ADBI Working Paper Series

Small Firms, Human Capital, and Productivity in Asia

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No. 582
July 2016

Asian Development Bank Institute

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Suggested citation:

Vandenberg, P., and L.Q. Trinh. 2016. Small Firms, Human Capital, and Productivity in Asia. ADBI Working Paper 582. Tokyo: Asian Development Bank Institute. Available: http://www.adb.org/publications/small-firms-human-capital-and-productivity-asia/

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Abstract

The paper analyzes the link between human capital and firm-level productivity in five Asian countries. It draws on a dataset of over 4,000 enterprises and considers both the prior educational attainment of workers and in-service training programs of enterprises. Differences between small, medium-sized, and large enterprises and between countries are also presented. The key finding is that both preservice education and in-service training are positively correlated with labor productivity. The productivity of small and medium-sized enterprises (SMEs) is enhanced by a higher level of skills and education of the workforce, just as it is with large firms. However, there are country differences. The policy implications are that competitiveness is enhanced both by raising the general level of education in the workforce and by encouraging enterprise-based training programs.

JEL Classification: J24, D22, D24

Contents

1. INTRODUCTION

The overwhelming majority of businesses in any economy are small and medium-sized enterprises. (SMEs). While the definition of what constitutes an SME varies greatly, in nearly all countries they account for over 95% of enterprises. Furthermore, they produce a substantial share of economic output and normally employ the majority of the workforce. With the expansion and deepening of regional and global value chains, SMEs have become important as local parts and component suppliers, as providers of logistics and other services and, for some, as exporters and overseas investors. SMEs account for over 40% of India's exports, for example.[1]

SMEs are often viewed as being dynamic and innovative, and while many are, as a group they are a highly variable lot. Along with the highly productive and competitive enterprises, there are many that remain small and rely on conventional technology to deliver standard products and services. This type of enterprise may be more in evidence in developing countries, where running an enterprise is often a family survival and get-ahead strategy in the context of limited employment opportunities or a need to diversify from farm income.

Enterprise survival and growth require high levels of efficiency and productivity in operations. These factors determine whether the enterprise can be competitive against other firms—be they small or large, domestic or foreign. The factors that support enterprise productivity and competiveness are many, including the knowledge and experience of the owner or entrepreneur, decisions about what markets to enter, the organization of production and distribution, investment in plant and equipment, financial management, supplier networks, marketing strategy, and others. Along with these various factors, human capital is a key factor that enhances enterprise competitiveness.

In this paper, we have assembled a rich dataset of enterprises in five Asian countries (the People's Republic of China [PRC], Indonesia, Malaysia, Thailand, and Viet Nam). We estimate the correlation between enterprise-level productivity and human capital. The latter is expressed in two variables: one that captures preemployment educational attainment (i.e., years of school) and another that indicates whether enterprises offer in-service training to their workers. We consider differences between small, medium-sized, and large enterprises and between the five countries. Furthermore, we assess whether preemployment and in-service human capital efforts can operate simultaneously and in parallel to raise productivity. The policy implications of the results are provided briefly at the end.

2. HUMAN CAPITAL AT THE ENTERPRISE LEVEL: A SHORT SURVEY

That there might be a link between workforce skills and education and the productivity of the enterprise is to be expected. A worker with more education is expected to contribute more to enterprise productivity than uneducated or unskilled workers. This would tend to hold if the education system does in fact impart knowledge and develop

[1] National statistics compiled by the Asian Development Bank (2015) and covering 2012 and 2013 indicate the economic important of SMEs. For example, they produce 37% of the gross domestic product of Thailand and 60% of Indonesia. They employ 58% of the workforce in Malaysia and 65% in the People's Republic of China. In addition, SMEs account for over 40% of India's exports.

intellectual capacity. At the very least, it may act as a screening mechanism for more capable individuals—those who are more capable to begin with may complete more years of education, even if they do not gain much for the experience. For in-service training, the intuition is only slightly different. An enterprise invests in training because it seeks to make its workers more capable of performing their tasks, either more quickly or at a higher standard of quality. Training programs that do not induce greater productivity are likely to be phased out over time due to a negative cost–benefit calculus for the enterprise.

Research conducted over the past 3 decades has sought to confirm this basic and plausible intuition, and most of the evidence does confirm that a higher-skilled workforce is correlated with higher productivity. Some of the more revealing results relate to what type of education or training contributes most to productivity and whether there are important sector differences. Studies can be divided between those that use in-service training as the human capital variable and those that use educational attainment. The choice of which variables to focus on is often determined by the variables that are available in enterprise datasets. Along with issues of variables, there are also questions of the estimation techniques used and whether they are capturing a legitimate correlation. The literature includes studies of firms of all sizes and others that focus specifically on SMEs.

