TURJE
www.turje.org

2024
Volume: 13 Issue: 4

Turkish Journal of Education

https://doi.org/10.19128/turje.1474213
Research Article

Received 26.04.2024
Accepted 19.10.2024

Investigation of the relationship between socioeconomic status and literacy in PISA Türkiye data

Mehmet Can Demir
Bartın University, Department of Educational Sciences, Bartın, Türkiye, mehmetdemir@bartin.edu.tr
Kübra Atalay-Kabasakal
Hacettepe University, Department of Educational Sciences, Ankara, Türkiye, kkatalay@gmail.com
Murat Doğan Şahin
Anadolu University, Department of Educational Sciences, Eskişehir, Türkiye, muratdogansahin@gmail.com

ABSTRACT Previous researchers have identified socioeconomic status as a significant predictor of achievement/literacy. However, it is important to recognize that the influence of socioeconomic status on literacy may vary at different levels of socioeconomic status. Thus, this study analyzes the relationship between socioeconomic status and literacy scores for all domains in PISA Türkiye data from 2003 to 2022 through the Classification and Regression Trees and linear regression methods. Upon examining the results, separate investigations carried out for the lower and upper socioeconomic status groups indicate that R^2 values were found to be equal to or greater than .80 in 37 out of the 42 analyses. From 2003 to 2009, the R^2 values in both groups were considerably high; however, there has been a notable decline in subsequent periods. The year 2009 demonstrated particularly high R^2 values by ESCS in all domains for both upper and lower groups. Consequently, socioeconomic status exhibited a greater predictive power on literacy scores across all domains in the lower socioeconomic group than upper socioeconomic group.

Keywords: *Classification and Regression Trees (CART), Economic, social, and cultural status (ESCS), Literacy, Programme for International Student Assessment (PISA), Socioeconomic status*

PISA Türkiye verilerinde sosyoekonomik düzey ve okuryazarlık arasındaki ilişkinin incelenmesi

ÖZ Önceki araştırmalar, sosyoekonomik düzeyin başarının/okuryazarlığın önemli bir yordayıcısı olduğunu göstermiştir. Ancak, sosyoekonomik düzeyin okuryazarlık üzerindeki etkisinin farklı sosyoekonomik düzeylerde değişebileceğini kabul etmek önemlidir. Bu nedenle, bu çalışmada, 2003-2022 yılları arasındaki PISA Türkiye verilerinde tüm alanlar için sosyoekonomik düzey ve okuryazarlık puanları arasındaki ilişki Sınıflandırma ve Regresyon Ağaçları ve doğrusal regresyon yöntemleriyle analiz edilmiştir. Sonuçlar incelendiğinde, alt ve üst sosyoekonomik düzey için ayrı ayrı yapılan incelemeler, 42 analizin 37'sinde R^2 değerlerinin .80'e eşit veya .80'den daha yüksek olduğunu göstermektedir. 2003'ten 2009'a kadar her iki grupta da R^2 değerleri oldukça yüksektir; ancak sonraki yıllarda kayda değer bir düşüş yaşanmıştır. 2009 yılı hem üst hem de alt gruplar için tüm alanlarda ESCS'ye göre özellikle yüksek R^2 değerleri göstermiştir. Sonuç olarak, sosyoekonomik düzey, alt sosyoekonomik grupta üst gruba göre daha iyi yordama gücüne sahiptir.

Anahtar Sözcükler: *Ekonomik, sosyal ve kültürel statü (ESCS), Okuryazarlık, Sınıflama ve Regresyon Ağaçlar (CART), Sosyoekonomik düzey, Uluslararası Öğrenci Değerlendirme Programı*

Citation: Demir, M. C., Atalay-Kabasakal, K., & Şahin, M. D. (2024). Investigation of the relationship between socioeconomic status and literacy in PISA Türkiye data. *Turkish Journal of Education, 13*(4), 360-378. https://doi.org/10.19128/turje.1474213

INTRODUCTION

Every three years, except for 2022, the Programme for International Student Assessment (PISA) collects data from approximately 500,000 15-year-old students from more than 70 countries through tests that measure literacy levels in reading, mathematics, and science and questionnaires on variables thought to affect students' literacy (or achievement; hereafter these terms will be used interchangeably) levels. With these data, the students' literacy performance and the variables affecting their performance are analyzed and countries' education systems are evaluated (OECD, 2020).

