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How is Higher Vocational Education's Contribution to Industry Reflected in Firm Productivity?

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Abstract

Using data on Shanghai and Shenzhen A-share listed firms from 2004 to 2023, this study constructs a provincial-level index of higher vocational education development and employs a two-way fixed-effects model to examine its relationship with firm productivity. Regional higher vocational education development is significantly and positively associated with total factor productivity (TFP), and this relationship remains when labor productivity is used as a supplementary outcome. R&D investment and patent output are not the main channels. The TFP association does not differ significantly by ownership, whereas state-owned enterprises (SOEs) show a stronger labor-productivity response. These findings suggest improving the evaluation of higher vocational education's contribution to industry, placing greater emphasis on technology application and production operations, and better aligning workforce development with firms' job requirements.

Keywords

Regional Higher Vocational Education Development; Total Factor Productivity; Labor Productivity; Formal Innovation; Ownership Heterogeneity.

1. Introduction

China's higher vocational education is both occupationally oriented and regionally embedded. Developing technically skilled workers and serving regional industries are central to its mission. As manufacturing becomes more digital and modern services adopt new technologies more rapidly, imported technologies must still pass through equipment commissioning, process adaptation, workflow integration, and quality control before generating stable output. These production tasks place new demands on workers' knowledge and practical competence [1]. Higher vocational institutions supply firms with practice-oriented, technically skilled workers and help solve production problems through technical services. Their performance should therefore be assessed not only by enrollment, employment, skills competitions, and research outputs, but also by what happens after graduates and technical services enter firms. Whether regional higher vocational education development is reflected in firm efficiency bears directly on the effectiveness of industry–education integration and on the capacity of China's modern vocational education system to support industrial development [2].

Existing research examines the industrial effects of education resources along three lines. The first studies how higher vocational education supports collaborative innovation, technology application, and school–enterprise cooperation [3]. The second analyzes how higher education resources, knowledge spillovers, and a larger supply of highly skilled workers affect regional innovation, income distribution, and firm performance [4–7]. The third considers how skill-based human capital shapes digital transformation and how vocational education reforms affect firms' human capital and factor productivity [8–9]. This work shows that vocational

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education matters not only for employment but also for firms' technological activity and production organization. Yet economic research typically measures human capital using average years of schooling or the share of highly educated workers, without distinguishing the functions of general higher education from those of higher vocational education. Research on higher vocational education, meanwhile, tends to evaluate particular reforms or construction programs rather than the relationship between a region's overall vocational education development and firm efficiency.

Firm productivity offers a new way to assess how higher vocational education serves industry. TFP measures how efficiently a firm turns capital, labor, and intermediate goods into output. New technology raises it, but so does what happens afterwards on the factory floor: whether workers can absorb the technology, run the equipment properly, and keep the stages of production in step. This is where most graduates of higher vocational institutions end up working. The technical services of vocational colleges are likewise aimed mostly at specific problems in production rather than at research. Such work rarely shows up as R&D spending or as patents. It can still lift efficiency, because it changes how technology is used and how production is organized. Looking at firm productivity therefore lets us follow vocational education beyond the school gate and into firms' production results.

We build a provincial index of higher vocational education development with three components: the foundation for workforce development, faculty and research support, and research output. Regional education data for 2004–2023 are then linked to a panel of A-share firms listed in Shanghai and Shenzhen, and the relationship is estimated with firm and year fixed effects. Labor productivity serves as a supplementary outcome. Two further questions are examined. Can R&D investment and patent output account for the link with TFP? And does the link look different in state-owned and private firms?

Our contribution is twofold. Evaluations of higher vocational education have so far looked mainly at training inputs, graduate employment, and innovation outputs; we look instead at the productivity of firms, treating firm-level outcomes as evidence of what regional vocational education contributes to industry. In addition, we separate production efficiency from formal innovation and test directly whether R&D and patents explain the productivity association. The answer helps clarify what higher vocational education does in technology application and day-to-day operations, and it bears on how its contribution to industry should be evaluated.

