

When Training Meets Education: Human-Capital Complementarities and Labour Productivity in Ghanaian Enterprises

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Abstract

Employee training and workforce education are central elements of firm human capital, but their joint productivity value remains uncertain in developing economies. This study examined whether formal employee training was associated with labour productivity in Ghanaian enterprises and whether the educational composition of the permanent workforce strengthened that relationship. The analysis used the Ghana World Bank Enterprise Survey 2023. Real labour productivity was calculated as annual sales, expressed in constant 2019 Ghana cedis, divided by permanent full-time employment. The natural logarithm of productivity was used because the raw distribution was highly skewed. Formal training was measured directly, while workforce education was harmonised from two mutually exclusive survey forms: the percentage of employees completing high school and a count converted to the same percentage scale. Following World Bank procedures, potentially unbounded sales and employment values were screened after log transformation, sampling weights were applied, and realized industry was used. The analytical sample contained 629 establishments. Survey-weighted regression controlled for firm age, employment size, manager sector experience, foreign ownership, industry and region. The weighted training rate was 48.3%, the mean workforce education share was 82.7%, and geometric labour productivity was GH¢45,412 per permanent employee. Formal training had a positive but statistically uncertain association with productivity, $b = 0.392$, $SE = 0.232$, $p = .091$. A 10-percentage-point increase in workforce education was associated with 14.7% higher productivity ($b = 0.137$, $SE = 0.050$, $p = .006$). The training-by-education interaction was near zero, $b = -0.009$, $SE = 0.086$, $p = .921$. Alternative weights, bootstrap analysis, sector controls and outlier tests supported the null interaction. The results show that workforce education is a strong productive resource, while formal training may add value independently but did not become more productive as the workforce education share increased. Firms should align training with specific performance gaps and evaluate learning transfer rather than assuming automatic complementarity with formal education.

Keywords: Formal Training; Workforce Education; Labour Productivity; Human Capital; Strategic Human Resource Management; Ghana.

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INTRODUCTION

Productivity is a central strategic challenge for firms and economies. Cross-country research also shows that management practices differ widely across firms and help explain productivity gaps (Bloom et al., 2019). It determines how much value an enterprise produces from its people, capital and other resources. Higher labour productivity can support stronger wages, greater competitiveness and sustained business growth. In lower- and middle-income economies, productivity differences across firms are often large, and internal management capabilities are part of the explanation. Human capital is especially important because technology, equipment and business processes create value only when employees possess the knowledge and skills needed to use them effectively.

Formal education and employer-provided training represent two different routes through which human capital develops. Education builds broad cognitive, literacy, numeracy and learning capabilities before or outside the current employment relationship. Training is usually closer to the firm and job. It can provide technical knowledge, improve the use of equipment, strengthen quality procedures and help employees adapt to organizational change. Both investments should improve productive capability, but their effects may not be identical. Education can make workers more able to learn, while training can convert that learning capacity into firm-specific performance.

This relationship is important in Ghana. Firms operate in an environment where access to technology, finance and skilled labour differs across sectors and regions. Ghanaian evidence has shown that education is positively associated with worker productivity in manufacturing (Jones, 2001). However, recent nationally representative evidence on the relationship between firm-provided training, workforce education and labour productivity remains limited. Many existing studies focus on wages, employee outcomes, training participation or selected industries. The present study uses direct establishment-level sales and employment measures to examine productivity across formal private enterprises.

The strategic human resource management literature argues that organizational performance depends not simply on single practices but on systems or bundles of mutually reinforcing practices. Meta-analytic evidence also links high-performance work practices with stronger organizational performance (Combs et al., 2006). Huselid (1995) demonstrated influential links between high-performance work practices, productivity and corporate performance. Becker and Gerhart (1996) subsequently stressed the importance of understanding how human resource systems create value. Later meta-analytic work showed that skill-enhancing practices influence organizational outcomes partly through human capital and motivation (Jiang et al., 2012). These arguments support the possibility that training and workforce education operate as complementary resources.

The complementarity expectation is not automatic. A highly educated workforce may already possess broad knowledge that reduces the marginal value of general training. Formal training may also be poorly designed, too short, unrelated to strategic problems or delivered to only a small share of employees. Conversely, firms with less educated workers may use practical training to address specific skill gaps. Training and education can therefore be substitutes, independent contributors or complements. Whether the combination creates additional productivity is an empirical question.

International evidence generally reports positive training-productivity relationships. Dearden et al. (2006) found that work-related training was associated with higher industry productivity

in Britain. Konings and Vanormelingen (2015) estimated that training raised firm productivity more than wages in Belgium. A meta-analysis of 119 primary studies also found a positive relationship between training and organizational performance, while showing that institutional and temporal conditions matter (Garavan et al., 2021a). Yet these studies do not establish that training becomes more valuable when a workforce is more formally educated.

The study makes five contributions. First, it examines a strategic human-capital bundle in Ghana rather than analysing training or education in isolation. Second, it uses a direct firm-level productivity outcome constructed from inflation-adjusted sales and permanent employment. Third, it harmonises the two education question forms used in the survey and reports a restricted-form sensitivity analysis. Fourth, it applies the World Bank sampling weights, realized-industry guidance and outlier procedures. Fifth, it reports conditional effects, predicted productivity, bootstrap inference, alternative weights and several robustness checks.

The central research question is whether formal employee training and workforce education jointly explain labour productivity. Two hypotheses are tested. The first concerns the independent training-productivity relationship—the second concerns positive complementarity between training and education. The article follows the IMRaD structure. The next section develops the theory and hypotheses, followed by the methods, results and discussion.

