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Is Educated Labor Really Productive?

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Abstract

Improving the quality of human resources through education is believed to increase labor productivity. The higher the investment in education, the greater the potential for someone to gain knowledge, expand access to jobs, and increase productivity. However, the increases in the number of educated workforces, truly unbalanced with the increase with aggregate productivity. The purpose of this study is to analyze at which one of the levels of education has the greatest contribution to increasing productivity. In order to bring the research in macro level, we used Mincer equation calibrated by Bils and Klenow (2000) to develop a human capital model. This kind of research formed in micro level and very rarely research is done at the macro level. Therefore, by using calibration from Bils and Klenow (1992), this study tries to bring the mincer model to the macro level. This model estimates by panel regression method and cointegration method (for identification long run existence) and using data from the period of 2010-2018. The results of the study show a positive integration between the level of education towards work productivity. The fact that vocational education is aimed at preparing workforce has no significant effect on aggregate productivity. The result driven us to conclusion that education has not been considered a human capital factor but signaling factor; schooling level of labor was not a driven factor to labor productivity, but the years of experience did and labor is tended to taking education just for formal reason not for academic reason.

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INTRODUCTION

After Romer (Romer et al., 1989) and (Lucas, 1988) revealed a new growth theory emphasized the importance of R & D (Research and Development) and knowledge of externalities, human capital has become the main concerning addition to physical capital. New growth theory stated that economic growth is believed to be result of not only the increased capacity and quality of human capital through increasing labor productivity (Mankiw, Romer, & Weil, 1992; Romer, 1990) , but also the enhanced competitive advantage through innovation and diffusion technology (Amavilah, 2014). The new growth theory proposed the importance of understanding the function of human capital concerning growth aspects.

Following Schultz (1961) and Becker (1962), human capital defined as the set of knowledge, skills, competencies, and abilities embodied in and acquired by individuals. By Ananta & Hatmadji (1985) determiner factors of human capital focused on three main factor, there are health status, education, and income per capita. From the three main factors, education is considered one of the most significant human capital factors. Modelling the role of human capital especially education can be divided into two sides. At the micro framework -in the level of individual and family-education will provide knowledge and skills thus it will increase individual productivity, earn income, and increase the chances of getting a decent job. While at the macro framework, education is an input to increase potential income, expand labor productivity and mobility, improve the health of parents and children, reduce child fertility and death, and seek voice of the less fortunate people in society and the political system (Bassanini & Scarpetta, 2002).

Various research has found that education (measured as years of schooling) has high correlation with individual earnings, and has interpreted as evidence of the impact of education on worker productivity. According from (Lucas, 1988), the higher the level of the labor force's education, the higher the aggregate productivity, as the educated labor force tends to be innovative, then these emerging innovations should affect labor productivity.

The robust relationship between education and productivity with earning was identified by Mincer (1974). Since the Mincer equation became the standard model to estimate the relationship between education and earnings in micro framework perspective, various studies that refer to the application of Mincer equation have been done. Their result generally proves that schooling has a high correlation to earnings (Fiaschi & Gabbriellini, 2013; Forbes, Barker, & Turner, 2010; Jones & Jones P., 2001; Uusitalo, 1999).

However, the result became different when earnings are seen from the aggregate or macro level. Although not much research in aggregate level, the study showed robust results and came conclusion that education does not contribute or has a weak correlation to income per capita, productivity, or growth (Benhabib & Spiegel, 1994; Bils & Klenow, 2000; Levine & Renelt, 1992; Pritchett, 2000). Studied by Appleton & Balihuta (1996) estimated the effect of education on labor productivity in the agricultural industries in African countries particularly in Uganda and found that the effect was usually either insignificant or small in magnitude. The result of estimation concluded that although primary education had a significantly positive effect in raising agricultural production, the returns to secondary school were insignificant and the overall returns were much lower than those usually found in earnings regressions. Further studied by Söderbom & Teal (2004) in Ghana examined the relationship between schooling and productivity identified different outcomes. When estimated using pooled OLS, the finding was significant in Cobb-Douglas production function of Ghana's manufacturing sector; however, when estimated using a fixed-effects estimator, the effect was disappeared. The result from the studies leads to conclude that worker education levels appeared not to be quantitatively very important in determining productivity (Söderbom & Teal, 2004).

