The Determinants of Indonesian Students' Mathematics Performance: An Analysis through PISA Data 2018 Wave

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Abstract. This study investigates the determinants of Indonesian students' performance of mathematics proxied by plausible value (PV) of mathematics provided by OECD PISA. The recent PISA data of 2018 wave is used to accomplish the research objective. A multivariate linear regression is used; as the response variable is PV of mathematics, while information concerning student's background is used as independent variables, i.e., student's personal characteristics: age, gender, learning time in mathematics, science, and reading; family background: index of economic, social, and cultural status, family wealth, ICT possession at home; and classroom's climate: perceived feedback from teacher, and discriminating school climate. Result shows that all determinants (independent variables) but student's age are significant at the level of 5%. We also perform several tests to examine the classical assumptions, such as normality of the residuals, test for heteroscedasticity and collinearity. According to these tests, no severe problems occur.

Keywords: Indonesia students; mathematics; multivariate regression; PISA.

1 Introduction

In the last twenty years, the development of international large-scale assessments has continually given educational researchers access to vast databases with various characteristics (for example, the performance of student, the background of student, the characteristics of school, etc.). The growth of educational research in the previous years has been significantly influenced by assessment programs like the PISA from OECD [1].

Because PISA is among the first ones which was made available to the public, it has been noted that the analyses and this report created directly by the OECD typically have an impact on educational policies [2]. Then there is a duty of the educational researchers to investigate the database deeper, to uncover relationships between variables, and draw interpretations that might not be provided in the report to enhance the discussion since the analysis can be constrained given the variables offered by PISA.

PISA data can be subjected to secondary analyses using a variety of approaches. Multilevel regression analysis is one of the most popular ones because it enables researchers to simultaneously account for heterogeneity at the level of students and schools, as in [3]. Different approaches have been used by other authors, such as structural equation modeling (e.g., [4]; [5]) or analysis of covariance (e.g., [6]; [7]). One of the new methods for analyzing PISA data that has recently emerged is the data mining technique (e.g., [8]; [9]; [10]).

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This study tried to extend the practice of multivariate linear regression to explore the determinants of Indonesia students' mathematics performance. Given that identifying the factors behind students' performances is crucial considering the importance of improving the educational system.

2 Data and Variables

The data were collected from OECD PISA database of 2018 wave. The data has rich information about student, school, and parent status. In this paper, I focus my attention on Indonesia data. The student's mathematics performance is proxied by the plausible value (PV) of mathematics literacy (I only used one PV). The other PVs will be used in the robustness check. This variable acts as a solely dependent variable. The description of independent variables is shown in Table 1. Note that indicators of are also given in Table 1.

3 Empirical Model

In order to analyze how different determinants influence student's performance on mathematics, I specify the following multivariate regression equation

$$\begin{aligned}\mathrm{PV\_MATH}_i = \alpha + \beta_1\mathrm{AGE}_i + \beta_2\mathrm{GENDER}_i + \beta_3\mathrm{SMINS}_i + \beta_4\mathrm{MMINS}_i + \beta_5\mathrm{RMINS}_i + \\ \beta_6\mathrm{ESCS}_i + \beta_7\mathrm{WEALTH}_i + \beta_8\mathrm{ICT}_i + \beta_9\mathrm{PERFEED}_i + \beta_{10}\mathrm{DISCRIM}_i + \varepsilon_{i,}\end{aligned} \qquad (1)$$

where $\mathrm{PV\_MATH}_i$ is the plausible value of PISA score on mathematics literacy of student *i* (*i* = 1, 2, … *N*), α is the common intercept, β_j is the corresponding coefficient regression, and ε_i is the statistical noise.

Table 1. Independent variables.

Variable	Description
AGE	Age of student.
GENDER	Gender of student.
SMINS	Learning time of science per week (min.)
MMINS	Learning time of math. per week (min.)
RMINS	Learning time of reading per week (min.)
ESCS	Index of economic, social, and cultural status. *Indicators*: • Highest occupation of the parent. • Education of the parent. • Possessions at home.
WEALTH	Index of family wealth. *Indicators*: Do you have this at home? • Room of your own. • Internet. • Washing machine. • Refrigerator.

