

An Empirical Investigation of the Effect of Manager's Level of Education on Labour Productivity In the Manufacturing Sector in Uganda: 2006–2013

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Abstract

This paper investigates the effect of education of firm managers on labour productivity in Uganda's manufacturing sector using enterprise survey data. Like in many Sub-Saharan economies, Uganda is grappling with labour productivity associated with deficiencies and mismatch in skills, which limit the adaptation of new production technologies. The human capital theory (HCT) and the endogenous growth theory (EGT) underpinned this investigation. On the basis of a Cobb-Douglas function we estimated a labour productivity equation. The paper found that attainment of higher levels of education by firm managers improved labour productivity, and mean productivity of individual workers at firm level. The strong linkage between managers' education and labour productivity implies that the government should focus on policies that improve higher education.

Keywords: *human capital theory, endogenous theory, Cobb-Douglas function, firm managers, level of education, labour productivity, skill deficiency*

JEL Classification: J24

1. Introduction

Education affects productivity through both workers and managers' levels of education (Barro & Lee, 2013; Okumu & Mwanjje, 2019; DfE, 2021). The human capital theory (HTC) suggests that the level of education is directly proportional to labour productivity. Therefore, through education more scarce resources should be directed to the development of skills that improves labour productivity. Granted, planners can use education effectively to address low labour productivity, among others, in the manufacturing sector. The level of investments in education determines the levels of skills and human capital accumulation (Schultz, 1961; Barro & Lee, 2013; UNESCO IIEP, 2022), and consequently labour productivity. The objective of this paper is to investigate the effects of managers' levels of education on labour productivity in manufacturing firms in Uganda.

In Uganda, like in many Sub-Saharan African (SSA) economies, the manufacturing subsector is grappling with labour productivity associated with skill deficiencies and mismatch, which limit abilities to marshal production resources and the adaptation of new technologies. The subsector lacks indigenous capability for technology and

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innovations, which further affects labour productivity (Ggoobi et al., 2017; DTDA, 2020). Improvement in productivity increases earnings and the quality of individual lives (World Bank, 2019; Psacharopoulos & Patrinos, 2018), leading to broader benefits to society. The choice of the period 2006 to 2013 was determined by the availability of data, but also there was a sudden rise in value-addition in manufacturing during this period (Figure A1). This rise was followed by a gradual drop attributed to inadequate and a mismatch of skills. The United Nations Economic Commission for Africa (UNECA, 2017) has ranked Uganda's manufacturing subsector as the third lowest in labour productivity among subsectors. The World Bank, on the other hand, ranked Uganda Human Capital Index (HCI) at the bottom; declining from 0.54 in 2019 to 0.52 in 2021 (World Bank, 2019; UNDP, 2022). Despite the abundance of youthful population (UBOS, 2019), these youth are said to be unproductive. The challenge is they lack appropriate and critical skills (Ggoobi et al., 2017; DTDA, 2020). This implies that there is need to carefully invest in education so as to boost labour productivity.

In the context of the human capital theory (HCT),¹ in conjunction with the endogenous growth theory (EGT),² the low level of labour productivity in the manufacturing sector in Uganda is explained by low levels of investment in education for human capital development. According to Adam Smith, the pioneer of HCT, formal education is highly instrumental for improving productivity (Smith, 1776). The theory posits that incremental education increases knowledge, skills, and life experiences; which in return yield economic and social benefits at individual and society levels. This implies that for every increase in schooling, there is an increase in the level of productivity that translates into earnings. On the other hand, according to the EGT, human capital integrates with physical capital and labour as major determinants of output (Lucas, 1988; Romer, 1990; Rebelo, 1991). The Cobb-Douglas function is used to account for the diminishing returns of factors of production. The theoretical linkage between education and labour productivity lies on the rational expectation and assumption that, through education, individuals gain skills and knowledge that increase efficiency in the utilization of physical capital. These skills accumulate to form a stock of human capital that creates new knowledge and technologies used to improve labour productivity, which in turn improves individual earnings.

The HCT is supported by some empirical studies on manufacturing firms in SSA countries, which attribute low levels of labour productivity to education and training on human capital (Niringiye, Luvanda, & Shitundu, 2010; Heshmati & Rashidghlam, 2018; Okumu & Mwanjje, 2019; Okunade, Alimi, & Olayiwola, 2022; Omolara & Aderinto, 2022; Okumu & Buyinza, 2019). Recent studies that specifically link firm managers' education to labour productivity in manufacturing

¹ The human capital theory attempts to explain the relations between education and income with the concept of human capital.

