Skill-capital Complementarities and the Effectiveness of Firm Training Programs

Vittorio Bassi, Imran Rasul,
Ottavia Anna Veroux, Anna Vitali

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Abstract

This study examines the impact of skill-capital complementarities on the effectiveness of firm training programs, using a field experiment in Uganda as a case study. While policy interventions placing trainees into firms often overlook their capital needs, this paper investigates how the interaction between labor constraints and indivisible capital investments affect firms' returns from training. We find that firms possessing higher machine spare capacity respond differently to the offer of a wage subsidy to train new workers compared to those with lower spare capacity. Specifically, firms with higher spare capacity are more likely to hire workers outside their existing network and invest more in on-the-job training and sector-specific skill development. This leads to sustained improvements in employment and profits up to three years post-intervention. By contrast, firms with lower spare capacity tend to hire workers from within their network and do not retain them beyond the subsidy period. These results underline the importance of considering the interplay between capital and labor constraints in the design of training policies and suggest that targeting firms based on their asset availability could significantly enhance the effectiveness of training initiatives.

Extended Abstract

The lack of adequate skills poses a significant challenge to both the employment prospects of young people and the growth of businesses throughout the developing world. Over the last two decades, governments have invested considerable resources to training programs aimed at bridging the gap between the skills possessed by labor market entrants and those demanded by employers. Firm training programs, in particular, are often viewed as serving the dual purpose of equipping workers with relevant skills and labor market experience, while also reducing firms' hiring costs and creating new jobs. However, the impact of such initiatives has been limited by low take-up and retention rates among firms (McKenzie, 2017; Caicedo et al., 2022; Carranza and McKenzie, 2023).

This study explores the role of skill-capital complementarities for the effectiveness of firm training programs. A large body of literature has documented the critical role that complementary assets play in boosting the productivity of skilled labor (Goldin and Katz, 1998; Acemoglu, 1998; Krusell et al., 2000; Giorcelli, 2018). Despite this, policy interventions that place trainees into firms often overlook the capital needs of these businesses, assuming that they can easily adjust their assets to maximize the returns from the additional worker. In low-income settings, however, the small size of the average firm, coupled with the indivisibility of key capital goods (Kaboski et al. 2022), may prevent firms from precisely aligning capital investments with the requirements of the additional worker. The challenge for small firms to undertake potentially large-scale investments to reap the benefits of training, coupled with the existence of financial frictions, might constrain the returns from training initiatives, thus undermining the effectiveness of these programs.

In this paper, we ask two questions. First, do capital adjustment costs affect the quality of training that firms provide when they receive subsidies to train new employees? Second, does the availability of complementary assets affect firms' returns to training workers? We answer these questions through a field experiment in Uganda that offers wage subsidies to firms to train a new worker for six months. The intervention targets a representative sample of nearly 800 SMEs across 15 urban locations nationwide. Targeted firms employ between 1 and 15 employees and operate in one of eight sectors: motor-mechanics, plumbing, construction, electrical wiring, welding, catering, tailoring, and hairdressing. Baseline data confirms that the main challenges faced by these firms are accessing capital and skilled labor (Table 1). Specifically, 92% of firms express a willingness to expand their business but face constraints related to purchasing new machines (73%), accessing credit (65%), and finding skilled workers (67%). On-the-job training is a common strategy for equipping workers with necessary skills. At baseline, 44% of the workers had received some form of training on the job. Nevertheless, our data shows that providing this training entails substantial costs for the firm, primarily related to the opportunity cost of the owner's time and the expenses associated with training equipment.[1]

To help firms overcome these costs, we randomly offer them a wage subsidy of UGX 120,000 (approximately $50) per month to hire and train a new worker of their choice. This amount is sizeable, corresponding to the 75th percentile of the distribution of unskilled wages at baseline and to 22% of firm monthly profits (Table 1). 85% of businesses express an interest in participating in the program and 71% successfully hire a trainee within the two-week time frame allotted for making a new hire.[2] The high take-up rates, along with the evidence that almost 70% of trainees do not receive any payment from the firm, suggest that finding unskilled workers willing to undergo training is not a significant obstacle in this setting.

We track firms and their workers over a period of four years through four follow-up surveys. We find that, pooled across all firms and follow-ups, the wage subsidy offer leads to a 18% increase in employment and an 11% increase in firm revenues, but has no significant impact on firm profits or investments in capital assets (Table 2). The dynamics reveal that these impacts are short-lived: the majority of trainees leave the business immediately after the end of the subsidy period, and by fourth follow-up the average firm in the wage subsidy treatment is not different from firms in the control group.[3]

[1] Table 1 shows that the firm owner was directly involved in the training of 96% of workers who received it, and was responsible for covering the costs related to the purchase of training equipment and material for 62% of workers. Trainees' wages do not represent a substantial cost to firms, with 47% of them being unpaid, and 28% paying the owner to receive training.