2. Theoretical Analysis and Hypotheses

2.1. Regional Higher Vocational Education Development and Firm Productivity

In China, where higher vocational colleges are located and what they teach is closely tied to local industry. Program offerings, training facilities, and technical services are usually planned with the regional industrial base and local employers' job requirements in mind. By regional higher vocational education development, we mean the overall capacity of a region's institutions, covering their basic educational conditions, practical training, teaching staff, and applied services. As this capacity grows, colleges can train more technically skilled workers under better conditions, and they are also in a better position to offer vocational training and technical services to firms. The effect on production thus comes through two functions at once: developing skills and serving firms technically.

Becker [10] separates general human capital from firm-specific human capital; the second kind is formed on, and pays off with, particular equipment, jobs, and production processes. Higher vocational programs put practical training and occupational competence first, so students leave with industry knowledge and a base of job-related skills [11]. That base is not yet firm-specific. Once hired, workers still have to learn on the job, with the firm's own machines, processes, and

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tasks. Where regional educational conditions are better, new hires arrive better prepared and need less time to adjust, which gives firms a stronger starting point for later in-house training.

Technology absorption is one link between the two. According to absorptive-capacity theory, how well a firm can recognize, assimilate, and use outside technologies depends on the knowledge it already has [12]. Workers who know the equipment and the production process are the ones who commission new machines, adapt them to local conditions, and get them running; in doing so they cut adjustment costs and operating errors. Chen et al. [8] report that highly skilled workers do more for digital transformation than human capital measured by academic degrees alone, with absorptive capacity as an important condition. In this sense, regional higher vocational education gives firms both the people and the services they need to put outside technologies to use.

Skill accumulation matters for shop-floor efficiency as well. X-efficiency theory traces part of a firm's efficiency loss to operating errors, friction between process steps, and poor coordination [13]. Skilled workers who have spent time on the line come to know how the equipment behaves and what each process requires. They make fewer mistakes, machines stop less often, and workflow and quality control improve. Evidence on workplace training points the same way: skills training on the job raises worker productivity and firm returns, with the gains passing through task execution and coordination in production [14]. Liu [9] finds that the High-Level Higher Vocational Schools and Programs initiative (the "Double High Plan") raises firms' skilled human capital and factor productivity, while Wang et al. [15] show that regional workforce conditions affect firm productivity. Skills therefore matter not only for job entry but also for how firms use existing technologies and inputs.

Regional higher vocational education should improve training conditions, strengthen firms' technology absorption through skilled workers and technical services, and reduce production inefficiencies. Regional development should therefore be positively associated with TFP.

H1: Regional higher vocational education development is positively associated with firm total factor productivity.

2.2. Regional Higher Vocational Education Development and Formal Innovation

Productivity growth may come from knowledge creation and technological breakthroughs, or from better use of existing technologies and continuous process improvement. R&D investment measures resources allocated to developing new knowledge and technologies, while patents record codifiable innovations that receive legal protection. Both capture organized R&D activity but omit much of the application process after a technology reaches production. Higher vocational education is oriented toward implementation in production and occupational practice, so there is little reason to expect its effects to track R&D spending or patent output closely.

R&D in firms is usually organized around new products, technologies, and processes, and it needs its own staff, budget, and organizational platform. Ma [16] finds that the larger supply of human capital created by China's college expansion promoted R&D and innovation in manufacturing, which fits a formal innovation channel for general higher education. Vocational graduates are in a different position. Most of them work in production operations, equipment maintenance, quality control, or process implementation, and what they contribute happens within routine production. The wages and adjustment costs involved are generally not booked as R&D. A firm can thus become more efficient without spending more on R&D.

A patent application needs content that is clearly novel and can be written down. Much of the improvement made on the shop floor is not like that. Retuning equipment parameters, changing an operating method, smoothing the handover between steps, or tightening quality checks tends to be incremental, based on experience, and specific to one setting. Such changes may cut

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losses or shorten commissioning time and still fall short of what patent law requires. Vocational colleges' technical services are directly connected with firms' production. Even so, whether a given type of education resource ends up as formal innovation output depends on how schools and firms cooperate and on the firm's own capabilities [17].

For these reasons, firms may benefit from regional higher vocational education without any rise in their R&D spending or patent counts.

H2: The positive association between regional higher vocational education development and firm TFP does not operate mainly through R&D investment or patent output.

