the primary production inputs as they define the very initial production function by labor and capital, both of which implicitly and mainly bring the concept of human capital (Adeleye et al., 2022; Jin et al., 2023; Tatar et al., 2024). In addition, productivity serves as a key indicator of the development level among enterprises, especially across the current intensively competitive environment of the world (Brandt et al., 2020; Shen et al., 2020; Taghvaee et al., 2024; Xiang & Chin et al., 2021). For this reason, productivity enhancement paves the way for the further acceleration of economic growth in countries like China decisively targeting the first largest global economy. Therefore, human capital and productivity have attracted substantial attention in the world (Faggian et al., 2019; Tan,2014; Wei & Hao; 2011; Zhang et al., 2023).

Human capital has different impacts on productivity both positively and negatively. From the positive aspect, skilled, educated, and experienced workers and managers enhance the innovation, creativity, efficiency, and technological levels of enterprises, which increase their productivity (Klimovskikh et al., 2023; Seleim et al., 2007; Tajeddini et al., 2020). Moreover, education and training as another dimension of human capital can help workers to adapt to rapid changes in technological equipment, competitive market conditions, and job requirements, which heighten the productivity level. In addition to its contribution to innovation and technology, human capital increases the productivity level by improving

the psychological atmosphere of firms (Adula et al., Marimuthu et al., 2009; Shrouf et al., 2020). For example, it can stimulate the teamwork and collaborative spirit of workers by improving their communication and coordination towards common targets. Like mental health, physical well-being can fully activate the potential of workers, thereby increasing the productivity level across enterprises. Thus, human capital can improve productivity via improving innovation, education, and health factors (Avan et al., 2022; Grawitch, et al., 2017; Jibir et al., 2023).

However, human capital, if inappropriately designed and structured, can threaten the productivity level of firms. The improvement of human capital through education and training requires much time and financial costs which reduce the current profit and productivity of firms for a probable and delayed return in the future (Deming, 2022; Liang et al., 2924; Obeidat et al., 2023). This return might not be yielded if the workers' skills mismatch the requirements of their own jobs and duties or if the specified education only overqualifies the workers. In this case, enterprises have to bear not only the cost of education but also the cost of higher wages for the mismatched and overqualified workers without any return. Furthermore, skilled, specialized, and experienced workers possess a higher ability to bring detrimental outcomes for organizations through for example misusing their own skills, resisting innovative and progressive changes in systems, and being exposed to security risks. Thus, human capital can decrease the productivity level of enterprises (Aslam et al., 2023; Ismail, 2018).

To address these two conflicting groups of impacts, this study aims to investigate the effects of human capital on productivity within Chinese enterprises. To this end, it innovatively considers the different dimensions of human capital including education, skill, and experience as well as various ranges of productivity from the lowest to the highest. In addition, it explores the mediating role of innovation in the effects of human capital on productivity. The results of this research can contribute to managerial decision-making helping enterprises how to manage human capital beneficially affects productivity. Furthermore, the findings can show managers the approaches to optimizing the constructive role of human capital in the productivity of enterprises.

2. Theoretical framework

There are specific theories regarding human capital and productivity establishing a foundation for the investigation of this study. The human capital theory expresses the beneficial impacts of human capital on productivity level (Fraumeni, 2012; Rahim et al., 2021; Sun et al., 2020). The learning curve effect implies that the heterogeneity of this impact depends on the range of productivity level (Gerhart & Feng, 2021; Hoang Manh, 2023; Peng et al., 2023; Wang et al., 2021). The endogenous growth theory indicates the mediating role of innovation in this impact. These theories pave the way for proposing the research hypotheses as follows.

The human capital theory stresses that human capital positively affects the productivity level of enterprises (Lai et al., 2017; Martin et al., 2013; Tan, 2014; Wilton, 2019). focusing on the beneficial impacts. According to this theory, individual laborers have a series of skills, educations, experience, and

abilities, which can be further improved via different methods, for example, university or learning by doing. In this way, they increase their expertise and technical level, accumulating further human capital (Deng & Yang, 2022; Hatch & Dyer, 2004; Lauder & Mayhew, 2020). This accumulation increases their market value since they can escalate the efficiency and productivity level of enterprises, thereby raising the profits. Therefore, the accumulation of human capital nurtures the productivity level of firms (Crook et al., 2011; Schulz et al., 2013; Tumsifu, 2023). This analysis proposes the following hypothesis.

Hypothesis 1

(H1): Human capital improves the productivity level.

The learning curve effect indicates that human capital has variable impacts on the productivity level of enterprises (Anwar & Abdullah, 2021; Ramírez et al., 2020). It rejects a constant impact based on the diminishing return to scale. According to the learning curve effect, the accumulation of human capital considerably improves productivity, efficiency, and profit at the lower levels of productivity (Tran & Vo, 2020). A possible reason is the high amount of capacity for increasing productivity at its lower amounts. With further productivity increases, the impact of human capital on productivity reduces since the structure of a certain enterprise allows a limited level of productivity (Sulasmiyati & Adila, 2023). Thus, human capital variably impacts productivity depending on the scale of productivity. This analysis introduces the subsequent hypothesis.

Hypothesis 2

(H2): The impact of human capital on productivity relies on the current level of productivity.

The endogenous growth theory, introduced by Paul Romer, considers that human capital affects productivity via the mechanism of innovation and creativity. Instead of an exogenous factor, it defines human capital as an endogenous factor resulting from effective and appropriate policies for the escalation of productivity and economic development (Jin et al., 2023; Lee et al., 2010; Liu et al., 2017). According to this theory, human capital promotes technological and innovative methods, equipment, and systems, thereby increasing the productivity level (Sun et al., 2020; Sulistyaningsih, 2023). Hence, innovation has a mediating role in the impact of human capital on productivity (Braunerhjelm, P., & Lappi, 2023). This consideration plans the succeeding hypothesis.

