THE DETERMINANTS OF INDONESIAN STUDENTS' MATHEMATICS PERFORMANCE: AN ANALYSIS THROUGH PISA DATA 2015 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 PISA 2015 data is used to answer this research question. A multivariate linear regression is used; as the dependent variable is PV of mathematics, while the information concerning student's background is used as independent variables, i.e., student's personal characteristics: age and gender; family background: index of economic, social, and cultural status as well as ICT possession at home; and classroom's climate: perceived feedback from teacher. Result shows that all determinants but student's gender are significant at the level of 5%. Several tests to examine the classical assumptions, such as normality of the residuals, test for heteroscedasticity and collinearity are performed. According to these tests, no severe problems occur.

Keywords: Indonesia, Students, Mathematics, Multivariate Regression, PISA.

INTRODUCTION

The emergence of international large-scale assessments in the past two decades has consistently provided educational researchers with large databases containing diverse types of variables (i.e., student's performance and background, school practices, etc.). Assessment schemes such as the Programme for International Student Assessment (PISA) from the Organisation for Cooperation and Economic Development (OECD) has had a noticeable impact on the development of educational research in past years (Gamazo et al., 2016).

It has been observed that educational policies are usually influenced by the reports and analyses elaborated directly by the OECD, because these are the first ones presented to the public after a given PISA wave (Wiseman, 2013). Because these analyses can be somewhat limited considering the vast array of variables that PISA offers, there is a certain responsibility for educational researchers to delve deeper into the databases and find relationships among variables and conclusions that might not be offered by the OECD reports in order to enrich the political debate around the topic.

Secondary analyses of PISA data can be performed through the use of different methodologies. One of the most common ones is multilevel regression analysis, given that it allows researchers to account for the variability at the level of students and schools at the same time, e.g., (Willms, 2010). Other authors have opted for different methods, such as Structural Equation Modelling (e.g., Acosta & Hsu, 2014; Barnard-Brak et al., 2018) or analysis of covariance (e.g., Smith et al., 2018; Zhu & Kaiser, 2020). The recent data mining technique also has appeared in the past few years as one of the emerging techniques to analyse PISA data (e.g., Gamazo & Martínez-Abad, 2020; She et al., 2019; Martínez-Abad, 2019).

This study tried to extend the practice of multivariate linear regression to explore the determinants of Indonesia students' mathematics performance. Given that

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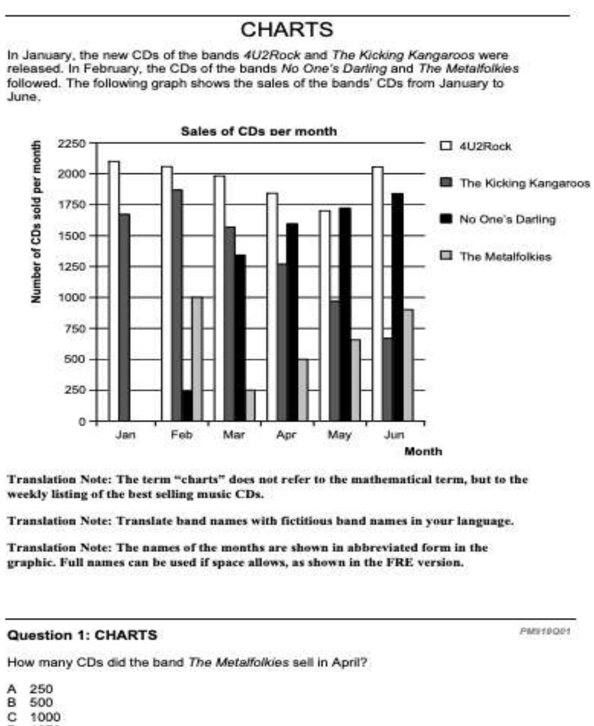
identifying the factors behind students' performances is crucial considering the importance of improving the educational system.

OECD PISA

PISA is an international assessment that measures 15-year-old students' reading, mathematics, and science literacy every three years. First conducted in 2000, the major domain of study rotates between reading, mathematics, and science in each cycle. PISA also includes measures of general or cross-curricular competencies, such as collaborative problem solving. By design, PISA emphasizes functional skills that students have acquired as they near the end of compulsory schooling. PISA is coordinated by OECD, an intergovernmental organization of industrialized countries. The PISA 2018 wave focused on reading, with science and mathematics as minor areas of assessment. The example of PISA question on mathematics literacy is shown in Figure 1.


CHARTS

In January, the new CDs of the bands *4U2Rock* and *The Kicking Kangaroos* were released. In February, the CDs of the bands *No One's Darling* and *The Metalfolkies* followed. The following graph shows the sales of the bands' CDs from January to June.

Translation Note: The term "charts" does not refer to the mathematical term, but to the weekly listing of the best selling music CDs.

Translation Note: Translate band names with fictitious band names in your language.

Translation Note: The names of the months are shown in abbreviated form in the graphic. Full names can be used if space allows, as shown in the FRE version.

Question 1: CHARTS *PM918Q01*

How many CDs did the band *The Metalfolkies* sell in April?

A 250
B 500
C 1000
D 1270

Figure 1. Example of PISA question on mathematics literacy

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 (or the determinants) is shown in Table 1. Note that indicators of a particular index are also given in Table 1.

Table 1. Description of independent variables (determinants)

Determinants	Description
AGE	Student's age.
GENDER	Student's gender.
ESCS	Index of economic, social, and cultural status. *Indicators*: • Highest parental occupation. • Parental education. • Home possessions.
ICT	ICT available at home. *Indicators*: Do you have this at home? • Educational software. • Internet. • Cell phone with internet access. • Computer (desktop computer, portable laptop, or notebook). • Tablet computers (e.g., iPad, BlackBerry, PlayBook). • E-book readers (e.g., Kindle, Kobo, Bookeen).

