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EDUCATION EFFECT ON LABOR PRODUCTIVITY IN MYANMAR: EVIDENCE FROM MSME SURVEY*

Sun Htoo Aung[1]

Abstract

Education is a key determinant of labor productivity, but it seems to be downplayed in the society. This would be a great treat to increase the productivity of firms and thus to enhance the economic growth. This paper aims to quantify the causal effect of education on labor productivity in Myanmar. Using the Micro, Small, and Medium Enterprises (MSMEs) surveys of 2017 and 2019, the causal effect of education is identified by controlling the characteristics of employees, owners/mangers, and firms. Estimation results show that education has positive causal effect on labour productivity after controlling important variables. This finding suggests that policy makers should ensure that every citizen attains an education level, which they are supported to have.

Key words: Education, labour productivity, MSME

Introduction

Economic growth and prosperity in Myanmar is largely driven by the growth of micro, small, and medium enterprises (MSMEs). Their contribution to the gross domestic product (GDP) of Myanmar is about 30 percent (Bala & Feng, 2019). The growth of MSMEs is, in turn, determined by three main productive factors: labor, capital, and technology (Nicholson & Snyder, 2016). To have an immediate growth, for which Myanmar is currently struggling, enhancing capital and technology is not feasible as it would take years. Improving labial productivity could be a viable policy option. labour productivity of Myanmar is currently low compared to the countries in the region such as China, Thailand, and Vietnam (ASEAN Productivity Organization, 2021). Among the determinants of labour productivity, education is consistently found as the most important factor by theoretical and empirical studies (Fallon, 1987; Lanzi, 2007; Mincer & Polachek, 1978). Despite its vital role, education seems to be downplayed in the society. According to the recent labour force survey (Central Statistical Organization, 2015, p. 9), only 13 percent of working age population have high school and above education level. These figures are alarming given the free education system in Myanmar. This paper, therefore, aims to analyze the role of education in determining labour productivity. In particular, the main objective of this paper is to estimate the causal effect of education on the labour productivity of the MSMEs in Myanmar.

Literature review

Microeconomic theory explains that the output of a firm is mainly determined by three primary inputs: labor, capital, and technology. Given the level of capital and technology, improvement in labor productivity will increase firm's output. Among the factors that can explain labor productivity, education plays an essential role. Intuitively, only with a certain level of education, employees can acquire knowledge and skills and can adopt new technology. This directly improves their productivity.

On average, about ten years of our life have been spent for studying at schools. While studying and pursuing a degree help us gain knowledge and better employment opportunities, this does not come without cost. The major costs for attaining higher education level involve time, energy, tuition fees, and other opportunities. Thus, the eligible question to ask is what the return from education to the labor market outcome, such as wage, is. This question has been addressed for decades. Amongst, Mincer's (1958) seminal work is often cited in this research area. He drives the earning equation from human capital theory and his equation is known as Mincer's earning equation. In its original form, the dependent variable is log-wage and the independent variables are schooling, experience, and experience-squared. The coefficient of

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[1]Department of Statistics, Yangon University of Economics

schooling measures the return to education. Since then, this equation has been used to study the effect of education on labor productivity in many countries, using cross-section, time-series, and panel data. At present, there are already many extended forms of Miner's earning equation, incorporating other control variables.

In studying the effect of one variable on another variable, most studies are correlational. Although these types of studies have their own right, finding a correlation between two variables does not necessarily mean one variable cause another. In the context of policy making, what is more important is causal evidence, which is often derived from an experiment.

A gold standard for an experiment is a randomized controlled trial (RCT) where treatment is randomly assigned into treatment and control groups. Although this approach is a main tool for social science such as medicine and physics, it was applied in economics by Fisher (1935). While he applied this method in agriculture, it is rare and not possible in social science, particularly where the unit of study is human beings. However, there are many methods, which can mimic the RCT design. Amongst, the multiple regression framework is a workhorse for empirical researchers and other methods are the extension of it. The main advantage of this framework is that unnecessary confounding factors can be explicitly controlled while using non-experimental data. The Frisch-Waugh-Lowell theorem guarantees that the population parameter of a multiple regression model is free from the confounding effect of the factors controlled in the model (Yamada, 2017).