2.3. Ownership and Productivity Returns

When skilled workers and education-based services reach a firm, how much they add to productivity depends on how the firm is organized internally. Outside education resources can supply skills and technical support. Turning these into productive capacity is the firm's job, through the way it assigns people, trains them, and coordinates production. Internal labor market theory [18] holds that stable employment, in-house training, and promotion ladders give firms longer to recoup what they invest in skills and give workers time to build up job experience. Not every firm, then, is equally able to absorb and use the resources that regional higher vocational education provides.

Technical skills are closely tied to particular jobs. What students learn at school, mostly industry knowledge and basic skills, becomes specific to a firm only after repeated practice on its equipment, processes, and tasks. When employment is stable, that learning is continuous, and the firm keeps the operating experience and process knowledge it has built up. Cammeraat et al. [19] show that the productivity return to skills is affected by organizational coordination and knowledge management. The same regional education conditions can therefore lead to different results in different firms.

State-owned enterprises (SOEs) and private firms in China handle employment, training, and job allocation differently. Employment and internal training in SOEs tend to be more stable, which helps workers keep accumulating job experience. Private firms usually have more room to adjust jobs and incentives, but higher turnover makes it more likely that a firm loses what it invested in a worker's skills. Studies of worker mobility find that the resulting knowledge effects depend on how strong and long-lasting the ties are and on their organizational setting [20]. Firms with different ownership may therefore absorb and use regional higher vocational education resources in different ways, with different productivity returns.

H3: The association between regional higher vocational education development and firm TFP is different for state-owned and private firms.

3. Research Design

3.1. Sample and Data

The sample covers Shanghai and Shenzhen A-share listed firms from 2004 to 2023. Financial, R&D, and patent data come from the China Stock Market & Accounting Research (CSMAR) database. Higher vocational education data come from the China Education Statistical Yearbook, the Compilation of Statistics on Science and Technology in Higher Education Institutions, and provincial statistical yearbooks. The provincial education index is matched to firms by registered location. Financial firms, firms designated ST or *ST (special treatment), and observations missing core variables are excluded. Continuous variables are winsorized at the 1st and 99th percentiles. The final unbalanced panel contains 47,131 firm-year observations for 4,913 firms.

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3.2. Variable Definitions

3.2.1. Outcome Variables

Firm TFP (tfp_acf) is estimated using the ACF semiparametric method of Ackerberg et al. [21]. Operating revenue measures output, net fixed assets measure capital, employee count measures labor, and cash paid for goods and services measures intermediate inputs. The Olley–Pakes (OP) method is used as a robustness check. Labor productivity (labor), the log of revenue per employee, is a supplementary outcome; it does not separately identify equipment maintenance, technology absorption, or process optimization.

3.2.2. Core Explanatory Variable

The core explanatory variable is the regional higher vocational education development index (gz_edu), which is meant to capture the overall level of development. Following the approach of Huang and Ding [22] and Ye et al. [6], we combine indicators of the foundation for workforce development, faculty and research support, and research output into a provincial index, with weights assigned by the entropy method (Table 1). A higher value means a more developed regional system.

Table 1. Indicators of Regional Higher Vocational Education Development

Level-1 index	Dimension	Subdimension	Indicator	Source
Regional HVE development	Workforce development	Institutions	Number of higher vocational institutions	China Education Statistical Yearbook
		Student scale	Number of enrolled students	China Education Statistical Yearbook
		Information-technology facilities	Teaching and research equipment	China Education Statistical Yearbook
		Faculty quality	Share of full-time faculty holding full senior professional titles	China Education Statistical Yearbook
	Faculty and research	Research faculty	Share of faculty with doctoral degrees	Higher Education S&T Statistics
		Research input	Research expenditure	Higher Education S&T Statistics
	Research output	Innovation output	Patent applications	Higher Education S&T Statistics

Note: HVE denotes higher vocational education.

3.2.3. Formal-innovation Channel Variables

R&D investment (rd) is measured as the natural log of one plus annual R&D expenditure, and patent output (pat) as the natural log of one plus the number of patent applications filed in the year. The first reflects what firms put into formal innovation; the second, what they get out of it in codified form.

3.2.4. Controls

Control variables follow Jin et al. [23], Huang and Zhao [24], and Wang et al. [15]: firm size, leverage, administrative expense ratio, firm age, operating margin, cash-flow ratio, managerial ownership, and Tobin's Q. Definitions of all variables are given in Table 2.

