# 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 in mathematics proxied by plausible value (PV) of mathematics provided by OECD PISA. The recent PISA data of the 2018 wave is used to answer this research question. Using multivariate linear regression, the student's background information is utilized as independent factors while the student's characteristics, or PV of mathematics, functions as the dependent variable. Age, gender, the learning time in mathematics, science, and reading; family background: indicator of family wealth, social class, and cultural status, ICT possession at home; and classroom's climate: perceived feedback from the teacher, and discriminating school climate. The result shows that all determinants (independent variables) but students' age are significant at the level of 5%. We also perform several tests to examine the classical assumptions, such as normality of the residuals, and test for heteroscedasticity and collinearity. According to these tests, no severe problems occur.

**Keywords:** Mathematic performance · Multivariate regression · PISA data · Student's achievement

## 1 Introduction

In the past two decades, the advent of international large-scale assessments has consistently given educational researchers access to vast databases with a variety of features (such as student performance and background, educational practices, etc.). Assessment schemes such as the Programme for International Student Assessment (PISA) from the Organisation for Cooperation and Economic Development (OECD) have had a noticeable impact on the development of educational research in past years [1].

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 [2]. There is a duty on the part of educational researchers to delve deeper into the databases and uncover relationships between variables and conclusions that might not be provided by the OECD reports in order to enrich the political discussion surrounding the subject because these analyses can be somewhat restricted given the vast array of variables that PISA offers.


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PISA data can be subjected to secondary analyses using a variety of approaches. 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., [3]. Other authors have opted for different methods, such as Structural Equation Modelling [4] or analysis of covariance [5, 6]. The recent data mining technique also has appeared in the past few years as one of the emerging techniques to analyze PISA data [7].

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

## 2 Ease of Use

A. OECD PISA

Every three years, the PISA international assessment evaluates the reading, math, and science literacy of 15-year-old children. The core subject area rotates between reading, mathematics, and science since it was conducted in 2000. in each cycle [8]. Measures of general or cross-curricular competencies, like collaborative problem-solving, are also included in PISA. By design, PISA emphasizes functional students' skills as they approach the end of their compulsory schooling. OECD oversees PISA coordination., an intergovernmental organization of industrialized countries. Science and mathematics were only assessed to a minor extent in PISA 2018's reading component. The example of a PISA question on mathematics literacy is shown in Fig. 1.

B. Data and Variables

The data were collected from the OECD PISA database of the 2018 wave. The data has rich information about the student, school, and parent status. In this paper, I focus my attention on Indonesian 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 a particular index are also given in Table 1. The template is used to style the text and format your paper. Please follow the recommended margins, column widths, line row spacing, and text fonts. You may notice oddities. For instance, this template's head margin measures proportionately more than is customary. This measurement and others are deliberate, utilizing standards that presume your report will be a component of the entire proceedings rather than a stand-alone piece of writing. Please don't change any of the identifiers that are in place right now.

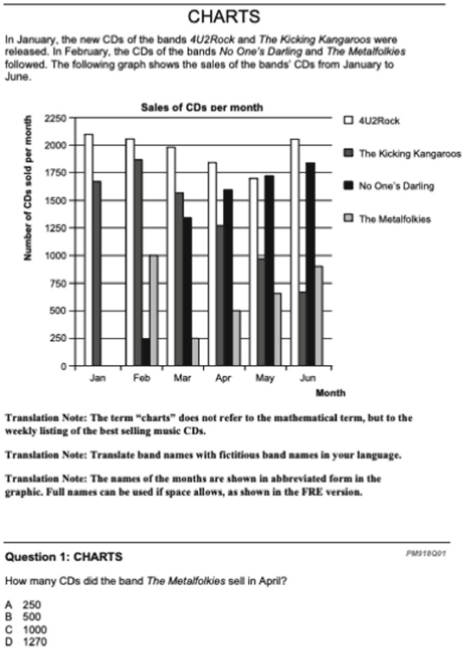



**Fig. 1.** Example of PISA question on mathematics literacy. (Source: OECD).

**Table 1.** Description of independent variables

| Variable | Description |
|---|---|
| AGE | Age of the student |
| GENDER | Gender of a 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 social, cultural, and economic status.<br>• Highest parental occupation is an indicator.<br>• Parental training.<br>• Items from the house. |

(*continued*)