[2] A parallel intervention provided firms with a wage subsidy to hire a worker we matched them with. This intervention imposed a split of the subsidy amount between the firm owner and the worker, with UGX 90,000 going to the worker, and UGX 30,000 going to the owner. The take-up rate was only 27%, with the main reason cited by firms for refusing to train a worker being that the amount provided was not sufficient to cover training costs.

[3] These results match the evidence from other similar experiments that found short-lived impacts of

Having documented the transient nature of the wage subsidy's effects, our study delves deeper into the underlying factors that might influence firms' returns to training. In particular, we turn our attention to the role of skill-capital complementarities. To do so, we leverage a key component of our data, which includes comprehensive information on the machines firms utilize in production. Specifically, for each sector, we collected data on the type, number and value of all machines that businesses have access to at baseline. We use this data to develop a measure of machine spare capacity. This measure is based on two assumptions: (i) firms within the same sector share the same production function, (ii) factor prices are constant within urban locations.[4] Under these assumptions and controlling for the specific types of machines used in production, firms operating in the same sector and geographical area should optimally choose the same labor to machine ratio. Deviations from this optimal ratio should capture variation in machine spare capacity across firms. Such deviations are likely to be sizeable in our context due to the small size of firms and the indivisibility of capital and labor,[5] which make it difficult for businesses to maintain an optimal level of utilization on their assets.

Our findings reveal that firms with higher machine spare capacity (and therefore lower capital adjustment costs) respond differently to the wage subsidy offer compared to those with lower spare capacity.[6] Specifically, spare capacity at baseline affects (i) the type of workers firms select for training; (ii) the quality of training provided; and (iii) the long-term effects of the subsidy on firm outcomes.[7]

To examine the first two aspects, we take advantage of the timing of the first follow-up, which occurs while the trainees are still employed at the firm. This timing allows us to gather detailed data on both the trainees and the training they receive. We find that treatment workers hired by firms with high spare capacity are similar to those newly hired by control firms along several dimensions: they possess comparable levels of formal education and vocational training, and are hired through similar recruitment strategies. By contrast, treatment workers in low spare capacity firms are significantly less educated and more likely to be recruited through network connections relative to their counterparts in the control group (Table 3). These differences extend to the characteristics of training. Despite the subsidy's requirement for training provision, only 80% of low spare capacity firms report providing on-the-job training to treatments workers. This figure increases to 100% for high spare capacity firms. In line this finding, we show that trainees at high spare capacity firms are more likely to have learnt a pre-specified sector specific task compared to those at low spare capacity firms (Table 4).

Differences in short-term training strategies result into heterogenous impacts of the subsidy on firm outcomes (Table 5). We find that firms with low spare capacity quickly return to their original employment level after subsidy period ends and do not experience significant changes in revenues or profits. However, in line with being more capital constrained

wage subsidy subsidy programs in low-income countries (Groh et al., 2016; De Mel et al., 2019; Hardy and McCasland, 2023).

[4]Our locations are areas within a 2km radius of one BRAC offices, our implementing partner. We therefore believe that this is a plausible assumption.

[5]Only 9% of employees work for less than 40 hours per week among firms in our sample.

[6]We do not find significant differences in take-up between firms with different machine utilization rates. This is not surprising given the generosity of the subsidy.

[7]Our analysis is conducted within a difference-in-differences framework, where we compare the difference in outcomes across firms with high and low rates of machine utilization between treatment and control group. This is to ensure that the estimated impacts do not capture differences in levels between firms with different endogenous spare capacity.

at baseline, these firms are more likely to invest in new machines relative to similar firms in the control group. On the other hand, firms with high spare capacity experience lasting effects: at fourth follow-up, conducted approximately three years after the end of the intervention, they have 19% more employees and 26% higher monthly profits compared to firms in the control group.[8]

Taken together, our results are indicative of the presence of complementarities between the availability of spare capacity on firms' machines and the returns to training. Firms with limited spare capacity struggle to adjust their assets level, as the monthly subsidy only corresponds to 18% of the average cost of a machine. Consequently, these firms allocate minimal resources to recruitment and training, often opting to hire individuals from their network to benefit from the cash transfer. Once the subsidy expires, they dismiss the trainee and return to their pre-subsidy levels of employment and profitability. In contrast, high spare capacity firms effectively use the subsidy to hire and train a new employee. This leads to improvements in employment and profits, which last up to three years after the end of the intervention.