There are many empirical studies on the effect of education on labour productivity. For Myanmar, Central Statistical Organization (2018; 2019) estimates the model of labor productivity of MSMEs with sets of covariates. It finds that education has positive effect on labor productivity. For other countries, this topic is analyzed at individual level (ElObeidy, 2016; Jajri & Ismail, 2010), and firm level (Asadullah & Rahman, 2009; Lebedinski & Vandenberghe, 2014). Regardless of the level of study, they consistently find that education improves labor productivity.

Methodology

Labor productivity can be measured in different ways such as output per unit of labor, and revenue per unit of labor. For a single firm, these measures are valid and precise. For multiple firms producing various kinds of products with different units of measurement, it is difficult to reconcile all distinct units into a single unit. A common solution to this problem is to use a theoretically consistent unit. According to the microeconomics theory, a firm chooses the optimal level of labor at which profit is maximized given the input and output prices. Under the assumption of the constant return to scale production function and the competitive market, firm's optimization problem is as follows:

$$\underset{\langle L,K\rangle}{Max}\ \Pi = pf(L,K) - wL - rK \tag{1}$$

$$\frac{\partial \Pi}{\partial L} = p.f_L - w = 0 \Rightarrow f_L = w/p \tag{2}$$

$$\frac{\partial \Pi}{\partial K} = p.f_K - r = 0 \Rightarrow f_k = r/p \tag{3}$$

where Π is a profit function; $f(L,K)$ is a production function; L is labor, K is capital; p is output price; w is wage rate; r is rental price of capital; f_L and f_K are marginal product of labor and capital, respectively. Equation (1) is the objective (profit) function of the firm for its optimization problem. Equations (2) and (3) are the optimal conditions for the demand for labor and capital inputs, respectively. Equation (2) indicates that at optimum, marginal product of labor, which measure the amount of output due to an extra unit of labor, is equal to the ratio of the nominal wage to output price (real wage). This clearly shows that real wage can be legitimately used to measure the labour productivity. Therefore, real wage will be used as a measure for labor productivity in the following sections.

The causal effect of education on labour productivity is identified in the framework of regression model. This effect can be isolated if important variables, which are potential to correlate with both education and labor productivity, are controlled in the model. The population regression model of wage variable is

$$wage_i = E(wage_i \mid educ_i, \mathbf{X}) + \varepsilon_i = \beta educ_i + \theta \mathbf{X} + \varepsilon_i \tag{4}$$

where $wage_i$ is the monthly wage of employee *i*; $educ_i$ is the education level of employee *i*; $\mathbf{X}$ is a vector of control variables; ε_i is the random error term which consists of individual-specific factors; β and θ are the population parameters. In Equation (4), the first equality shows that the variation of wage can be decomposed into (i) a systematic part, which is represented by the condition mean of wage, and (ii) a random part. The second equality indicates that the conditional mean function is approximated by a linear function.

On the right hand side of the model, the key variable of interest or policy variable is education, and the parameter, β , is supposed to measure the causal effect of education. The role of control variables in the model is twofold: to reduce the bias on β and to reduce the standard error of the model. Three groups of control variables for employees, owner/mangers, and firms are included in the model. Control variables for employees include experience, tenure, and gender. Experience represents general skills about the sector while tenure captures firm-specific skills. While both variables are expected to have positive effect, their effect should not be constant. While gender quantifies potential wage differential between male and female, its effect is an empirical question. Control variables for owner/manager include education level, experience, and gender. As more educated and more experienced owners are expected to manage their firms well, they can help improve their labor productivity. Whether male owner is more productive than female can be determined only with the empirical result. Control variables for firm include firm size and being located in the industry zone. Both variables are anticipated to enhance productivity. In addition to controlling observed characteristics, unobserved fixed effects of state/region and sector are also controlled by using dummy variables. For the functional relationship among variables, the left-hand side variable is a linear function of all right-hand side variables, except experience and tenure, for which a quadratic function is used. Since all parameters in the model are in linear, ordinary least squares (OLS) estimation method is used to estimate the parameters. The key identification assumption for Equation (4) is the conditional mean independent as shown below:

$$E(\varepsilon_i \mid educ_i, \mathbf{X}) = 0 \tag{5}$$

Equation (5) implies that in the presence of control variables, the random error term is independent of the policy variable, education level. Under this assumption, OLS estimators are consistent (Wooldridge, 2019). Consistency is a large sample property and is particularly important for policy research. Regarding this, Clive W. J. Granger, the Noble Price-winning econometricians, once noted that “If you can’t get it right as the sample size goes to infinity, you shouldn’t be in this business” as cited in (Wooldridge, 2019, p. 164).