² The endogenous growth theory provides a production function whose growth of output is through improvement in technology and accumulation of human capital. It has been used to derive expression for labour productivity.

sector are scarce. Equally, studies that endeavour to isolate the effects of different levels of education on labour productivity are rare due to scarcity of data. In Uganda, the most recent World Bank Enterprise Survey data on manufacturing are panels 2006 and 2013. A few available and related studies, therefore, tend to aggregated scanty data from selected African countries to generalized results. These studies also do not isolate the effects of firm managers' education on labour productivity. Suffice to say that SSA countries have common characteristics of data scarcity and low labour productivity. In one particular case, Niringiye, Luvanda and Shitundu (2010) investigated labour productivity in East African manufacturing firms (Kenya, Tanzania and Uganda) using enterprise survey data. The study found the effect of education on labour productivity to be positively significant.

Similarly, Okumu and Buyinza (2019) used data from the Enterprise Survey 2013 to assess the relationship between innovation and firm performance. It is acknowledged that the ability to research and innovate is closely correlated with the use of high technology and higher levels of education and training. The findings of the study by Okumu and Buyinza (*ibid.*) showed that firms that engaged in a combination of product, process, marketing and organizational innovations improved labour productivity. In Kenya, a closely related study by Heshmati and Rashidghalam (2018) analysed the determinants of labour productivity based on the Enterprise Survey 2013 data by using the ordinary least square method, and found education and training to be positively associated with higher labour productivity. Noteworthy, at least one earlier study on manufacturing in Ghana failed to establish the existence of a positive and significant relationship between the level of education and labour productivity (Söderbom & Francis, 2004). Contrary to this, the curricula in Ugandan education system show that different levels of education delve into different depths of teaching and training that defines the level of skills and intensity of knowledge acquired. This study attempts to revisit this, and specifically focusses on the effect of the level of education of firm managers on labour productivity in the case of Uganda.

Elsewhere in Africa, Okunade, Alimi and Olayiwola (2022) aggregated data from seventeen (17) African countries to explore the linkage between human capital development and labour productivity in Africa. The findings showed that human capital development beyond the threshold of 50% had a robust significant positive effect on productivity growth by 11.2%. In another study, Okumu and Mwanjje (2019) studied labour productivity in African manufacturing using World Bank Enterprise Survey data from twenty even (27) African countries, collected in the period 2011–2017. The study found that high school graduates increased average firm productivity by 42%, while university graduates increased productivity by 48%. The study further concluded that completing the formal educational cycle was important in enhancing labour productivity. Similarly, a related study by Omolara and Aderinto (2022), using data from thirty (30) SSA countries spanning from 2000 to 2019, examined the effect of human capital development on labour productivity. The findings showed that human capital had a positive and significant effect on labour productivity.

2.3 Synthesis of the Review

Previous studies used firm level data to investigate aggregated effect of either human capital or education on labour productivity in the countries of interest (Niringiye, Luvanda, & Shitundu, 2010; Okumu & Buyinza, 2018; Okumu & Mwanje, 2019; Okunade, Alimi & Olayiwola, 2022; Omolara & Aderinto, 2022). However, in the case of Uganda, none have investigated the effect on productivity of firm manager's education in the manufacturing sector. A study by Lekfuangfu et al. (2012) investigated the impacts of managers' level of education on productivity, but only in the agricultural sector. Also, even though previous studies in Uganda have investigated labour productivity in manufacturing based on Uganda National Household Survey dataset (see, e.g., Kavuma et al., 2015), there is a need to utilize alternative available data since each source has unique methodological challenges.

This study seeks to fill the existing gaps and the dearth of literature to better guide policymakers and planners by focusing on sector-specific effects of firm managers' education on productivity in Uganda. The analysis is based on World Bank Enterprise Surveys data of 2006 and 2013, which offered an opportunity to explore other salient issues. As pointed out earlier, data scarcity in African countries has made it rare to get country-specific studies; and previous studies aggregated manufacturing data from several African countries to draw conclusion on labour productivity in SSA (Okumu & Mwanje, 2019; Okunade, Alimi & Olayiwola, 2022; Omolara & Aderinto, 2022). Thus, this paper seeks to address the specific case for Uganda using the Enterprise Survey 2006 and 2013 panel data that was available at the time of the study.

The rest of this paper is organized as follows. Section 2 dwells on the methodology of the study; while section 3 presents and discusses the empirical results. Section 4 concludes by presenting the key findings and their policy relevance.

2. Methodology

2.1 Theoretical Model

The human capital theory underscores the importance of education in human capital development. Specifically, knowledge and skills acquired on education increase efficiency in the utilization of physical capital, which ultimately raises the level of labour productivity. The estimation models used in the analysis of that theory often rests on a production function that reads:

$$Y = f(L, K, AK) \quad (1)$$

where Y is output or income, A is the technology, L is the labour force, K is physical capital stock, and H is human capital. Given constant returns to scale, labour productivity ($y = \frac{Y}{L}$) depends on capital intensity ($k = \frac{K}{L}$).