Evaluating student literacy in various fields and the ranking of countries' performance occupy a significant place in the public eye of all countries participating in PISA. The PISA is designed to evaluate students' capacity to apply their knowledge in practical, real-world contexts (Banerjee & Eryilmaz, 2024). The great significance attributed to the results obtained in PISA has substantial effects on countries' educational policies. In short, large-scale exam results, like PISA, provide countries with detailed information regarding the effectiveness of the elements constituting their education systems such as schools and educational resources, the profiles of students, teachers, and administrators in the system, and the general functioning of educational systems (Arıkan et al., 2020). In light of all this information, it can be argued that identifying the factors that predict student achievement is of utmost importance for the development of countries' educational policies (Strietholt et al., 2019). It is anticipated that the correct identification of these factors and interventions to the most important ones will yield a positive impact on literacy.

Socioeconomic status (SES) refers to the position of an individual or group on the socioeconomic scale, based on social and economic factors such as income, education level and type, occupational prestige, place of residence, and, in some societies, ethnic or religious background (American Psychological Association [APA], 2019). There is a growing body of evidence suggesting that among other factors, SES is a prominent predictor of student achievement (Berliner, 2013; Coşkun & Karadağ, 2023; Erdem & Kaya, 2021; Gamazo & Martínez-Abad, 2020; Perry & McConney, 2010; Schulz, 2005; Wang et al., 2023). A fundamental issue in educational studies is understanding not only the most important predictors but also how to diminish educational disparities (Perry et al., 2022). Therefore, researchers have been increasingly focusing on particularly low SES students to address concerns about educational equity (Lam, 2014). Low SES students typically underperform in their academic endeavors, displaying significantly lower educational achievements (Hair et al., 2015). Conversely, students originating from advantaged SES backgrounds typically exhibit superior performance in PISA (Neuman, 2022).

SES and Literacy in PISA

The social sciences all take it for granted that SES has a significant impact on important life outcomes for individuals. Its significance for academic success is also widely acknowledged (O'Connell, 2019). This can be exemplified by studies conducted on PISA data. After student literacy scores, the index of economic, social, and cultural status (ESCS) is likely the variable that is most frequently utilized in reports and secondary analyses of data from the PISA (Avvisati, 2020). This index aids in addressing pertinent concerns about educational opportunities and inequalities in learning outcomes based on student responses to the context questionnaire. The conception of ESCS, inspired by the North American approach to SES measurement, implies formulating ESCS by integrating various indicators of financial, social, cultural, and human capital resources accessible to students into one cumulative score (Avvisati, 2020) and this index is derived from a principal component analysis of three components; the possessions at home (HOMEPOS), the highest educational level of the parents-in years (PAREDINT) and the highest occupational status of the parents (HISEI) (OECD, 2019a). Based on OECD (2023), these variables can be briefly expressed as follows:

- Home possessions were employed as a surrogate indicator of family wealth. In PISA 2022, students responded to questions regarding the availability of household items at home, including books and country-specific household items that were deemed to be appropriate measures of family wealth in the context of the country. HOMEPOS is a summary index of all household and possession items.

- The index of parents' highest level of education was derived from the median cumulative years of education deemed requisite for completion of the highest level of education attained by parents. The highest parental education index was recoded in PAREDINT.

- Employment data for both the student's father and mother were gathered from responses to open-ended questions. The answers were assigned to four-digit ISCO codes (International Labour Organization, 2007) and then matched to the International Socio-economic Index of Occupational Status (ISEI) using the 2008 version of both (Ganzeboom & Treiman, 2003). Based on this information, the HISEI was calculated, which corresponds to the higher ISEI score of either parent or the ISEI score of the only parent available.

