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Exploring the impact of various typologies of human capital on firms' productivity

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Abstract

Purpose – Although the impact of human capital on productivity has long been discussed in prior studies, empirical evidence for African firms remains limited. The existing few studies have focussed on one type of human capital in isolation and failed to explore the distinct role of different types of human capital on productivity. The aim of this study is to examine the extent to which various typologies of human capital – schooling, on-the-job training (OJT) and slack time –, both in isolation and as a combination, contribute to the productivity of African firms.

Design/methodology/approach – To this end, a cross-sectional firm-level data set from 13 African countries was used. To unravel the casual relationship, propensity score matching (PSM) and multinomial endogenous switching treatment regression (MESTR) techniques were employed.

Findings – Results indicate that all typologies of human capital – schooling, slack time and OJT – have a significant and positive impact on firms' productivity. The findings of the study further point out that the highest payoff, in terms of increased productivity, is achieved when various typologies of human capital are used in combination, rather than in isolation, in the production process.

Practical implications – The policy implications are that productivity of African firms can be improved by increasing the general level of schooling; encouraging firm-sponsored OJT; and giving employees time to develop new ideas.

Originality/value – The present study provides important insights into the distinct role of different types of human capital on productivity. In addition, it provides empirical evidence for a region where empirical evidence is scant.

Keywords Human capital, Enterprise survey, PSM, MESTR, Africa

Paper type Research paper

I. Introduction

Although one of the richest continents in the world in terms of natural resources, Africa constitutes the largest percentage of poor in the world. It is the only region where the overall number of people living in poverty has grown in the last two decades. In 1990, more than 30% of the world population was poor, and nearly half of them lived in East Asia while 15% lived in Africa. By 2015, not only that global poverty declined to one-tenth but also the geographical composition was reversed: while Africa accounts for half of the global poor, East Asia constitutes only 12%. Accordingly, people living in extreme poverty in Africa grew from 278m in 1990 to 413m in 2015 (World Bank, 2016). The worst part is that poverty reduction is showing few signs of improvement in most African countries, indicating most countries are off track to achieving the first goal of UN sustainable development goals. The question of how to lift these people out of poverty and change their life has been one of the main conundrums of our time.

Both theoretical and empirical studies in development economics suggest that the ability of a country/region to improve the living standard of its people is mainly determined by its

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ability to enhance the productive capacity of firms (Cosar, 2011; Hall, 2011; UNCTAD, 2006). Higher firm-level productivity is expected to contribute to the poverty reduction effort of a country in at least three ways. First, as firms expand their production activities, because of higher productivity, new job opportunities will be created in the economy (Islam, 2004). [1] Second, the price of goods and services, especially food prices, is also expected to fall, thereby, increasing the real wage of workers. Third, as their business expands, firms pay more taxes to the government which can be used to finance public services such as schools, health facilities and infrastructure projects that directly affect the well-being of citizens (UNCTAD, 2006, pp. 77–80).

In light of these, there is a renewed emphasis on how African countries can improve the productive capacity of their firms to raise the quality of their citizens. The literature identified several mechanisms through which firms' productivity can be enhanced including, but not limited to, innovation, institutional reform and human capital. From this list, human capital is considered as a key element due to the fact that not only it increases productivity but it also ensures the long-term competitiveness of firms and improves their capacity to adopt technologies already existed elsewhere (Danquah and Ouattara, 2014; Nelson and Phelps, 1966; Papageorgiou, 2003; Romer, 1990). This is due to the fact that human capital helps people to perceive, evaluate and implement new production techniques and inputs. A considerable amount of empirical literature, both at the firm level and the economy as a whole, has also indicated that the level of human capital explains a significant part of the variation in productivity (Backman, 2014; Ballot *et al.*, 2001; Black and Lynch, 1996; Engelbrecht, 1997). However, the findings of these studies are generally based on only one aspect of human capital, mostly formal schooling, without considering other aspects and a sample data of a single country (Colombo and Stanca, 2014).

Human capital is defined as the stock of knowledge, skills and social and personal qualities embodied in individuals that enable the creation of personal, social and economic well-being (OECD, 2001, p. 18). From this definition, it becomes clear that human capital encompasses a wider set of components and schooling (education in general) is only one of its components. Since various typologies of human capital accomplish distinct tasks, as Cosar (2011) argued, each typology of human capital could have different impacts on productivity (Tan *et al.*, 2016). Therefore, examining the effect of each typologies of human capital on productivity provides a more comprehensive picture of the relationship. In addition, whether various typologies of human capital are complementary or alternatives from which firms should choose in their quest to increase productivity has not been examined empirically.

It is against this backdrop that the present study examines the extent to which various typologies of human capital contribute to firms' productivity. Following van Uden *et al.* (2017), three sets of human capital typologies are identified: schooling, on-the-job training (OJT) and employee slack time [2]. While schooling reveals the firm's endowment of stock of human capital, OJT and slack time represent an investment by the firm to increase the stock of human capital. In this study, the impact of these typologies of human capital – both in isolation and as a combination – on firm-level productivity is examined using propensity score matching (PSM) and multinomial endogenous switching treatment regression (MESTR) techniques that control selection bias and potential endogeneity on a sample of African firms. Our empirical investigation, based on PSM technique, indicates that all typologies of human capital have a significant and positive impact on firms' productivity. More importantly, our further empirical investigation based on MESTR indicates that these typologies of human capital are not alternatives from which a firm should choose but rather complementary to each other. Thus, firm productivity could be enhanced to a greater degree by combining various typologies of human capital in the production process.