**Table 1.** (*continued*)

| Variable | Description |
|---|---|
| WEALTH | Index of family wealth.<br>*Indicators*: Do you have this at home?<br>• Room of your own.<br>• Internet.<br>• Washing machine.<br>• Refrigerator.<br>• Car.<br>• Television.<br>• Cell phones with internet access;<br>• Bathrooms with a bathtub or shower.Computer (desktop computer, portable laptop, or notebook).<br>• Tablet computers (e.g., iPad, BlackBerry, PlayBook).<br>• E-book readers (e.g., Kindle, Kobo, Bookeen). |
| ICT | ICT available at home.<br>*Indicators*: Do you have this at home?<br>• Educational software.<br>• Internet.<br>• Cell phone with internet access.<br>• Technology (desktop computer, portable laptop, or notebook).<br>• Tablet computers (e.g., iPad, BlackBerry, PlayBook).<br>• E-book readers (e.g., Kindle, Kobo, Bookeen). |
| PERFEED | Index of perceived feedback from teacher.<br>*Indicators*: How often does this happen in [mathematics lessons]?<br>• My teacher offers feedback on how I did in this course.<br>• The teacher gives me feedback on my strengths [mathematics lessons] subject.<br>• The tutor clarifies for me which areas I can still improve.<br>• My tutor provides feedback on how I can raise my performance..<br>• My teacher offers guidance on how to achieve my learning objectives. |
| DISCRIM | Index of discriminating school climate.<br>*Indicators*: Teachers in your school:<br>• They have misconceptions about the history of some cultural groups.<br>• They say negative things about people of some cultural groups.<br>• They blame people of some cultural groups for problems faced by Indonesia.<br>• They have lower academic expectations for students of some cultural groups. |

## 3 Empirical Model

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

$$\begin{aligned}\mathrm{PV\_MATHi} &= \alpha + \beta_1\mathrm{AGE}_i + \beta_2\mathrm{GENDER}_i + \beta_3\mathrm{SMINS}_i + \beta_4\mathrm{MMINS}_i \\ &+ \beta_5\mathrm{RMINS}_i + \beta_6\mathrm{ESCS}_i + \beta_7\mathrm{WEALTH}_i + \beta_8\mathrm{ICT}_i \\ &+ \beta_9\mathrm{PERFEED}_i + \beta_{10}\mathrm{DISCRIM}_i + \varepsilon_i,\end{aligned} \tag{1}$$

**where**:

$PV_{\_MATHi}$ = plausible value of PISA score on mathematics literacy of student $i$ ($i = 1, 2, \ldots N$).

$\alpha$ = intercept.

$\beta_j$ = corresponding coefficient regression.

$\varepsilon_i$ = statistical noise.

## 4 Result

Students' average performance in mathematics for each country in Southeast Asian countries is displayed in Fig. 2. On average across six Southeast Asian countries, students scored 431 points in mathematics. Countries with similar performance are mostly located in Latin America and Southeast Europe, such as Bulgaria, Colombia, Romania, Serbia, and Uruguay. Singapore has the highest point of 561; whereas the Philippines has the lowest point of 353. Other than the Philippines, Indonesia's and Thailand's points are below South-east Asia's average points.

Note: BRN stands for Brunei Darussalam; IDN for Indonesia; MYS for Malaysia; PHL for the Philippines; SGP for Singapore; THA for Thailand; and VNM for Vietnam.

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 the given emphasis is. When the coefficient is positive, it means that the independent variable increases, the dependent variable's anticipated value similarly tends to rise., and 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 [9]. This property is crucial because it allows assessing the effect of each variable in isolation from the others. Not only the sign, but we also have to look at the significance of the coefficients. All variables but GENDER have statistically significant coefficients. It means that only a student's gender does not have an influence on a student's performance measured by PV of mathematics.