The endogenous growth theory assumes returns to investment in human capital do not necessarily diminish. Rather, human capital depreciates through knowledge decay and memory lapse; meaning it depreciates like any other capital. As in other studies, use is made of the Cobb-Douglas production function that allows for diminishing returns. In a Cobb-Douglas form output, Y is expressed as equation (2):

$$Y = AK^{\alpha}L^{\beta}; \frac{\partial Y}{\partial L} > 0 \quad (2)$$

Where α and β are elasticity parameters, and other variables as already defined.

From equation (2), the average productivity of labour is thus: ($y/L = AP_L$).

$$AK^{\alpha}L^{\beta-1} \quad (3)$$

Then the marginal product of labour is ($\frac{\partial Y}{\partial L} = MP_L$)

$$\frac{\partial Y}{\partial L} = A\beta K^{\alpha}L^{\beta-1} \quad (4)$$

And the marginal product of capital $\frac{\partial Y}{\partial K} = MP_K$ is:

$$\frac{\partial Y}{\partial K} = A\alpha K^{\alpha-1}L^{\beta} \quad (5)$$

It follows that the rate of Marginal rate of Technical Substitution $MRTS_{KL}$ of capital for labour reads as:

$$MRTS_{KL} = \frac{\beta K}{\alpha L} \quad (6)$$

At optimal point:

$$AP_L = MP_L; AK^{\alpha}L^{\beta-1} = A\beta K^{\alpha}L^{\beta-1} \quad (7)$$

Incorporating individual i and longitudinal effects t , the efficiency output is expressed as:

$$Y_{it} = AK_{it}^{\alpha}L_{it}^{*\beta} \quad (8)$$

Where L^* represents efficient units of effective labour:

$$L_{it}^* = L_{it}L_{1it}^{\theta_1}L_{2it}^{\theta_2}L_{3it}^{\theta_3}L_{4it}^{\theta_4} \quad (9)$$

where L_{it} measures effective labour input that goes into production of the value created measured in total annual hours worked by employees. $L_{rit}^{\theta_r}$ represents the number of employees with average level of education r ; and θ_r represents contribution of respective level of education.³

Substituting equation (9) in (8), followed by a division by effective labour (L_{it}) throughout give the dynamic effects of labour represented by equation (10):

$$\frac{Y_{it}}{L_{it}} = A\left(\frac{K_{it}}{L_{it}}\right)^{\alpha}L_{it}^{\alpha+\beta-1}(1 - L_2 - L_3)^{\beta(1-\theta_2-\theta_3)}L_{1it}^{\beta\theta_1}L_{2it}^{\beta\theta_2}L_{3it}^{\beta\theta_3}L_{4it}^{\beta\theta_4} \quad (10)$$

Application of natural logarithm operator into (10) gives equation (11).

³ Using total annual hours worked is more appropriate for estimating productivity given the full time and part time composition of workers.

$$\ln \frac{Y_{it}}{L_{it}} = \ln A + \alpha \ln \left(\frac{K_{it}}{L_{it}} \right) + (\alpha + \beta - 1) \ln L_{it} + \ln \beta \theta_1 L_{1it} + \dots + \ln \beta \theta_4 L_{4it} + u_i + \varepsilon_{it} \quad (11)$$

where L_1, \dots, L_4 are average weighted proportions of effective labour for different skill levels.

Equation (11) is the model estimated for labour productivity. This equation was augmented by other determinants of labour, including capacity utilization, mean wage and mean energy utilization, the proportions of skilled, mean years of workers' schooling, workers experience, and firm age in line with economic theories. Firm size and occupation absorb part of the effects of education (Kavuma, Morrissey & Upward, 2015), therefore, excluded in the model. Specifically, the variables are as follows:

$\ln y_{it}$ = labour productivity which was computed as total annual sales divided by average annual labour hours

$\ln k_{it} = \ln(K_{it}/L_{it} * cap_util)$: Capital intensity measured as cost of equipment and machinery divided by average annual hours then multiplied by capacity utilization ($x/100$).

$\ln w_{it} = \ln(W_{it}/L_{it})$: Annual wage divided by annual hours worked

$\ln e_{it} = \ln(E_{it}/L_{it})$: Annual energy consumption divided by average annual hours worked

$\ln(s_{it}) = \ln(skil * pfr)$: Fraction of production labour force that is skilled labour

edu_{it} : Mean years of schooling of total labour force

exp_{it} : Mean Worker's experience

$fage_{it}$: Firm age (Year when survey was done less year the firm started operation)

$u_i + \varepsilon_{it}$: Within and between error terms respectively

The labour productivity model was extended to include attributes of managers, that is, their level of education (mle), experience ($mexp$), and gender ($mgen$).