- In computing the ESCS, values were imputed for students with missing data on one of the three components (PAREDINT, HISEI, or HOMEPOS) (see Avvisati, 2020). If students had missing data for more than one component, the ESCS was not imputed, and a missing value was assigned instead. In PISA 2022, the ESCS was computed by giving equal weight to the three components. The final ESCS variable is standardized so that 0 is the score of an average OECD student and 1 is the standard deviation across approximately equally weighted OECD countries.

In brief, the socioeconomic variable in PISA is referred to as ESCS; within this context, it should be taken into account that within the scope of this study, ESCS is considered as the PISA version of SES, and it should not be overlooked that these two concepts are treated as equivalent.

Ever since Coleman's (1968) groundbreaking research on Equality of Educational Opportunity, it has been recognized that SES is a powerful indicator of student performance. Coleman posited that the impact of a student's background surpasses any activities that occur within schools (Jehangir et al., 2015). A considerable amount of research conducted on PISA to date has reported a medium to high correlation between ESCS and literacy (Chi et al., 2018; Chmielewski, 2019; Gorard, 2006; Perry et al., 2022; Tang et al., 2021). Yet another significant consideration is how this relationship varies across different levels of SES. The literature characterizes the relationship between SES and academic achievement as either a socioeconomic gradient, given its gradual increase across the SES continuum, or as a socioeconomic gap, given that it suggests a disparity in academic achievement between students from high and low SES (Jehangir et al., 2015). From this perspective, it can be argued that the relationship between these two variables may not be consistent at every level and that there is a need to focus mainly on the low and high levels in terms of SES.

In numerous studies conducted, it is observed that SES is construed as being low-high (Perry et al., 2022; Tang et al., 2021). However, it appears that studies categorizing this continuous variable as low-high are relatively intuitive. For instance, in their research examining the predictive variables of the 2015 PISA science literacy in low ESCS students, Chi et al. (2018) defined low ESCS students as those in the bottom third of the ESCS score distribution within the sample. Some studies also classified SES as low from one standard deviation below, and conversely, as high (Von Stumm & Plomin, 2014).

In the scope of this study, while focusing on the relationship between ESCS and literacy, an attempt has been made to determine how this relationship varies at low-high ESCS levels. In this study, unlike other studies, the lower-upper groups of the ESCS variable were formed with cut-off values obtained with the CART algorithm instead of distribution values such as median or standard deviation. The study differs from other studies in terms of determining the cut-off point based on the data. Accordingly, Türkiye’s data obtained within the scope of PISA for science, reading, and mathematics performance between 2003-2022 have been used. In each period, regression trees have been used for low-high ESCS students’ classification for each domain. The study primarily focuses on the following research question:

In the 2003-2022 PISA Türkiye data,
1) How does the level of ESCS's prediction of reading literacy scores differ at low and high ESCS levels?
2) How does the level of ESCS's prediction of science literacy scores differ at low and high ESCS levels?
3) How does the level of ESCS's prediction of mathematics literacy scores differ at low and high ESCS levels?

METHOD

The study is descriptive research as it is conducted to describe an existing situation (Fraenkel et al., 2012). The population was 15-year-old students from Türkiye, who participated in PISA 2003, 2006, 2009, 2012, 2015, 2018, and 2022 cycles. Data from the Turkish students in the six cycles were used, and the dataset comprised 39,516 students. The number of students by cycle is given in Table 1.