Since the enactment of Presidential Instruction No. 1 of 1994 on the implementation of 9 years of compulsory education, Indonesia has committed to improving the quality of human capital. Below, diagram in Figure1 illustrates education attainment of labor force in Indonesia.

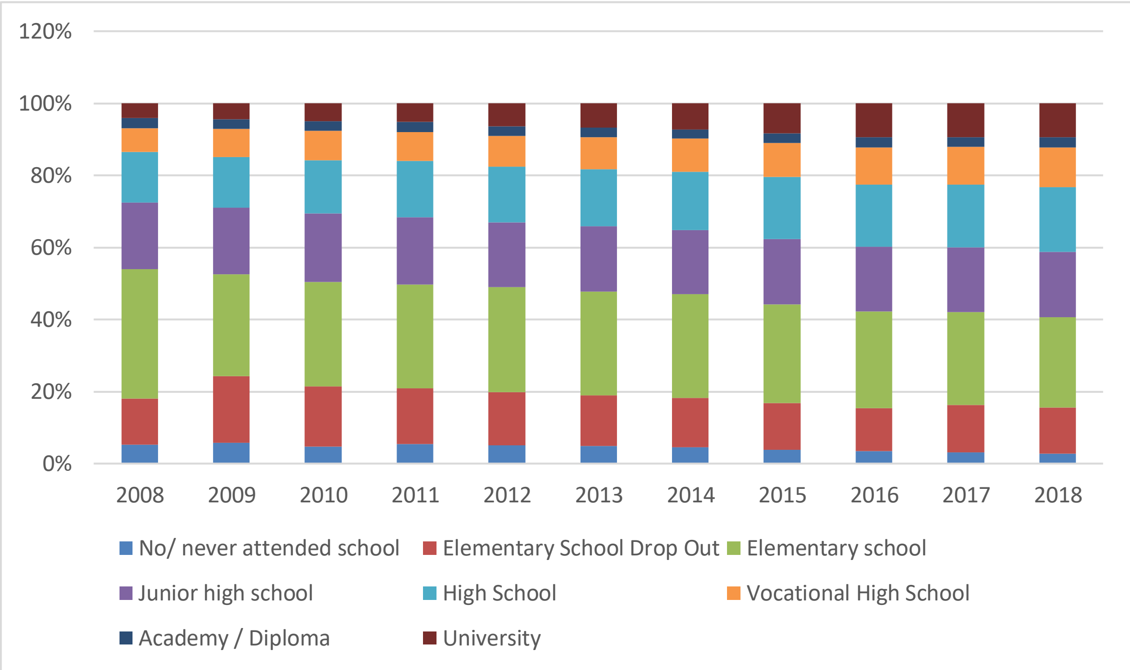

Figure 1. Education Attainment in Indonesia Labor Force 2008-2018
Source: Badan Pusat Statistik, 2019

Figure.1 exhibit that approximately 47 percent of the composition of the Indonesian labor force is dominated by labor with never attended school (4 percent), Drop Out (unfinished elementary School) (14 percent) and Elementary level (29 percent). The highest workforce group is dominated by the workforce with the highest level of education in elementary school. This condition shows that educational attainment in the Indonesian labor force was truly low. If the low of educational attainment of labor force is compared with productivity level of Indonesian workforce, then we get this rank result presented by APO (Asian Productivity Organization) and shows in Table 1.

Compared to other countries in the ASEAN region, productivity of Indonesia labor is low, for the productivity rank that shows only get in 45th. Besides that, compared to another country in ASEAN, Indonesia is in rank 4th after Singapore, Malaysia, and Thailand.