The present paper contributes to the existing literature in two ways. First, unlike most previous studies, the present study provides important insights into the distinct role of different types of human capital on productivity. The existing literature mostly concentrated on one type of human capital in isolation. [3] This study, however, explores the causal impact of various typologies of human capital – both in isolation and as a combination – on firms' productivity using a novel empirical strategy. Second, while the positive impact of human capital on firm-level productivity has long been acknowledged, empirical evidence for African firms remains limited. Thus, the present study provides empirical evidence for a region where empirical evidence is scant.

The paper proceeds as follows: The next section outlines a review of literature on the topic. The data source and empirical methodology of the study are presented in section 3. Section 4 presents and discusses the empirical result of the study, and the final section concludes the study and provides policy recommendations.

2. Literature review

Growth literature indicates that much of the cross-country per capita income and long-run growth are significantly explained by variation in productivity (Hall and Jones, 1999). One of the mechanisms through which productivity can be improved, both at firm and country levels, is through human capital accumulation (Acemoglu and Pischke, 1999). In this regard, Becker (1964, p. 1) indicated that physical capital "explains only a relatively small part of the growth of income in most countries". Similarly, Krueger (1968) indicated that the difference in human capital explains a significant portion of the difference in per capita income.

Subsequent empirical studies also confirm the claim of the aforementioned studies and showed that initial level of schooling is positively related to economic growth and productivity growth (Barro, 1996; Benhabib and Spiegel, 1994; Krueger and Lindahl, 1999). For instance, Sianesi and Reenen (2003) indicated that increasing the average level of education by one year leads to a 3–6% increase in per capita output. Similarly, OECD (2003) estimated that the effect of education on productivity and found that an increase of average education by one year increases productivity by 5%. In the same vein, Mason *et al.* (2012) demonstrated that a 1% increase in average education of the workers increases labour productivity by 0.3%.

The effect of human capital on firm-level productivity has also been acknowledged by several authors. It has been argued that highly educated individuals have higher ability to acquire and interpret information about other inputs (Welch, 1970), adapt themselves to technological change (Nelson and Phelps, 1966), facilitate innovation (Leiponen, 2005); therefore, significantly impact on the companies' abilities to exploit increasing returns and enhance the scale of their operations (Majumdar, 1998). The bulk of empirical literature reveals that human capital contributes significantly to explaining inter-firm differences in productivity. Lynch and Black (1995) demonstrated that firms that hire highly educated workers have higher productivity in the United States. Using a firm-level data set, Black and Lynch (2001) also found a significant and positive effect of workers' level of education on firm productivity. Chowdhury *et al.* (2014) indicated that in addition to the workers' education, task-specific and firm-specific experiences are also important determinants of firms' competitiveness and productivity. A study by Backman (2014) examined the effect of human capital on firm productivity using a sample of firms from Sweden and found that human capital significantly affects firm-level productivity.

Most of the aforementioned studies examined the effect of human capital on either country- or firm-level productivity using schooling (education level) as a proxy of human capital. However, human capital is understood as multidimensional, and according to Blundell *et al.* (1999), it consists of at least the following three components: (1) early ability which is either acquired or innate; (2) formal education which represents qualifications and knowledge acquired through formal schooling; (3) training which includes competencies and expertise acquired through training on the job. In the same vein, OECD (2001, p. 18) defines human capital as "the knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being". Therefore, it is worth noting that human capital encompasses a wider set of components, and examining the effect of these components on productivity provides a more comprehensive picture of the nexus between human capital and productivity.

While many studies analysed the effect of workers' formal education on firm productivity, there are relatively few studies on the impact of other typologies of human capital such as OJT. Most of these studies indicate that providing training to workers improves firms' ability to adapt to new technology and its productivity (De Grip and Sauermann, 2013; Dearden *et al.*, 2006; Zwick, 2006). For instance, in their study on the impact of training on the productivity of British firms, Dearden *et al.* (2006) showed that a 5% increase in training participation would increase firm productivity by 4%. Similarly, Konings and Vanormelingen (2015) found that OJT has a significant positive impact on productivity. Using a randomized experimental approach to control for selection bias, De Grip and Sauermann (2012) found that not only the productivity of workers who participated in the training program increases but also the performance of their co-workers. In their study, the author randomly assigned individuals into treatment and control groups for a five-day training program. Comparing the performance of the treated and control group post-treatment period, the authors found that the performance of the treated group had increased by 10%. The author further indicated that working with treated groups also increases the performance of untreated workers.