Table 1.
Number of Students by Cycle

Cycle	2003	2006	2009	2012	2015	2018	2022
n	4845	4934	4967	4806	5859	6855	7250

As shown in Table 1, the number of students participating in PISA has increased each year. The reason for this is thought to be the change in the law that extended compulsory education in Türkiye from 8 to 12 years, aiming to prevent early school leaving and ensure equality in education by increasing enrolment (Ministry of National Education [MoNE], 2012). In Türkiye, 15-year-old students mostly attend grade 10; before the compulsory education law, grade 10 was not compulsory, but became mandatory in 2012. In 2009, the school enrolment rate of 15-year-old Turkish students was 64%, but after the law, it increased to 83% in 2012 (OECD, 2012, 2017).

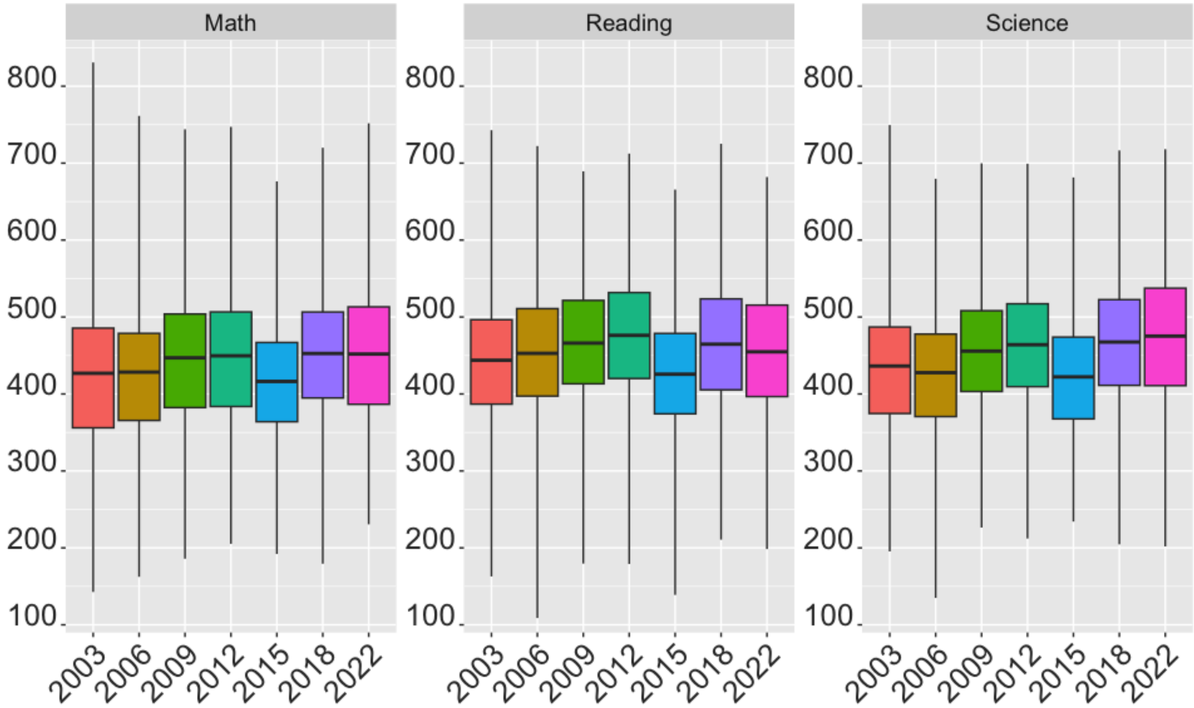
The study was conducted using the measures developed by the OECD: context questionnaires and achievement tests. The context questionnaires comprise items that included economic, educational, socio-demographic information about student outcomes (OECD, 2019b). Performance tests in reading, mathematics, and science involve booklets and each student responded to only a group of these items.

Data analyses were conducted with two main variables: Literacy scores and ESCS. The mean of the plausible values calculated for the relevant domain in each cycle was used as the literacy score for the reading, science, and mathematics domains. Plausible values (PV) are multiple imputations of the unobservable latent literacy for each student and represent the range of abilities that a student might reasonably have, given the student's item responses (Wu, 2005). ESCS index, calculated by PISA for each cycle, was used to classify students into low and high ESCS categories.

