Proceeding International Conference on Religion, Science and Education (2023) **2**, 1061-1066

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

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Abstract: This study investigates the determinants of Indonesian students' performance of science proxied by the PISA score of science provided by OECD PISA. The recent PISA data 2018 is used to answer the objective of the research. A multivariate linear regression is used; as the dependent variable is the PISA score of science, while the information concerning student's background is used as independent variables, i.e., (i) student's personal characteristics: age and gender; (ii) family background: index of economic, social, and cultural status (ESCS), family wealth, ICT possession at home; and (iii) classroom's climate: learning time in mathematics, science, and reading, perceived feedback from teacher, and discriminating school climate. Result shows that Indonesian students' science performance is driven by age, learning time in mathematics, science, and reading, ESCS, family wealth, ICT possessions at home, perceived feedback from teacher, and discriminating school climate. 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. This study is expected to provide insight on how to improve student's performance in the field of science.

Keywords: Indonesian students, multivariate regression, PISA, science performance.

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 and Hsu (2014), Barnard-Brak et al. (2018) or analysis of covariance, e.g., Smith et al. (2018), Zhu and 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 and Martínez-Abad (2020), She et al. (2019), Martínez-Abad (2019).

ISSN 2829-3355 | EISSN 2828-8467

This study tried to extend the practice of multivariate linear regression to explore the determinants of Indonesia students' science performance. Given that 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 science literacy is shown in Figure 1.

Read the following newspaper article and answer the questions which follow.

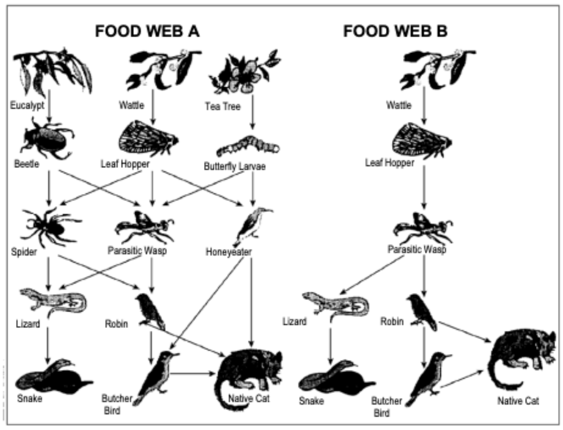
BIODIVERSITY IS THE KEY TO MANAGING ENVIRONMENT

An ecosystem that retains a high biodiversity (that is, a wide variety of living things) is much more likely to adapt to human-caused environment change than is one that has little.

Consider the two food webs shown in the diagram. The arrows point from the organism that gets eaten to the one that eats it. These food webs are highly simplified compared with food webs in real ecosystems, but they still illustrate a key difference between more diverse and less diverse ecosystems.

Food web B represents a situation with very low biodiversity, where at some levels the food path involves only a single type of organism. Food web A represents a more diverse ecosystem with, as a result, many more alternative feeding pathways.

Generally, loss of biodiversity should be regarded seriously, not only because the organisms that have become extinct represent a big loss for both ethical and utilitarian (useful benefit) reasons, but also because the organisms that remain have become more vulnerable (exposed) to extinction in the future.



Source: Adapted from Steve Malcolm: 'Biodiversity is the key to managing environment', *The Age*, 16 August 1994.

Question 3: BIODIVERSITY *S126Q03*

In lines 9 and 10 it is stated that "Food web A represents a more diverse ecosystem with, as a result, many more alternative feeding pathways."

Look at FOOD WEB A. Only two animals in this food web have three direct (immediate) food sources. Which two animals are they?

A Native Cat and Parasitic Wasp
B Native Cat and Butcher Bird
C Parasitic Wasp and Leaf Hopper
D Parasitic Wasp and Spider
E Native Cat and Honeyeater

Figure 1. Example of PISA question on science 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 science performance is proxied by the plausible value (PV) of science 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.

Table 1. Independent variables

Variables	Description
AGE	Student's age.
GENDER	Student's gender.
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 parental occupation, parental education, home possessions.
WEALTH	Index of family wealth. *Indicators*: Do you have this at home? room of your own, internet, washing machine, refrigerator, car, television, rooms with a bath or shower, cell phones with internet access, computer (desktop computer, portable laptop, or notebook), and tablet computers (e.g., iPad, BlackBerry, PlayBook). E-book readers (e.g., Kindle, Kobo, Bookeen).
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), and 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.
DISCRIM	Index of discriminating school climate. *Indicators*: Teachers in your school: • They have misconceptions about the history of some cultural groups. • They say negative things about people of some cultural groups. • They blame people of some cultural groups for problems faced by Indonesia. • They have lower academic expectations for students of some cultural groups.