THEORETICAL BACKGROUND

Human Capital and Labour Productivity

Human capital refers to the knowledge, skills, abilities and other productive characteristics embodied in individuals. At the firm level, human capital becomes strategically valuable when employee knowledge supports activities that competitors cannot easily reproduce. Resource-based theory proposes that valuable, scarce and difficult-to-imitate resources can contribute to sustained advantage (Barney, 1991). Human capital can satisfy these conditions when it is combined with experience, routines and organisational relationships.

Education can improve productivity through several channels. Educated employees may understand instructions more quickly, communicate more clearly, solve unfamiliar problems and adapt to new technology. They may also generate fewer errors and require less supervision. The productive benefit is not limited to individual output. Educated workers can support team learning and knowledge transfer, creating spillovers beyond their own tasks. Evidence from Ghanaian manufacturing found that education was positively correlated with productivity and that wage differences reflected productive differences (Jones, 2001).

Firm-level human capital is not simply the sum of individual qualifications. Crook et al. (2011) found a positive meta-analytic relationship between human capital and firm performance, with stronger effects when human capital was firm-specific. This distinction matters because education is usually broad while training can be adapted to the organization. Education supplies learning capacity; the firm must still organize work so that this capacity becomes productive.

Labour productivity in the present study is sales per permanent full-time employee. This measure is widely used in enterprise research because it connects business output with the core labour input. It is not a complete production-function estimate and does not separate labour from capital intensity, input prices or market power. Controls for firm size, industry and

location reduce some confounding, but the measure remains an indicator of realized commercial productivity rather than pure technical efficiency.

Formal Training and Productivity

Formal training is an organized learning activity provided by or through the employer. It can improve technical skill, product knowledge, customer service, supervisory ability, safety and the use of digital or production systems. Training may raise productivity by reducing mistakes, shortening task time, improving quality and enabling employees to use more advanced methods. It can also support organizational change by giving workers a shared understanding of new procedures.

The ability-motivation-opportunity framework places training within skill-enhancing human resource practices. Such practices develop employees' capacity to perform, while other practices strengthen motivation and opportunities to contribute. Jiang et al. (2012) found that skill-enhancing systems had strong relationships with human capital, which then supported operational and financial outcomes. Training is therefore expected to matter most when learning is transferred to work and connected to organizational priorities.

Influential empirical studies support the productivity argument. Black and Lynch (2001) showed that the implementation of workplace practices and human-capital investments was related to establishment productivity. Dearden et al. (2006) found that training gains in productivity exceeded associated wage gains. Konings and Vanormelingen (2015) similarly reported a substantial productivity premium from trained workers. Reviews by Arthur et al. (2003), Aguinis and Kraiger (2009), and Garavan et al. (2021a) conclude that training can benefit individuals, teams and organizations.

Training may nevertheless fail to produce measurable productivity. Training is more likely to matter when it is connected to technological or organizational change and when learning becomes embedded in work routines (Neirotti & Paolucci, 2013; Sung & Choi, 2014). Firms may provide training because productivity is already low, creating negative selection. Programmes may focus on compliance rather than productive skill. Managers may record the existence of formal training even when participation is limited. Employees may learn but lack equipment, authority or incentives to apply the learning. Cross-sectional data can therefore show a positive, zero or negative association even when some training programmes are effective.

In Ghana and other African settings, training decisions are shaped by resource constraints and labour-market conditions. Mano et al. (2012) found that basic management training improved practices and performance among Ghanaian micro and small enterprises, showing that capabilities can be developed. Research on business practices in developing countries similarly highlights the productivity relevance of basic management capability (McKenzie & Woodruff, 2017). Recent evidence also suggests that staff and manager training can have different productivity effects (Schwarz et al., 2026). Okumu and Mawejje (2020) found that skills development matters for labour productivity in African manufacturing. These findings support a positive expectation while also emphasizing context.

A further caution concerns endogeneity. Because the Enterprise Survey is cross-sectional, a positive training–productivity association may reflect reverse causality rather than a training effect: highly profitable and productive firms have surplus budget to afford formal training programmes, so productivity may lead to training rather than the reverse. Selection can

therefore operate in either direction, and unobserved characteristics such as management quality or access to finance may drive both. Hypothesis 1 is accordingly framed as an association, and the estimates are interpreted as conditional correlations rather than causal effects.

Hypothesis 1: Formal employee training is positively associated with labour productivity in Ghanaian enterprises.

Workforce Education as a Complementary Resource

Complementarity exists when the return to one practice is greater in the presence of another practice. In this study, the question is whether formal training has a stronger productivity association when a larger share of permanent workers has completed high school. The logic rests on learning ability. Employees with stronger literacy, numeracy and general knowledge may absorb formal instruction more quickly and transfer it more effectively to work.

Education can support training through comprehension and problem solving. A technically trained employee may need to read manuals, interpret measurements, compare alternatives and communicate new procedures. General education provides foundations for these activities. It may also increase confidence in classroom-style learning and reduce the cost of delivering advanced training. Under this view, education is an absorptive platform for firm-specific learning.

Strategic human resource management reinforces this argument. High-performance systems are expected to create value through internal fit, where practices reinforce one another rather than operate separately (Becker & Gerhart, 1996; Huselid, 1995). Education is not itself an employer practice, but it represents the human-capital stock on which the training practice operates. A firm that trains educated employees may therefore achieve stronger learning transfer than a firm that provides the same programme to a workforce with weaker foundational skills.