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Table 2. Variable Definitions and Data Sources

Type	Variable	Symbol	Definition	Source
Outcome	Total factor productivity	tfp_acf	Semiparametric ACF estimate	Calculated from firm financial data
Supplementary outcome	Labor productivity	labor	Log revenue per employee	CSMAR
Explanatory	Regional HVE development	gz_edu	Entropy-weighted index on [0,1]	Table 1
Channel	R&D investment	rd	Log annual R&D expenditure plus 1	CSMAR
	Patent output	pat	Log patent applications plus 1	CSMAR
Control	Firm size	size	Log total assets	CSMAR
	Operating margin	ros	Operating profit/revenue	CSMAR
	Firm age	age	Log(current year–founding year+1)	CSMAR
	Administrative expense ratio	mcf	Administrative expenses/revenue	CSMAR
	Leverage	lev	Total liabilities/total assets	CSMAR
	Managerial ownership	con	Executive shares/total shares	CSMAR
	Cash-flow ratio	cash	Operating cash flow/revenue	CSMAR
	Tobin's Q	tobinq	Market value/total assets	CSMAR

3.3. Model Specification

3.3.1. Baseline Model

To examine the relationship between regional higher vocational education development and firm total factor productivity, this study estimates a two-way fixed-effects model:

$$tfp_acf_{it} = \alpha_0 + \alpha_1 gz_edu_{pt} + \sum_{k=1}^{K} \beta_k Control_{k,it} + \mu_i + \lambda_t + \varepsilon_{1,it} \quad (1)$$

where i, p, and t denote firm, province, and year, respectively. tfp_acf_{it} is the total factor productivity of firm i in year t, estimated by the ACF method; gz_edu_{pt} is the higher vocational education development index of province p in year t; $Control_{k,it}$ denotes the kth firm-level control variable; and K is the total number of control variables. μ_i and λ_t denote firm and year fixed effects, respectively, and $\varepsilon_{1,it}$ is the error term.

Firm fixed effects absorb unobserved firm characteristics that do not change over time. Year fixed effects pick up shocks common to all firms in a given year, such as nationwide macroeconomic conditions or policy changes. In the baseline, standard errors are clustered by firm. Because results can depend on the clustering level, the robustness section also reports province-clustered standard errors and wild cluster bootstrap p values. A significantly positive α_1 would mean that, conditional on the controls, regional higher vocational education development is positively associated with firm TFP, as H1 predicts. Because the research design does not fully eliminate reverse causality or omitted-variable bias, α_1 is interpreted as an association rather than a strictly causal effect.

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3.3.2. Supplementary Labor-productivity Test

To examine the relationship between regional higher vocational education development and output per worker, labor productivity replaces the dependent variable in equation (1), while the remaining model specification is unchanged:

$$labor_{it} = \sigma_0 + \sigma_1 gz_edu_{pt} + \sum_{k=1}^{K} \psi_k Control_{k,it} + \mu_i + \lambda_t + \varepsilon_{2,it} \quad (2)$$

3.3.3. Formal-innovation Channel Tests

To examine whether R&D investment and patent output account for the positive association between regional higher vocational education development and firm TFP, this study draws on the mediation-analysis framework and estimates the following equations:

$$M_{it} = \delta_0 + \delta_1 gz_edu_{pt} + \sum_{k=1}^{K} \gamma_k Control_{k,it} + \mu_i + \lambda_t + \varepsilon_{3,it} \quad (3)$$

$$tfp_acf_{it} = \varphi_0 + \varphi_1 gz_edu_{pt} + \theta M_{it} + \sum_{k=1}^{K} \eta_k Control_{k,it} + \mu_i + \lambda_t + \varepsilon_{4,it} \quad (4)$$

where M_{it} denotes either firm R&D investment (rd_{it}) or patent output (pat_{it}). The coefficient δ_1 captures the relationship between regional higher vocational education development and the formal-innovation variable. The coefficient θ captures the relationship between the formal-innovation variable and firm TFP, conditional on the regional education index. The coefficient φ_1 represents the conditional association between regional higher vocational education development and firm TFP after the formal-innovation variable is included.