Even though human capital has long been acknowledged by numerous studies as one of the key factors influencing firms' productivity, the corresponding empirical evidence for the case of Africa remains limited. The focus of most studies has been on a sample of firms in developed countries. The existing few studies that examine the impact of human capital, relying only on the schooling dimension, on productivity have provided mixed results. Using a panel data set for Ghanaian firms, Söderbom and Teal (2004) found that the impact of education on firm productivity varies depending on the estimation method used. While ordinary least square (OLS) estimation produces a significant impact, fixed-effect estimation of the productivity equation produces an insignificant impact of education on productivity. In contrast, the recent study by Burger and Teal (2015) provides empirical evidence on the positive impact of schooling on productivity using the South African industry-level data set. The author conducted various estimators and indicated that their estimation results were robust across various estimation methods. Tan *et al.* (2016) analysed the nexus between firm productivity and various human capital measures in Tanzania. The results of their study indicate that the effect of human capital on productivity varies depending on the measure of human capital used. The author found that firms with a higher proportion of high school graduate workers are not productive than their counterparts. However, tertiary education has a significant impact on firms' productivity. A recent study by Okumu and Mawejje (2019) examined the skill characteristics of employees and firm productivity for selected African firms and found that increasing the share of highly educated labourers increases firms' productivity.

3. Data and empirical methodology

3.1 Data

To examine the impact of various typologies of human capital on firm productivity, firm-level data obtained from WBES was used. The WBES conducts a firm-level survey in developing countries using a representative sample. The survey contains information regarding firm characteristics such as size, age, ownership and business environment such as infrastructure, competition, access to finance. In addition, the survey reports on firm performance such as sales, innovation, employment and exports. [4] In this study, we use a sample of more than 10,000 firms from 13 African countries. Table 1 provides a list of countries and the corresponding number of firms used in the present study [5].

3.2 Empirical methodology

In examining the impacts of various typologies of human capital on productivity, the easiest approach would be to compare the level of productivity between treated (firms with a higher percentage of high school graduate workers, train their employees and provide slack time) and control (counterfactual) groups. Let's assume that P_i a dichotomous variable that represents 1 if ith firm is in the treated group and 0 otherwise, and Y_i represents outcome variable, that is, firm productivity measured by the log of sales per total number of workers. The difference between productivity with treatment ($P = 1$) and productivity without treatment ($P = 0$) indicates the impact of schooling, training and slack time. Mathematically it can be expressed as:

$$\partial = (Y_i|P_i = 1) - (Y_i|P_i = 0)$$

However, the firm can't be in both states: the firm is either hired a certain percentage of educated workers, provided OJT and slack time or not. Therefore, it is not possible to examine the causal impact of treatment for each firm, that is, what would have happened to firm i if it had not hired educated workers, provided OJT and/or slack time. One way to address this problem is to randomly assign a certain percentage as a treatment group and remaining as the control group. In such kind of experimental studies, the difference in outcome (productivity) of the treated and control groups is the impact of the treatment (ATT), which can be expressed as: [6]

$$ATT_l = E_l(Y_{i1} - Y_{i0}) = E_l(Y_1) - E_l(Y_{i0})$$

But, in observational studies, like ours, assignment into treated and control group is not random. In our study, firms in the treated group are intrinsically different with regard to innovation performance, age, ownership, etc., compared to the control group, and these intrinsic differences are likely correlated with performance, creating selection bias. One way to address this problem is to control for this difference using a matching approach known as propensity score matching (PSM) proposed by Rosenbaum and Rubin (1983).

In PSM, firms with similar characteristics are matched based on observed characteristics and averages in differences in outcomes within pairs are computed. The first step in PSM is

Country	Survey year	Number of firms
Democratic Republic of Congo	2013	529
Ghana	2013	720
Kenya	2013	781
Malawi	2014	523
Morocco	2013	407
Namibia	2014	580
Nigeria	2014	2,676
South Sudan	2014	738
Sudan	2014	662
Tanzania	2013	813
Tunisia	2013	592
Uganda	2013	762
Zambia	2013	720
Total		**10,503**

Table 1. Sample country and year surveyed

thus to estimate the propensity score, which is the probability of being in the treated group, using a probit/logit model on a set of observed covariates. Matching on a single index (propensity score) could achieve consistent estimates of the treatment effect in the same way as matching on all covariates. Thus, the following logistic regression model is estimated to uncover the probability of being in the treated group:

$$p(x) = log\left(\frac{p(y=1}{1-(p=1}\right)_i = \beta' X_i + \varepsilon_i$$

$$p(x) = prob(D = 1|x) = E(D|x)$$

Where D is dichotomous variable equal to 1 if the firm is in the treated group, 0 otherwise. Whereas y is a dummy variable that takes the value 1 if the firm adopts one of the various typologies of human capital. In a WBES, firms were asked how many percentages of their permanent employees are high school graduates, whether they had provided OJT and whether they had given slack time to the workers. To change the continuous variable, high school graduates, firms with higher share (more than 80%) of high school completed workers are coded 1 while others coded 0; hence, all of the dependent variables become binary. Therefore, the dependent variables for logistic regression are the dummy variables that take the value 1 if the firm adopts one of the typologies of human capital, as outlined in Table 2. β is a (k×1) vector of unknown parameters; and ε_i is the error term, which is assumed to follow the standard logistic distribution. X_i is a (1×k) vector of explanatory variables that affect the probability of adopting various typologies of human capital including firms' characteristics such as the size, being part of a large group, ownership (private vs government and domestic