The empirical model was obtained by substituting explanatory variables into (11) to get labour productivity equation (12)

$$\ln y_{it} = \beta_0 + \beta_1 \ln k_{it} + \beta_2 \ln w_{it} + \beta_3 \ln e_{it} + \beta_4 \ln s_{it} + \beta_5 edu_{it} + \beta_6 exp_{it} + \beta_7 fage_{it} + u_i + \varepsilon_{it} \quad (12)$$

2.2 The Estimation Model

Basic estimation model, which build on (12) reads as:

$$\ln y_{it} = \beta_0 + \beta_1 \ln k_{it} + \beta_2 \ln w_{it} + \beta_3 \ln e_{it} + \beta_4 edu_{it} + \beta_5 \ln s_{it} + \beta_6 exp_{it} + \beta_7 fage_{it} + \beta_8 mle_{it} + \beta_9 mexp_{it} + \beta_{10} mgen_{it} + u + \varepsilon_{it} \quad (13)$$

Notable, the model includes attributes of the managers in the sample used, including their education (mle), experience ($mexp$), and gender ($mgen$). The assumption was that a decision made by top management in firms influence labour productivity. From HCT, the skills and knowledge obtained by managers from education equally enhance their productivity.

2.2 Data Description

The study was based on a secondary data of 696 firms in Uganda that was obtained from the World Bank data base generated by enterprise surveys carried out in 2006 and 2013 (Appendix Table A1). While the two surveys covered 1,325 firms, only 696 that were in manufacturing have been included in the analysis.⁴ It is noteworthy that the enterprise survey data was collected by the World Bank for other purposes. Thus, several transformations were necessary to make it suitable for the analysis in this study. In this analysis, output of the firms was measured by the volume of their annual sales.

Labour productivity—which measures how efficient and effectively a firm utilizes human capital in turning a set of inputs into a physical product or output from a given quantity of inputs at a minimum cost—is commonly measured by output per labour hour. The first alternative measure—namely output per worker—was previously used by Niringiye (2014) to measure labour productivity in Uganda; but it is not used in this study due to the existence of intermittent labour supply on part-time engagements. Also, the second alternative measure of labour productivity, sales per employee—as used by Heshmati and Rashidghlam (2018) in a study on Kenya—was also not used because the workers had varying contractual agreements: some were on part-time basis, while others were on full-time employment.

2.4 Choice of Panel Data Model

Panel models were examined to determine the most appropriate model for the study. According to Kennedy (2008), equality of intercepts is a prerequisite for the estimation of a panel data model by using ordinary the least squares method (OLS), else the Hausman test should be used (Kennedy, 2008). If the group effect is not correlated with the error term, then random effect (*RE*) estimators can be used, otherwise the fixed effect (*FE*) estimator should be used.

Table 2 shows that the intercepts of the estimation model are not equal, which signified that the suggested pooled OLS (POOLS) was not the appropriate estimator, and the robust *SE* were slightly downward biased. The *FE* model allows for differences in the intercept parameter for each observation. Since heteroscedasticity was anticipated, this was accomplished using the *xtreg* command with the '*fe vce(cluster panel_id)*' option, which allowed for corrected standard errors. The *RE* model treats the heterogeneity across individuals as a random component. The R^2 for the *FE* robust model obtained $dife(r2) = 0.57$, implying the model explained approximately 57% of the variations in labour productivity. The pooled OLS does not include *RE* or *FE*. It assumes a constant intercept and slopes regardless of group and time period.

The POOLS model fits the data at the 0.05 significance level $F(8, 443) = 215.4$, $p < 0.0$). The R^2 of 0.748 means this model accounts for 74.8% of the total variance in labour productivity. Firm age was not significant in the estimation of labour

⁴ Out of the remaining firms, 283 were in retail and 346 were dealing in other businesses.

productivity across all models; while capital, wage, skill, experience and education were all significant. The *RE* model incorporates a composite error term, $(u_i + v_{it})$. The '*v*' and '*u*' are assumed independent of the error term, also the regressors independent of each other for all *i* and *t*, i.e., $corr(u_i, X) = 0$. The *RE* model returns chi-square statistic ($Wald\ chi2(8) = 1264.5, Prob > chi2 = 0.$), and overall R^2 of 0.748; giving a similar explanatory power of 74.8% variance in labour productivity as in the pooled OLS model. The *rho* in *RE* and *FE* models represents the ratio of individual specific error variance to the composite error variance. Larger *rho* shows that a bigger proportion of individual specific errors are accounted for in the composite error variance. In the *RE model*, for instance, the individual specific error explained 12.8% of the entire composite error variance. This *rho* may be interpreted as a goodness of fit of the model. The *FE* model returns F-statistic ($F(8, 329) = 13.76$, with $Prob > F = 0$). The $R^2 = 0.563$ implied the *FE* robust model explained 56.3% of variations in labour productivity.