Hypothesis 3

(H3): Innovation has a mediating role in the impact of human capital on productivity.

3. Methodology

Following (Backman, 2014; Wang & Li, 2021; Zhao & Li, 2020), this study estimates the impacts of human capital on the productivity of enterprises in China within 2008 and 2015, using econometric

methods. To this end, it defines human capital as a function of three dimensions including education, technical skills, and experience.

$$Pro_{it} = C + \sum_{j=1}^{4} \alpha_{j_i} Education_{j_{it}} + \sum_{k=1}^{3} \beta_{ki} Skill_{kit} + \sum_{l=1}^{3} \theta_{li} Experience_{lit} + e_{it}$$

1

where Pro is productivity of labor, Education shows the education of level of labor, Skill indicates the technical skill level of labor, Experience denotes the job experience of labor measured in year, C signifies intercept, e represents the error term, i shows enterprise, t indicates time, and α, β, and θ are coefficients. If the coefficients are significant and positive, they confirm H1 and human capital theory, implying the constructive role of human capital in productivity. Eq. (1) decomposes human capital into three dimensions: education, technical skills, and experience. Furthermore, it classifies each dimension into the following indicators.

$$Education = (Doc, Mas, Ung, Col)$$

$$Skill = (Sen, Mid, Ele)$$

$$Experience = (1-3, 3-5, > 5)$$

where Doc, Mas, Ung, and Col show education degrees of Doctorate, Master, undergraduate course, and junior college, respectively; Sen, Mid, and Ele represent senior, middle rank, and elementary, respectively; and 1–3, 3–5, and > 5 indicate years of working experience of labor equivalent to 1–3, 3–5, and more than 5 years, respectively. Accordingly, Education includes four categories: doctorate, master, undergraduate course, and junior college. Technical skill involves three classes: senior, middle rank, and elementary. Experience covers three groups of people with 1–3, 3–5, and more than 5 years of work experience. Since all the variables are in natural logarithm form, their coefficients are interpreted as elasticities, comparable to each other.

To examine the validity of the estimations and results, this research tests the fixed- or random-effects character of the regression as well as the robustness, multicollinearity, and endogeneity of the results. To decide on the fixed- or random-effects, the Hausman test examines the null hypothesis of the random-effects model (Mattei et al., 2021; Nasrollahi et al., 2021). To check the robustness of the results, it examines the estimates of Eq. (1) using three approaches including dependent variable replacement, panel tool variable method, and bilateral censoring (Backman, 2014). The first method, dependent variable replacement, replaces productivity level with per capita income to check whether the results are stable even if the dependent variable changes. In addition, the Variance Inflation Factor (VIF) indicates the degree of multicollinearity. A VIF around 10 or higher indicates a serious multicollinearity but a VIF ranging about 1 and 2 rejects the issue of a problematic multicollinearity. Finally, an endogeneity test omits macroscopic variables to address any possible endogeneity issues (Aiyar & Feyrer, 2002;

Moghimbeygi & Nodehi, 2022; Xie et al., 2021). To test the endogeneity issues, this research supplements three possible missing variables into Model (1) to check if the results consistently confirm those of Model (1). The missing variables include urbanization rate, Consumer Price Index (CPI), and educational expenditure per student in higher education institutions. If Model (1) produces similar and consistent results with and without the missing variables, the estimations reject any endogeneity problems.

Furthermore, this study measures the heterogeneity effects of human capital and the corresponding mediating role of innovation (Wang & Li, 2021; Zhou, Y., & Huang et al., 2019; Zhu, J., & Ding, 2017). To check how the impacts of human capital vary depending on the current level of productivity, this study classifies enterprises into five groups (i.e., 10%, 25%, 50%, 75%, and 90%) according to their productivity levels. The results can reveal the heterogeneity characteristics of human capital impacts on productivity in enterprises with various ranges of labor productivity. Moreover, this research measures the heterogeneity of human capital effects on productivity in enterprises with or without innovation. If the outcomes confirm the heterogeneity of human capital effects, its relationship with productivity differs in enterprises with various levels of innovation. In addition to the heterogeneous character, such results can reveal the possible mediating role of innovation on this effect. More specifically, a mediating effect test measures the role of innovation using the following equation.

$$Ino_{it} = C + \sum_{j=1}^{4} \gamma_{j_i} Education_{j_{it}} + \sum_{k=1}^{3} \delta_{ki} Skill_{kit} + \sum_{l=1}^{3} \mu_{li} Experience_{lit} + e_{it}$$

2

where Ino presents innovation level. The innovation has two proxies including the number of effective patents and per capita technology income. In addition, γ, δ, and μ are coefficients of the variables whose statistical significance signalizes the possibility of innovation mediating role.

$$Pro_{it} = C + \sum_{j=1}^{4} \rho_{j_i} Education_{j_{it}} + \sum_{k=1}^{3} \sigma_{ki} Skill_{kit} + \sum_{l=1}^{3} \tau_{li} Experience_{lit} + \omega_l Ino_{it} + e_{it}$$

3

where ρ, σ, τ, and ω are coefficients of the variables. Given the statistical significance of the coefficient in Eq. (2), the results confirm the mediating role of innovation in the effects of human capital on productivity, if ω is also statistically significant in Eq. (3).