Variable	Description
	• Car. • Television. • Rooms with a bath or shower. • Smart phones with internet access. • Computer. • Tablet computers. • E-book readers.
ICT	ICT available at home. *Indicators*: Do you have this at home? • Educational software. • Internet. • Cell phone with internet access. • Computer. • Tablet computers. • E-book readers.
PERFEED	Index of perceived feedback from teacher. *Indicators*: How often does this happen? The teacher: • communicates to me how I am doing in this course. • provides feedback on my strengths. • communicates to me in which fields I can develop. • communicates to me how I can develop my performance. • gives an opinion to me on how to attain my goals of learning.
DISCRIM	Index of discriminating school climate. *Indicators*: Teachers in your school: • have false impressions about the history of some cultural groups. • tell discouraging opinions about people of some cultural groups. • blame people of some cultural groups for Indonesia's problems. • have lower academic expectations for students of some cultural groups.

4 Results

4.1 Parameters estimation

Student's average performance in mathematics for each country in South-east Asian countries is displayed in Figure 1. On average across six South-east Asian countries, students scored 431 points in mathematics. Singapore (SGP) has the highest point as 561; whereas the Philippines (PHL) has the lowest points as 353. Other than the Philippines, Indonesia's (IDN) and Thailand's (THA) points are below the South-east Asia's average points, whereas Brunei Darussalam (BRN), Malaysia (MYS), and Vietnam (VNM) have the average points above the average.

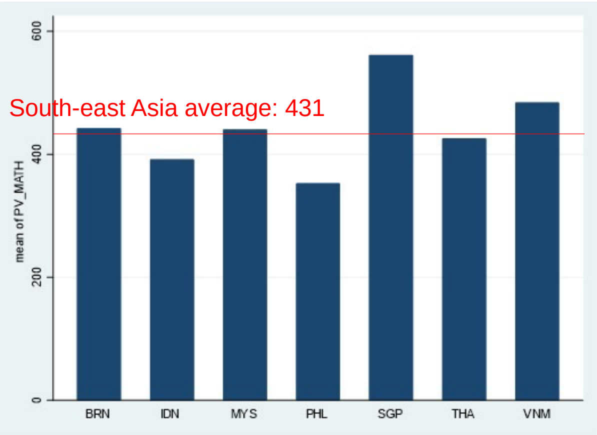


Fig. 1. PISA score of mathematics literacy for countries in South-east Asia.

Parameters are estimated using the ordinary least square method. The result is shown in Table 2. A sign of the coefficient can be translated as the following. The sign of the positive coefficient shows that as the value of the independent variable rises, the expected value of the dependent variable also tends to rise; and as the independent variable's value decreases, the dependent variable's expected value also tends to decrease. This value indicates how much the expected value of the dependent variable changes given a one-unit shift in the specific independent variable while holding other independent variables constant. It is critical as it allows to evaluate the influence of each variable in isolation from the others. Not only the sign, but we also have to look at the significancy of the coefficients. All variables but GENDER have statistically significant coefficients. It means that only student's gender does not have influence on student's performance measured by PV of mathematics.

Table 2. Parameters estimation.

Variable	Coef.	Standard Error	*p-value*	VIF	PV2
Constant	438.796	39.69477	0.000*		374.486*
GENDER:					
Male	-5.331	1.418	0.000*	1.03	-1.117
AGE	1.448	2.505	0.563	1.00	5.410*
SMINS	0.062	0.005	0.000*	2.31	0.049*
MMINS	0.033	0.007	0.000*	3.79	0.030*
RMINS	-0.808	0.006	0.000*	2.88	-0.066*
ESCS	9.801	1.052	0.000*	2.84	10.783*
WEALTH	-4.322	1.362	0.002*	4.94	-7.380*
ICT	26.323	1.325	0.000*	4.09	23.226*
PERFEED	-9.544	0.756	0.000*	1.01	-6.190*
DISCRIM	-14.629	0.685	0.000*	1.04	-15.920*