Generally, micro-level analysis of the relationship between education and training and enterprise performance is fairly recent. Only 2 decades ago, Black and Lynch (1996, p. 263) would assert that there have been "few studies" in the United States (US) testing the impact of "education and employer-provided training on productivity." A decade later, Dearden, Reed, and Van Reenen (2005) would still argue that despite the interest by policy makers in the United Kingdom (UK), there "are hardly any papers that examine the impact of work-related training on direct measures of productivity." In the same vein, Zwick (2006, p. 27) noted that the evidence on the link between training and productivity effects is "thin and partly contradictory." These researchers, and others, have since deepened the research in this area through their work. Much of the research has focused on single-country studies of the US and countries in Europe.

Black and Lynch (1996) found a significant and positive impact of education level on enterprise productivity for both the manufacturing and nonmanufacturing sectors, using data from the US. Furthermore, the total number of workers receiving enterprise training did not affect productivity, although more detailed analysis showed that in-service but off-the-job training for manufacturing workers and computer-based training of nonmanufacturing workers was correlated with higher productivity. The study also found that off-the-job training was less disruptive of the production process and could generate better outcomes. Haltiwanger, Lane, and Spletzer (1999) found clear evidence that enterprises with more educated workers are more productive. The results, based on data from the US state of Maryland, suggested that "high-productivity workplaces are also high-skill workplaces" (p. 97).

Dearden, Reed, and Van Reenen (2006) found a statistically significant impact of training on productivity in the UK. However, the researchers used a vague training variable from a survey that asked respondents if they had been engaged in any type of work-related education or training over the previous 4 weeks. Nonetheless, an increase in training of 1 percentage point increased production output by about 0.7%—a rather large impact. In a similar study, Zwick (2006) found that German firms that trained a large share of their workers in the first half of 1997 had higher productivity in subsequent years.

Several studies have focused on Asia. Batra and Hong (2003) found that formal training is an important determinant of technical efficiency—a measure closely related to productivity. They employ data on a cross-section of SMEs in three countries in Latin America, Indonesia, Malaysia, and Taipei,China. The study also found that the most efficient firms combine formal and informal training but that informal training by itself is negatively correlated with firm efficiency, except in the case of Mexico. The general results confirm the findings of an earlier study (Tan and Batra 1995).

Vu (2003) found that a larger share of skilled workers in the enterprise workforce was correlated with higher technical efficiency of state-owned enterprises in Viet Nam. The two other key factors were engagement in export activities and location in Ho Chi Minh City. Hara (2011) studied the impact of training on the productivity of nonregular workers in Japan. Those who received training, both on and off the job, demonstrated higher productivity. Productivity was measured imprecisely as the increase in work assignments, work levels, and work responsibilities.

Charoenrat and Harvie (2014) found that the share of skilled workers in small Thai manufacturing firms is positively correlated with technical efficiency. However, the relationship does not hold for medium-sized firms—a puzzling result. Combining small and medium-sized firms, the study does find a significant correlation between skills and technical efficiency across eight industry subsectors.

3. A MODEL OF LABOR PRODUCTIVITY AND HUMAN CAPITAL

We use a standard model of labor productivity to test the correlation (and possible impact) of human capital on firm performance. Productivity is defined as the value added of the enterprise divided by the number of regular, full-time workers. Productivity is determined by the capital input, represented by the capital–labor ratio, and human capital input. We use two measures of human capital: educational attainment of the enterprise workforce and whether the enterprise provides formal training to its workers. Control variables are included as provided below. The equation is as follows:

$$L_P = c + \beta_1 k + \beta_2 H + \beta_3 S + \beta_4 A +, \beta_5 T + \beta_6 L + \beta_7 C + \varepsilon,$$

in which

L_P = labor productivity,
k = capital–labor ratio, and
H = human capital (preemployment education or in-service training),

and we include control variables

S = size of the enterprise,
A = age of the enterprise,
T = sector,
L = location, and
C = country.

The constant term is c, the error term is ε, and the coefficients are represented by βs, following standard notation. We run ordinary least squares regressions on three versions of the model. Model 1 includes the education variable, model 2 includes the training variable, and model 3 includes both.