4. Data

In this research, the enterprise labor productivity is calculated by the added value of the enterprise in 2008 divided by the number of employees at the end of the period. In addition, industrial added value is a summation of workers' remuneration, depreciation, net production tax, and operating surplus (Deng et al,

2022). The remuneration of the worker is measured by the remuneration payable to the employee. Depreciation is depreciation of the current year. In case of a missing value of depreciation in the current year, the fixed capital stock is multiplied by the depreciation rate (15%), where the fixed capital stock is measured by the total fixed assets index. Net production tax is equal to the summation of taxes and surcharges, taxes in management expenses (take 0), and VAT payable in the current year minus subsidy income (Zhang, 2019) (take 0). Operating surplus is equal to the summation of operating profit and subsidy income (take 0) minus fair value change income (take 0) and investment income (Zhang, 2019). Due to the difficulty of obtaining the "tax in management expenses", the above method ignores some indicators compared with the strict enterprise value-added accounting method. However, this method basically conforms to the definition and accounting caliber of the value-added of commercial and trade enterprises, which increases the credibility of the estimation of enterprise value-added. Moreover, only 196 data of the "fair value change income" indicator are non-zero, and the rest of the values are zero, implying that this indicator can be ignored. In addition, this research divides the added value of enterprises by the price index to produce the added value of enterprises at constant prices in 2008, removing the inflation effect. Finally, productivity is defined as the natural logarithm of enterprise labor productivity plus one.

Table 1
Variables and proxies description

Variable	Symbol	Proxy	Symbol
Productivity	Pro		
Education degree	Education	Doctorate degree	Doctorate
		Master degree	Master
		Undergraduate degree	Undergraduate
		College degree	College
Technical skill	Skill	Senior level	Senior
		Middle level	Middle
		Elementary level	Elementary
Work experience	Experience	1–3 years	1–3
		3–5 years	3–5
		More than 5 years	> 5
Innovation level	Ino	Number of valid patents per capita	Patents
		Technology income per capita	Tech income

Zhongguancun Haidian Park is the core park of Zhongguancun National Independent Innovation Demonstration Zone, known as the "Silicon Valley of China", and is also known as the birthplace and rise

of China's strategic emerging industries, where more than 70% of the leading enterprises in China's strategic emerging industries are located. Therefore, it is representative to discuss the influence of multi-dimensional human capital structure on labor productivity in strategic emerging industries with the enterprises in Haidian Park as the research object. This paper uses the enterprise data of Zhongguancun National Independent Innovation Demonstration Zone in Haidian District, Beijing for 8 years from 2008 ~ 2015, and the dataset includes a total of 799989 observations from 18433 enterprises. The database contains basic information such as the overall enterprise, legal person, human capital and, scientific and technological innovation of the enterprise, as well as the production, operation and financial status such as sales revenue, total assets, paid-in capital, intermediate inputs, and various expenses.

The data was collated with reference to the existing data exclusion procedures (Nie & Jia, 2011; Lu & Lord, 2012). The final excluded sample contains 39899 observations, of which 9,156 were strategic emerging enterprises.Table 1 lists the description of Variables and proxies.

5. Result

The estimates of this study confirm that human capital has a significant and positive effect on labor productivity in Chinese enterprises. In addition, they show that this effect varies across enterprises with different values of productivity. Moreover, they reveal the mediating role of innovation in this effect.

Table 2 represents the results of estimating the relationship between human capital indicators and productivity in Model (1). According to the results, the coefficients of education level including college, undergraduate, master, and doctorate degrees are 0.110, 0.205, 0.419, and 0.517, respectively, which are positive, increasing, and significant at 1% level, except for the college degree, significant at 10% level. Due to the ascending order of the estimated coefficients, the results show that labors with higher education levels have greater impacts on productivity. Regarding the technical skills, the coefficient of elementary rank is -0.014, negative and statistically insignificant. However, the coefficients of people with senior and middle ranks are 0.168 and 0.145, which are positive and statistically significant at 5% and 1% level, respectively. These estimates, similar to the effects of education indicators, show that labors with high skills have a stronger influence on productivity. Likewise, the experience indicators follow an increasing order. Accordingly, they are 0.277, 0.375, and 0.469 for people with 1–3 years, 1–5 years, and more than 5 years, respectively, which are positive, ascending, and statistically significant at 1% level. Therefore, all three dimensions of human capital including education, technical skills, and experience show a constructive effect on productivity level, confirming hypothesis 1 (H1).

The estimation of Model (1) involves the results of two additional tests including the VIF and Hausman test. The Hausman test rejects its null hypothesis, implying that the model follows a fixed-effects pattern. In addition, the results of VIF range within 1.07 and 2.52 rejecting any serious multicollinearity issues. Therefore, Model (1) is estimated using a fixed-effects model, whose results are valid due to no serious multicollinearity.

Table 2
Estimated impact of human capital on productivity in Model (1)

Variable	Coefficient (t-statistics)	VIF price
Education		
College	0.110*	1.83
	(1.95)	
Undergraduate	0.205***	1.89
	(4.18)	
Master	0.419***	1.48
	(4.44)	
Doctor	0.517***	1.22
	(2.77)	
Skill		
Elementary	-0.014	1.07
	(-0.32)	
Middle	0.145***	1.14
	(3.10)	
Senior	0.168**	1.23
	(2.40)	
Experience		
1 ~ 3 years	0.277***	2.16
	(6.58)	
3 ~ 5 years	0.375***	1.68
	(8.11)	
> 5 years	0.469***	2.52
	(9.44)	
Constant	4.150***	

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

Variable	Coefficient (t-statistics)	VIF price
	(36.58)	
Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.		

The results of the robustness tests validate the estimates of Model (1). Table 3 represents the results of the robustness tests. The results of all three robustness tests confirm the beneficial effects of human capital on productivity. In addition, they indicate a higher effect among people with higher education, technical skills, and experience, consistent with the results of Model (1). For example, the results of the bilateral censoring method indicate that the coefficients of education indicators including college, undergraduate, master, and doctorate degrees are 0.074, 0.165, 0.354, and 0.522, respectively. They are positive and statistically significant at 1% level, except for the statistically insignificant college degree. They indicate an increasing order. In addition, the coefficients of the technical skill indexes including middle and senior ranks are 0.146, and 0.172, respectively, which are positive and statistically significant at 1% level, respectively. Although the coefficient of the elementary level is -0.020, which is negative and statistically insignificant, the three estimated coefficients display an ascending order, confirming the results of Model (1). Moreover, the coefficients of experience indicators including 1–3, 3–5, and more than 5 years are 0.280, 0.380, and 0.480, respectively, which are statistically significant at 1% level. According to these results, all the estimated coefficients of the robustness tests affirm that labor with higher education, technical skills, and experience have a stronger beneficial effect on productivity, verifying the results of estimating Model (1). Therefore, the results of Model (1) are stable, robust, and valid.