Table 2: Pooled OLS, Random Effects Models and FE Robust Models

	Pooled OLS	RE	FE
<i>lnk</i> (Capital intensity) in mean cost	0.167*** (0.032)	0.167*** (0.032)	0.181*** (0.069)
<i>lnw</i> (Mean Annual wage)	0.448*** (0.066)	0.440*** (0.047)	0.288* (0.121)
<i>lne</i> (Mean annual energy consumption)	0.223*** (0.047)	0.238*** (0.039)	0.375*** (0.096)
<i>lns</i> (Proportion of skilled workers)	0.194*** (0.057)	0.203*** (0.056)	0.287* (0.144)
<i>exp</i> (Mean workers experience)	0.030*** (0.007)	0.030*** (0.006)	0.044*** (0.009)
<i>fage</i> (Age of the firm)	0.003 (0.007)	0.004 (0.006)	0.001 (0.026)
<i>edu</i> (Mean years of workers schooling)	0.118*** (0.018)	0.118*** (0.018)	0.116** (0.042)
_cons	1.382*** (0.360)	1.393*** (0.367)	1.546 (1.024)
N	452	452	452
<i>R - sq</i>	0.748		0.573
<i>Sigma_u</i>		0.413	1.177
<i>Sigma_e</i>		1.079	1.079
<i>rho</i>		0.128	0.534

Note: Standard errors in parentheses. *p<0.05, **p<0.01, ***p<0.001

Source: Authors analysis and computations

The following was deduced from the output in Table 2:

- The coefficients and standard errors (SE) for the models (pooled OLS, *RE*, and *FE*) differed, hence the panel data cannot be pooled; and the OLS model may not be appropriate. This presupposes conducting the Hausman test (Kennedy, 2008).
- The *rho* measured goodness of fit of the *FE* and *RE* models represent the proportion of variations due to individual specific terms in the model. The higher the *rho*, the better; implying the *FE* robust (54.3%) model provides a better fit as compared to the *RE* (12.8%) model.

- (c) Capital intensity (*k*), mean annual wage (*w*), mean energy utilization (*e*), skilled labour proportion (*lns*), mean workers years of schooling (*edu*), and mean years of workers experience (*exp*): were all significant in explaining labour productivity.
- (d) The R² value of 0.569 implies the variables included in the fixed effect model collectively explain 56.9% of the variations in labour productivity in the manufacturing sector, leaving 43.1% to the error term.

2.4.1 Breusch-Pagan LM test for Random Effect Versus OLS Model

The Breusch-Pagan Lagrange multiplier (LM) tested the existence of RE. The null hypothesis was $H_0: \sigma_u^2 = 0$; i.e., the variance of individual-specific or time-specific error components were zero. The decision rule: if *p* – value < 0.05 reject the null hypothesis, otherwise the RE would be a better model.

Table 3: Breusch-Pagan LM Test for Random Effect Versus OLS Model

	<i>var</i>	<i>sd = sqrt(var)</i>
<i>ln</i> (Mean annual output)	5.528	2.351
<i>e</i>	1.164	1.079
<i>u</i>	0.171	0.413
Test:	<i>Var(u)</i> = 0	
	Chibar2(01) = 3.12	
	<i>Prob > chibar2</i> = 0.039	

Source: Authors analysis and computations

The Breusch-Pagan LM test for RE versus OLS model returned p-value = 0.039, which shows significant differences across firms. The null was rejected, $\hat{\beta}_{RE}$ was chosen $\hat{\beta}_{OLS}$. The RE and FE models were then assessed for consistency using the Hausman test.

2.4.2 Hausman Test for Fixed Effect Versus Random Effects Model

Table 4 summarises the Hausman test for RE versus FE models.