The indirect effect is calculated as $\delta_1 \times \theta$, and its confidence interval is estimated using a firm-clustered bootstrap procedure. A confidence interval that excludes zero indicates that the corresponding formal-innovation variable has a statistically stable indirect association. If the confidence interval includes zero, the available evidence is insufficient to establish that channel. Because the analysis relies on observational data and linear regression models, these estimates are interpreted as evidence concerning potential channels rather than as strictly identified causal mediation effects.

3.3.4. Ownership Heterogeneity

We first estimate equation (1) separately for state-owned enterprises and private firms to see whether the relationship between regional higher vocational education development and firm productivity depends on ownership. A coefficient that is significant in one group but not in the other does not, however, show that the two groups differ significantly. For that reason we also estimate an interaction model on the full ownership-analysis sample:

$$Y_{it} = \omega_0 + \omega_1 gz_edu_{pt} + \omega_2 SOE_{it} + \omega_3 (gz_edu_{pt} \times SOE_{it}) + \sum_{k=1}^{K} \rho_k Control_{k,it} + \mu_i + \lambda_t + \varepsilon_{5,it} \quad (5)$$

where Y_{it} is either firm TFP or labor productivity, and SOE_{it} equals one for state-owned enterprises and zero for private firms. ω_1 is the association between regional higher vocational education development and productivity for private firms; for SOEs, the corresponding association is $\omega 1 + \omega 3$. Whether ownership makes a significant difference is judged from the interaction coefficient ω_3, or equivalently from a test comparing coefficients across groups.

3.4. Descriptive Statistics

Descriptive statistics are given in Table 3. TFP has a mean of 14.621 and a standard deviation of 1.142, so productivity differs considerably from firm to firm. Labor productivity averages

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13.416 (SD 1.342) and has slightly fewer valid observations than the full sample. For the education index, the mean is 0.419 and the SD 0.191. An analysis of variance finds significant differences both across provinces and across years ($F = 12{,}555.61$ and $2{,}248.37$; $p < 0.01$), so there is enough variation for panel estimation. The median of R&D investment is 17.332, while the median of patent output is zero: in at least half of the firm-years, no patent application was filed. Formal innovation is very unevenly spread across firms.

Table 3. Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
tfp_acf	47,131	14.621	1.142	11.963	14.537	18.054
labor	46,317	13.416	1.342	7.602	13.525	16.384
gz_edu	47,131	0.419	0.191	0.040	0.429	0.785
rd	47,131	13.252	7.983	0.000	17.332	21.750
pat	47,131	0.615	1.427	0.000	0.000	5.867
lev	47,131	0.445	0.211	0.058	0.439	0.978
age	47,131	2.830	0.395	1.609	2.890	3.555
size	47,131	22.109	1.308	19.547	21.927	26.191
con	47,131	11.302	18.256	0.000	0.140	67.177
mcf	47,131	0.090	0.079	0.008	0.069	0.508
ros	47,131	0.054	0.224	−1.203	0.066	0.572
cash	47,131	0.092	0.180	−0.613	0.083	0.697
tobinq	47,131	0.631	0.252	0.115	0.632	1.180

Note: N denotes the number of observations; SD denotes standard deviation.

4. Empirical Results

4.1. Baseline and Supplementary Results

Table 4 presents the estimates. TFP is the outcome in columns (1)–(3) and labor productivity in columns (4)–(5). Every model has firm fixed effects; year fixed effects enter from column (2) onward, and controls are added in columns (3) and (5).

In column (1), the coefficient on gz_edu is small (0.094) and not significant. Once year fixed effects are included it rises to 0.592, significant at 1%. With controls added it is 0.503, again significant at 1%. Thus, after accounting for firm heterogeneity and macro time trends, regional higher vocational education development remains positively associated with TFP, supporting H1.

With labor productivity as the outcome, the fully controlled estimate is 0.498 and significant at 1%. Regional development is therefore associated with both overall productivity(TFP) and output per worker. Labor productivity is only a supplementary outcome and does not identify specific mechanisms such as technology absorption, equipment maintenance, or process optimization.