Our findings carry two important implications for policy makers. First, they underscore the necessity for policies aimed at stimulating firm growth to consider how the simultaneous presence of capital and labor constraints may impact their effectiveness. Our results reveal that wage subsidies provided to firms with limited spare capacity fail to alter the growth trajectory of businesses. By contrast, subsidies allocated to high spare capacity firms yield greater returns, facilitating job creation and increased profits. Second, firm training programs designed to enhance skills would benefit from either screening firms based on their assets availability or facilitating access to new capital, ensuring the effective implementation of training programs.

This paper contributes to the growing body of literature on firm training, specifically focusing on how businesses can be effectively incentivized to provide training. In particular, three recent studies have emphasized the role of positive externalities in causing firms to underprovide training. These externalities are due to the possibility of trainees leaving their trainer to join other firms (Caicedo et al. 2022; Cefala et al., 2023) or to set up up their own business, thus becoming a direct competitor (Brown et al. 2022). We contribute to this literature by showing how the availability of assets can impact the productivity of trained workers, thereby influencing firms' incentives to invest in training.

Our study also contributes to the large literature on the constraints to firm growth in low-income countries. Understanding why developing country economies are characterized by the presence of a myriad of small, unproductive businesses has been a longstanding puzzle in this literature (Bloom et al., 2010; Hsieh and Olken, 2014). Several papers have studied the role of labor and capital constraints, but have typically done so in isolation (see Woodruff (2018) for a review). A recent paper by Hardy et al. (2023) uncovers important interactions between labor and capital among small firms in Ghana, showing that workers supply both labor and capital to the firms they are employed in. In line with this study, we consider the possibility of labor and capital constraints interacting with one another, and show that the returns to training workers depend on the availability of machines that can enhance their productivity.

[8]All the results are robust to including a measure of managerial ability which we construct from a set of questions about managerial practices at the firm level. This indicates that our measure of spare capacity does not merely capture differences in the managerial ability of the firm owner. Indeed, we show that spare capacity is negatively correlated with the firm reporting difficulties in accessing machines at baseline, but is uncorrelated with managerial ability.

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Tables

Table 1: Firm Descriptives

		Mean	St Dev
A. Firm Characteristics	Number of employees	2.936	(2.294)
	Average monthly profits (USD)	224.1	(343.2)
	Total value of assets (USD)	1,247	(2,325)
	Average asset value (USD)	186.0	(833.7)
	Firm age	6.513	(4.698)
	Owner is female	0.530	(0.499)
	Owner age	34.44	(7.483)
	Owner years of education	10.45	(3.219)
B. Constraints	Difficulty finding reliable machines	0.723	
	Lack of skilled workers applying for jobs	0.671	
	Difficulty / high costs of borrowing	0.653	
	Lack of trustworthy workers applying for jobs	0.568	
	Difficult screening good workers	0.509	
	Lack of unskilled workers applying for jobs	0.295	
	Inability to manage more employees	0.210	
C. Training Characteristics	Received any training	0.435	
	Any cost for training equipment	0.860	
	Owner paid for most training equipment	0.617	
	Employee paid for most training equipment	0.304	
	Trainee was unpaid	0.467	
	Trainee paid the owner for training	0.282	
	Training mainly conducted by owner	0.486	
	Training conducted by owner and employees	0.469	
	Training conducted by employees	0.041	

Note: Data is from the baseline survey of firms. Monthly profits and the total value of assets variables are truncated at the 99th percentile. All monetary amounts are deflated and expressed in terms of the price level in January 2013 using the monthly Producer Price Index for the manufacturing sector (local market), published by the Uganda Bureau of Statistics. The monetary amounts are then converted in Januaty 2013 USD.

Table 2: Pooled Treatment Effects

	Number of Workers (1)	Number of Workers Hired Post Treatment (2)	Number of Workers Fired Post Treatment (3)	Number of Workers at endline (4)	Log (Average Monthly Profits) (5)	Log (Average Monthly Revenues) (6)	Log (Net Investments in Capital Assets) (7)
Wage Subsidy	0.401***	0.363***	0.341***	0.057	0.033	0.114*	0.147
	(0.100)	(0.107)	(0.066)	(0.161)	(0.062)	(0.065)	(0.113)
Mean of outcome in Control	2.246	1.182	0.945	2.193	4.821	5.706	1.807
Number of observations	3,036	3,036	3,036	655	2,294	2,556	2,614