Table 4: Hausman Test FE versus RE Models

	(b)	(B)	(b-B)	<i>Sqrt(diag(v_b - v_B))</i>
	<i>Fixed</i>	<i>Random</i>	<i>Differences</i>	<i>S.E</i>
<i>lnk</i> (Capital intensity)	0.179	0.166	0.131	0.060
<i>lnw</i> (Mean annual wage)	0.280	0.442	-0.152	0.084
<i>lne</i> (Mean annual consumption)	0.374	0.244	0.151	0.086
<i>lns</i> (Proportion of skilled workers)	0.322	0.203	0.119	0.121
<i>exp</i> (Mean experience)	0.044	0.030	0.014	0.073
<i>fage</i> (Firm age)	0.001	0.004	-0.023	0.025
<i>edu</i> (Mean years of schooling)	0.116	0.117	-1.003	0.030

b=consistent under *H*₀ and *H*_a; obtained from *xtreg*
 B=inconsistent under *H*_a, efficient under *H*₀; obtained from *xtreg*
 Test: *H*₀: difference in coefficients not systematic
 $Chi2(8) = (b - B)'[(v_b - v_B)^{-1}](b - B) = 26.97$
 $Prob > chi2 = 0.0007$

Source: Authors analysis and computations

The decision rule here was if the p-value < 0.05 , then the *FE* model would be preferred to *RE*. The results showed that the difference between (b) and (B) is significant, with a p-value = 0.0007; therefore the $\hat{\beta}_{FE}$ model was more consistent than the $\hat{\beta}_{RE}$. Having chosen the *FE* model, it was then subjected to a series of tests and diagnostics before using it for analysing the effects of education on labour productivity.

2.4.3 Fixed Effects Model Tests and Diagnostics

The *FE* model was subjected to model tests and diagnostics to allow for appropriate model corrections to ensure accurate estimation. These included time-fixed effects, heteroscedasticity, and comparing balanced and unbalanced panels models. Serial correlation was not tested because the data was from a short panel of only 2 years, thus common observations were not expected.

2.4.4 Testing for Time-fixed Effects

The time-fixed effect test checked if the dummies for all years were jointly equal to 0 using a ‘*testparm i. year*’ command. The decision rule was that if the p-value is < 0.05 , we reject the null. The p-value was found to be 0.13, which is greater than 0.05; meaning the coefficients for all years are jointly equal to zero, therefore no time fixed effects were needed.

2.4.5 Testing for Heteroscedasticity

The presence of heteroscedasticity was tested using the command ‘*xttest3*’ for the fixed-effects model. The decision rule was if *chisq value* < 0.05 , then heteroscedasticity was present. The *chisq value* = 0.00, thus we reject the null and conclude that heteroscedasticity was present. This was corrected by running the *FE* model with a ‘robust option’ to obtain a heteroscedasticity-robust *SE*.

2.4.6 Adjusting Labour Productivity Model for Selection Bias

The assumption that wages were only observed for people who were participating in the manufacturing sector could introduce selection bias in the estimation. The Heckman procedure for adjusting selection bias (Heckman, 1979) was applied with a Stata command ‘*xheckmanfe*’. The results showed a negligible variation in the coefficients after adjustments (Table 5). For example, the coefficient for education changed from 0.116 to 0.12 which, when rounded into two decimal places, became 0.12. The coefficients for the levels of education equally remained unchanged.

Table 5: FE Models Before and After Bias Adjustment

Variable	<i>Fe_educ</i>	<i>Fe_educ Adjusted</i>
<i>lnk</i> (Capital intensity)	0.18**	0.18***
<i>lnw</i> (Mean annual wage)	0.28*	0.31**
<i>lne</i> (Mean annual consumption)	0.37***	0.32***
<i>lns</i> (Proportion of skilled workers)	0.32*	0.33*
<i>educ</i> (Mean years of schooling)	0.116**	0.12***
<i>exp</i> (Mean experience)	0.04***	0.04***
<i>fage</i> (Firm age)	-0.001	-0.002
_cons	1.318	1.14*
<i>sigma_u</i>		1.18
<i>sigma_e</i>		1.08
<i>rho</i>		0.543

Note: Standard errors in parentheses; *p <0.05 , **p <0.01 , ***p <0.001

Source: Authors analysis and computations

3. Findings

3.1 Effects of Education on Labour Productivity

The labour productivity equation was regressed considering years of schooling before extending the model to include managers' characteristics. The results in Table 5 showed that education was significant in measuring labour productivity. The Mills adjusted results in column *Fe_edu_Adj* showed that additional year of workers' schooling was associated with a 12% increase in labour productivity. This was slightly higher than the 11.6% which was obtained before the Mills adjustment.