Table 3
Results of the robustness tests on the impact of human capital on productivity

Method	Variable replacement	Panel tool variable	Bilateral censoring
Variable	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
Education			
College	0.257***	0.109**	0.074
	(4.01)	(2.36)	(1.62)
Undergraduate	0.376***	0.200***	0.165***
	(6.50)	(4.90)	(4.12)
Master	0.591***	0.413***	0.354***
	(5.67)	(6.17)	(4.93)
Doctor	0.674***	0.510***	0.522***
	(3.33)	(4.86)	(3.54)
Skill			
Elementary	0.022	-0.013	-0.020
	(0.49)	(-0.37)	(-0.55)
Middle	0.248***	0.147***	0.146***
	(4.66)	(4.07)	(4.03)
Senior	0.131	0.165***	0.172***
	(1.52)	(3.08)	(2.96)
Experience			
1 ~ 3 years	0.407***	0.277***	0.280***
	(9.16)	(8.49)	(8.58)
3 ~ 5 years	0.551***	0.375***	0.380***
	(10.80)	(10.59)	(10.72)
> 5 years	0.745***	0.470***	0.480***
	(13.47)	(12.72)	(13.02)

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

Method	Variable replacement	Panel tool variable	Bilateral censoring
Constant	5.482***		4.186***
	(43.56)		(38.75)
Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.			

Table 4 represents the results of the endogeneity tests which reject any endogeneity issue in the estimations. According to the results, supplementing the missing variables to the regression produces similar outcomes. For example, adding urbanization rate estimates the coefficients of education indicators including college, undergraduate, master, and doctorate degrees equal to 0.110, 0.205, 0.419, and 0.517, respectively. They are positive and statistically significant at 1% level, except for the coefficient of college degree which is statistically significant at 10% level. Likewise, the coefficients of technical skills indexes including middle and senior levels are 0.145 and 0.168, which are positive and statistically significant at 1% and 5% levels, respectively. Although the coefficient of the elementary level is -0.014, which is negative and statistically insignificant, the estimated coefficients follow an ascending order from the lowest to the highest technical skills, which is consistent with the results of Model (1). Moreover, the coefficients of experience years, i.e., 1–3, 3–5, and more than 5 years, are 0.277, 0.375, and 0.469, respectively, which are positive and statistically significant at 1% level. Accordingly, the results of the endogeneity tests consistently show an ascending order, implying that labors with higher education, technical skills, and experience have a more beneficial impact on productivity. Therefore, the results reject any endogeneity issues and accept the outcomes of Model (1).

Table 4
Results of the endogeneity tests on the impact of human capital on productivity

Method	Urbanization rate	CPI	Educational expenditure
Variable	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
Education			
College	0.110*	0.110*	0.110*
	(1.95)	(1.95)	(1.95)
Undergraduate	0.205***	0.205***	0.205***
	(4.18)	(4.18)	(4.18)
Master	0.419***	0.419***	0.419***
	(4.44)	(4.44)	(4.44)
Doctor	0.517***	0.517***	0.517***
	(2.77)	(2.77)	(2.77)
Skill			
Elementary	-0.014	-0.014	-0.014
	(-0.32)	(-0.32)	(-0.32)
Middle	0.145***	0.145***	0.145***
	(3.10)	(3.10)	(3.10)
Senior	0.168**	0.168**	0.168**
	(2.40)	(2.40)	(2.40)
Experience			
1 ~ 3 years	0.277***	0.277***	0.277***
	(6.58)	(6.58)	(6.58)
3 ~ 5 years	0.375***	0.375***	0.375***
	(8.11)	(8.11)	(8.11)
> 5 years	0.469***	0.469***	0.469***

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

Method	Urbanization rate	CPI	Educational expenditure
	(9.44)	(9.44)	(9.44)
Urbanization rate	19.92***		
	(7.36)		
CPI		1.828***	
		(7.36)	
Educational expenditure			0.115***
			(7.36)
Constant	-12.76***	2.322***	3.869***
	(-5.62)	(9.55)	(35.38)
R^2	0.074	0.074	0.074
Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.			

The results of heterogeneity tests show that human capital has a stronger impact on enterprises with higher levels of productivity. Table 5 represents the results of the heterogeneity tests, according to the different quantiles of productivity levels. According to the results, with changing the labor productivity from low to high conditional quantiles, human capital with high education and more than 3 years of working experience shows an obviously prominent role. In addition, the human capital of bachelor's degree or below, intermediate and senior skills and 1 ~ 3 years of work experience reveal a U-shape relationship. Moreover, primary-skilled human capital is a hindrance to labor productivity. Therefore, human capital has different patterns of effects among enterprises with various productivity levels, but it shows stronger effects in enterprises with a higher level of productivity, highlighting the positive role of human capital in enterprises with higher levels of productivity. This result affirms hypothesis 2 (H2).