3.1 Countries and Data

We use data from five medium-sized to large middle-income countries in Asia: the PRC, Indonesia, Malaysia, Thailand, and Viet Nam. The data are drawn from the World Bank's Enterprise Surveys, which use a standard methodology for surveying businesses in developing countries.[2] This provides confidence that the country data can be pooled without concern for differences in variables and their definitions. Our sample comprises a total of 4,045 enterprises, thus providing a fairly large sample and avoiding bias based on small sample size (Table 1). For the PRC and Thailand, the sample includes over 1,000 firms each, and for the three other countries the sample is between 500 and 800 firms.

The countries use different definitions for firm size, which we could not use because we make estimates on a sample that pools the five countries. The World Bank uses a standardized classification with a threshold differentiating medium-sized and large firms set at 100 workers. However, we find this threshold too low. As a result, we use a classification in which small firms are defined as having fewer than 100 workers and medium-sized firms having fewer than 250 workers. We feel that this is more in line with classifications used in Asia and other regions.

Using this classification, just under 60% of the firms are considered small, with the share of small firms in each country ranging from 52% to 60%, except for Indonesia where it is higher at 75% (Table 1). The remaining firms are fairly evenly distributed between medium-sized (22%) and large (19%) firms. The average firm has 200–300 workers, again with the exception of Indonesia, which has an average size of 166 workers.

Value added is calculated from the survey data on output value and costs. The two human capital variables are dummies. The education variable takes the value 1 if the average education of the enterprise workforce is 10 years or more and takes the value 0 otherwise. The training variable takes the value 1 if the enterprise provides formal in-service training and takes the value 0 if it does not. The age of the enterprise is expressed in years and the other control variables (sector, location, and country) are dummies. Location signifies the province where the enterprise is located, or subnational state in the case of Malaysia.

Table 1: Enterprise Sample, by Size

	SMALL Share of enterprises with < 100 workers (%)	**MEDIUM Share of enterprises with ≥ 100 and < 250 workers** (%)	**LARGE Share of enterprises with ≥ 250 workers** (%)	**Total number of enterprises**	**Average number of workers per enterprise**
PRC	58	25	17	1,214	275
Indonesia	75	11	13	504	166
Viet Nam	56	20	24	565	251
Thailand	52	25	23	1,024	252
Malaysia	60	22	19	738	209
Total	59	22	19	4,045	236

Note: Workers refers to full-time, regular workers.

[2] The data were obtained from the World Bank Group through the Enterprise Survey website at www.enterprisesurveys.org.

3.2 Results

The estimation results of the three models are provided in Table 2. All variables are significant and have the expected signs. Model 1 indicates that that enterprises that provide formal training programs to their workers have significantly higher labor productivity than enterprises that do not provide such training. The results for model 2 indicate that enterprises with an average educational level of the workforce of 10 years or more have higher productivity than enterprises where the average education is less than 10 years. This difference is also statistically significant. These results confirm our intuition that higher-quality human capital through education and training contributes to higher enterprise productivity.

Model 3 includes both of the human capital variables in the regression. Both variables remain significant with only a small reduction in the size of the coefficient—for training the coefficient falls from 0.129 to 0.109 and for education it falls from 0.190 to 0.182. The result suggests that prior education and in-service training are not substitutes for the enterprise to choose from but that both can, at the same time, contribute to productivity increase.[3] Enterprises can hire workers that are more educated, and can raise productivity further by providing training after hiring.

Table 2: Determinants of Labor Productivity

	1	2	3
Capital intensity (K/L)	0.270***	0.266***	0.264***
	[0.014]	[0.014]	[0.014]
Training	0.129***		0.109**
	[0.044]		[0.044]
Education		0.190***	0.182***
		[0.037]	[0.037]
Medium-sized firms	0.157***	0.168***	0.142***
	[0.046]	[0.044]	[0.046]
Large firms	0.165***	0.185***	0.151***
	[0.050]	[0.049]	[0.050]
Firm age	0.081***	0.088***	0.084***
	[0.028]	[0.028]	[0.028]
Industry dummies	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Number of observations	4,045	4,045	4,045

Notes: Dependent variable is labor productivity. Standard errors in parentheses. Significance levels: *** = 1%, ** = 5%, * = 10%.

[3] We are not arguing that preservice education and in-service training are complements. The economic sense of "complement" would imply that an increase in one of the human capital variables raises the use or impact of the other variable. It could be argued that the benefits of in-service training to the enterprise might be higher if the workforce is already more educated. More educated workers might pick up new skills faster or more readily. However, the coefficients on the human capital variables both fall slightly when both are included in model 3 and this suggests they are not complements but parallel factors having a similar impact.