Table 1. Southeast Asia's Global Competitiveness Report 4.0 2018

Country	Score	World Rank
Singapore	85.6	2
Malaysia	74.7	25
Thailand	67.5	38
Indonesia	64.9	45
Philipines	62.1	56
Brunei	61.4	62
Vietnam	58.1	77
Cambodia	50.2	110
Lao	49.3	112

Source: APO (Asian Productivity Organization), 2019

Educational attainment is the highest educational level completed by a person, verified with the receipt of a letter of completion/certificate (BPS, 2015). Which is the level of education that is commonly known, is the first primary education that is 9 years (6 years of elementary and 3 years of junior high school), second is senior high school, consisting of 2 types of senior high school which is regular and vocational senior high school and last higher education, i.e. diploma then bachelor and postgraduate. The largest group of labor education showed in Figure 1 is Low education attainment's group (no schooling or did not pass elementary school). So, that the low of labor productivity brought a question that the economy might have been driven by low-educated labor. To answer the question, the object of this study is to examine the relationship between educational attainment and productivity with different levels of education corresponded to their productivity differentials. By focusing on research questions; Are educated workers more productive than workers with low educated level or no formal schooling? this study took object in 34 provinces in Indonesia and formed levels of educational attainment. From the result of this research, the level of education could be classified into the one that encourages or discourage productivity.

This research applied Macro Mincer models to answer the research question. As mentioned before, the Mincer equation has become the standard for modelling the relationship between schooling and earning. Using the Mincer equation, Bils & Klenow (2000) performs a calibration between Mincer equation and production function through human capital stock. The findings from Bils & Klenow (2000) itself are quite interesting. The research found that the impact of schooling on growth explains less than one-third of the empirical cross-country relationship. In other words, not all empirical relationships between schooling and growth should be interpreted as a schooling impact on growth, but vice versa.

Furthermore, Krueger & Lindahl (2001) bring the Mincer equation to be applied to macro variable models. According to Krueger & Lindahl (2001), the research motivated for using the aggregate data to estimate the effect of education on the growth rate of GDP is based on two reasons, first, the relationship between education and growth in aggregate data can generate insights into endogenous growth theories and possibly allow one to discriminate between alternative theories. Second, estimating relationships with aggregate data can capture external returns to human capital that is missing in the microeconomic literature.

Before running into the model, here short review about Solow Labor Augmented growth model and literature on modelling education, followed the work of Mincer's 1974-log-linear earnings function. Consider a constant return to scale production function at time t of Hall and Jones (1998), the equation is written as:

$$Y(t) = K(t)^{\alpha}[A(t)H(t)]^{1-\alpha} \text{..........................} (1)$$

K is capital, A is knowledge level expressing the effectiveness of Labor, and H is the total labor's productivity in all level of skills; while, t describes the continuous-time dimension. This production function is in term of Labor Augmenting model. In order to perform the decomposition of output differences per workers and to see the capital contribution per workers, both sides of the Equation (1) is divided by Lt and is written in the following logarithm as:

$$ln\frac{Y_t}{L_t} = \alpha ln\frac{K_t}{L_t} + (1-\alpha)ln\frac{H_t}{L_t} + (1-\alpha)lnA_t \text{..}(2)$$

By referring to the Solow residual concept, the estimation of the Equation (2) calculates A as residual. Thus, Equation (2) explains the role of physical capital per worker and human capital per worker towards the output growth per worker. Hall & Jones (1999) and Klenow & Rodríguez-Clare (1997) transformed the Equation (2) by deducting the left and right side of the equation with $\alpha ln\frac{Y_i}{L_i}$ into:

$$(1-\alpha)ln\frac{Y_t}{L_t} = \left(\alpha ln\frac{K_t}{L_t} - \alpha ln\frac{Y_t}{L_t}\right) + (1-\alpha)ln\frac{H_t}{L_t} + (1-\alpha)lnA_t \text{...}(3)$$

To simplify, the Equation (3) is divided by $\left(1\text{-}\alpha\right)$ into:

$$ln\frac{Y_t}{L_t} = \frac{\alpha}{1-\alpha}ln\frac{K_t}{Y_t} + ln\frac{H_t}{L_t} + lnA_t \text{..................}(4)$$

The Equation (4) explains output per worker *(Y/L)* as the function of physical capital intensity (capital-output ratio, K/Y), labor services per worker, H/L and residual. A's contribution is measured as residual, it reflects not just technology or knowledge but all forces that determine output for given amounts of physical capital and labor services. Then, if each parameter is written as $\acute{y} = ln\frac{Y_t}{L_t}$, $\acute{k} = ln\frac{K_t}{Y_t}$, dan $\acute{h} = ln\ \frac{H_t}{L_t}$, then Equation (5) can be written as:

$$\acute{y} = \frac{\alpha}{1-\alpha}\acute{k} + \acute{h} \text{ ....(5)}$$

From Equation (5), it is possible to decompose the difference output per worker into the difference in capital-output ratio or differences in human capital or educational level, or productivity.