Table 2.
List of variables

	Treatment variables	
Slack	Slack time	Dummy variable with value 1 if the firm gives employees time to develop new idea
School	Schooling	Dummy variable with value 1 if 80% of workers with high school degree
Training	Training	Dummy variable with value 1 if the firm provides on-the-job training
Outcome variable		
Product	Labour productivity	Logarithm of sales per worker
Control variables		
Gov_owned	Government-owned	Dummy variable with value 1 if the government has at least 10% ownership
Age	Log (years) firm age	Survey year minus year of firm's establishment
For1	Foreign ownership	Dummy variable with value 1 the firm is at least 10% owned by foreigner
Mang	Manager experience	Log of (years) experience of the manager in the sector of the firm
size_numlog	Employment	Log of full-time employee
Expo	Exporter	(0/1) if the firm exports
part	Part of the group	(0/1) if the firm is part of a large group of companies
corpo	Corporation	(0/1) if the firm is a corporation
product_inn	Product innovation	(0/1) if the firm introduced new product in the last three years
process_inn	Process innovation	(0/1) if the firm introduced new process in the last three years

vs foreign), age and innovative performance of the firm. The selection of these variables is based on previous studies in this realm [7].

The next step is to estimate the treatment effect which is conditional on the propensity score, then firms in the treatment and comparison group with the closest propensity score are matched, and the difference in outcome is calculated within each matched pair as follows:

$$ATT = E(y_1|p(x), D = 1) - E(y_0|p(x), D = 0)$$

Where y represents labour productivity measured as logarithms of sales per worker.

The matching procedure is then repeated for all individuals in the treatment group, and averages in differences in outcomes within pairs are computed.

$$ATT = \frac{1}{n_1} \sum_{i \in \{D=1} \left[y_{1,i} - \sum_j w(i,j) y_{0,j} \right]$$

Where i and j represent each treated and controlled firm, respectively, and w is weight (matching algorithms). A range of matching algorithms can be used to calculate the closest match such as the nearest neighbour matching (NNM), the radius matching (RM) and the kernel matching (KM). The NNM approach is to compare the outcome of the treated firms with the closest and most similar non-treated firms based on their propensity scores. The RM, on the other hand, compares the outcome of the treated firms with non-treated firms that fall within a specified radius (r). The KM is such that each treated observation "i" is matched (using the propensity scores) with other control observations that have weights that are inversely proportional to the distance between the two groups (Cerulli, 2015, p. 83). In this study, we applied all three matching algorithms.

The second aim of this study is to empirically examine if combining various typologies of human capital enhances productivity even more. The alternative combination of typologies of human capital is given in the following table:

Since there are more than two possible ways of combining typologies of human capital, a MESTR approach is employed to examine the impact of combining various typologies of human capital on productivity. MESTR assumes that firms may endogenously choose a combination of various typologies of human capital and their choice may be affected by unobserved factors that are likely correlated with productivity [8]. Therefore, it is estimated in two stages. In the first stage, the probability that a firm i will choose human capital j is estimated using a multinomial logit model. It is assumed that firms aim to maximize their profit A_i by comparing the profit provided by n alternative combination. Let A^*_{ji} is a latent variable that represents the expected profit of the ith firm from choosing j combination of human capital over any other alternative combination, n. This latent variable is determined by observed exogenous variables, such as firm characteristics (X_{ji}) and unobserved variable $\in_{ji}$:

$$A^*_{ji} = \delta_j X_{ji} + \in_{ji}$$

Although a firm will choose a combination of human capital that maximizes its profit, a firm's profit is not observable, only the firm's decision is observable. Following Bourguignon *et al.* (2007), it can be stated that the ith firm will choose a combination j to maximize its expected benefit if it provides a greater expected profit than the other alternatives n. Thus, a firm's choice with respect to any other n can be indicated mathematically as:

$$A = \begin{cases} 1 \text{ if } A^*_{ji} > \max\limits_{n \neq 1}(A^*_{ni}) \text{ or } \partial_{1i} < 0 \\ \cdot \\ j \text{ if } A^*_{ji} > \max\limits_{n \neq j}(A^*_{ni}) \text{ or } \partial_{ji} < 0 \end{cases} \quad \text{for all } n \neq j$$

Assuming that $\in_{ji}$ are independent and Gumbel distributed, the probability that firm i with characteristics X will choose j can be specified by a multinomial logit model (McFadden, 1973):

$$p_{ji} = pr(\partial_{ji} < 0 | X_{ji}) = \frac{\exp(\delta_j X_{ji})}{\sum_{n \neq 1}^{j} \exp(\delta_n X_{ni})}$$

The second stage estimates the impacts of combined typologies of human capital using OLS with the inverse Mill ratio for each combination taking $j = 0$ (None) as a reference (Bourguignon *et al.*, 2007). The productivity equation for each possible regime j is given as:

$$\begin{cases} Regime\,1 : y_{1i} = \alpha_1 Z_{1i} + \sigma_1 \widehat{\lambda}_{1i} + \mu_{1i} \text{ if } i = 0 \\ \quad\quad \ldots \\ Regime\,j : y_{ji} = \alpha_j Z_{ji} + \sigma_j \widehat{\lambda}_{ji} + \mu_{ji} \text{ if } i = j \end{cases} \quad j = 1, 2, 3, 4$$

Where y_{ji} is the productivity of the ith firm in regime j, $\widehat{\lambda}$ is the inverse Mill ratio calculated from multinomial logit that corrects selection bias and endogeneity originating from unobserved heterogeneity. The given equation is thus used to generate actual and counterfactual outcomes.