Data source

The main data source is the 2017 and 2019 MSMEs surveys. These surveys are funded by the government of Denmark and jointly implemented by the Central Statistical Organization (CSO) and the foreign experts from United Nations University of World Institute for Development Economic Research (UNU-WIDER) and University of Copenhagen. They are nation-wide surveys, covering 35 townships across 14 states and regions and Nay Pyi Taw council. The target population is micro, small, and medium enterprises in the manufacturing sector. As about 30 percent of enterprises in the sampling frame are rice mills, the population is divided into two strata: rice mills and other manufacturing firms. The sampling scheme is thus stratified into two-stage sampling. In the first stage, townships are selected with probability proportional to size method, using the number of enterprises in each township as a size variable. In the second stage, sample enterprises are randomly drawn from the chosen townships. In addition to formal/registered firms, non-formal/unregistered manufacturing firms, for which sampling frame is not available, are also surveyed using snow-ball sampling method. From each sampled enterprise, at most five production workers are interviewed. Data are collected by face-to-face method using three set of survey questionnaires. The first questionnaire consists of questions about owner/manager and firm characteristics. The second questionnaire mainly includes economic accounts of firms. The last questionnaire is only concerned with employee characteristics. Data from the same sample units were collected in both 2017 and 2019. About 10 percent of sample units in 2019, which were included in the 2017 survey, were run out of business or temporally closed. For these missing units, new sample units were collected using the updated sampling frame. The final sample consists of 2,946 enterprises and 6,722 employees in 2017 and 2,497 enterprises and 5,017 employees in 2019. The detailed information about sampling can be found in CSO (2018, 2020).

While this research is based on the above two surveys, it does not use the whole sample but has imposed three restrictions. The data used in this paper include only (i) registered/formal firms, (ii) only firms with at least one production worker, and (iii) only permanent, full-time workers because there could be differences in distribution and behavior between the units in restricted and unrestricted samples. Therefore, the final sample for this paper includes 1,646 firms and 4,423 employees in 2017 and 1,911 firms and 4,283 employees in 2019.

Summary statistics

Definition and construction of key variables in the model are reported in Table (1). They all are self-explanatory.

Table (1) Definition and construction of key variables

Variable	Definition/Construction	Measurement Level
lnwage	Natural logarithm of monthly wage (in kyat)	Continuous
noedu	1 if employee has no education; 0 otherwise	Binary
primary	1 if employee has completed primary school; 0 otherwise	Binary
middle	1 if employee has completed middle school; 0 otherwise	Binary
high	1 if employee has completed high school; 0 otherwise	Binary
higher	1 if employee has completed university; 0 otherwise	Binary
exp	Employee's experience in this sector (in year)	Continuous
tenure	Employee's experience in this firm (in year)	Continuous
male	1 if employee is male; 0 otherwise	Binary
o_noedu	1 if owner has no education; 0 otherwise	Binary
o_primary	1 if owner has completed primary school; 0 otherwise	Binary
o_middle	1 if owner has completed middle school; 0 otherwise	Binary
o_high	1 if owner has completed high school; 0 otherwise	Binary
o_higher	1 if owner has completed university; 0 otherwise	Binary
ownermale	1 if owner is male; 0 otherwise	Binary
ownerexp	Owner's experience in this sector (in year)	Binary
zone	1 if firm is located in industry zone; 0 otherwise	Binary
firmsize	Number of full-time employees	Continuous

By looking at the summary statistics shown in Table (2), it is confirmed that there is no mistake in variable construction as all data are in their possible range. Compared to 2017, there was an increase in wage in 2019. This may be due to pure inflation. The percentage of educated employees has slightly changed between the two years. Percentage of employees with primary education was larger whereas percentage of employees with other levels of education was smaller in 2019. Employee's experience and tenure increased in 2019. More than 66 percent of employees are male. Given the nature of enterprises, the majority of owners/mangers are not highly educated. About 70 percent of owners/mangers are male and nearly 30 percent of firms are located in industry zones. Average firm size is about 22 employees.