After formulating the economic growth model, the next step is to formulate the human capital stock equation. Bils and Klenow (2000) developed a structural model to analyze the sense of casualty between education and economic growth. This model was built referring to Mincer Wage Equation which is a standard equation to capture the relationship among schooling, labor's work experience, and earning. Furthermore, Bils and Klenow (2000) proposed two possible correlations between economic growth and initial schooling attainment; first, schooling attainment helps economic growth through different channels (direct channel), and second, economic growth gives incentives to people to study more because of higher expected future outcomes (indirect channel). Bils and Klenow (2000) then resolve the problem by using mathematical formulation.

This research referred to direct channel model by Bils and Klenow (2000). By referring to the equation (1), two channels from schooling to growth may exist; first, a direct channel by increasing the level of human capital Ht, and second, indirect channel by increasing the level of technology use or adoption At. The direct channel can be formulated in the following way if *h(a.t)* is the level of human capital for cohort a at time t and *L(a,t)* as its size, individuals go to the school from age 0 to s, and work from s to T. Therefore:

$$H(t) = \int_s^T h(a,t)L(a,t)\,da \text{ ....(6)}$$

Individual human-capital stocks follow:

$$h(a.t) = h(a+n,t)^{\emptyset} e^{f(s)+g(a-s)}\ \forall a > s \text{ .....(7)}$$

In which *(a-s)* is a proxy for individual's experience and ϕ is a key parameter of the model, it is measures the influence of teachers in human capital. If ϕ = 1, h grows from cohort to cohort even if s remains constant. Otherwise, either s or T increases or it is necessary. Applying logs, then:

$$\ln h(a.t) = \emptyset \ln h(a+n.t) + f(s) + g(a-s)\ \forall a > s \text{ ....(8)}$$

In which *h(a)* is human capital level per labor, *f(s)= θs, s* is years of schooling, *(a-s-6)* is experience calculated from age at time t (a) minus years of schooling (s), early school ages (6, count yearly), and $(a\text{-}s\text{-}6)^2$ is square experience. When $\phi=0$, taking $h(a+n,t)=K$, $f(s)=\theta s$, and $g\left(a\text{-}s\right)=\gamma_1\left(a\text{-}s\right)+\gamma_2(a\text{-}s)^2$, the equation become Mincer wage equation's specification. By Bils and Klenow (2000), equation (8) is defined as human capital stock and rewritten in equation (9) as follows:

$$\ln[h(a)] = f(s) + \gamma_1(a-s-6) + \gamma_2(a-s-6)^2 \text{ ....(9)}$$

RESEARCH METHODS

This To analyze whether education level and productivity were correlated, we calibrated human capital stock from Mincer Equation with growth function, as well as the work of Bils & Klenow (2000). The procedure of our calibration was that first, consider that $\boldsymbol{\acute{h}}$ from the Equation 5 is defined as human capital per labor in logarithm term, therefore $\boldsymbol{\acute{h} = ln[h(a)]}$, so that the Equation 9 is rewritten as:

$$\acute{h} = f(s) + \gamma_1(a-s-6) + \gamma_2(a-s-6)^2 \text{ ....(10)}$$

According to Heckman, Lochner, & Todd (2003), in the Mincer Equation framework, the use of experience variables and square experience in one equation will cause omitted variables. Furthermore, Heckman, Lochner, and Todd (2013) added proposed variable in the mincer equation. Besides resolving the omitted variable problems, added variable also makes it easier for adding determinants factors in the model as well. Therefore, after adding variable Z in Equation 10, Equation 11 is written as:

$$\acute{h} = f(s) + \gamma_1(a - s - 6) + \gamma_2(a - s - 6)^2 + \sum_{i=1}^{n} b_i Z_1 \qquad (11)$$