The results for the enterprise size variables are also interesting and expected. Small firms (the base case) have the lowest productivity whereas large firms have the highest. This is consistent with many other studies that indicate that while SMEs are often touted as being dynamic, flexible, and innovative, they in fact tend to achieve a lower productivity level than larger firms.[4] Our estimations do account for differences in skills, education, capital intensity, and sector and thus the differences in labor productivity by firm size are likely derived from economies of scale, management capacity, and/or other factors.

We expand the estimates to explore country differences and to see whether certain countries are driving the general results. To do so, we drop the country dummies and replace them with variables that interact the country variable with the training variable in model 1 and the country variable with the education variable in model 2. Both interaction terms are included in model 3. The results are presented in Table 3 which shows only the new variables used, as the coefficients for the other variables remain similar to those in the initial estimations discussed above. The results are revealing.

In Table 3, all but 2 of the 20 coefficients exhibit the expected correct sign (positive). The two cases with a negative sign have very small coefficients that are not significant and thus are not a concern. Of the remaining 18 coefficients, 11 are significant. For the PRC, none of the interaction terms for education and training are significant. For training, the lack of significance may be due to the high share of PRC enterprises that train, which stands at 85% of firms in our sample and is much higher than the sample average of 61% and the share for the next highest country, which is Thailand at 71% (figures not shown). With such a high share of training (i.e., little variation) it may be difficult to establish a correlation with differences in productivity among the PRC firms. However, the same argument cannot be made for the lack of significance on the education variable. Some 47% of firms in the PRC have a workforce with 10 years or more of schooling but this is only slightly above the average for the whole sample (41%) and is not the highest among the five countries.

In Malaysia and Thailand, both training and education are strongly correlated with productivity as seven of the eight variables are found to be significant. Viet Nam and Indonesia offer interesting contrasts. Education is important in the case of Viet Nam but training does not seem to impact productivity. The opposite is the case with Indonesia, where training is the key human capital variable.

Table 3: Heterogeneity by Country

	Model	PRC	Thailand	Viet Nam	Malaysia	Indonesia
Training	1a	0.032	0.423***	0.024	0.120*	0.208**
		[0.078]	[0.144]	[0.096]	[0.065]	[0.103]
Education	2a	0.088	0.618***	0.222**	0.190***	0.031
		[0.065]	[0.129]	[0.093]	[0.054]	[0.102]
Training	3a	0.035	0.283*	–0.002	0.090	0.226**
		[0.078]	[0.148]	[0.096]	[0.065]	[0.105]
Education	3a	0.093	0.587***	0.227**	0.183***	–0.002
		[0.065]	[0.135]	[0.093]	[0.054]	[0.103]

Notes: Standard errors in brackets. Significance level: *** = 1%, ** = 5%, and * = 10%. Training and education are included in a single estimation of Model 3a; the results are provided in separate rows for presentational purposes.

[4] Vandenberg (2004) provides a review of the evidence on productivity and firm size which indicates generally that smaller firms have lower productivity than larger firms.

We also investigate differences by firm size. We wish to determine whether training and education are likely to have a greater impact on firms of a particular size—and indeed whether human capital has a statistically significant impact on all sizes of firms. Our supposition is that human capital is important for enhancing the productivity of enterprises of all sizes. The size variables are dropped and replaced with variables that interact size with training in model 1b and size with education in model 2b. In model 3b, both sets of interacted terms are included. The results are provided in Table 4. They show a significant correlation between all the interaction terms and productivity, with one exception. In model 3b, the interacted term of training and medium-sized enterprises is the right sign but not significant. The overall results suggest that education and training raise productivity for enterprises of all sizes and that hiring educated workers and training the workforce is as important for small enterprises as it is for larger firms. However, in the first two models we see that the strength of the correlation rises with firm size (i.e., larger coefficients) and that the pattern is consistent through the three size classifications for both human capital variables. This suggests that education and training may have more of an impact on raising the productivity of larger firms than smaller ones. Model 3b provides no pattern in this regard.