Table (2) Summary statistics of key variables

Variable	2017					2019				
	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
lnwage	4423	11.77	0.42	9.2	13.6	4283	12.01	0.44	9.2	14.2
noedu	4423	0.07	0.26	0	1	4283	0.13	0.34	0	1
primary	4423	0.32	0.47	0	1	4283	0.43	0.50	0	1
middle	4423	0.31	0.46	0	1	4283	0.28	0.45	0	1
high	4423	0.21	0.41	0	1	4283	0.09	0.28	0	1
higher	4423	0.09	0.29	0	1	4283	0.07	0.26	0	1
exp	4423	2.94	4.97	0	39	4283	3.86	5.85	0	65
tenure	4423	5.62	5.97	0	50	4283	6.28	5.95	0	61
male	4423	0.66	0.47	0	1	4283	0.67	0.47	0	1
o_noedu	4423	0.01	0.08	0	1	4283	0.03	0.18	0	1
o_primary	4423	0.18	0.39	0	1	4283	0.17	0.37	0	1
o_middle	4423	0.21	0.41	0	1	4283	0.22	0.42	0	1
o_high	4423	0.17	0.38	0	1	4283	0.16	0.37	0	1
o_higher	4423	0.43	0.50	0	1	4283	0.42	0.49	0	1
ownermale	4423	0.70	0.46	0	1	4283	0.68	0.47	0	1
ownerexp	4423	12.56	9.25	0	58	4283	15.13	9.80	0	61
zone	4423	0.28	0.45	0	1	4283	0.27	0.44	0	1
firmsize	4423	19.45	50.35	1	510	4283	22.10	52.97	1	650

Source: Own calculation based on MSME 2017 and 2019 surveys.

Figure (1) shows the relationship between lnwage and education for 2017 and 2019. It indicates that average wage also increases as education level becomes higher. This means that education will have a positive effect on wage. The figure also suggests that the use of linear function is appropriate.

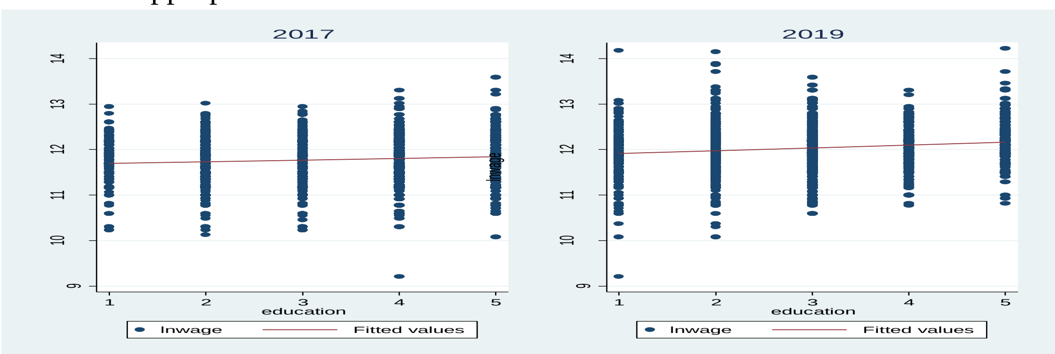

Figure (1) Relationship between lnwage and education

Distributions of lnwage by five education levels for 2017 and 2019 are shown in Figure (2). Among the five different levels of education, the distributions of the first four lower levels of education are not much different while the wage distribution of employees with university level education is far right to the other four. This suggests that the average wage of university-level employees could be significantly higher than those with the other four education levels. This feature is appeared in both 2017 and 2019.