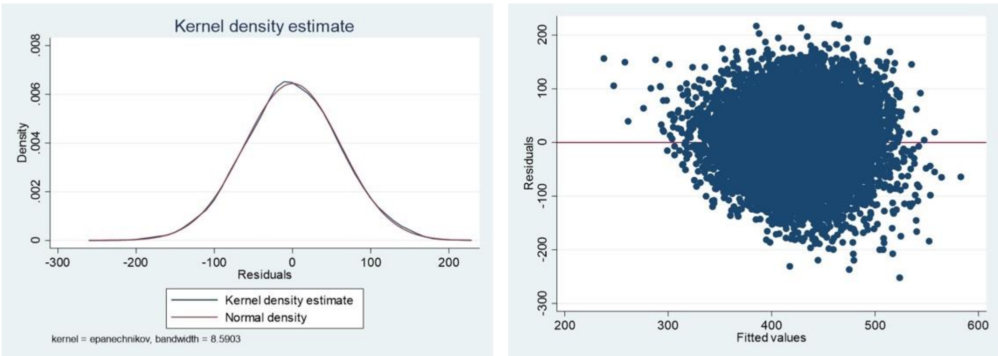
*significant at the level of 5%

The anticipated positive value of ESCS specifies as the higher the economic, social, and cultural status of the student, the higher the PISA score on mathematics will be obtained. This finding confirms the result of other studies (e.g., [11], [12], [13], [14]). The positive sign is also found in ICT, meaning that the more student has ICT-related devices (e.g., desktop computer, tablet computer, cell phone), the higher the PV would be.

4.2 Testing the classical assumptions

In this section, I will show how to test the classical assumption. The first test is checking the normality of the residual. I use a kernel density plot which is shown in Figure 2 (a). Note that the residual plot resembles normal distribution. The Shapiro-Wilk test for normality is also used; result shows that *p*-value is 0.3255 (more than the significant level of 5%). It means that the null hypothesis that the residual follows normal distribution cannot be rejected. Other classical assumption is the homogeneity of the residuals' variance. If the residuals' variance is not constant, then the variance of the residual is "heteroscedastic". The homoscedastic condition reflects when there is no pattern if the residuals are plotted against the fitted values. A graphical method is used to investigate the heteroscedasticity, as shown in Figure 2 (b). As we can see in Figure 3 (b), there is pattern in the graph, indicating no problem of heteroscedasticity.

The next is to identify the multicollinearity. Collinearity denotes the condition that two variables are almost perfect linear combinations of the other. Multicollinearity denotes when more than two variables are involved. As the degree of multicollinearity increases, the regression model estimates of the coefficients become unstable and the standard errors for the coefficients can get wildly inflated. To check this issue, I use the variance inflation factor (VIF). As a rule of thumb, a variable whose VIF values are greater than 10 may merit further investigation. The result is shown in Table 2 under the column VIF. Note that the VIF values for all independent values are lower than 10, indicating no multicollinearity issue.



(a) Normality assumptions (b) Homogeneity of variance of residuals

Fig. 2. Testing the classical assumptions.

4.3 Robustness Checking

I then perform a test to examine the robustness of the finding. Specifically, I examine whether the sign and significancy of the variables differs when another PV as dependent variable is used. In the literature of academic performance, we actually cannot observe student proficiencies as these must be inferred from the observed item responses (in PISA, they are item questions in the PISA assessment). PISA uses the imputation methodology referred to as PVs.

They are a selection of likely proficiencies for students that attained each score. In this examination, it is expected that if the dependent variable is changed with other similar value which measures (as a proxy of) student proficiencies, the result would not change that much. If so, the model is said to be not robust. Result of the robustness analysis is shown in Table 2 under the column PV2.

Notice that the sign and significancy of all coefficients are not changed. For instance, the coefficients of AGE, ESCS, and ICT are still significant with positive value. The coefficients of RMINS, WEALTH, and PERFEED are still significant with negative value. The coefficient of GENDER is still not statistically significant. The values of the coefficients, if one observes, are slightly similar; the difference is trivial. In sum, it could be said that the model is robust.

5. Conclusion

This paper investigates the determinants of Indonesian students' performance proxied by PV score of mathematics provided by OECD PISA. The recent PISA data of 2018 wave is used to answer this research question. A multivariate linear regression is used. Result shows that student's performance on mathematics is driven by student's age, learning time in mathematics, science, and reading, index of economic, social, and cultural status, family wealth, ICT possession at home, perceived feedback from teacher, and discriminating school climate. The classical assumption is also tested (i.e., normality, heteroscedasticity, and multicollinearity) to show that the estimation is valid. The robustness check is also performed to show that the model is robust.

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