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Table 4. Higher Vocational Education Development and Firm Productivity

Variable	(1) tfp_acf	(2) tfp_acf	(3) tfp_acf	(4) labor	(5) labor
gz_edu	0.094 (1.36)	0.592*** (4.87)	0.503*** (4.37)	0.582*** (4.55)	0.498*** (4.06)
Controls	No	No	Yes	No	Yes
Year FE	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	47,131	47,131	47,131	46,317	46,317
Within R^2	0.000	0.163	0.248	0.141	0.179

Note: t statistics are in parentheses; standard errors are clustered at the firm level. FE denotes fixed effects. *** p < 0.01, ** p < 0.05, * p < 0.10.

4.2. Formal-Innovation Channels

The analysis next tests whether the two formal-innovation measures, R&D investment and patent output, explain the TFP association, using firm-clustered bootstrap confidence intervals for indirect effects.

4.2.1. R&D Investment

Column (1) reproduces the baseline coefficient of 0.503. The education index does not significantly predict R&D investment in column (2) (p = 0.131). In column (3), R&D has a coefficient of −0.008, significant at 1%, while the education coefficient remains 0.511 and significant at 1%. The bootstrap interval includes zero, providing no evidence that R&D investment is a stable channel.

4.2.2. Patent Output

The education index does not significantly predict contemporaneous patents in column (4) (p = 0.852). In column (5), the patent coefficient is −0.010 and significant at 1%, while the education coefficient remains 0.503. The bootstrap interval again includes zero.

4.2.3. Assessment

Table 5. Formal-Innovation Channel Tests

Variable	(1) tfp_acf	(2) rd	(3) tfp_acf	(4) pat	(5) tfp_acf
gz_edu	0.503*** (4.37)	0.960 (1.51)	0.511*** (4.46)	−0.026 (−0.19)	0.503*** (4.37)
rd			−0.008*** (−4.68)		
pat					−0.010*** (−2.80)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	47,131	47,131	47,131	47,131	47,131
Within R^2	0.248	0.506	0.251	0.026	0.248
Bootstrap indirect effect		−0.008		0.0003	
95% bootstrap CI		[−0.020, 0.001]		[−0.002, 0.004]	

Note: t statistics are in parentheses; standard errors are clustered at the firm level. *** p < 0.01, ** p < 0.05, * p < 0.10. Indirect effects are estimated using 2,000 firm-level cluster bootstrap replications, and bias-corrected 95% confidence intervals are reported.

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Neither indirect effect is significant, while the direct education coefficient remains positive. H2 is supported. Regional higher vocational education's contribution to industry appears more closely tied to technology application, process execution, and production organization than to higher R&D spending or patent counts. The negative contemporaneous coefficients on R&D and patents may reflect delayed innovation returns and do not imply that formal innovation reduces productivity.

4.3. Ownership Heterogeneity

Table 6 reports estimates by ownership for TFP and labor productivity, together with full-sample interactions between state ownership and the education index.

For TFP, the coefficients are 0.422 for private firms and 0.572 for SOEs, both significant at 1%. The gap between the two subsample estimates is not statistically significant: the interaction term in the full-sample model is small and insignificant (−0.061, between-group p = 0.624). Its sign differs from the subsample comparison because the full-sample model constrains the control-variable coefficients to be the same for both groups, and with a difference this close to zero the sign is not informative. The evidence therefore does not show that the TFP association differs by ownership, and H3 is not supported for TFP.

For labor productivity, the corresponding estimates are 0.413 and 0.659, both significant at 1%. The full-sample interaction is 0.319 and significant at 5%, indicating a stronger response among SOEs.

Ownership does not significantly alter the TFP association but does matter for labor productivity. More stable employment, training, and promotion systems in SOEs may support continued accumulation of job experience. But TFP is also shaped by capital allocation, technical efficiency, and management quality, and an advantage in labor efficiency will not necessarily carry over in full to overall productivity.

Table 6. Ownership Heterogeneity

Variable	(1) Private tfp_acf	(2) SOEs tfp_acf	(3) Full tfp_acf	(4) Private labor	(5) SOEs labor	(6) Full labor
gz_edu	0.422*** (3.42)	0.572*** (2.98)	0.514*** (4.60)	0.413*** (3.02)	0.659*** (3.11)	0.342*** (2.67)
SOE			−0.163** (−2.28)			−0.322*** (−4.04)
gz_edu × SOE			−0.061 (−0.49)			0.319** (2.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,829	18,842	44,671	25,359	18,542	43,901
Within R^2	0.227	0.273	0.253	0.181	0.178	0.178
Between-group p value			0.624			0.026

Note: t statistics are in parentheses; standard errors are clustered at the firm level. *** p < 0.01, ** p < 0.05, * p < 0.10. Only state-owned enterprises and private firms enter the ownership analysis.