Then, $\acute{h}$ production function in Equation 5, is substituted with human capital stock (equation 11) and written as Equation 12. This step changed up Mincer equation from micro framework to macro framework as what Krueger & Lindahl (2001) did. The educational level variable added was *Low (Z_1)*, *Basic (Z_2)* and High *School (Z_3), Vocational High School (Z4), Vocational school-*D3 *(Z_5), Tertiary education (Z6).* Equation 12 can be described as follows:

$$\acute{y} = \frac{\alpha}{1-\alpha}\acute{k} + \theta s + \gamma_1(a - s - 6) + \gamma_2(a - s - 6)^2 + \sum_{i=1}^{6} b_i Z_1 \qquad (12)$$

If for each coefficient is rewritten as:

$$\beta_1 = \frac{\alpha}{1-\alpha}, \beta_2 = \theta, \beta_3 = \gamma_1, \beta_4 = \gamma_2, \beta_n = b_n,$$

Then the equation 12 is rewritten as:

$$\acute{y} = \beta_1\acute{k} + \beta_2 s + \beta_3(a - s - 6) + \beta_4(a - s - 6)^2 + \beta_5 Z_1 + \beta_6 Z_2 + \beta_7 Z_3 + \beta_8 Z_4 + \beta_9 Z_5 + \beta_{10} Z_6 \qquad (1)$$

In which; $\acute{y}$: Labor productivity; $\acute{k}$: Stock Capital; s: Schooling; $(a - s - 6)$: Experience; $(a - s - 6)^2$: Square Experience; Z_1: Low education; Z_2: Basic education; Z_3: Senior High school; Z_4: Senior Vocational high school; Z_5: Vocational school (Diploma); Z_6: Tertiary schooling

A unique dataset of 34 provinces in Indonesia from 2010 until 2018 was retrieved from *Badan Pusat Statistik (BPS)*. In highlighting the model, the Equation 13 was rewritten into Equation 14 as econometric functions as:

$$y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \varepsilon_{it} \qquad (13)$$

In detail, the *Labor Productivity* (y_{it}) is measured as a ratio of real GDP to Labor (PROD). *Stock Capital (X_1)* is measured as a ratio of Gross Fixed Capital Formation to Output (STOCKCAP), Schooling (X_2) is measured by *Average Years of Schooling* (YOS), *Experience (X_3)* is calculated from *Life Expectancy* minus *average years of schooling* minus initial school ages (6 year) (EXPER), and *Squared Experience* (X_4) is calculated by Experience squared (EXPER2). *Labor Productivity* (y_{it}) and *Stock Capital* (X_1) is in a log form.

Education level in this research measured as; Low Education (X5) is measured as a ratio of ratio of total labor without schooling and not yet completed primary school to the total workforce (LOW), Basic Education (X6) is measured as a ratio of labor finish basic school (elementary and junior high school) to the total workforce (BASIC), Senior Highschool (X7) is measured as a ratio of labor finish senior high school to the total workforce (HIGH), Senior Vocational Highschool (X8) calculated from ratio of labor finish vocational senior high school to the total workforce (VOCHIGH), Vocational School D3 (X9) calculated from ratio of labor finish vocational school (D3) to the total workforce (ASSOC), Tertiary schooling (X10) calculated from ratio of labor finish Tertiary schooling (university or polytechnic school) to the total workforce (BACHELOR), ε is a stochastic element and α, β are parameters to be estimated

RESULTS AND DISCUSSION

Statistical descriptive analysis of the series shows standard deviations vary in reaching an extremely wide range. Table 2 present the results of statistical descriptive of dependent and independent variables in the model.