3.3 The outcome of adopter with adoption

$$E(y_{ji} | A = j, \alpha_j Z_{ji} + \sigma_j \widehat{\lambda}_{ji})$$

The outcome of adopters had they decided not to adopt (counterfactual).

$$E(y_{1i} | A = j, \alpha_j Z_{ji}, \sigma_j \widehat{\lambda}_{ji})$$

Thus, ATT is estimated by calculating the difference in the outcome of adopters with adoption and adopters had they decided not to adopt (counterfactual), that is,

$$\begin{aligned} \text{ATT} &= E(y_{ji} | A = j, \alpha_j Z_{ji} + \sigma_j \widehat{\lambda}_{ji}) - E(y_{1i} | A = j, \alpha_j Z_{ji}, \sigma_j \widehat{\lambda}_{ji}) \\ &= Z_{ji}(\alpha_j - \alpha_1) + \widehat{\lambda}_{ji}(\sigma_j - \sigma_1) + \bar{Z}_{ji}(\theta_j - \theta_1) \end{aligned}$$

4. Empirical results

4.1 Descriptive statistics

Before presenting the empirical results of the study, it would be worthwhile to provide the descriptive statistics of the variable used in the study; hence, Table 3 shows the descriptive statistics. As shown in the table, firms in the sample differ in terms of productivity. While the minimum level of productivity is 0, the maximum is 18.1. The table further indicates that almost half of the firms are engaged in innovation. Concerning the treatment variables, nearly 29% of firms in our sample provide OJT, 39% give slack time and in 30% of firms, the proportion of workers who completed high school is 80% (see Table 4).

4.2 Determinants of adopting various typologies of human capital

In general, firms hire educated workers, provide OJT and slack time in the expectation of gaining a return in the future, in terms of productivity/profitability. However, previous literature on this realm indicated that, besides the aforementioned variables, firm characteristics and other external factors also affect the productivity of the firm. This indicates that firms that adopt various typologies of human capital, that is, hire educated workers, provide OJT and slack time might have achieved a higher level of productivity even if they had not adopted. Thus, to control for these observable characteristics and isolate the intrinsic impact of adopting various typologies of human capital, logistic regression was employed and the propensity score of each scenario was calculated. The estimated results of the logistic regression are presented in Table 5 [9].

The table presents the factor that drives/determines the propensity of adopting various typologies of human capital. The results show that most of the variables affect adopting various typologies of human capital in the same way. More specifically, firms which are part of a larger group of companies, larger firms, product innovative and process innovative firms are more likely to hire educated workforce, provide training and give employees time to develop a new idea. The age of the firm seems to be insignificant in firms' decision to adopt any of human capital typologies. The empirical results further indicate that manufacturing, exporting and government-owned firms are in general less likely to hire education workers. The effect of foreign ownership and the experience of the top-level manager is mixed. Compared to their counterpart, foreign-owned firms are more likely to hire highly educated individuals and provide training, but there is no significant difference for other typologies of

Choices (j)	Combination	Description
0	None	Only one type of human capital or not at all
1	schol_train	More than 80% of firm's workers are with high school degree and also provided on-the-job training
2	schol_slack	More than 80% of firm's workers are with high school degree and also the firm gives employees time to develop new idea
3	slack_train	The firm provides both on-the-job training and gives employees time to develop new idea
4	schol_slack_training	Not only more than 80% of firm's workers are with high school degree but also the firm provides on-the-job training and gives employees time to develop new idea

Table 3. Adoption of combination of multiple human capitals

Variables	(1) *N*	(2) Mean	(3) Sd	(4) Min	(5) Max
Productivity	7,409	8.670	2.168	0.866	18.91
product_inn	10,392	0.517	0.500	0	1
process_inn	10,228	0.603	0.489	0	1
corpo	10,349	0.154	0.361	0	1
Gov_owned	10,118	0.0266	0.161	0	1
For1	10,099	0.146	0.353	0	1
Expo	9,841	0.139	0.346	0	1
size_log	10,196	2.767	1.191	0	8.987
Age	9,998	2.460	0.834	0	7.578
Mang	10,075	2.437	0.808	0	4.205
Part	10,503	0.249	0.432	0	1
Manufacture	10,503	0.424	0.494	0	1
Training	10,325	0.286	0.452	0	1
slack_time	10,314	0.399	0.490	0	1
School	9,479	0.300	0.458	0	1