There are competing possibilities. First, training may substitute for formal education by teaching practical skills to employees who lack academic qualifications. Second, firms with highly educated employees may provide training that is ceremonial or general because employees already possess necessary capabilities. Third, high education shares can reflect occupational composition: professional service firms may have educated workers but use fewer formal production-training programmes. Fourth, the binary training measure does not capture programme quality, intensity or alignment.

Recent reviews caution that training-performance research often treats training as an isolated input rather than part of a system (Garavan et al., 2021b). They call for stronger attention to context, complementarities and implementation. The present study responds by testing interaction directly while avoiding the assumption that a positive training coefficient proves complementarity.

Hypothesis 2: Workforce educational attainment positively moderates the association between formal employee training and labour productivity, such that the training association becomes stronger as the percentage of permanent employees completing high school increases.

METHODS

Data Source and Survey Design

The study used the Ghana World Bank Enterprise Survey 2023. Interviews were conducted between February 2023 and February 2024 with formal private establishments in eligible non-agricultural sectors. The establishment was the unit of analysis. The survey covered business characteristics, infrastructure, sales, innovation, finance, management practices, labour and performance.

The World Bank used stratified random sampling by industry, establishment size, geographical region and panel status (World Bank Group, 2025). The public-use full-data file contained 713 establishments and 355 variables. Sampling weights account for unequal selection probabilities and alternative assumptions about establishments whose eligibility could not be fully confirmed. The median-eligibility weight was used in the main analysis, and the weak-eligibility weight was used as a sensitivity check.

The World Bank recommends using realized industry reported during the interview instead of relying solely on the original sampling-frame category. Four-digit ISIC Revision 4 codes were therefore used. The primary model grouped activities into manufacturing, wholesale and retail, and other eligible sectors to limit the number of parameters. A sensitivity model retained six sectors.

The analysis used the World Bank's current indicator guidance for labour productivity and outlier treatment (World Bank Group, 2026). Annual sales were divided by permanent full-time employment, and sales were converted into constant prices. Ghana's cumulative GDP-deflator change between 2019 and 2022 was used to express 2022 sales in 2019 Ghana cedis. This common deflation factor changes the level of productivity but does not alter cross-sectional rankings or slope coefficients within the single survey year.

Data Inspection and Sample Construction

Prior to econometric modelling, thorough data inspection and cleaning were conducted. Establishment identifiers were unique. Variable labels, response options, skip patterns and negative codes were reviewed. Negative World Bank codes, including "do not know," were treated as missing. Blank values were considered in relation to questionnaire routing rather than automatically treated as nonresponse.

Formal training had 703 valid yes or no responses. Workforce education was collected through two mutually exclusive questionnaire forms. For 517 establishments, variable l9b reported the percentage of permanent full-time employees who had completed high school. For 178 establishments, l9b1 reported the number of such employees. The count was divided by permanent full-time employment and multiplied by 100. No count-derived value exceeded 100%, and there was no overlap between the two forms. This produced 695 valid harmonised education observations.

Annual sales were positive for 664 establishments, and permanent employment was positive for all 713. The World Bank outlier procedure was applied separately to potentially unbounded raw sales and employment. Each variable was transformed as $\ln(x + 1)$, and values more than three standard deviations from the survey mean were identified. No sales observation was excluded. Six employment observations—ranging from 433 to 1,000 permanent workers—were excluded under the rule. A sensitivity model retained them.

The regression also required valid firm age, manager sector experience, foreign ownership, realized industry, region and both sampling weights. The final complete-case sample contained 629 establishments: 276 with formal training and 353 without training. The education measure came from the percentage form for 463 analytical observations and from the converted count form for 166.

Raw labour productivity was strongly right-skewed. Its weighted arithmetic mean was GH¢375,846 per worker, while the weighted median was GH¢45,432 and the geometric mean was GH¢45,412. The natural logarithm of real sales per worker was therefore used as the primary dependent variable. Log transformation reduces the influence of very high values and permits coefficients to be interpreted approximately as percentage differences.

Measures

Labour Productivity: Real labour productivity was annual sales divided by permanent full-time employees. Sales were divided by 1.5722 to express 2022 values in 2019 Ghana cedis. Productivity was then transformed using the natural logarithm. The measure reflects realized sales per permanent worker and should not be interpreted as total factor productivity.

Formal Employee Training: Variable l10 asked whether the establishment had formal training programmes for permanent full-time employees during the previous fiscal year. “Yes” was coded one and “no” was coded zero. The survey item does not identify training duration, content, quality, employee coverage or provider.

Workforce Education: The moderator was the percentage of permanent full-time employees completing high school. Direct percentages from l9b and percentages calculated from l9b1 were harmonised. The variable was divided by 10 so that coefficients represented a 10-percentage-point change, then centred at the weighted mean of 82.69%.

Control Variables: Firm age was calculated from the year operations began and transformed as $\ln(\text{age} + 1)$. Permanent employment was logged. Top manager sector experience was measured in years. Foreign ownership was coded one when foreign private individuals, companies or organizations owned at least 10% of the firm. Realized industry and World Bank region were categorical controls. Continuous controls were centred at weighted means. Firm age and employment size were included because older and larger establishments typically benefit from accumulated learning, scale advantages and greater resources for structured training, all of which are associated with higher technical efficiency (Black & Lynch, 2001; Okumu & Buyinza, 2018). Top manager sector experience and foreign ownership were included as proxies for management capability, since experienced managers and foreign owners tend to bring stronger management practices and technology transfer that raise productivity independently of training (Bloom et al., 2019; McKenzie & Woodruff, 2017).