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4.4. Robustness Tests

We check robustness in four ways: estimating TFP differently, clustering at a different level, lagging the education index, and comparing matched samples.

4.4.1. Alternative TFP Measure

When TFP is re-estimated with the OP semiparametric method [25], the education coefficient is 0.192 and significant at 1%. The result, in other words, does not hinge on the ACF estimator.

4.4.2. Alternative Clustering

Since gz_edu varies only by province and year, errors for firms in the same province may be correlated. Clustering by province gives a coefficient of 0.503 (p = 0.024), and the wild cluster bootstrap p value is 0.094. The size and sign of the estimate do not change, but significance is weaker once the stricter small-cluster inference is applied.

4.4.3. Timing

Lagging the education index by one year gives a coefficient of 0.460. It is significant at 10% with province-clustered standard errors, although the wild cluster bootstrap p value rises to 0.196. The relationship shows some persistence but remains sensitive to inference and does not establish a strict causal effect.

Table 7. Robustness Tests

Variable	(1) Baseline	(2) OP	(3) Province clustered	(4) Lagged index
Outcome	tfp_acf	tfp_op	tfp_acf	tfp_acf
gz_edu	0.503*** (4.37)	0.192*** (3.34)	0.503** (2.37)	
L.gz_edu				0.460* (1.98)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Province	Province
Wild bootstrap p			0.094	0.196
N	47,131	47,131	47,131	41,326
Within R^2	0.248	0.637	0.248	0.244

Note: t statistics are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Columns (3)–(4) use Webb weights, 9,999 wild cluster bootstrap replications, and 31 province clusters.

4.4.4. Propensity-score Matching

Regional higher vocational education development may not be randomly distributed across provinces and may reflect local economic conditions and industrial structure. As a complementary check on selection bias, propensity-score matching (PSM) is used to construct a counterfactual comparison. Firms located in provinces whose education index exceeds the annual sample median form the treatment group (treat = 1), and all other firms form the control group. Propensity scores are estimated with a logit model using the firm-level controls in Table 2 as matching covariates, and each treated firm is matched to one control firm by nearest-neighbor matching (1:1).

Table 8 reports the balance test. After matching, the standardized bias of every covariate is below 3%, and the mean absolute standardized bias falls from 8.2% to 1.5%, so treated and control firms become considerably more comparable. Differences in firm size and leverage

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remain statistically significant at the 5% level, and those in firm age and managerial ownership at the 10% level, but their standardized biases are small (2.3% or less), as is expected in a sample of this size.

Table 8. Covariate Balance before and after Propensity-Score Matching

Variable	Unmatched			Matched			
	Treated	Control	Bias (%)	Treated	Control	Bias (%)	p value
Firm size (size)	22.087	22.131	−3.3	22.087	22.114	−2.0	0.025
Operating margin (ros)	0.063	0.045	8.2	0.063	0.065	−0.6	0.454
Firm age (age)	2.824	2.836	−3.1	2.824	2.830	−1.5	0.095
Administrative expense ratio (mcf)	0.087	0.093	−8.0	0.087	0.086	1.3	0.118
Leverage (lev)	0.430	0.460	−14.0	0.430	0.426	2.3	0.012
Managerial ownership (con)	13.654	8.931	26.1	13.654	13.350	1.7	0.090
Cash-flow ratio (cash)	0.090	0.093	−1.5	0.090	0.088	1.1	0.217
Tobin's Q (tobinq)	0.630	0.633	−1.2	0.630	0.627	1.2	0.180
Mean absolute bias (%)			8.2			1.5	

Note: Treated firms are located in provinces whose HVE index exceeds the annual sample median. Bias (%) is the standardized bias; the p value is from a t test of the mean difference between treated and control firms. Mean absolute bias is the average of the absolute standardized biases across the eight covariates.