Table 4. Descriptive statistics

Table 5.
Determinants of productivity-improving measures

Variables	(1) slack_time	(2) School	(3) Training
Manufacture	0.0923*	−0.479***	−0.332***
	(0.0530)	(0.0551)	(0.0552)
Part	0.163**	0.217***	0.318***
	(0.0668)	(0.0687)	(0.0671)
Mang	0.0394	0.00739	0.149***
	(0.0394)	(0.0403)	(0.0416)
Age	0.0535	−0.0450	0.0349
	(0.0397)	(0.0415)	(0.0412)
Expo	0.103	−0.595***	0.162**
	(0.0780)	(0.0894)	(0.0765)
size_log	0.130***	0.0983***	0.332***
	(0.0243)	(0.0255)	(0.0244)
For1	0.0943	0.144*	0.211***
	(0.0766)	(0.0815)	(0.0772)
Gov_owned	0.262	−1.194***	0.0162
	(0.169)	(0.214)	(0.162)
corpo	0.304***	−0.155*	0.356***
	(0.0791)	(0.0893)	(0.0769)
product_inn	0.828***	0.0149	0.625***
	(0.0562)	(0.0615)	(0.0618)
process_inn	1.436***	0.154**	0.671***
	(0.0626)	(0.0653)	(0.0674)
Constant	−2.893***	−0.612***	−3.411***
	(0.158)	(0.139)	(0.168)
Observations	8,656	7,795	8,669
Country dummies	yes	yes	Yes

Note(s): Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

human capital. Similarly, the effect of the experience of the top-level manager on the propensity of giving slack time to employees and hiring highly educated workforce is insignificant. However, it has a significant positive effect on other types of human capital.

Overall, the logistic regression results provide evidence that firms' characteristics such as, being part of a large firm, innovativeness affect the probability of adopting various typologies of human capital in the same way. Second, few of the others only affect probability of adopting one type of human capital than the other. Third, no significant relationship was found between the age of the firm and propensity of adopting any of the human capital type.

4.3 The impact of human capital on firm-level productivity: PSM approach

Before estimating the causal effects of various typologies of human capital on firm-level productivity, we tested the quality of the matching process. After estimating the propensity scores for the adopter and non-adopter groups, we checked the common support condition.

Figure 1 compares the kernel density distribution of propensity score before and after matching. From this figure, we can clearly see that the matching procedure improved the propensity score distribution. As a robustness check for the common support, we also conducted the covariate bias test. The test estimates the standardized difference (i.e. bias) of all the covariates used in the estimation of the propensity score. In the following (Figure 2), the dot represents the standardized percentage bias before matching and the star represents standardized percentage bias after the matching procedure was conducted. As shown in Figure 2, the standardized bias is less than 5% after matching, indicating that the common support condition was satisfied.

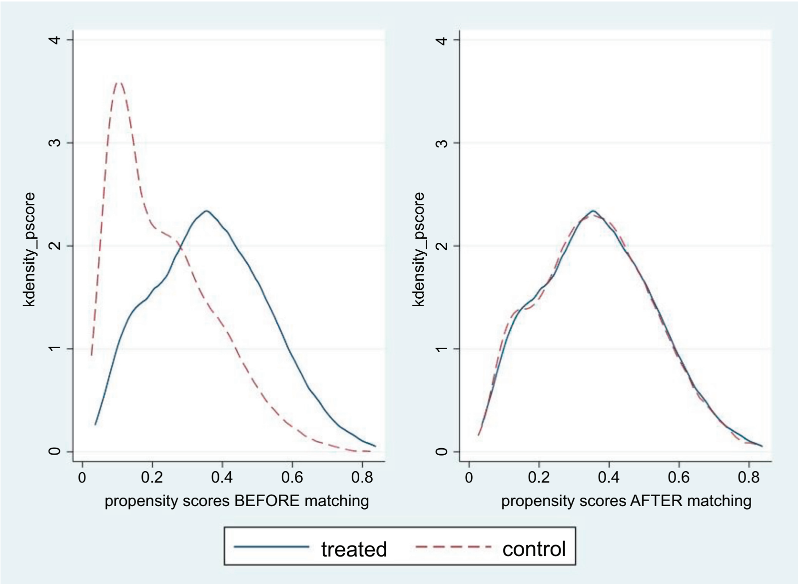


Figure 1.
Density plot

After ensuring the matching quality of the estimated propensity score, the ATT of the three types of human capital on productivity is estimated using the three matching algorithms and the result is presented in Table 6.

The empirical results indicate that all typologies of human capital have a positive and significant impact on firm-level productivity. More specifically, firms that provide OJT to their employees were able to increase their productivity by 20–22%, under the three algorithms, above what they could have had assuming they did not provide OJT. Giving slack time to workers also found to be a significant productivity-improving measure as our empirical findings indicate that firms that give slack time to their employees were able to increase their productivity by 18–20% above what they could have had assuming they did not give slack time to their employees. Finally, schooling also significantly and measurably affects firms' productivity. Under the three matching algorithms used in this study, firms with a higher share (80%) of high school completed workers were able to increase their productivity by nearly 50% above what they could have had assuming they did not give slack time to their employees.