Statistical Analysis

Weighted descriptive statistics were first calculated for productivity, training, education and the controls. Productivity patterns were then examined across training status and four education bands: below 50%, 50–79%, 80–99% and 100%. These comparisons were descriptive and not treated as causal effects.

The main analysis used survey-weighted ordinary least squares regression with HC1 heteroskedasticity-consistent standard errors (White, 1980). A Breusch–Pagan test strongly rejected constant error variance, confirming the need for robust inference. Sampling weights

were divided by their analytical-sample mean so that relative design weights were preserved without inflating residual degrees of freedom.

Four hierarchical models were fitted. Model 1 included the controls. Model 2 added formal training. Model 3 added workforce education. Model 4 added the training-by-education interaction. Hypothesis 1 was evaluated from the training coefficient, while Hypothesis 2 was evaluated from the product term. Because the moderator was centred, the training coefficient in Model 4 represented the training association at the weighted mean education share.

Conditional training effects were calculated at 25%, 50%, 75% and 100% workforce education. Education slopes were calculated separately for establishments with and without training. Coefficients from the log model were converted to percentage changes using $100[\exp(b) - 1]$. Average productivity predictions were retransformed using Duan's smearing method. Because productivity was highly skewed, these monetary predictions were treated as illustrative and accompanied by wide simulation intervals.

Robustness checks used the weak-eligibility weight, unweighted regression, six realised sectors and a model without employment size. Additional checks retained the six employment outliers, trimmed the extreme tails of log productivity, removed influential cases, used a binary 80% education threshold and restricted the analysis to the direct percentage-form education item. A stratified bootstrap with 1,000 replications resampled establishments within World Bank strata. Ten-fold cross-validation assessed out-of-sample prediction error.

Multicollinearity was evaluated using variance inflation factors. Cook's distance was used to identify observations with unusual influence. The 4/N rule was treated as a diagnostic rather than an automatic deletion criterion because legitimate high-productivity firms can be substantively important. All statistical tests were two-sided, with $p < .05$ considered statistically significant. The analysis was conducted in Python using pandas, statsmodels, NumPy, patsy and scikit-learn.

Ethical Considerations

The study analysed anonymised secondary establishment data. No respondent was contacted, and no attempt was made to identify an establishment or individual. The data were used under the World Bank Enterprise Surveys Data Access Protocol. Only aggregated descriptive and model results are reported.

RESULTS

Descriptive Findings

The analytical sample contained 629 establishments. The weighted proportion providing formal training was 48.3%. The weighted mean share of permanent employees completing high school was 82.7%, with a standard deviation of 26.4 percentage points. The median education share was 100%, indicating that many firms reported that all permanent employees had completed high school. At the same time, a meaningfully lower-education tail remained, allowing the interaction to be estimated.

The weighted geometric mean of real labour productivity was GH¢45,412 per permanent worker, while the arithmetic mean was GH¢375,846. The very large difference reflects a small number of highly productive establishments. The weighted interquartile range was

approximately GH¢11,577 to GH¢157,805. This distribution justified the log transformation and the cautious presentation of retransformed monetary estimates.

Training and productivity did not follow a simple pattern across every education band. Among firms with less than 50% education, geometric productivity was GH¢17,123 without training and GH¢18,393 with training. At 50–79%, the corresponding values were GH¢43,202 and GH¢46,046. The largest descriptive gap appeared in the 80–99% group, where trained firms had geometric productivity of GH¢71,847 compared with GH¢21,163 for untrained firms. At 100% education, trained firms also had higher geometric productivity, GH¢66,493 compared with GH¢50,494. These unadjusted differences varied considerably and required multivariable analysis.

Table 1: Weighted Characteristics of the Analytical Sample

Characteristic	Unweighted n	Weighted % or M	Weighted SD / IQR
Real sales per permanent full-time worker, 2019 GH¢	629	375,845.74	IQR 11,577–157,805
Log real sales per permanent full-time worker	629	10.72	1.87
Formal employee training, yes	276	48.3	
Permanent workers completing high school, %	629	82.69	IQR 71–100
Firm age, years	629	14.02	11.57
Permanent full-time employees	629	25.72	44.82
Top manager sector experience, years	629	15.75	9.98
At least 10% foreign ownership	59	10.0	
Realised Sector			
Manufacturing	198	15.1	
Construction	38	6.7	
Wholesale and retail	188	41.3	
Transport and storage	19	6.6	
Accommodation and food	143	17.6	
Other services	43	12.7	
Region			
Region 1	253	68.6	
Region 2	152	16.4	

Characteristic	Unweighted n	Weighted % or M	Weighted SD / IQR
Region 3	123	11.6	
Region 4	101	3.5	

Note: N = 629. Statistics use the World Bank median-eligibility weight. Monetary productivity is real annual sales per permanent full-time worker in 2019 Ghana cedis. IQR = interquartile range.

Table 2: Labour Productivity by Formal Training and Workforce Education Band

Formal Training	Education Band	N	Weighted Sample %	Geometric Productivity	Arithmetic Productivity
No	Below 50%	52	6.3	GH¢17,123	GH¢98,409
No	50-79%	72	10.3	GH¢43,202	GH¢640,748
No	80-99%	97	9.9	GH¢21,163	GH¢91,192
No	100%	132	25.1	GH¢50,494	GH¢147,875
Yes	Below 50%	35	4.1	GH¢18,393	GH¢80,601
Yes	50-79%	41	5.8	GH¢46,046	GH¢486,964
Yes	80-99%	71	8.6	GH¢71,847	GH¢501,108
Yes	100%	129	29.7	GH¢66,493	GH¢613,937

Note: Values are unadjusted weighted summaries. Geometric productivity is $\exp(\text{weighted mean log productivity})$. Education is the percentage of permanent full-time employees completing high school.