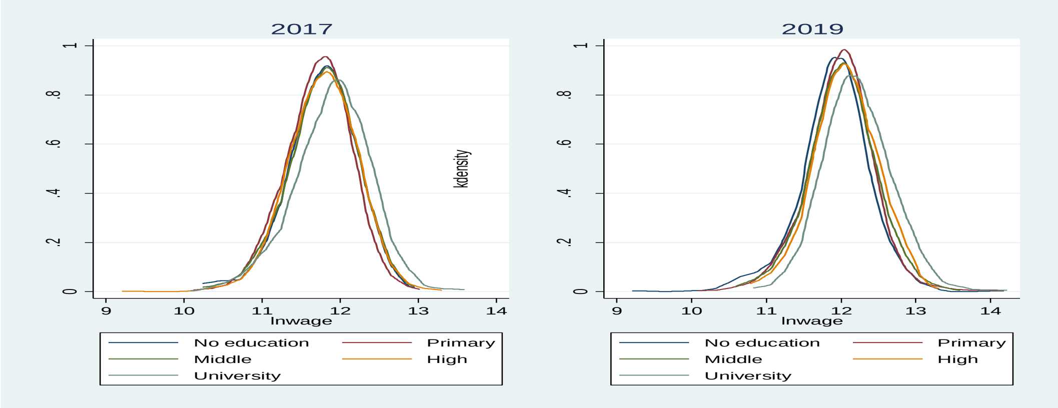

Figure (2) Wage distributions by education levels

Estimation results

Table (3) reports the OLS results from three models with different controls variables. Model (1) only includes key variables: education level, and experience and tenure. Model (2) adds the control of owner's education level, experience, and gender. Model (3) includes additional control of firm size and industry zone. In all three models, state/region fixed effect or/and sector fixed effect are also controlled. Since employees are randomly selected from each enterprise, it is likely that the random error term for each employee within an enterprise cannot be independent. This could invalid the use of ordinary standard errors of OLS estimates and result in misleading inference. To allow the possible dependence of the error terms of the employees in the same enterprises, cluster standard errors are used at firm level.

Among all the results, the primary interest of this paper is on the estimates of education levels of employees. As the base education group is employees without any education, the estimates of education levels should be interpreted with reference to the base group. In Model (1), the signs of the coefficients of all education levels are positive, as expected. This means that education has positive effect on wage. The sizes of these coefficients are also consistent. As education level becomes higher, wage differentials are also higher. While signs and sizes of the coefficients of education levels are correct, only the coefficient of university level education is statistically significant at 1 percent. This estimate shows that compared to the average salary of employees with no education, the average salary of employees with university level education is approximately 14 percent higher. The signs of experience and tenure estimates are also in line with empirical findings. The fact that the linear term is positive while the quadratic term is negative indicates that the relationship between lnwage and these two independent variables is inverted U-shape. This implies that as experience and tenure increase, lnwage also increases but the increment is diminishing over time. The estimate of male coefficient indicates that average salary of male is 23 percent higher than female. This wage differential between male and female is substantial.

In Model (2), the estimation results are not much different from Model (1). The estimates of education levels of owner/mangers have positive signs and statistically significant. The coefficients of male owners and experience suggest that male owner are more likely to raise wage than female owners, and experienced owners tend to enhance more wage than inexperienced owners. These two effects are, however, statistically insignificant.

In Model (3), firm size and effect of being in industry zone are considered. The coefficient of the industry zone indicates that average wage of the firms inside the industry zone are 4 percent higher than those outside the industry zone. The positive coefficient of firm size shows that labor productivity in the larger firms is higher than the smaller firms. While this effect is statistically significant, it is not practically significant.

Table (3) Estimation results for 2017

Variables	**Model (1) Standard**	**Model (2) With owner control**	**Model (3) With firm control**
primary	0.00	0.01	0.00
	(0.03)	(0.03)	(0.03)
middle	0.01	0.01	0.00
	(0.03)	(0.03)	(0.03)
high	0.03	0.03	0.02
	(0.03)	(0.03)	(0.03)
higher	0.14***	0.13***	0.11***
	(0.04)	(0.04)	(0.04)
exp	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
expsq	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
tenure	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
tenuresq	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
male	0.23***	0.19***	0.19***
	(0.02)	(0.02)	(0.02)
o_primary		0.30**	0.30**
		(0.12)	(0.12)
o_middle		0.29**	0.29**
		(0.12)	(0.12)
o_high		0.32**	0.31**
		(0.12)	(0.12)
o_higher		0.38***	0.36***
		(0.12)	(0.12)
ownermale		0.00	0.00
		(0.02)	(0.02)
ownerexp		0.00	0.00
		(0.00)	(0.00)
zone			0.04*
			(0.02)
firmsize			0.00***
			(0.00)
Constant	11.43***	11.06***	11.06***
	(0.05)	(0.13)	(0.13)