Table 5
Estimated impacts of human capital on productivity under different conditional quantiles

Quantile	**0.1**	**0.25**	**0.5**	**0.75**	**0.9**
Variable	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
Education					
College	0.303***	0.227***	0.222***	0.255***	0.304***
	(204.79)	(205.18)	(34.40)	(67.86)	(215.46)
Undergraduate	0.462***	0.453***	0.511***	0.538***	0.583***
	(313.63)	(416.23)	(96.96)	(154.83)	(492.39)
Master	0.853***	1.028***	1.062***	1.141***	1.169***
	(365.71)	(863.66)	(291.57)	(896.04)	(508.63)
Doctor	-0.442***	-0.100***	0.539***	0.662***	0.700***
	(-48.20)	(-26.93)	(43.35)	(85.14)	(110.14)
Skill					
Elementary	0.049***	-0.050***	-0.068***	-0.106***	-0.156***
	(45.32)	(-29.51)	(-7.50)	(-17.93)	(-160.58)
Middle	0.107***	0.037***	0.037***	0.034***	0.056***
	(44.63)	(23.44)	(37.48)	(17.31)	(21.73)
Senior	0.161***	0.002*	-0.034***	0.148***	0.146***
	(127.93)	(1.69)	(-2.84)	(136.10)	(51.44)
Experience					
1 ~ 3 years	0.211***	0.190***	0.206***	0.235***	0.291***
	(31.95)	(62.80)	(19.55)	(55.15)	(74.92)
3 ~ 5 years	0.152***	0.167***	0.176***	0.182***	0.214***
	(23.07)	(72.55)	(23.93)	(35.92)	(78.10)
> 5 years	0.282***	0.327***	0.351***	0.467***	0.646***

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

Quantile	0.1	0.25	0.5	0.75	0.9
	(63.95)	(235.94)	(41.09)	(129.14)	(251.82)

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

The results of the heterogeneity tests reveal that human capital has a stronger impact on the productivity level of enterprises with R&D investment than those without such investment. Table 6 represents the results of the heterogeneity tests on enterprises with and without R&D investment. According to the estimates, in terms of education and skills, the higher the academic qualifications, skill level, and length of service of human capital, the greater the promotion effect on the labor productivity of R&D enterprises. However, in non-R&D enterprises, 3–5 years of work experience, master's degree, and intermediate skilled employees have a greater impact on the labor productivity of the enterprise. It shows that employees with solid professional basic knowledge, advanced skills, and rich work experience have room to give full play to the scientific and technological innovation activities of R&D enterprises, but do not have full room for exertion in non-R&D enterprises.

Table 6
Estimated impact of human capital on productivity in Model (1) for two sample enterprises with and without R&D investment

Sample	**With R&D investment**	**Without R&D investment**
Variable	Coefficient (t-statistics)	Coefficient (t-statistics)
Education	0.148**	0.094
College	(1.97)	(0.91)
	0.210***	0.240**
Undergraduate	(3.20)	(2.53)
	0.284**	0.492***
Master	(2.16)	(2.75)
	0.867***	0.451
Doctor	(2.92)	(1.46)
Skill	-0.040	-0.056
Elementary	(-0.82)	(-0.60)
	0.144**	0.191**
Middle	(2.49)	(2.01)
	0.208**	0.044
Senior	(2.13)	(0.35)
Experience	0.261***	0.331***
1 ~ 3 years	(4.87)	(3.85)
	0.324***	0.472***
3 ~ 5 years	(5.37)	(5.10)
	0.481***	0.410***
> 5 years	(7.30)	(4.37)
Constant	4.323***	3.845***
	(34.81)	(12.69)

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

Sample	With R&D investment	Without R&D investment
R^2	0.092	0.060
Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.		

The results of the mediating tests reveal that innovation has a positively mediating role in the effects of some human capital indicators on enterprises. Table 7 represents the results of estimating the mediating effects of innovation. According to the results, doctorate degree, master degree, and middle level of technical skills show a considerable mediating effect in both regressions with two different proxies of the number of effective patents and per capita technology income. In Model (2), the coefficients of doctorate degree are 0.104 and 1.051 in the case of the number of effective patents and per capita technology income, which are positive and statistically significant at 5% and 1% levels, respectively. Similarly, the coefficients of master degree are 0.044 and 1.757, which are positive and statistically significant at 1% level. Likewise, the coefficients of the middle level of technical skills are 0.023 and 0.254, which are positive and statistically significant at 5% and 1% levels, respectively. Therefore, the results of Model (2) confirm the effects of doctorate degree, master degree, and middle level of technical skills on both innovation indicators.

In addition, the results of Model (3) indicate the considerable effects of both the innovation proxies on the productivity level. The coefficients of the number of valid patents and per capita technology income are 0.188 and 0.087, respectively, which are statistically significant at 1% level. Thus, doctorate degree, master degree, and middle level of technical skills considerably affect innovation, which in turn impacts productivity. In conclusion, innovation has a mediating role in the impact of human capital on productivity, especially through labor with doctorate degree, master degree, and middle level of technical skills, supporting hypothesis 3 (H3).

Table 7
Estimated mediation role of innovation on the effects of human capital on productivity

	Model (2)		**Model (3)**	
Moderator	Patents	Tech income	Patents	Tech income
Variable	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)	Coefficient (t-statistics)
Education				
College	0.013	0.824***	0.225***	0.142**
	(1.14)	(7.09)	(3.57)	(2.52)
Undergraduate	0.009	1.374***	0.400***	0.264***
	(1.44)	(14.06)	(8.01)	(5.80)
Master	0.044***	1.757***	0.894***	0.695***
	(2.94)	(10.82)	(10.21)	(8.78)
Doctor	0.104**	1.051***	0.322*	0.237
	(2.28)	(3.31)	(1.86)	(1.59)
Skill				
Elementary	0.018	0.192**	-0.028	-0.051
	(1.59)	(2.21)	(-0.58)	(-1.19)
Middle	0.023**	0.254***	0.084*	0.056
	(2.13)	(2.83)	(1.69)	(1.27)
Senior	-0.011	0.318**	0.014	0.002
	(-0.90)	(2.26)	(0.18)	(0.04)
Experience				
1 ~ 3 years	0.004	0.083	0.183***	0.189***
	(0.44)	(1.13)	(4.03)	(4.78)
3 ~ 5 years	0.028***	-0.066	0.233***	0.248***
	(2.76)	(-0.77)	(4.70)	(5.69)

Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.