Hierarchical Regression Results

Model 1 included the controls and explained 6.9% of the variation in logged productivity. Wholesale and retail establishments had significantly higher productivity than manufacturing firms. Foreign ownership had a large positive coefficient that was close to significance. Firm age, employment size and manager experience were not significant in the controls-only model.

Adding formal training in Model 2 improved the Akaike information criterion from 2943.89 to 2937.42 and increased R^2 from .069 to .082. The training coefficient was positive, $b = 0.455$, $SE = 0.239$, $p = .057$. The estimate corresponded to approximately 57.6% higher productivity, but the 95% confidence interval included zero. The conventional .05 threshold was therefore not met.

Model 3 added workforce education. A 10-percentage-point increase in the education share was associated with approximately 14.3% higher labour productivity, $b = 0.133$, $SE = 0.040$, $p < .001$. The training coefficient remained positive but became slightly smaller, $b = 0.393$, $SE = 0.232$, $p = .091$. Model fit improved substantially: AIC declined to 2917.12, and R^2 increased to .114.

Model 4 added the interaction. At the weighted mean education share, formal training was associated with an estimated 48.0% productivity difference, $b = 0.392$, $SE = 0.232$, 95% CI [-0.063, 0.848], $p = .091$. Workforce education remained significant among firms without formal training: each 10-point increase was associated with 14.7% higher productivity, $b = 0.137$, SE

= 0.050, $p = .006$. The interaction was nearly zero and not significant, $b = -0.009$, $SE = 0.086$, 95% CI [-0.178, 0.160], $p = .921$.

Hypothesis 1 was not supported at the conventional significance level, although the positive magnitude and bootstrap result indicated statistical uncertainty rather than evidence of no possible training value. Hypothesis 2 was clearly not supported. The interaction did not improve fit, and the Model 4 AIC was higher than Model 3.

Table 3: Survey-Weighted Models Predicting Log Real Labour Productivity

Predictor	Model 1 b (SE)	Model 2 b (SE)	Model 3 b (SE)	Model 4 b (SE)
Formal training		0.455 (0.239)	0.393 (0.232)	0.392 (0.232)
Workforce education, per 10 points			0.133*** (0.040)	0.137** (0.050)
Training × education				-0.009 (0.086)
Logged firm age	-0.019 (0.176)	0.008 (0.176)	-0.001 (0.171)	0.000 (0.172)
Logged employment	0.042 (0.125)	-0.016 (0.124)	-0.030 (0.120)	-0.029 (0.120)
Manager sector experience	0.007 (0.013)	0.005 (0.013)	0.013 (0.012)	0.013 (0.012)
Foreign ownership ≥10%	0.874 (0.453)	0.802 (0.434)	0.859* (0.412)	0.864* (0.412)
Other sectors	0.213 (0.231)	0.176 (0.230)	0.119 (0.220)	0.121 (0.222)
Wholesale and retail	0.867*** (0.257)	0.815** (0.250)	0.749** (0.244)	0.751** (0.243)
Region 2	-0.456 (0.335)	-0.512 (0.332)	-0.439 (0.328)	-0.440 (0.328)
Region 3	0.259 (0.349)	0.405 (0.343)	0.589 (0.345)	0.592 (0.342)
Region 4	-0.580 (0.302)	-0.482 (0.296)	-0.317 (0.304)	-0.317 (0.304)
AIC	2943.89	2937.42	2917.12	2919.10
R ²	0.069	0.082	0.114	0.114

Note: N = 629. HC1 robust standard errors are in parentheses. Sampling weights are normalised to the analytical sample size. Manufacturing and Region 1 are reference categories. Continuous predictors are centred. * $p < .05$. ** $p < .01$. *** $p < .001$.

Conditional Effects and Predicted Productivity

The estimated training difference remained positive across the full education range but did not reach statistical significance. At 25% workforce education, the estimated training difference was 55.6%, $p = .415$. At 50%, it was 52.3%, $p = .242$. At 75%, it was 49.0%, $p = .096$. At 100%, it was 45.9% ($p = .178$). The small decline in the estimated percentage difference reflects the slightly negative interaction, but the change was substantively small relative to its uncertainty.

Workforce education had a positive slope in both training groups. Among firms without formal training, each 10-percentage-point increase was associated with 14.7% higher productivity, 95% CI [4.0%, 26.5%], $p = .006$. Among trained firms, the corresponding estimate was 13.7% (95% CI [-0.5%, 29.9%], $p = .059$). The slopes were almost parallel, which is consistent with the null interaction.

Smearing-adjusted predictions illustrated the scale, as well as the uncertainty created by productivity skewness. At 75% education, adjusted expected productivity was GH¢240,039 without training and GH¢357,720 with training. At 100%, the corresponding estimates were GH¢338,231 and GH¢493,354. The confidence intervals were wide, and none of the training differences at the four education levels was statistically significant. These predictions should be read as model-based illustrations rather than forecasts for individual firms.