Variables	Model (1) Standard	Model (2) With owner control	Model (3) With firm control
Observations	4,423	4,423	4,423
R-squared	0.218	0.266	0.278
State/Region FE	Yes	Yes	Yes
Sector FE	No	Yes	Yes

Source: Own calculation based on MSME 2017 survey. Note: *, **, and *** represent 10%, 5%, and 1% significance level, respectively. The numbers in the parentheses are standard errors, which are clustered at firm level.

Table (4) presents the estimation result for 2019. Compared to the results in Table (3), the signs of coefficients do not change at all. However, the sizes of coefficients are larger and more coefficients become significant.

In Model (1), the coefficient of education levels should be interpreted as a wage differential to the base group (no education group). In line with intuition, wage differential becomes larger as education level higher. As before, experience and tenure have an inverted U-shape relationship with lnwage. Wage differential between male and female is approximately 24 percent.

In Model (2), all coefficients carry the same signs as before while their sizes become smaller due to the additional controls on owners/managers. The coefficients on education levels of employees are positive and the sizes are sequentially consistent. Experience and tenure has diminishing positive effect on lnwage. Wage differential between male and female is still significant and is about 19 percent. Control variables for owners' education, gender, and experience are all have positive effect.

In Model (3), the control variables for firm size and industry zone are incorporated. Compared to the results from the previous two models, only a few coefficients have become smaller. Compared to the average wage of firms outside the industry zone, those in the industry zone are about 7 percent higher. The effect of firm size has a significant positive effect although it is not practically significant.

Table (4) Estimation results for 2019

Variables	Model (1) Standard	Model (2) With owner control	Model (3) With firm control
primary	0.05*	0.04	0.04
	(0.02)	(0.02)	(0.02)
middle	0.07***	0.06**	0.06**
	(0.03)	(0.03)	(0.03)
high	0.11***	0.10***	0.08***
	(0.03)	(0.03)	(0.03)
higher	0.23***	0.21***	0.16***
	(0.04)	(0.04)	(0.03)
exp	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
expsq	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
tenure	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
tenuresq	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
male	0.24***	0.19***	0.20***
	(0.02)	(0.02)	(0.02)

Variables	Model (1) Standard	Model (2) With owner control	Model (3) With firm control
o_primary		0.10	0.10
		(0.06)	(0.06)
o_middle		0.07	0.07
		(0.06)	(0.06)
o_high		0.13**	0.11*
		(0.06)	(0.06)
o_higher		0.17***	0.14**
		(0.06)	(0.06)
ownermale		0.04*	0.03*
		(0.02)	(0.02)
ownerexp		0.00	0.00
		(0.00)	(0.00)
zone			0.07***
			(0.02)
firmsize			0.00***
			(0.00)
Constant	11.65***	11.49***	11.50***
	(0.04)	(0.07)	(0.07)
Observations	4,283	4,283	4,283
R-squared	0.190	0.237	0.259
State/Region FE	Yes	Yes	Yes
Sector FE	No	Yes	Yes

Source: Own calculation based on MSME 2019 survey. Note: *, **, and *** represent 10%, 5%, and 1% significance level, respectively. The numbers in the parentheses are standard errors, which are clustered at firm level.

Conclusion

After controlling for observed characteristics of employees, owners/mangers, and firms, and unobserved fixed effects of state/region and sector, it is found that education has positive causal effect on wage. This finding highlights the importance of education on labor productivity and thus economic growth. The policy makers should ensure that every citizen attain an education level, which they are supported to have. As in other research papers, this paper is also not flawless. In particular, individual fixed effect (ability) and time-varying factor (technology change) need to be controlled. This constraint will be considered in the future when panel data are available.

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