Our empirical findings also reveal a clear ranking of productivity gains from different typologies of human capital. As shown in the given table, employing highly educated workers is the best productivity-improving measure followed by OJT and providing slack time, respectively. Our empirical finding, which indicates a significant and positive impact of human capital on firm-level productivity, corroborates the findings of previous studies such as (Lynch and Black, 1995; Okumu and Mawejje, 2019).

4.4 Combining various typologies of human capital pays off

The second aim of this study is to empirically examine whether combining various typologies of human capital enhances productivity even more. To test this, MESTR approach is used and the results are presented in the following table [10].

Table 7 presents the ATT of combining various typologies of human capital. As shown in the table, ATT is significant at the conventional level in all cases, indicating that firms that combine more than one type of human capital are more productive, on average, than their

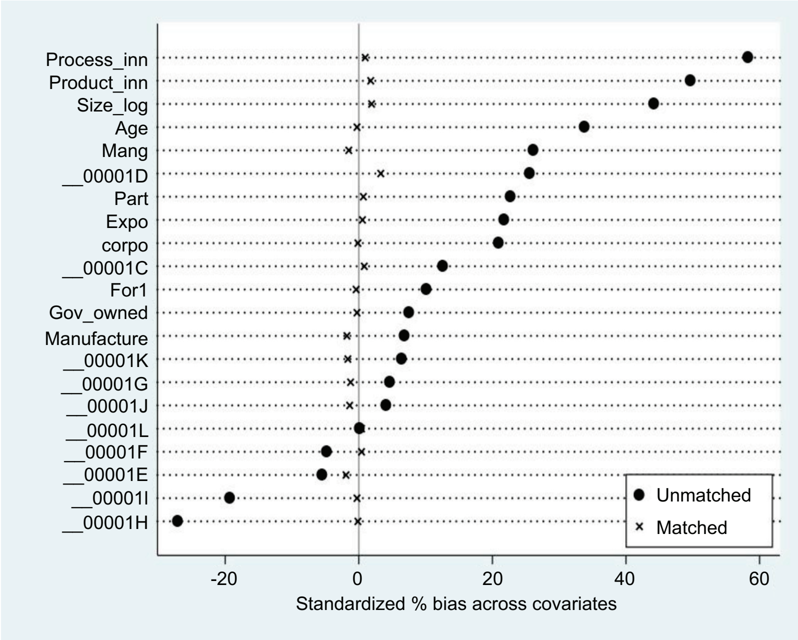


Figure 2. Percentage of bias before and after matching

Table 6. Average treatment effect for productivity (ATT)

Treatment	Nearest neighbour matching ATT	Std. Err	Kernel matching ATT	Std. Err	Radius matching ATT	Std. Err
Training	0.205***	0.071	0.223***	0.182	0.22***	0.066
Slack time	0.177***	0.068	0.196***	0.064	0.198***	0.0645
School	0.461***	0.068	0.492***	0.064	0.492***	0.064

Note(s): The subscripts *, ** and *** imply significance levels at 10, 5 and 1%, respectively. The productivity variable is in log form; thus, any coefficient in the table will be interpreted as percentage change

counterparts. More explicitly, firms that combine schooling and OJT were able to increase their productivity by 42% above what they could have had assuming they either adopted one type of human capital in isolation or not at all. Firms that combine both highly skilled workers and give slack time to workers were able to increase their productivity by 64% above what they could have had assuming they either adopted one type of human capital in isolation or not at all. Combining both slack time and training increases productivity by 90% on average. Firms that combine all the three typologies of human capital were able to increase their productivity by nearly 130% above what they could have had assuming they either adopted one type of human capital in isolation or not at all, indicating that combining various aspects of human capital pays off.

Overall, our empirical investigation indicates that all typologies of human capital significantly and positively affect firms' productivity, and the highest payoff, in terms of increased productivity, is achieved when various typologies of human capital are used in combination, rather than in isolation, in the production process. The combination that contains all types of human capital – schooling, OJT and slack time – provides the highest productivity. This has important policy implications for improving the productive capacity of African firms.

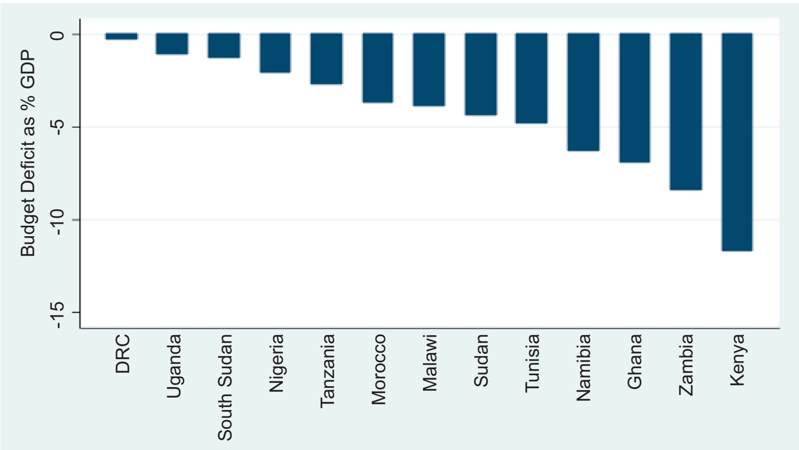
Our empirical investigation indicates that providing primary education does not suffice to improve the productive capacity of firms and the economic growth of African countries as a result. Governments need to expand post-primary education such as secondary and vocational schools, as those who graduate from these schools are more productive than their counterparts. In doing so, however, governments across Africa face financial challenges to allocate public resources to the education sector. Since the government's total expenditures outweigh its revenue, these countries are confronted with budget constraints. The following figure (Figure 3) presents the budget deficit (as a percentage of GDP) of the sampled countries.