Note: Table 2 reports results from OLS regressions run on a panel dataset including four rounds of follow-up data, and controlling for the value of the outcome at baseline when available. The table shows Inverse-Probability-Weighting (IPW) OLS coefficients and standard errors in parenthesis. Standard errors are adjusted for heteroskedasticity and clustered at the branch-trade level. The instruments for the IPW estimates are a dummy for whether the owner reported at baseline an intention to relocate in the future, and the number of network firms reported at baseline. All regressions include baseline controls, branch and trade fixed-effects, survey wave dummies and dummies for month of interview. Baseline controls include owner's sex, business age (measured as number of years since the business was established) and business age squared, firm's size at baseline and owner's years of education. All monetary amounts are deflated and expressed in terms of the price level in January 2013 using the monthly Producer Price Index for the manufacturing sector (local market), published by the Uganda Bureau of Statistics. The monetary amounts are then converted in Januray 2013 USD (1USD=2385UGX). The dependent variables in Columns 5 to 8 are defined as the log of one plus average monthly profits, revenues and net investments and are truncated at 99th percentile. The number of employees is also truncated at 99th percentile. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 3: Characteristics of Hired Trainees, by Machines Spare Capacity

	Demographics				**Recruitment**		
	Age (1)	Female (2)	Level of education (3)	Ever attended VTI (4)	Recruited Formally (5)	Worker walked into the Firm (6)	Recruited through Connections (7)
Wage Subsidy	-2.210***	0.017	-0.397***	-0.178***	-0.042	-0.386***	0.319***
X Treatment Employee, Low Capacity	(0.615)	(0.054)	(0.110)	(0.049)	(0.026)	(0.074)	(0.086)
Wage Subsidy	-1.634**	0.066	-0.134	-0.025	-0.012	-0.200***	0.041
X Treatment Employee, High Capacity	(0.739)	(0.033)	(0.116)	(0.045)	(0.032)	(0.066)	(0.090)
P-value: Low Capacity = High Capacity	[0.468]	[0.363]	[0.031]	[0.032]	[0.438]	[0.085]	[0.018]
Mean of outcome in Control	22.91	0.54	1.899	0.195	0.0164	0.416	0.422
Number of observations	492	496	495	488	428	428	428

Note: Table 3 reports results from OLS regressions run on a dataset that includes the first worker hired by firms in the control group after the intervention and the workers in the wage subsidy treatment hired through the intervention (treatment employees). All outcomes are at the employee level. The table shows Inverse-Probability-Weighting (IPW) OLS coefficients and standard errors in parenthesis. Standard errors are adjusted for heteroskedasticity and clustered at the branch-trade level. The instruments for the IPW estimates are a dummy for whether the owner reported at baseline an intention to relocate in the future, and the number of network firms reported at baseline. All regressions include baseline controls, branch and trade fixed-effects, survey wave dummies and dummies for month of interview. Baseline controls include owner's sex, business age (measured as number of years since the business was established) and business age squared, firm's size at baseline, owner's years of education, as well as the average characteristics of workers employed in the firm prior to the intervention. These characteristics include average age, percentage of female employees, average level of education, percentage of vocationally trained workers, percentage of skilled workers, percentage of workers recruited formally, and percentage of workers recruited via connections. Low (High) Capacity firms are defined as the firms with a value of spare capacity at baseline below (above) the median. Spare capacity is defined as the residual from a regression of the number of employees on the number of sector-specific machines of a given type utilized by the firm at baseline. Each machine type corresponds to a different explanatory variable. All regressions include sector FE, branch FE. The number of machines is equal to 0 if the asset is no relevant to the firm's sector. Relevant variables are selected via a Lasso regression including all the possible machine types and sector FE. In Column 5 the outcome is a dummy equal to 1 if the employee was recruited by posting a job-ad or through a middleman. In Column 7 the outcome is a dummy equal to 1 if the employee was recruited through family members or friends. In Column 9 we identified a specific task for each of the study sectors and asked the owner whether the worker was able to perform that task when they joined the firm. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 4: Characteristics of Training, by Machines Spare Capacity

	Training costs				Trainer		Skills learnt	
	Received on-the-job Training (1)	Paid at re-cruitment (2)	Any training costs for tools (3)	Owner paid for most training tools (4)	Owner conducted the training (5)	Other employees conducted the training (6)	Learnt to perform sector-specific task (7)	Change in productivity [0 to 10 scale] (8)
Wage Subsidy	0.214***	0.075	0.086	0.360***	-0.101	-0.009	1.768**	0.290***
X Treatment Employee, Low Capacity	(0.069)	(0.101)	(0.075)	(0.083)	(0.094)	(0.055)	(0.693)	(0.094)
Wage Subsidy	0.402***	-0.0311	0.126*	0.378***	0.067	0.035	2.388***	0.516***
X Treatment Employee, High Capacity	(0.055)	(0.094)	(0.069)	(0.088)	(0.074)	(0.022)	(0.561)	(0.102)
P-value: Low Capacity = High Capacity	[0.008]	[0.187]	[0.669]	[0.881]	[0.113]	[0.415]	[0.328]	[0.060]
Mean of outcome in Control	0.593	0.491	0.810	0.405	0.476	0.068	3.105	0.369
Number of observations	472	468	354	354	354	354	472	418