Empirical Model

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

$$PV\_SCIE_i = \alpha + \beta 1AGE_i + \beta 2GENDER_i + \beta 3SMINS_i + \beta 4MMINS_i + \beta 5RMINS_i + \beta 6ESCS_i + \beta 7WEALTH_i + \beta 8ICT_i + \beta 9PERFEED_i + \beta 10DISCRIM_i + \varepsilon_i, \quad (1)$$

where PV_SCIE is the plausible value of PISA score on science literacy, α is the common intercept, βi is the corresponding coefficient regression, εi is the statistical noise, and i is the subscript indicating the student (i = 1, 2, … N).

Results

Estimation parameters

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 science.

Table 2. Parameters estimation

Variables	Coef.	Std. Error	*t*-value	*p*-value
Constant	314.551	34.227	9.19	0.000*
GENDER:				
Male	-0.215	1.223	-0.18	0.860
AGE	9.570	2.160	4.43	0.000*
SMINS	0.051	0.004	11.33	0.000*
MMINS	0.027	0.006	4.22	0.000*
RMINS	-0.069	0.005	-12.71	0.000*
ESCS	9.950	0.907	10.97	0.000*
WEALTH	-6.607	1.174	-5.62	0.000*
ICT	24.863	1.143	21.75	0.000*
PERFEED	-6.425	0.652	-9.85	0.000*
DISCRIM	-17.051	0.590	-28.87	0.000*

*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 science 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., Ulkhaq (2021, 2022a, b, c), Perelman and Santín (2011), Salas-Velasco (2020). The positive sign is also found in ICT, meaning that the more student has 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 2. Note that the residual plot resembles normal distribution. I also use the Shapiro-Wilk test for normality; result shows that p-value is 0.3255 (more than significant level of 5%). It means that we cannot reject that residual is normally distributed.

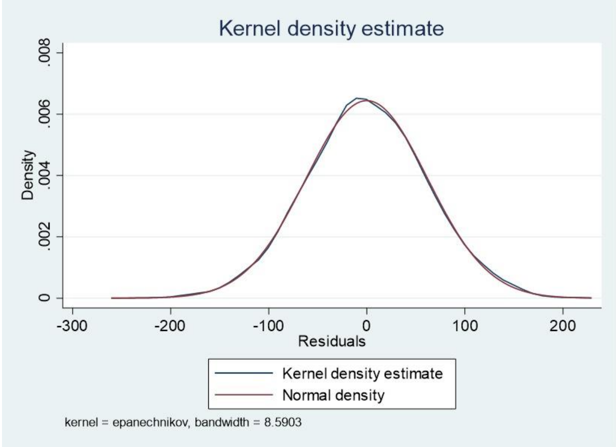


Figure 2. Normality of residuals checking.

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. As we can see in Figure 3, there is pattern in the graph, indicating no heteroscedasticity.

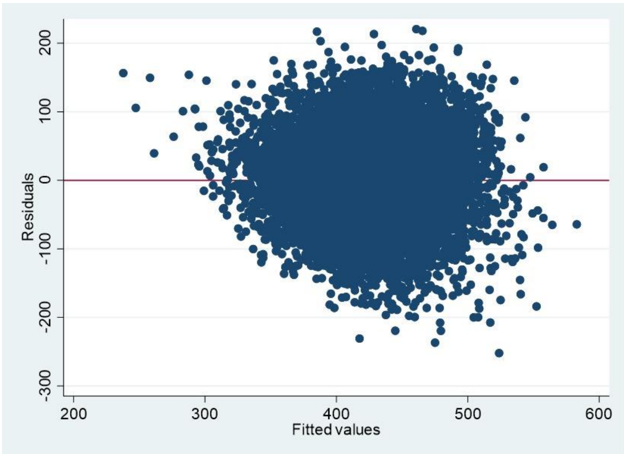


Figure 3. Heteroscedasticity checking.

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 3. Note that the VIF values for all independent values are lower than 10, indicating no multicollinearity issue.

Table 3. VIF values.

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

Robustness checking

I also 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. The result is shown in Table 4 under column PV2.

Table 4. Robustness checking's result

Variables	Coef.	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 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.

Conclusion

This paper investigates the determinants of Indonesian students' performance proxied by PV score of science 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 science 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 multi-collinearity) to show that the estimation is valid. The robustness check is also performed to show that the model is robust.

Conflict of Interest: o conflicts of interest concerning the publication of this article.

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