As shown in the given figure, all sampled countries registered a budget deficit which ranges from −0.3 to −11.70%. This budget deficit was mostly financed through loans which in turn contributed to the higher debt profile of countries. Thus, improving the human capital stock of the region should not be left to the government only. A reasonable approach could be that various stakeholders such as non-governmental organizations (NGOs), private companies and individuals should work together to improve the human capital stock of the region. In this regard, NGOs might provide grants and private companies training to

	Exogenous		Endogenous	
Treatment (human capital choice j)	ATT	Std. Err	ATT	Std. Err
schol_train	0.436***	0.127	0.42 **	0.215
schol_slack	0.528***	0.097	0.640 ***	0.218
slack_train	0.135	0.082	0.908***	0.175
schol_slack_training	0.662***	0.097	1.301***	0.204
λ schol_train			0.021	0.184
λ schol_slack			−0.108	0.212
λ slack_train			−0.876***	0.177
λ schol_slack_training			−0.696 ***	0. 0.198

Note(s): The subscripts *, ** and *** imply significance levels at 10, 5 and 1%, respectively. The productivity variable is in log form; thus, any coefficient in the table will be interpreted as percentage change

Table 7. Average treatment effect for productivity (ATT) based on MESTR



Source(s): U.S. CIA, The World Factbook

Figure 3. Government budget deficit as % GDP for selected African countries in 2017

support the education system. Similarly, individuals can also contribute by sharing educational expenses. Equally important, governments in the region should improve domestic resource mobilization and reduce non-essential expenses. Thus, a sufficient amount of financial resources would be available for projects which improve the stock and quality of human capital in the region.

5. Conclusion and policy implications

Previous theoretical and empirical studies in development economics suggest that much of the cross-country income difference is significantly explained by variation in the productive capacity of the economy. Hence, enhancing the productivity of individuals, firms and the economy as a whole has been the main aim of policymakers in most countries. Although several productivity-enhancing mechanisms have been suggested, human capital is considered to be a key element due to its benefit to ensure the long-term competitiveness of firms and improve its capacity to adopt technologies already existed elsewhere. In light of this, the past 30 years have seen increasing empirical literature on the impact of human capital on productivity. Yet, the debate continues about the effect of various typologies of human capital and whether these typologies of human capital are complementary or alternatives from which a firm should choose in their quest to increase productivity. In addition, since the vast majority of empirical studies in this realm has focussed on a sample of firms from developed countries, empirical evidence for African firms remains limited.

It is against this backdrop that the present study examines the extent to which various typologies of human capital – schooling, OJT and slack time –, both in isolation and as a combination, contribute to firms' productivity. To this end, a firm-level data set for African firms was used and analysed using PSM and MERTS approach. Three important findings emerge from our empirical investigation. First, firm characteristics such as, being part of a large firm, innovativeness affect the probability of adopting various typologies of human capital in the same way. Second, all typologies of human capital have a significant positive impact on firm productivity, and increasing the proportion of educated workers has a higher impact than others. Third, these aspects of human capital are not alternatives from which a firm should choose. Rather they are complementary to each other, and combining various aspects of human capital in the production process amplifies the productive capacity of firms to a greater extent.

The policy implications that can be drawn from this study are three-fold. First, firms can enhance their productivity by recruiting more educated workforces, offering OJT and providing slack time. Second, these aspects of human capital are not mutually exclusive or alternatives from which a firm should choose; therefore, productivity can further be improved by combining more than one aspect of human capital simultaneously. Finally, the government can play its role by improving the education system and incentivizing firms that provide training. This is an indication that various stakeholders should work together to improve the quality and stock of human capital in the region.

Notes

1. An increase in income and job creation is dependent on other factors.
2. Slack time refers to giving employees time to develop new ideas.
3. See van Uden *et al.* (2017).
4. The data is available for researchers at www.enterprisesurveys.org.
5. Note that sample countries are selected based on the availability of data, especially different typologies of human capital.

6. See Duflo *et al.* (2007) and Gertler *et al.* (2016, p. Chapter 4) for detailed discussion on randomized experiment approach.
7. See, for instance, Huang and Verma (2018) and Teixeira (2002)
8. See Bourguignon *et al.* (2007) for a detailed explanation on multinomial endogenous switching treatment regression.
9. Note that these logistic estimation results are also used derive the propensity scores of firms.
10. The first-stage multinomial regression estimates are not reported to conserve space but are available upon request from the authors.

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