Table 4: Heterogeneity by Enterprise Size

	1b	**2b**	**3b**	**3b**
	Training	High school	Training	High school
Small	0.110**	0.107**	0.143***	0.097**
	[0.049]	[0.044]	[0.050]	[0.047]
Medium	0.174***	0.322***	0.070	0.341***
	[0.051]	[0.058]	[0.065]	[0.076]
Large	0.224***	0.339***	0.161**	0.277***
	[0.058]	[0.062]	[0.064]	[0.071]

Notes: Standard errors in parentheses. Significance level: *** = 1%, ** = 5%, and *= 10%. Training and education are included in a single estimation of model 3b; the results are provided in separate columns for presentational purposes only.

3.3 Endogeneity

It may be argued that the foregoing estimations suffer from the problem of endogeneity.[5] Two sources of endogeneity might arise: one stemming from reverse causality and the other from a missing variable that might affect both human capital and productivity independently. Both concerns should be considered.

Regarding reverse or dual causality, there is a possibility that not only might human capital raise productivity but that firms with higher productivity may be more likely to engage in training and to hire educated workers. While this concern is very real, we need to consider the underlying economics and business decision making that is taking place. More productive firms may invest more in hiring and training but they are not doing so simply because they are more productive firms. They do it because they know that better-skilled workers are more productive and contribute to the overall productivity of the enterprise. So while it is possible that there may be some degree of reverse causality, it is based on the singular understanding by firms that greater human capital

[5] The issue was raised by participants at a presentation of the initial results during the SMEs in Developing Asia: New Approaches to Overcoming Market Failures workshop, held on 19–20 November 2015 at the Asian Development Bank Institute, Tokyo, Japan.

contributes to productivity. If their experience, over time, showed otherwise, they would reduce the resources allocated to training and not pay higher wages to new recruits.

The other endogeneity problem—a missing or unobserved variable that affects both productivity and human capital—is a possibility, but it is difficult to imagine what variable or type of variable this might be. Given that productivity is a performance variable and human capital is an input, the mostly likely arrangement is of an input affecting performance. There are no obvious candidates for a factor that might influence both independently. It may be that the owner or entrepreneur is driven to reach high productivity and also has faith in human capital so that it is promoted along with other efforts to raise productivity. This endeavor may occur simultaneously before the increase in human capital has an opportunity to affect productivity. In addition, there may be factors at play of which we are just not aware.

To account for the possibility of endogeneity, we re-run the main estimations with the use of instrumental variables. In doing so, we use the generalized method of moments (GMM) technique. We focus our efforts on the training variable. We estimate a probit equation with training as the dependent variable and the identification variable as the enterprise's perception of whether the lack of availability of skilled workers affects its growth. This variable is available in our dataset. (We experimented with another indicator—the perception of labor regulation as a constraint for the enterprise—but the results were weak.) As there may be an endogeneity problem in this estimation as well, we created two instruments: one in which that identification variable is crossed by province or state and the other by industry. All tests for instrumental variables were passed, including the Hansen test, the weak instrument test, and the under-identification test. We generated the fitted values of training and used them as the instrument.

The results are presented in Table 5. Models 1c and 2c include the instrumental training variable; the former with the identification variable crossed with province or state and the latter with industry. We exclude the education variable from these two estimations. In models 3c and 4c we again use the two instruments but now also include education. The results for our key variables of interest are similar to the earlier estimations. The instrumented training variable is significant and with the expected sign in all four estimates, although with a reduced level of significance. Education is significant as in previous estimates. These results provide us with greater confidence that training, at least, is causing higher productivity at the enterprise level.

However, we do find that firm size is no longer significant (and the coefficients are negative) across all four estimates. This stands in rather bold contrast to the earlier results, which were positive and significant and suggested the size of the enterprise had a significant bearing on differences in labor productivity even when taking into account human capital, industry, and other factors. The negative signs here, if they had been significant, would have suggested that small firms have higher productivity than medium-sized or large ones.

We check the robustness of the results by trimming. This technique is used to determine whether the results are driven by the top performers (who would always provide training for their workers) and the weakest performers (who may never provide training for their workers). We drop 5% of the enterprises with the highest level of labor productivity and 5% of those with the lowest level. The sample size is reduced to 3,613 firms. The results, not shown, are very similar to the results in Table 5, suggesting that the latter are robust. The signs are the same on all variables. The level of significance (1%, 5%, or 10%) remains unchanged, except that age is no longer significant at the 10% level. The size of the coefficients falls in all cases but only slightly.[6] We have similar minor changes when conducting trimming for model 3 of Table 2 (the model without instruments). Therefore, we can continue to conclude that training and education have a significant effect on firm productivity.