The object of this research from 34 provinces became 33 provinces. One province was excluded from the sample because the data was not yet available, that is the province of

North Kalimantan. Table 2 shows that the distribution of data for all high variables, seen from the value of skewness and kurtosis that is worth above the cut off value. But, although the standard deviation value is smaller than the average value, the value is quite large

In the panel regression method, there are two types of effects; random effects and fixed effects. To avoid the bias in the model and to choose the best method to be used in estimating first we performed Hausman tests. From the Hausman Test shows that Chi Square Statistic is 9.136 and the prob 0.519; greater than the level of significance α: 0.05. It concluded that the best panel model chosen was Random Effect Panel Model. Table 3 shows the result obtained using econometric analysis with Random Effect Model (REM).

Table 3. Random Effect Panel Model in Period 2010-2018

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STOCKCAP	-0.464	0.097	-4.774	*
YOS	0.084	0.034	2.465	**
EXPER	1.969	0.388	5.072	*
EXPER2	-0.018	0.004	-4.910	*
LOW	-0.915	1.167	-0.784	
BASIC	0.662	0.581	1.139	
HIGHSCHOOL	4.673	0.737	6.339	*
VOCHIGH	4.199	1.010	4.157	*
ASSOC	-0.450	1.892	-0.238	
BACHELOR	1.625	0.611	2.659	*
C	-56.565	10.477	-5.399	*
Weighted Statistics				

Notes : Numbers in the table are the coefficients of each variables

*** : 10% significance level

** : 5% significance level

* : 1% significance level

Source: Eviews 10 output, 2020

From the initial estimation, heteroscedasticity and autocorrelation problems appeared. In order to solve this problem, Period Weights Panel Corrected Standard Error (PCSE) with covariance (no d.f. correction) method (Beck and Katz, 1995) was used in this random panel regression estimation (Table 3). From the regression, the F test which is 63.61631and probability F test which is 0.000 remain significance at 1% level of significance. From the F test result, we concluded that the model was specified correctly, on other word that the goodness of fit of the estimation was achieved. Meanwhile, the adjusted R-squared of 0.694378 showed that the impact of the independent variables through dependent variable was 69.43 percent and the rest of 30.6 percent was affected variables outside of the model.

The results showed that STOCKCAP has negative significant to productivity. These results were consistent with the results obtained in theory, which is the negative and significant value for Capital per Output showed that economic is going to be more efficient. From human capital blocks, schooling as measured by the average years of schooling (YOS) has positive significant effect to productivity, again these results of YOS were consistent with the results obtained in theory. Experience (EXPER) and Square Experience (EXPER2) was gain as post-school investment in human capital and the result showed that it has significant effect to productivity, Experience (EXPER) has positive relationship and Square Experience (EXPER2) has negative relationship with productivity; this result was consistent with theory.

Meanwhile, from education level's variables, Low Education (LOW) and Basic Education (BASIC) has no significant effect to productivity, but High School (HIGH) and Vocational High School does. In higher level of education, Vocational School/Diploma (ASSOC) has no significant effect but tertiary schooling (BACHELOR) has significant effect to productivity even in positive sign.

What we have done in this research could be concluded that even though the years of schooling level of labor was found significant effect and could be driven factor to labor productivity, but in level schooling the result seems different (even though the model is fit). It remain us from study by Pritchett (2000) entitled "Where has education gone" that prove that education is not a main driven of productivity.

However, labor would reach the maximum working limit at a certain age; so that, at some point, productivity would decrease even though experienced were gained, it shows from the result of variable EXPER2. Labor with low education level proves not give high contribution to productivity. But compared to labor educational attainment, 40 percent labor mostly uneducated or graduated from elementary school, so that this biggest group of labor has no contribution to productivity.

In basic education, elementary school plus Junior High school also shows not significant to productivity. Labor with elementary school and Junior High school cannot enter the industry, it tends to that they are work as blue-collar worker. Next, from the educational level, the labor group with education attainment at the high school has proved to be positive and significant to productivity. From elasticity coefficient, the highest contribution of labor productivity was dominated by labor groups at high school. This finding was interesting because the level of vocational high school education and diploma, which is the education that is set to produce a workforce was not given good contribution to productivity. Vocational high school is positive significant to productivity, but the elasticity coefficient is small but Diploma has not significant to productivity. This result was different from the one of Jones (2001). Jones (2001) settled a model consisting of education level in order to capture the relationship between level of education and productivity. According to Jones (2001), all of education level variables are positive significant contributed to productivity. One of the fundamental things is the perception of the people who enter vocational education, which is vocational education is considered as an alternative rather than a goal. Furthermore, according to Kumaat (2010), the growing perception or assumption in the community that Vocational High School is "lower" when compared to High School. Not only because there is a fundamental difference between Vocational High School and High School particularly in curriculum and education system, but also the number of parents who send their children to Vocational High School generally come from middle to lower family. This condition also occurs in vocational schools (Diploma) that are considered second opinion for tertiary schooling.