	Model (2)		Model (3)	
> 5 years	0.030***	-0.146	0.345***	0.379***
	(3.17)	(-1.56)	(6.73)	(8.28)
Moderator				
Patents			0.188***	
			(4.06)	
Tech income				0.0878***
				(20.50)
Constant	-0.003	3.095***	4.537***	4.212***
	(-0.25)	(14.00)	(45.57)	(45.77)
R^2	0.022	0.052	0.156	0.182
Note: Parentheses show t-statistics. *, **, and *** represent statistical significance at 10%, 5%, and 1%, levels, respectively.				

6. Discussion

The findings of this research show that human capital including education, technical skills, and experience considerably improves the productivity level, supporting hypothesis 1 (H1). This finding is consistent with (Crook et al., 2011; Lai et al., 2017; Martin et al., 2013; Tan, 2014; Schulz et al., 2013; Tumsifu, 2023; Wilton, 2019) but inconsistent with (Aslam et al., 2023; Deming, 2022; Ismail, 2018; Obeidat et al., 2023). A reason for this positive impact is that labors with high education, skills, and experience have great abilities to handle tasks efficiently and effectively. In addition, they can rapidly and accurately adapt to the new technologies and equipment, maintaining and upgrading the competitive level of their enterprises. Moreover, they are more likely to possess the power of effective communication and collaboration to enhance teamwork and cohesively work to accomplish the goals of their enterprises. Furthermore, they have a deep insight into the processes and systems of their enterprises, leading to fewer errors and rework.

Another finding of this study is that human capital reflects different patterns of effects among enterprises with various productivity levels, while stronger effects are in enterprises with higher levels of productivity, highlighting the positive role of human capital in enterprises with higher levels of productivity. This finding accepts hypothesis 2 (H2) which is consistent with (Anwar & Abdullah, 2021; Ramírez et al., 2020; Sulasmiyati & Adila, 2023; Tran & Vo, 2020). An explanation for this finding is that enterprises with high productivity involve advanced and complex systems and processes. In this environment, educated, skilled, and experienced labors can more effectively and efficiently work to further enhance productivity.

Furthermore, the findings indicate that employees with high education, technical skills, and experience have more potential to implement scientific and technological innovation activities in enterprises with R&D investment, affirming hypothesis 3 (H3). This finding implies that innovation intensifies the beneficial effects of human capital on productivity. In other words, innovation mediates this impact, especially in terms of labors with a doctorate degree, master degree, and middle level of technical skills. This finding confirms (Braunerhjelm & Lappi, 2023; Jin et al., 2023; Lee et al., 2010; Liu et al., 2017; Sun et al., 2020; Sulistyaningsih, 2023) This mediating role is rooted in the high ability of human capital to enhance the innovation level of enterprises by offering new ideas to conduct the tasks and upgrading the technology advancement by effectively utilizing the new tools and systems. This approach needs a high degree of education, technical skills, and experience, highlighting the role of workers with doctorate degree, master degree, or high technical skills.

7. Conclusion

This study supports the constructive effects of human capital on productivity among enterprises in China during 2008–2015, using an econometric approach including a fixed effects model, quantile regression, and mediating effect test. More specifically, education, technical skills, and experience in the labor force improve productivity levels. This beneficial impact is especially evident in enterprises with higher degree of productivity due to their more advanced and complex systems and environments which need educated, skillful, and experienced workers to further enhance productivity. Furthermore, this effect relies on the mediating effect of innovation remarkably regarding workers with a doctorate degree, master degree, and middle level of technical skills, highlighting the mediating role of creativity and innovation to intensity the human capital impacts.

The findings of this research, which support the positive impact of human capital, propose the following implications for managers and researchers, particularly in human resource management. Enterprises should promote the investment in human capital including educational progress and technical skills training, thereby enhancing their productivity level. Although this approach improves the productivity level of all enterprises, it should be followed by human resource managers, especially in enterprises with more advanced technologies and higher levels of productivity. The higher the productivity level, the more the managers need to escalate the human resource level aiming at further enhancement of productivity. In addition to the managers of enterprises at the microeconomic level, policy-makers at the macroeconomic level like the government should adopt policies to promote the education degree and technical skills training of workers. In other words, the government should pursue this strategy at the macroeconomic level to heighten aggregate productivity at the national and country level. Furthermore, the decision-makers should devise plans to promote the culture of innovation across enterprises, intensifying the beneficial role of human capital. To this end, they need to provide and increase investment in R&D to incentivize workers to generate new ideas.

Despite the valuable findings of this study regarding the beneficial impact of human capital, it has some limitations paving the way for further investigation in future research. Although the findings reveal the

heterogenous nature of human capital effects on productivity, this research considers only a comprehensive analysis of enterprises without a sector-specific consideration. This finding attaches great importance to the investigation of the human capital impact on the productivity of enterprises in specific sectors or subsectors. Such microscopic exploration can provide more specific insights into the mechanism of escalating productivity in distinctive groups of economic activities. Therefore, future studies can follow this study by measuring the impact of human capital on productivity levels in specific sectors or subsectors of the economy.

Declarations

Author Contribution

The author contributed to the conception of the study; process the data; contributed to analysis and manuscript preparation; performed the data analyses and wrote the manuscript; perform the analysis with constructive discussions.

References

1. Adeleye, B. N., Bengana, I., Boukhelkhal, A., Shafiq, M. M., & Abdulkareem, H. K. (2022). Does human capital tilt the population-economic growth dynamics? Evidence from Middle East and North African countries. Social Indicators Research, 162(2), 863–883.
2. Adula, M., Kant, S., & Birbirsa, Z. A. (2022). Systematic Literature Review on Human Resource Management Effect on Organization Performance. Annals of Human Resource Management Research, 2(2), 131–146.
3. Aiyar, S. S., & Feyrer, J. (2002). A Contribution to the Empirics of Total Factor Productivity. Social Science Electronic Publishing.
4. Anwar, G., & Abdullah, N. N. (2021). The impact of Human resource management practice on Organizational performance. International Journal of Engineering, Business and Management (IJEBM), 5.
5. Avan, A., Hachinski, V., Brain Health Learn and Act Group, Aamodt, A. H., Alessi,C., Ali, S., … Wilk, P. (2022). Brain health: Key to health, productivity, and well-being.Alzheimer's & Dementia, 18(7), 1396–1407.
6. Backman, M. (2014). Human capital in firms and regions: Impact on firm productivity. Papers in Regional Science, 93(3), 557–575.
7. Braunerhjelm, P., & Lappi, E. (2023). Employees' entrepreneurial human capital and firm performance. Research Policy, 52(2), 104703.
8. Brandt, L., Litwack, J., Mileva, E., Wang, L., Zhang, Y., & Zhao, L. (2020). China's productivity slowdown and future growth potential.