PERFEED	Index of perceived feedback from teacher. *Indicators*: How often does this happen in [class]? • The teacher tells me how I am performing in this course. • The teacher gives me feedback on my strengths subject. • The teacher tells me in which areas I can still improve. • The teacher tells me how I can improve my performance. • The teacher advises me on how to reach my learning goals.

EMPIRICAL MODEL

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

$$PV\_MATH_i = \alpha + \beta_1 AGE_i + \beta_2 GENDER_i + \beta_3 ESCS_i + \beta_4 ICT_i + \beta_5 PERFEED_i + \varepsilon_i, \quad (1)$$

where PV_MATHi is the plausible value of PISA score on mathematics literacy of student *i* ($i = 1, 2, \ldots N$), α is the common intercept, β_j is the corresponding coefficient regression, and ε_i is the statistical noise.

RESULTS

Student's average performance in mathematics for each country in South-east Asian countries is displayed in Figure 2. On average across six South-east Asian countries, students scored 431 points in mathematics. Countries with a similar performance are mostly located in Latin America and Southeast Europe, such as Bulgaria, Colombia, Romania, Serbia, and Uruguay. 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.

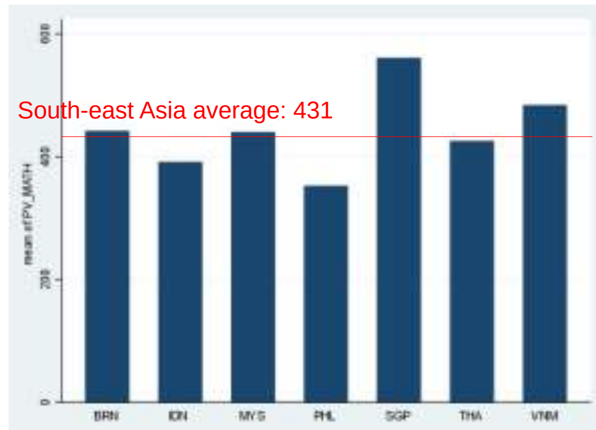


Figure 2. PISA score of mathematics literacy for countries in South-east Asia

Parameters estimation

Parameters are estimated using the ordinary least square method. The result of the regression analysis is shown in Table 2. The sign of the regression coefficient can be interpreted as follows. A positive coefficient indicates that as the value of the independent variable increases, the expected value of the dependent variable also tends to increase, vice versa. The value of the coefficient signifies how much the expected value of the dependent variable alters given a one-unit shift in the particular independent variable while holding other independent variables constant. This property is crucial because it allows to assess the effect 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

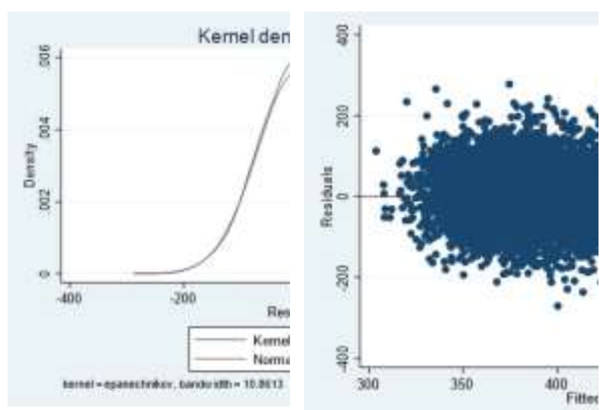
Variable	Coef.	Standard Error	*p*-value	VIF	PV2
Constant	340.5405	52.11573	0.000**		301.1861**
GENDER: Male	1.539922	1.838702	0.402	1.01	0.5964986
AGE	7.586661	3.325144	0.023**	1.00	10.20445**
ESCS	16.14249	1.243912	0.000**	2.30	16.23016**
ICT	17.87351	1.304479	0.000**	2.31	18.12146**
PERFEED	-10.521	1.147819	0.000**	1.01	-9.636422**

**significant at the level of 5%

The anticipated positive value of ESCS indicates as the higher the economic, social, and cultural status of the student, the higher the PISA score on mathematics will be obtained. As no direct income measure has been available from the PISA data, the existence of household items has been used as a proxy for family wealth. This finding confirms the result of other studies (e.g., Perelman & Santín, 2011; Salas-Velasco, 2020; Ulkhaq, 2021, 2022). 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.

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 that can be thought of as a histogram with narrow bins and moving average. The graph is shown in Figure 3 (a). Note that the residual plot resembles normal distribution. It means that we cannot reject that residual is normally distributed. Other classical assumption is the homogeneity of variance of the residuals. If the model is well-fitted, there should be no pattern to the residuals plotted against the fitted values. If the variance of the residuals is non- constant, then the residual variance is said to be "heteroscedastic". A commonly used graphical method is to plot the residuals versus fitted values as shown in Figure 3 (b). As we can see in Figure 3 (b), there is pattern in the graph, indicating no heteroscedasticity. The term collinearity implies that two variables are near perfect linear combinations of one another. When more than two variables are involved, it is called multicollinearity. The primary concern in this sense is that 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 assumption

(b) Heteroscedasticity test

Figure 3. Testing the classical assumptions

Robustness checking

Next, I 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. They are like missing data that must be inferred from the observed item responses (in PISA, they are item questions in the PISA assessment). There are several possible alternative approaches for making the inference. 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 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.

CONCLUSION

This paper investigates the determinants of Indonesian students' performance proxied by PV score of mathematics provided by OECD PISA. The PISA 2015 data 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, index of economic, social, and cultural status, ICT possession at home, and perceived feedback from teacher. 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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