3.2 Effect of Top Managers Level of Education on Labour Productivity

In examining the effect of top managers' level of education in labour productivity, the study used extended form of labour productivity equation that included top managers' attributes (eqn.13). Table 6 compares *FE* model coefficients with robust *SE* before (column *Fe_robust*), and after (column *Fe_robExtended*), extending the model to include top managers attributes. The model estimates were then substituted into equation (13) to obtain equation (14).

$$\ln y_{it} = 0.34 + 0.21 \ln k_{it} + 0.27 \ln w_{it} + 0.36 \ln e_{it} + 0.13 \text{edu}_{it} + 0.32 \ln s_{it} - 0.02 \ln us_{it} + 0.05 \text{exp}_{it} - 0.03 \text{fage}_{it} + 0.35 \text{mle}_{it} + 0.03 \text{mexp}_{it} + 1.04 + 1.06 \quad (14)$$

Table 6: Coefficients of Fixed Effects Models With Top Managers Attributes

	<i>FE robust</i>	<i>FE extended</i>
<i>lnk</i> (capital intensity)	0.18** (0.069)	0.22** (0.076)
<i>lnw</i> (Mean annual wage)	0.28** (0.121)	0.27* (0.124)
<i>lne</i> (Mean annual energy consumption)	0.37*** (0.096)	0.35*** (0.096)
<i>lns</i> (Proportion of skilled workers)	0.32* (0.144)	0.34* (0.143)
<i>exp</i> (Mean years of experience for workers)	0.04*** (0.009)	0.045*** (0.009)
<i>fage</i> (Firm age)	-0.001 (0.026)	-0.02 (0.026)
<i>edu</i> (Mean years of workers education)	0.116** (0.042)	0.13** (0.045)
<i>mle</i> (Managers level of education)		0.35* (0.170)
<i>mexp</i> (Managers years of experience)		0.032* (0.015)
_cons	1.318 (1.024)	0.18 (1.171)
N	452	297
<i>R - sq</i>	0.573	0.588
<i>Sigma_u</i>	1.177	1.04
<i>Sigma_e</i>	1.079	1.05
<i>rho</i>	0.543	0.49

Notes: Standard errors in parentheses *p<0.05, **p<0.01, ***p<0.001

Source: Authors analysis and computations

The regression results indicate that the total number of observations was 452, and the number of observations with managers attributes was 297; while the total number of entities was 184. The robust option was added to control for heteroscedasticity, which generated a statistic $F(9,183) = 12.8, Prob > 0.000$. The F-test checks if all the coefficients in the model are different than zero. The probability value is less than the threshold value of 0.05, which confirms all values are different from zero. The variables in the model were further tested to see if they significantly influenced labour productivity. The decision rule was that if the p-value is less than 0.05 we reject the null, and conclude the variable had a significant effect. The result showed that other than firm age ($p - value = 0.33$), all other variables ($p - value < 0.05$), significantly influenced labour productivity. Specifically, employee's education ($p - value = 0.005$), and managers level of education ($p - value = 0.04$): all had a significant effect on labour productivity. These test results indicated that the model was satisfactory. The coefficient of employee's education other than managers ($\beta_4 = 0.13$) indicates that a unit change in employee's years of schooling improved labour productivity by 13%. Similarly, the coefficient of managers' level of education ($\beta_{11} = 0.35$) indicates that a unit change in a manager's level of education improves labour productivity by 35%.

The following economic implications were deduced from the model.

- (a) Other than firm age (*fage*), all significant other variables were significant in explaining labour productivity.
- (b) The extension of the fixed effects model to include top manager's attributes showed that a unit increase in manager's level of education improved log labour productivity by 35%. The top manager's education was captured by level: therefore, a unit increase in a manager's education refers to a change from one level to the next. Including top managers' level of education also improved the effect of workers' education from 11.6% to 13%.
- (c) Manager's level of education influenced the effect of workers education by approximately 1%; skill levels by 1%; and energy consumption reduced by 2%: from 37% to 35%. This indicates economic benefit of having managers with higher levels of education.
- (d) The explanatory power of the model also improves from 57.3% ($R^2 = 0.573$) to 59.3% ($R^2 = 0.593$), implying that top managers' inputs are important aspects in influencing labour productivity in the manufacturing sector.

4. Discussion

Earlier studies on labour productivity did not consider managers level of education. However, contrary to the findings by Söderbom and Teal (2004) on Ghana's manufacturing sector, who found that education was quantitatively irrelevant in determining labour productivity, this study found that education was positively significant in improving labour productivity.