9. Crook, T. R., Todd, S. Y., Combs, J. G., Woehr, D. J., & Ketchen Jr, D. J. (2011). Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. Journal of Applied Psychology, 96(3), 443.
10. Deng, J., & Yang, J. (2022). Labor productivity in the economic transition period: Influencing factors and growth decomposition. Population and Economy.
11. Deng, Z., Pang, R., & Chen, Y. (2022). From market power to effective market power — Take China's chemical pharmaceutical preparation manufacturing industry as an example. Managing the World, (1), 90–106.
12. Deming, D. J. (2022). Four facts about human capital. Journal of Economic Perspectives, 36(3), 75–102.
13. Faggian, A., Modrego, F., & McCann, P. (2019). Human capital and regional development. Handbook of regional growth and development theories, 149–171.
14. Fraumeni, B. M. (2012). Human capital productivity: A new concept for productivity analysis. International Productivity Monitor, (24), 20.
15. Grawitch, M. J., Waldrop, J. S., Erb, K. R., Werth, P. M., & Guarino, S. N. (2017). Productivity loss due to mental-and physical-health decrements: Distinctions in research and practice. Consulting Psychology Journal: Practice and Research, 69(2), 112.
16. Gerhart, B., & Feng, J. (2021). The resource-based view of the firm, human resources, and human capital: Progress and prospects. Journal of Management, 47(7), 1796–1819.
17. Hatch, N. W., & Dyer, J. H. (2004). Human capital and learning as a source of sustainable competitive advantage. Strategic Management Journal, 25(12), 1155–1178.
18. Hoang Manh, C. (2023). Agglomeration, Human Capital, and Productivity in Vietnam (Doctoral dissertation).
19. Ismail, R. (2018). The impact of human capital and innovation on labor productivity of Malaysian small and medium enterprises. International Journal of Productivity and Quality Management, 25(2), 245–261.
20. Jin, W., Gao, S., & Pan, S. (2023). Research on the impact mechanism of environmental regulation on green total factor productivity from the perspective of innovative human capital. Environmental Science and Pollution Research, 30(1), 352–370.
21. Jibir, A., Abdu, M., & Buba, A. (2023). Does human capital influence labor productivity? Evidence from Nigerian Manufacturing and Service Firms. Journal of the Knowledge Economy, 14(2), 805–830.
22. Klimovskikh, N., Sekerin, V., Makushkin, S., Kuzmicheva, A., Leontev, M., & Kochetkov, E. (2023). Impact of human resource management on improving the innovation potential of an enterprise to achieve the principles of sustainable development. Journal of Law and Sustainable Development, 11(1), e0274-e0274.
23. Lai, Y., Saridakis, G., & Johnstone, S. (2017). Human resource practices, employee attitudes and small firm performance. International Small Business Journal, 35(4), 470–494.

24. Lauder, H., & Mayhew, K. (2020). Higher education and the labour market: an introduction. Oxford Review of Education, 46(1), 1–9.
25. Liang, Y., Jin, X., & Taghvaee, V. (2024). Sustainable development spillover effects among selected Asian countries: Analysis of integrated sustainability perspective. Socio-Economic Planning Sciences, 91, 101781. https://doi.org/10.1016/j.seps.2023.101781
26. Lee, S. Y., Florida, R., & Gates, G. (2010). Innovation, human capital, and creativity. International Review of Public Administration, 14(3), 13–24.
27. Liu, D., Gong, Y., Zhou, J., & Huang, J. C. (2017). Human resource systems, employee creativity, and firm innovation: The moderating role of firm ownership. Academy of Management Journal, 60(3), 1164–1188.
28. Lu, X., & Lord, L. Y. (2012). Estimation of total factor productivity of Chinese industrial enterprises: 1999–2007. Economics: Quarterly, 11(2), 541–558.
29. Martin, B. C., McNally, J. J., & Kay, M. J. (2013). Examining the formation of human capital in entrepreneurship: A meta-analysis of entrepreneurship education outcomes. Journal of Business Venturing, 28(2), 211–224.
30. Mattei, A., Mealli, F., & Nodehi, A. (2021). Design and Analysis of Experiments. In K.F. Zimmermann (Ed.), Handbook of Labor, Human Resources and Population Economics. Springer, Cham
31. Moghimbeygi, M., & Nodehi, A. (2022). Multinomial Principal Component Logistic Regression on Shape Data. Journal of Classification, 39, 578–599.
32. Nasrollahi, Z., Hashemi, M.-S., Bameri, S., & Mohamad Taghvaee, V. (2020). Environmental pollution, economic growth, population, industrialization, and technology in weak and strong sustainability: using STIRPAT model. Environment, Development and Sustainability, 22(11), 1105–1122.
33. Nie, H., & Jia, R. (2011). Chinese manufacturing enterprises. The World Economy, 34(07), 27–42.
34. Obeidat, S. M., Abdalla, S., & Al Bakri, A. A. K. (2023). Integrating green human resource management and circular economy to enhance sustainable performance: an empirical study from the Qatari service sector. Employee Relations: The International Journal, 45(2), 535–563.
35. Aslam, M., Shafi, I., Ahmed, J., de Marin, M. S. G., Flores, E. S., Gutiérrez, M. A. R., & Ashraf, I. (2023). Impact of Innovation-Oriented Human Resource on Small and Medium Enterprises' Performance. Sustainability, 15(7), 6273.
36. Peng, D., Elahi, E., & Khalid, Z. (2023). Productive Service Agglomeration, Human Capital Level, and Urban Economic Performance. Sustainability, 15(9), 7051.
37. Pham, N. T., Hoang, H. T., & Phan, Q. P. T. (2020). Green human resource management: a comprehensive review and future research agenda. International Journal of Manpower, 41(7), 845–878.
38. Ramírez, S., Gallego, J., & Tamayo, M. (2020). Human capital, innovation and productivity in Colombian enterprises: a structural approach using instrumental variables. Economics of Innovation and New Technology, 29(6), 625–642.