Table 5: Determinants of Labor Productivity, Instrumented

Dependent Variable: Labor Productivity	[1c]	[2c]	[3c]	[4c]
Training (instrumented)	0.958***	0.820**	0.719*	0.693*
	[0.367]	[0.396]	[0.410]	[0.421]
Education			0.141***	0.143***
			[0.051]	[0.052]
Capital intensity	0.252***	0.254***	0.251***	0.252***
	[0.013]	[0.013]	[0.013]	[0.013]
Medium-sized firms	–0.054	–0.020	–0.054	–0.020
	[0.101]	[0.107]	[0.101]	[0.107]
Large firms	–0.102	–0.058	–0.102	–0.058
	[0.127]	[0.135]	[0.127]	[0.135]
Firm age	0.043	0.048	0.053*	0.054*
	[0.031]	[0.032]	[0.032]	[0.032]
Industry dummy	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes
Intercept	6.412***	5.892***	5.912***	5.922***
	[0.480]	[0.540]	[0.535]	[0.535]
Number of observations (enterprises)	3,998	3,998	3,998	3,998

Notes: Standard errors in brackets. Significance level: *** = 1%, ** = 5%, and * = 10%. Training and education are included in a single estimation of model 3b; the results are provided in separate columns for presentation purposes only.

4. POLICY IMPLICATIONS

The policy implications that can be drawn from the foregoing analysis are clear and direct. Efforts to increase human capital in the private sector workforce can be an important strategy for raising the productivity and competitiveness of enterprises of all sizes. The link between education and training on the one hand and enterprise productivity on the other is important for SMEs and is not a factor that they should ignore in their quest to develop competitive, productive, and sustainable enterprises. Furthermore, skills and education policy can be—and based on our results probably should be—an important part of the SME strategy of governments in Asia. Efforts to focus SME support narrowly on access to finance may miss the wider factors that are important to small firms.

[6] For example, the coefficient on training falls from 0.719 in model 3c of Table 5 to 0.586 after trimming. Other coefficients decrease less. The trimming results are not presented to avoid presenting too many results.

The empirical analysis tested two human capital variables—the education of workers and the training programs that firms offer their workers. We found that both are strongly correlated with labor productivity and that both, together, can have an impact. In other words, preservice education and in-service training are not alternatives from which an enterprise owner should choose. Rather they are parallel supporting factors: firms can both hire more educated workers and provide them with additional training and both efforts, undertaken simultaneously, will contribute to improved productivity.

The results do not allow us to provide more detailed policy measures, which require deeper and more specific analysis. For example, our education variable differentiated between firms with an average workforce education level of 10 years or more and those with less than 10 years. This is a fairly vague yardstick. It equates in many countries with the end or the near-end of secondary school. More detailed analysis might indicate the value of postsecondary and vocational education. Our training variable was similarly broad, indicating only whether enterprises provided formal training to their workers and not exploring the extent of training (what share of the enterprise workforce had access to the training), the frequency of training offered, or the quality and nature of the training. More detailed analysis of these issues, which would require a richer dataset, would help to determine what specific types of training programs are more beneficial. Finally, the analysis did not provide a cost–benefit analysis from the perspective of the employer. More educated workers are attracted by higher wages while in-service training is costly to the enterprise not only in terms of paying in-house or external trainers but also the production that is foregone while employees are in the training room instead of on the shop floor or at the service counter.

What the results do indicate, however, is that governments need to both build a good education system and ensure that young people are completing high school. For their part, enterprises need to be selective and hire educated young people. Furthermore, governments can consider whether to support (through subsidies) enterprise-based training, knowing it has a positive effect on developing the competitiveness of SMEs and large enterprises and increasing productivity in the economy.

5. CONCLUSION

SMEs play an important role in the development of economies in Asia, as they do in other regions of the developing world. Their contributions to job creation, investment, innovation, and exports make them an important policy area for governments. Understanding the key factors that support enterprise productivity and competitiveness is critical to knowing where governments—and enterprises themselves—can focus their energies.

This paper has examined the connection between productivity and human capital based on data on 4,000 enterprises in five countries. The results indicate a strong positive correlation and probably a causal effect of two measures of human capital—preemployment education and in-service training—on labor productivity. SMEs can increase productivity by hiring a workforce that has been educated to at least the secondary school level and by providing training to their workers through in-service programs. The relationship between human capital and productivity is valid for different sizes of enterprises. SMEs benefit from progressive hiring and training practices just as large firms do. It is an area of enterprise management that they avoid at their own peril.

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