Note: Table 4 reports results from OLS regressions run on a dataset that includes the first worker hired by firms in the control group after the intervention and the workers in the wage subsidy treatment hired through the intervention (treatment employees). All outcomes are at the employee level. The table shows Inverse-Probability-Weighting (IPW) OLS coefficients and standard errors in parenthesis. Standard errors are adjusted for heteroskedasticity and clustered at the branch-trade level. The instruments for the IPW estimates are a dummy for whether the owner reported at baseline an intention to relocate in the future, and the number of network firms reported at baseline. All regressions include baseline controls, branch and trade fixed-effects, survey wave dummies and dummies for month of interview. Baseline controls include owner's sex, business age (measured as number of years since the business was established) and business age squared, firm's size at baseline, owner's years of education, as well as the average characteristics of workers employed in the firm prior to the intervention. These characteristics include average age, percentage of female employees, average level of education, percentage of vocationally trained workers, percentage of skilled workers, percentage of workers recruited formally, and percentage of workers recruited via connections. Low (High) Capacity firms are defined as the firms with a value of spare capacity at baseline below (above) the median. Spare capacity is defined as the residual from a regression of the number of employees on the number of sector-specific machines of a given type utilized by the firm at baseline. Each machine type corresponds to a different explanatory variable. All regressions include sector FE, branch FE. The number of machines is equal to 0 if the asset is no relevant to the firm's sector. Relevant variables are selected via a Lasso regression including all the possible machine types and sector FE. In Column 7 we identified a specific task for each of the study sectors and asked the owner whether the worker was able to perform that task when they joined the firm and at the time of the survey. The outcome in this column is the difference between dummies indicating whether the worker was able to perform the task at these two points in time. In *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Table 5: Treatment Effects, by Machines Spare Capacity

	Number of Employees (1)	Log (Average Monthly Profits) (2)	Log (Average Monthly Revenues) (3)	Log (Net Investments in Capital Assets) (4)
Wage Subsidy, Low Capacity	0.274*	-0.146	-0.010	0.275*
	(0.156)	(0.100)	(0.104)	(0.163)
Wage Subsidy, High Capacity	0.513***	0.190***	0.219***	0.017
	(0.155)	(0.063)	(0.069)	(0.153)
P-value: Low Capacity = High Capacity	[0.314]	[0.003]	[0.052]	[0.232]
Mean of outcome in Control	2.246	4.821	5.706	1.807
Number of observations	3,023	2,294	2,556	2,642

Note: Table 5 reports results from OLS regressions run on a panel dataset including four rounds of follow-up data, and controlling for the value of the outcome at baseline when available. The table shows Inverse-Probability-Weighting (IPW) OLS coefficients and standard errors in parenthesis. Standard errors are adjusted for heteroskedasticity and clustered at the branch-trade level. The instruments for the IPW estimates are a dummy for whether the owner reported at baseline an intention to relocate in the future, and the number of network firms reported at baseline. All regressions include baseline controls, branch and trade fixed-effects, survey wave dummies and dummies for month of interview. Baseline controls include owner's sex, business age (measured as number of years since the business was established) and business age squared, firm's size at baseline and owner's years of education. Low (High) Capacity firms are defined as the firms with a value of spare capacity at baseline below (above) the median. Spare capacity is defined as the residual from a regression of the number of employees on the number of sector-specific machines of a given type utilized by the firm at baseline. Each machine type corresponds to a different explanatory variable. All regressions include sector FE, branch FE. The number of machines is equal to 0 if the asset is no relevant to the firm's sector. Relevant variables are selected via a Lasso regression including all the possible machine types and sector FE. All monetary amounts are deflated and expressed in terms of the price level in January 2013 using the monthly Producer Price Index for the manufacturing sector (local market), published by the Uganda Bureau of Statistics. The monetary amounts are then converted in Januray 2013 USD (1USD=2385UGX). The number of employees is truncated at 99th percentile. The dependent variables in Columns 2 to 4 are defined as the log of one plus average monthly profits, revenues and net investments truncated at 99th percentile. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.