Table 4: Conditional Training Effects and Education Slopes

Contrast	Estimated % change	95% CI	p
Training effect at 25% education	55.6	[-46.2, 350.1]	.415
Training effect at 50% education	52.3	[-24.7, 208.0]	.242
Training effect at 75% education	49.0	[-6.8, 138.3]	.096
Training effect at 100% education	45.9	[-15.7, 152.5]	.178
Education slope per 10 points without training	14.7	[4.0, 26.5]	.006
Education slope per 10 points with training	13.7	[-0.5, 29.9]	.059

Note: Effects are calculated from the full interaction model. Training effects compare trained with untrained establishments at the stated education share. Education slopes represent a 10-percentage-point increase.

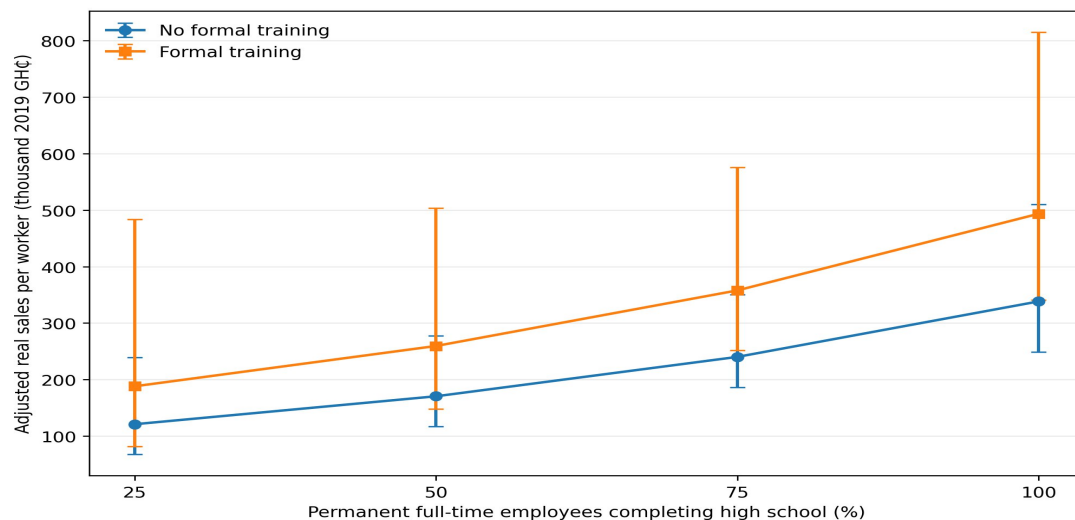


Figure 1: Adjusted Real Labour Productivity by Formal Training and Workforce Education

Note: Predictions use Model 4 and Duan's smearing retransformation. Values are expressed in constant 2019 Ghana cedis per permanent full-time employee. Shaded areas show simulated 95% confidence intervals.

Diagnostics and Robustness Checks

The largest substantive variance inflation factor was 1.82 for workforce education. The interaction VIF was 1.77, and all other values were below 1.46. Multicollinearity was therefore not a concern. The Breusch–Pagan test was significant ($p < .001$), supporting the use of heteroskedasticity-consistent standard errors.

Cook's distance had a maximum value of .038, well below one. Forty-three observations exceeded the $4/N$ screening threshold. Removing only the most influential observation left the focal results essentially unchanged. Removing all 43 reduced the training estimate and left the interaction nonsignificant, while the positive education association remained significant. Because the observations were valid and wholesale deletion can distort a representative sample, the full sample was retained.

The weak-eligibility weight produced a training estimate of 50.4% ($p = .086$), an education estimate of 15.6% per 10 points ($p = .004$), and a null interaction ($p = .834$). The unweighted model made both training and education statistically significant, but the interaction remained nonsignificant. This difference confirms the importance of survey weighting when interpreting population-level associations.

Six-sector controls, removal of the employment-size control, inclusion of the six employment outliers and trimming of log-productivity tails all preserved the positive education result and null interaction. A binary high-education specification also produced no interaction. The stratified bootstrap yielded a training coefficient interval of $[-0.010, 0.811]$, an education interval of $[0.056, 0.225]$ and an interaction interval of $[-0.187, 0.134]$.

The direct percentage-form-only analysis contained 463 establishments. In that restricted sample, the education and training estimates were positive but nonsignificant, and the interaction was also nonsignificant. The direct-form firms differed from count-form firms in size and education distribution so that this result may reflect reduced information and sample

composition. It nevertheless limits the strength of the education conclusion and is reported transparently.

Ten-fold cross-validation produced a mean weighted root mean square error of 1.843 log points and mean absolute error of 1.501. The model therefore had limited firm-level predictive accuracy. It is more appropriate for estimating broad sample associations than for predicting productivity at a particular establishment.

Table 5: Sensitivity Analysis of Focal Coefficients

Analysis	n	Training b (p)	Education b (p)	Interaction b (p)
Primary median-eligibility weight	629	0.392 (.091)	0.137 (.006)	-0.009 (.921)
Weak-eligibility weight	629	0.408 (.086)	0.145 (.004)	-0.018 (.834)
Unweighted OLS	629	0.473 (.003)	0.094 (.018)	-0.051 (.366)
Six realised sectors	629	0.349 (.114)	0.120 (.020)	-0.048 (.593)
No employment-size control	629	0.378 (.101)	0.138 (.006)	-0.010 (.904)
Direct percentage-form education only	463	0.246 (.325)	0.045 (.320)	0.109 (.244)
Including employment outliers	633	0.391 (.092)	0.137 (.006)	-0.007 (.936)
Trimmed log-productivity tails	624	0.355 (.126)	0.131 (.009)	-0.013 (.883)
Drop Cook D above 4/N	586	0.277 (.163)	0.145 (.002)	-0.061 (.364)
Education threshold at 80%	629	0.165 (.723)	0.430 (.170)	0.322 (.550)

Note: Coefficients are on the log-productivity scale. The 80% threshold analysis uses a binary education measure, so its education and interaction coefficients are not directly comparable with the continuous models.