The empirical literature reviewed on labour productivity in Uganda showed that researchers ignored managers' level of education in the estimation of labour productivity in the manufacturing sector (Buyinza, 2011; Niringiye, 2014; Okumu

& Buyinza, 2018). Equally, a study in the neighbouring Kenya considered managers' experience but ignored managers' level of education (Heshmati & Rashidghalam, 2018). This study addressed this gap by extending the labour productivity fixed effects' model to include top managers' level of education. The results showed that managers' level of education was significant in improving labour productivity. A unit increase in managers' level of education (one level higher) was associated with 35% increase in labour productivity. This concurs with the study findings by Lekfuangfu et al. (2012) on the agriculture sector in Uganda. Correspondingly, the workers effect of education on labour productivity also improved by approximately 1%, while skill levels improved by 1%, and energy consumption reduced by 2%. This finding, therefore, is a significant contribution to the empirical literature on labour productivity in the manufacturing sector in Uganda. The findings have shown that manager's level of education not only increased firms' labour productivity by 35%, but also improves the contribution of mean workers schooling on labour productivity by at least 1%.

4.3 Policy Implications and Recommendation

The strong linkage between higher education and labour productivity implies that the government should strengthen higher education by providing adequate funding. These funds should target strengthening higher education quality assurance, research and innovation, and staff development in areas with limited capacities. As confirmed in this paper, education positively influences labour productivity through skills accumulated by workers and managers from education. The government should also target the accumulation of appropriate and specialized stock of human capital that support labour productivity through specialized skills centres for managers and production workers. Skill development, research and innovation should be linked with industry, who are the final consumers.

4.4 Limitations of the Study

While it is true that formal education equips labour force with skills that enhance productivity, it is unclear how these skills and knowledge are acquired through formal education. This is because skills are correlated with education, on-job training, and experience; thus isolating the skill component attributable to education alone is still a challenge because there is no known satisfactory method for measuring skills. The implication is that there is a possibility that the effect of education on productivity may be over- or under-estimated. Hence, future studies should attempt to isolate these two sources of labour productivity: skills acquired from formal education, and indirectly from other highly educated workers. This study was based on secondary data from an enterprise survey whose objective was quite different from the objectives of the study. Data had to be transcribed to meet the requirement of the study. Also, the proxies used for estimation of education derived from the data are input rather than output measures; and this may have equally had effect on the accuracy of estimated results. Nevertheless, no study is clean of methodological challenges, and the findings are within the range of findings in previous studies. Suffice to say that previous studies used similar estimation procedures; therefore, we can confidently use the findings for comparisons and decision-making.

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Appendices

Table A1: Summary of Descriptive Statistics

Variable	2006					2013				
	Obs	Mean	Std. Dev.	Min.	Max.	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Panel ID</i>	307	1230.42	233.23	1001	728	389	3204.087	233.23	1001	728
<i>Total annual sale</i>	307	2.67e+09	1.31e+10	420000	1.37e+11	352	9.32e+09	6.40e+10	500000	9.75e+11
<i>Managers level of education</i>	307	2.26	0.913	0	4	320	2.26	0.973	0	4
<i>Managers experience</i>	306	11.81	8.787	0	45	131	18.786	8.144	0	47
<i>Education</i>	242	10.62	3.376	0	16	230	11.309	3.269	0	17
<i>Wage</i>	307	1.66e+08	7.23e+08	850000	8.31e+09	352	5.12e+08	3.62e+09	175000	3.73e+09
<i>Annual Energy Consumption</i>	307	6.56e+07	3.63e+08	100000	4.92e+09	352	1.19e+08	7.25e+08	200000	8.01e+09
<i>Annual capital costs</i>	307	9.81e+08	6.67e+09	500000	1.08e+11	352	4.11e+11	7.62e+12	300000	1.43e+11
<i>Capital utilization</i>	307	70.52	14.981	25	100	352	81.077	13.645	15	100
<i>Total number of employees</i>	307	51.61	239.536	5	4000	386	62.373	301.898	2	4000
<i>lny (mean annual sales)</i>	307	10.837	1.963	6.329	18.190	338	10.878	2.544	4.740	19.224
<i>lnk (capital intensity)</i>	307	9.471	2.205	4.565	16.279	351	9.111	2.693	3.771	23.673
<i>lnw (mean annual wage)</i>	307	7.276	1.595	5.156	14.840	351	8.676	2.071	3.578	15.272
<i>lne (mean annual energy consumption)</i>	307	1.764	1.952	3.079	13.590	351	7.516	2.055	3.450	14.340
<i>lns (proportion of skilled workers)</i>	304	1.764	1.277	-0.968	6.633	384	2.024	1.275	-1.237	6.061
<i>Mean workers experience</i>	307	11.95	9.605	2	39	388	15.619	9.289	2	45
<i>firm age</i>	307	12.09	9.474	1	79	389	16.288	10.509	2	86
<i>Mean annual hours</i>	307	3549.71	1414.60	1040	8736	380	3923.28	2117.35	260	8736

Source: Extracted from enterprise Survey World Bank Database



Figure 1: Manufacturing Value Added (% of GDP) 1960–2020

Source: World Bank in Statistics, 2020