39. Rahim, S., Murshed, M., Umarbeyli, S., Kirikkaleli, D., Ahmad, M., Tufail, M., & Wahab, S. (2021). Do natural resources abundance and human capital development promote economic growth? A study on the resource curse hypothesis in Next Eleven countries. Resources, Environment and Sustainability, 4, 100018.
40. Schulz, E., Chowdhury, S., & Van de Voort, D. (2013). Firm productivity moderated link between human capital and compensation: The significance of task-specific human capital. Human Resource Management, 52(3), 423–439.
41. Seleim, A., Ashour, A., & Bontis, N. (2007). Human capital and organizational performance: a study of Egyptian software companies. Management Decision, 45(4), 789–801.
42. Shen, Y., Yue, S., Sun, S., & Guo, M. (2020). Sustainable total factor productivity growth: The case of China. Journal of Cleaner Production, 256, 120727.
43. Sulasmiyati, S., & Adila, F. D. (2023, September). The Effect of Human Capital on Profitability with Productivity as Intervening Variable. In Brawijaya International Conference on Business, Administration, Taxation, and Tourism (BICBATT 2022) (pp. 154–165). Atlantis Press.
44. Sulistyaningsih, E. (2023). Improving Human Resources Technology Innovation as a Business Growth Driver in the Society 5.0 Era. ADI Journal on Recent Innovation, 4(2), 149–159.
45. Sun, X., Li, H., & Ghosal, V. (2020). Firm-level human capital and innovation: Evidence from China. China Economic Review, 59, 101388.
46. Shrouf, H., Al-Qudah, S., Khawaldeh, K., Obeidat, A., & Rawashdeh, A. J. M. S. L. (2020). A study on relationship between human resources and strategic performance: The mediating role of productivity. Management Science Letters, 10(13), 3189–3196.
47. Tajeddini, K., Martin, E., & Altinay, L. (2020). The importance of human-related factors on service innovation and performance. International Journal of Hospitality Management, 85, 102431.
48. Taghvaee, V., Sharifpour, Y., Akbari, F., Arani, A. A., & Tatar, M. (2023). Integrated sustainability of social, environment and economy: Defining the hypotheses and theories interconnecting the pillars of sustainable development.
49. Tatar, M., Harati, J., Farokhi, S., Taghvaee, V., & Wilson, F. A. (2024). Good governance and natural resource management in oil and gas resource-rich countries: A machine learning approach. Resources Policy, 89, 104583. https://doi.org/10.1016/j.resourpol.2023.104583
50. Tumwine, S., Nasiima, S., & Kamukama, D. N. (2014). Human capital elements and their influence on performance: evidence from Uganda's manufacturing firms.
51. Tan, E. (2014). Human capital theory: A holistic criticism. Review of Educational Research, 84(3), 411–445.
52. Tumsifu, E. (2023). The Relationship Between Human Resource Competencies and Firm Performance: The Case of Financial Institutions in Tanzania. Tanzania Journal of Development Studies, 20(2).
53. Tran, N. P., & Vo, D. H. (2020). Human capital efficiency and firm performance across sectors in an emerging market. Cogent Business & Management, 7(1), 1738832.

54. Wang, M., Xu, M., & Ma, S. (2021). The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. Structural Change and Economic Dynamics, 59, 427–441.
55. Wang, Z., & Li, R. (2021). Human capital, technological innovation, and regional economic growth. Shanghai Economic Research, (07), 55–68.
56. Wei, Z., & Hao, R. (2011). The role of human capital in China's total factor productivity growth: A cross-Province analysis. The Developing Economies, 49(1), 1–35.
57. Wilton, N. (2019). An introduction to human resource management. An Introduction to Human Resource Management, 1-632.
58. Xiang, Z. T., & Chin, J. F. (2021). Implementing total productive maintenance in a manufacturing small or medium-sized enterprise. Journal of Industrial Engineering and Management (JIEM), 14(2), 152–175.
59. Xie, Q., Liu, W., & Zhang, P. (2021). Imported intermediate products embedded technology and enterprise productivity. Manage the World, 37(02), 66–80 + 6 + 22–23.
60. Yin, J. (2013). Study on the Evaluation System of Human Capital and Its Influencing Factors in University Students Based on Information Technology. Educational Science and Technology, 9(2), 253–258.
61. Yin, R. (2022). Analysis of the relationship between university human capital investment and local economic development based on the grey relational degree method. Technological Development and Innovation, 25(08), 98–101 + 126.
62. Yue, D. (2011). Research on the Human Capital Value Orientation of University Students in the New Era. Academic Journal of Human Capital, 08, 218–220.
63. Yu, X. (2018). Study on the Relationship Between University Human Capital and Regional Economic Growth. Academic Exploration, 04, 163–166.
64. Zhang, M. (2019). Analysis of urban-rural differences in total factor productivity growth in Chinese retail enterprises. Statistical Research, 36(12), 81–93.
65. Zhang, Y., Kumar, S., Huang, X., & Yuan, Y. (2023). Human capital quality and the regional economic growth: Evidence from China. Journal of Asian Economics, 86, 101593.