Table 6: Stratified Bootstrap Results

Term	Mean b	Bootstrap SE	95% percentile CI	Two-sided p
Formal training	0.386	0.214	[-0.010, 0.811]	.064
Education per 10 points	0.136	0.044	[0.056, 0.225]	.006
Training × education	-0.020	0.082	[-0.187, 0.134]	.836

Note: The bootstrap used 1,000 replications and resampled establishments within World Bank survey strata. All replications converged.

DISCUSSION

Interpretation of the Findings

This study examined formal employee training, workforce education and labour productivity in Ghanaian enterprises. The strongest result was the positive association between workforce education and productivity. In the complete weighted model, a 10-percentage-point increase in the share of permanent employees completing high school was associated with approximately 14.7% higher real sales per permanent worker. The result remained significant under most alternative specifications and in the stratified bootstrap.

The training result was positive but statistically uncertain. The central estimate suggested a large productivity difference at the weighted mean education level, but the confidence interval crossed zero and the p value was .091. The bootstrap interval nearly excluded zero, while the unweighted model was significant. These patterns do not justify stating that training had no value. They show that the representative weighted data did not estimate the training association precisely enough for a conventional conclusion.

The proposed complementarity was not supported. The interaction estimate was very close to zero, and predicted lines were nearly parallel. Training was not systematically more productive in firms with a larger education share. Education showed a similar positive slope whether or not the firm reported formal training. This finding challenges a simple assumption that education and training automatically reinforce one another.

The education result is consistent with Ghanaian evidence from Jones (2001), who found a positive relationship between worker education and productivity in manufacturing. The current study extends that logic across a wider group of formal sectors and uses a contemporary Enterprise Survey. It also aligns with broader evidence that human capital is positively related to firm performance (Crook et al., 2011).

The positive but uncertain training result is consistent with the mixed and context-dependent training literature. Dearden et al. (2006) and Konings and Vanormelingen (2015) found significant productivity benefits in panel settings with detailed training measures. Garavan et al. (2021a) reported an overall positive meta-analytic relationship but emphasised moderators. The binary survey item used here is less detailed, and the cross-sectional design can weaken precision and obscure programme quality.

There are several explanations for the null interaction. First, formal education may support productivity directly through communication, problem solving and technology use, while training addresses separate job-specific gaps. The resources can be additive rather than multiplicative. Second, training may be compensatory: firms with less educated workers may use practical programmes to close skill gaps. Third, training quality and alignment may vary. A strong complementarity requires programmes that build on employees' prior knowledge and connect to strategic work processes.

Fourth, the education distribution was concentrated at high values. The weighted median was 100%, reducing information about differences at the upper end. Fifth, the count-form and percentage-form questionnaire groups differed. The education association was weaker in the direct-form-only sample, indicating that measurement form and sample composition deserve attention. Sixth, productivity may be influenced by capital, market power, technology and product mix, which are not fully captured by sales per worker.

Theoretical Implications

The results refine the human-capital complementarity argument. Human-capital resources can contribute independently without creating a statistically detectable interaction. Strategic human resource theory should distinguish between a bundle that merely coexists and a bundle that is aligned in content, timing and implementation. The presence of training and educated workers is not enough to establish internal fit.

The findings also illustrate the value of separating human-capital stock from human-capital development practices. Workforce education represents accumulated capability, while formal training is an organizational intervention. The strong education result and uncertain training result suggest that stocks may be easier to observe than the effectiveness of practices. Future theory should pay greater attention to training transfer and the organizational conditions that convert learning into performance.

The null interaction is informative for the resource-based view. Resources create advantage through deployment, not possession alone. Education is productive when work design uses employee knowledge. Training is productive when the programme addresses valuable tasks, and employees can apply learning. Complementarity therefore depends on organizational integration, managerial support and opportunity to perform, not simply on the simultaneous presence of two resources.

The study further contributes to research in developing economies by showing that nationally representative weighted results can differ from unweighted estimates. Strategic-management conclusions should respect survey design when sample strata are intentionally disproportionate. Unweighted significance is not a substitute for representative inference.

Managerial Implications

Ghanaian managers should treat workforce education as a strategic capability but should not use formal qualifications as the only indicator of productive skill. Recruitment and promotion systems can consider education alongside practical competence, experience and learning ability. Firms should also create work arrangements that allow educated employees to solve problems and share knowledge.

Training decisions should begin with a performance diagnosis. Managers should identify specific gaps in quality, speed, safety, customer service or technology use before selecting a programme. Training objectives should be linked to observable work behaviours and operational indicators. This approach is more likely to generate productivity than general training chosen mainly to satisfy a policy or annual plan.

Programme design should match the educational profile of participants. Employees with weaker academic preparation may benefit from demonstrations, practice and coaching rather than text-heavy instruction. Highly educated employees may need advanced analytical, digital or supervisory content. A single standard course may not create complementarity because it does not build appropriately on prior knowledge.