Table 9 shows that, after matching, mean TFP remains higher in the treatment group than in the control group. The ATT of 0.119 is significant at 1% and has the same sign as the baseline estimates. We treat it only as supplementary evidence, not as a causal estimate, because treatment is defined at the province–year level whereas the matching relies on firm-level covariates alone.

Table 9. Average Treatment Effect on the Treated after Propensity-Score Matching

Variable	Sample	Treated	Control	Difference	SE	t
TFP (tfp_acf)	Unmatched	14.698	14.543	0.155	0.011	14.75***
TFP (tfp_acf)	ATT	14.698	14.579	0.119	0.014	8.52***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. A firm is treated if its province's HVE index is above that year's sample median. The ATT is obtained after 1:1 nearest-neighbor propensity-score matching. SE denotes standard error.

Taken together, the coefficient stays positive whichever TFP measure, clustering level, lag structure, or matched sample is used. The direction of the main relationship is robust, even though its statistical significance is weaker under stricter inference.

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5. Conclusion and Implications

5.1. Main Findings

Using Chinese A-share listed firms from 2004 to 2023, this study constructs a provincial higher vocational education development index and examines its relationship with firm TFP, formal-innovation channels, and ownership heterogeneity.

First, regional higher vocational education development is positively associated with both TFP and labor productivity. Its contribution to industry is therefore reflected not only in training, employment, and technological outputs but also in firm efficiency. The analysis extends evaluation from school conditions and graduate outcomes to the production process and provides firm-level evidence on the education–efficiency link.

Second, R&D investment and patent output do not adequately explain the positive productivity association. Neither channel has a significant indirect effect. Higher vocational education may create value through production adaptation, process execution, and shop-floor application without expanding firms' recorded R&D or patent counts. Evaluation should therefore distinguish the creation of technical knowledge from its application.

Third, higher vocational education's contribution to industry depends on both school-based training and firms' conditions for using and further developing skills. Both SOEs and private firms show positive TFP estimates, and the gap between them is not significant. For labor productivity, however, SOEs respond more strongly. Competence acquired at school seems to need further practice on the job, and continued training, before it becomes reliable productive capacity.

5.2. Policy and Practical Implications

First, education authorities and higher vocational institutions should look at what happens after their graduates and technical services reach firms. Existing instruments such as graduate tracking surveys, employer surveys, and acceptance reviews of industry–education projects could add items on how long graduates take to adapt to their jobs, how much they use their occupational skills, whether they take part in firm training, and whether firms adopt the results of technical services. The purpose of such indicators is to judge how well a region's higher vocational education matches industry needs. They should not be turned into a firm-productivity score for individual colleges. Used in this way, they keep education evaluation professionally grounded while still showing what higher vocational education actually contributes to industry.

Second, research and social service in higher vocational institutions should not be judged by the standards of research universities, which center on papers, grants, and patents. A better basis would be technical-service files built around problems that firms bring to colleges, for example in equipment commissioning, process improvement, quality control, or the use of digital technology. Each file would record the problem, the solution, whether the firm adopted it, and what changed in operation afterwards. Solutions that firms use but that were never patented could then be credited, on the basis of firm certification, peer review, and operating records, in faculty workload, in the certification of dual-qualified teachers, and in social-service performance assessment.

Third, field-engineer training can join school education to skill formation inside firms. Colleges and firms can agree on competency standards, curricula, and practical tasks for jobs in manufacturing, testing and commissioning, shop-floor control, and equipment maintenance. If work–study alternation is organized around real production projects, students build competence by solving actual problems such as debugging equipment or tracing quality defects. Such programs need not stop at students: incumbent workers can take technology-updating and career-progression courses designed jointly by colleges and firms. Industry–education

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integration then covers the whole course of skill development, not just the hand-over of graduates to employers.

5.3. Limitations and Future Research

This study has limitations. The provincial index is matched to firms through their registered location, which may differ from where they produce or where their employees actually work, and it ignores the movement of skilled workers across regions. The index also describes regional educational and research conditions; it does not tell us which technical workers a firm employs or how they are deployed. Data on graduate destinations, the skill composition of firms' workforces, workplace training, and school–enterprise technical services would make it possible to trace more precisely how vocational education resources enter firms.

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