Noted in the panel regression method, by using the data panel makes data vulnerable to being non-stationary. Models which use non-stationary variables are likely to have long-term relationships between variables. Cointegration is an adjustment for long-term balance between variables, even though data is not individually stationary, but linear combinations between intervals can be stationary. Therefore, it is necessary to examine the existence of cointegration in the model. The Kao Residual Cointegration Test is a cointegration test based on Engle-Granger and based on the Pedroni cointegration test model, which is to test the residual whether it has integrated properties on first diff. From the cointegration test results using Kao Residual Cointegration shows Kao's t-Statistic -13.95315 and prob. 0.000. We can conclude that there is cointegration in the research model. In other word, it says that in the long run, productivity has a significant relationship between independent variables in the model.

At last, this result of this research indicated that education should not be considered as human capital, but education is a signal that someone might have a high education but in contradiction have low productivity. According to Spencer (1973), the signaling of education happened because education is taken only aims to give a signal to the employer to provide wages in accordance with the level of education.

CONCLUSION

This paper highlights the important contribution of education level to productivity. The higher educated labors are considered to be a driven factor of productivity but the vocational education seems failed to fulfil the main purpose; which is to prepared labor to prepare a workforce ready for work in the labor market or industry. Also, schooling level of labor was not a driven factor to labor productivity, but the years of experience did. This result shows that there is a tendency that labor's educational investment shows that education has not been considered a human capital factor but signaling factor. However, labor would reach the maximum working limit at a certain age therefore at some point the productivity would decrease even though experienced were gained. Labor with high education level also might not give high contribution to productivity because the number of employments was limited. It's implied that the unemployment rate in high rate, or the workforces were not working fit to educational qualifications.

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APPENDIX

Tabel 2. Descriptive Statistics Of Variables

Statistic Measure	PRODUC TIVITY	STOCK CAP	YOS	EXPER	EXPER2	LOW	BASIC	HIGH SCHOOL	VOC HIGH	ASSOC	BACH
Mean	-2.729	5.734	7.911	55.362	3070.698	0.042	0.135	0.093	0.050	0.024	0.066
Median	-2.826	5.725	7.890	55.304	3058.489	0.041	0.136	0.086	0.038	0.022	0.065
Maximum	-1.002	6.250	11.050	61.285	3755.843	0.120	0.251	0.228	0.151	0.058	0.154
Minimum	-3.850	5.110	5.590	50.118	2511.836	0.007	0.034	0.034	0.018	0.011	0.018
Std. Dev.	0.556	0.227	0.981	2.401	267.436	0.018	0.046	0.032	0.031	0.008	0.024
Skewness	1.178	-0.136	0.363	0.250	0.364	0.891	0.036	1.404	1.397	1.114	0.666
Kurtosis	4.276	2.649	3.386	2.832	2.895	4.565	2.778	5.732	4.231	4.510	3.623
Jarque-Bera	86.998	2.393	8.203	3.376	6.569	68.239	0.662	186.114	112.960	87.822	26.217
Probability	0.000	0.302	0.017	0.185	0.037	0.000	0.718	0.000	0.000	0.000	0.000
Sum	-794.053	1668.465	2302.100	16110.340	893573.000	12.182	39.237	26.968	14.687	6.868	19.257
Sum Sq. Dev.	89.704	14.947	278.857	1672.274	20741339.000	0.097	0.618	0.292	0.275	0.019	0.163
Observations	291.000	291.000	291.000	291.000	291.000	291.000	291.000	291.000	291.000	291.000	291.000

Source: Eviews 10 output, 2020