Firms should evaluate training transfer. Attendance records show that training occurred but not that work improved. Managers can compare performance before and after training, observe changed behaviour and ask supervisors whether new skills are used. Follow-up coaching and access to suitable tools can prevent knowledge from fading after the course.

The results also caution against overinterpreting the large central training estimate. The confidence interval was wide, and predicted monetary differences were uncertain. Managers should use pilot programmes, measure outcomes and expand training that demonstrates value rather than assuming that every formal programme will raise productivity.

Policy Implications

Education policy remains closely connected to enterprise productivity. The positive education association supports continued attention to high-school completion, literacy, numeracy and problem-solving quality. Completion alone is not enough; employers need graduates who can apply foundational knowledge in changing work environments.

Enterprise-support programmes should combine training subsidies with quality assurance and evaluation. Support agencies can require a simple needs analysis, clear learning objectives and post-training performance measures. Programmes should avoid counting only the number of firms or employees trained. The relevant question is whether training changes productive practice.

Universities, technical institutions and business associations can develop modular programmes that respond to sector-specific needs. Manufacturing firms may prioritise maintenance and quality control, while service firms may need customer analytics, digital systems and process design. Employers should help define content so that courses address real constraints.

Policymakers should also recognize that firms with lower-educated workforces may need additional support. Practical training, workplace literacy and mentoring can make learning accessible. At the same time, the null interaction means that resources should not be directed only to highly educated firms on the assumption that they will necessarily receive larger returns.

Better data are needed. Future Enterprise Surveys or national firm surveys could collect training expenditure, duration, employee coverage, content, provider and evaluation. Linking these measures to repeated productivity observations would permit stronger causal and policy conclusions.

Limitations and Future Research

First, the study is cross-sectional. Productive firms may be more able to pay for training and attract educated employees. Reverse causality and unobserved managerial quality cannot be excluded. Panel data or experimental training support would provide stronger causal evidence.

Second, formal training was measured as a binary practice. The survey did not identify duration, quality, content, participant share or learning transfer. Measurement error can attenuate both the training coefficient and the interaction. Detailed programme measures are a priority for future research.

Third, the education variable combined two questionnaire forms. The conversion of employee counts to percentages is mathematically direct, but the form change may influence response behaviour. The direct-percentage-only sensitivity did not reproduce the significant education slope, which limits the certainty of the result. Future survey waves should use a single consistent form.

Fourth, sales per worker is not total factor productivity. High values may reflect capital intensity, mark-ups, imported inputs, sector structure or temporary demand. The models controlled for size, industry and region but did not contain reliable capital-stock and intermediate-input measures for a full production function.

Fifth, sales were self-reported. Some establishments may round or misreport financial values. The World Bank outlier procedure and log transformation reduce the influence of extreme values but do not eliminate all measurement error.

Sixth, workforce education was measured as high-school completion. It did not distinguish tertiary education, vocational qualifications, field of study, skill quality or differences between production and managerial employees. More detailed occupational education measures could reveal stronger complementarities.

Seventh, the overall Enterprise Survey response rate creates the possibility of nonresponse bias. Sampling weights account for the known design and alternative eligibility assumptions but cannot correct unobserved differences between participants and nonparticipants.

Eighth, the model had limited cross-validated predictive accuracy. Labour productivity is shaped by many variables not included here, including capital equipment, product quality, market power, management systems and energy reliability. The model should be used for association and theory testing rather than individual prediction.

Future studies can follow firms over time, compare sectors, and examine whether specific training types interact with education. Randomised or phased training programmes could test whether curriculum adaptation to educational background creates genuine complementarity. Qualitative work can also identify why learning is or is not transferred into productive routines.

CONCLUSION

This study used the Ghana World Bank Enterprise Survey 2023 to examine formal training, workforce education and real labour productivity. Workforce education had a positive and statistically significant association with productivity. Formal training had a positive but imprecisely estimated association. The training-by-education interaction was near zero and consistently nonsignificant.

The evidence therefore supports the productive importance of workforce education but does not support automatic complementarity between education and formal training. Human-capital practices create value when they are relevant, well designed and transferred into work. Ghanaian firms and policymakers should focus not only on whether training exists, but on whom it serves, what problem it addresses, and whether productivity changes afterwards.

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APPENDIX

Variable Coding and Reproducibility Summary

Construct	WBES variable	Coding or construction
Real labour productivity	d2 and l1	2022 sales divided by 1.5722, then divided by permanent full-time employment; natural log used in models
Formal employee training	l10	1 = formal training programmes for permanent full-time employees; 0 = no
Workforce education	l9b or l9b1/l1	Direct percentage completing high school, or count divided by permanent employment × 100; scaled per 10 points and centred
Firm age	a14y and b5	Interview reference year minus year operations began; ln(age + 1), centred
Employment size	l1	Natural logarithm of permanent full-time employees, centred
Manager sector experience	b7	Years of top manager experience in the

Construct	WBES variable	Coding or construction
		sector, centred
Foreign ownership	b2b	1 when foreign private ownership $\geq 10\%$; otherwise 0
Realised industry	d1a2_v4	Four-digit ISIC grouped into three categories; six-category sensitivity
Region	a2	Four World Bank Ghana survey regions
Primary weight	wmedian	Median-eligibility survey weight normalised to mean one
Alternative weight	wweak	Weak-eligibility survey weight used in sensitivity analysis
Sampling stratum	strata	Used for within-stratum bootstrap resampling

Note: World Bank negative response codes were treated as missing. The primary sample excluded six employment observations identified by the World Bank three-standard-deviation rule after $\ln(x + 1)$ transformation.