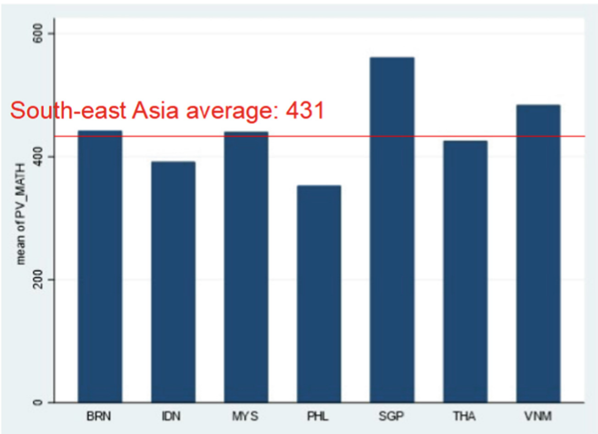



**Fig. 2.** PISA score of mathematics literacy for countries in South-east Asia

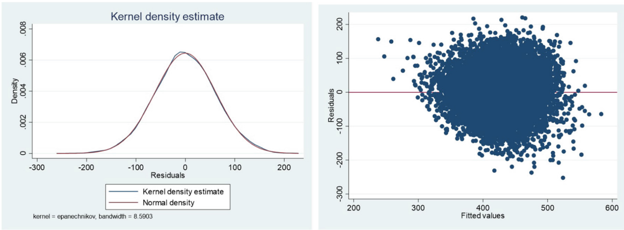
**Table 2.** Parameters estimation

| Variable | Coef. | Standard Error | *p-value* |
|---|---|---|---|
| Constant | 438.796 | 39.69477 | 0.000* |
| GENDER: Male | −5.331 | 1.418 | 0.000* |
| AGE | 1.448 | 2.505 | 0.563 |
| SMINS | 0.062 | 0.005 | 0.000* |
| MMINS | 0.033 | 0.007 | 0.000* |
| RMINS | −0.808 | 0.006 | 0.000* |
| ESCS | 9.801 | 1.052 | 0.000* |
| WEALTH | −4.322 | 1.362 | 0.002* |
| ICT | 26.323 | 1.325 | 0.000* |
| PERFEED | −9.544 | 0.756 | 0.000* |
| DISCRIM | −14.629 | 0.685 | 0.000* |

The anticipated positive value of According to ESCS, the higher the country's economic, social, and cultural student, the higher the PISA score on mathematics will be obtained. The existence of home items has been utilized as a stand-in for family wealth because there has been no direct income measure available from the PISA data. This finding confirms the result of other studies [10–12]. 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**

I'll show how to verify the classical premise in this part. The residual's normality is tested as the first step. I employ a kernel density plot, which is a moving average-based histogram with narrow bins.. The graph is shown in Fig. 3 (a). Note that the residual plot resembles a normal distribution. I also use the Shapiro-Wilk test for normality; the result shows that the p-value is 0.3255 (more than the significant level of 5%). It means that we cannot reject that residual is normally distributed. The residuals' homogenous variance is a further fundamental premise. The residuals shown against the fitted values should just not show any trend if the model is well-fitted. The residual variance is said to as "heteroscedastic" if the residual variance is non-constant. Plotting the residuals versus the fitted values is a typical graphic technique. as shown in Fig. 3 (b). As we can see in Fig. 3 (b), there is a pattern in the graph, indicating no heteroscedasticity. The term collinearity implies that two variables are near-perfect linear combinations of one another [11]. Multicollinearity is the term used when more than two variables are present. The main issue in this sense is that the estimates of the regression model coefficients become unstable as the degree of multicollinearity rises, and the standard errors for the coefficients might become greatly inflated. To examine this problem, I use the variance inflation factor (VIF). It is generally advised to look at a variable further if




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

**Fig. 3.** Testing the classical assumptions

**Table 3.** VIF values

| Variable | VIF Values |
|---|---|
| GENDER | 1.03 |
| AGE | 1.00 |
| SMINS | 2.31 |
| MMINS | 3.79 |
| RMINS | 2.88 |
| ESCS | 2.84 |
| WEALTH | 4.94 |
| ICT | 4.09 |
| PERFEED | 1.01 |
| DISCRIM | 1.04 |

its VIF values are more than 10. The result is shown in Table 3. Note that the VIF values for all independent values are lower than 10, indicating no multicollinearity issue.

**Robustness Checking**

We perform a test to examine the robustness of the finding. Specifically, I examine whether the sign and significance of the variables differ when another PV as a dependent variable is used. In the literature on 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) [13]. Making the inference can be performed in a number of different ways. The imputation technique known as PVs is used in PISA. They provide a sample of students' predicted proficiencies for 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 as displayed in Table 4.

**Table 4.** Robustness checking

| Variable | Baseline | PV2 |
|---|---|---|
| Constant | 314.551* | 374.486* |
| GENDER: Male | −0.215 | −1.117 |
| AGE | 9.570* | 5.410* |
| SMINS | 0.051* | 0.049* |
| MMINS | 0.027* | 0.030* |
| RMINS | −0.069* | −0.066* |
| ESCS | 9.950* | 10.783* |
| WEALTH | −6.607* | −7.380* |
| ICT | 24.863* | 23.226* |
| PERFEED | −6.425* | −6.190* |
| DISCRIM | −17.051* | −15.920* |

Significant at the level of 5%

Notice that the sign and significance of all coefficients are not changed. For instance, the coefficients of AGE, ESCS, and ICT are still significant with positive values. The coefficients of RMINS, WEALTH, and PERFECTED are still significant with a 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 the PV score of mathematics provided by OECD PISA. The recent PISA data of the 2018 wave is used to answer this research question. Multivariate linear regression is used. The result shows that students' performance in mathematics is driven by student age, learning time in mathematics, science, and reading, index of economic, social, and cultural status, family wealth, ICT possession at home, perceived feedback from the 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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