ESCS and PV by Year

Before starting the analyses, missing data were checked. According to the missing data analysis, ESCS values of 165 students were missing and these cases were removed (which is less than 5% of the data). Then, descriptive statistics of the PVs and the components of ESCS were given in Figure 1 and 2.

Figure 1.
Boxplots of PVs by Year

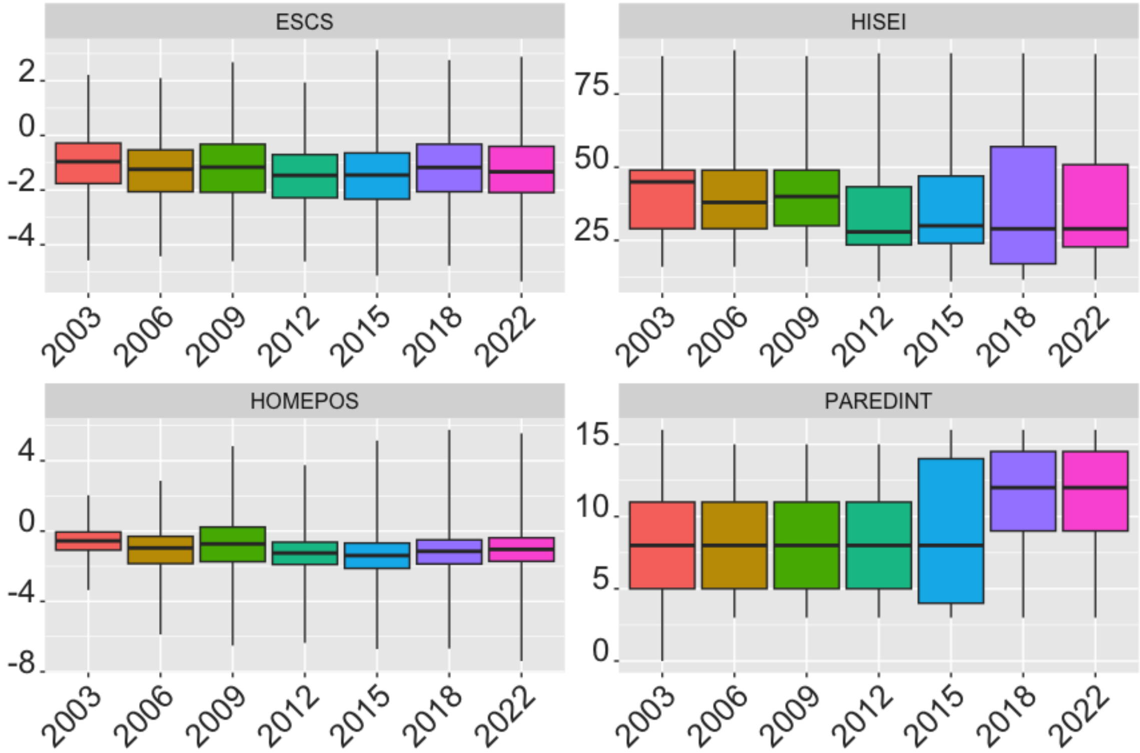


Based on Figure 1, the mean scores for all domains have either remained close to or increased from the previous year, except for 2015, where scores were lower than the preceding and following years. The ranges show that scores typically fall between 200 and 700, although a score above 800 was achieved in 2003, and scores of 150 or less were recorded in 2003, 2006, and 2015.

Upon analyzing the domain scores, it can be observed that the first quartile values for mathematics scores fall within the range of 356 to 395 (356, 365.6, 382.3, 383.7, 363.9, 394.8, 386.6, respectively for the seven cycles), the third quartile values fall within the range of 466 to 513 (485.6, 478.8, 503.9, 506.6, 466.9, 506.5, 513.2, respectively for the seven cycles), and the mean values fall within the range of 427 to 453 (427, 428, 447, 450, 416, 453, 452, respectively for the seven cycles). Similarly, the first quartile values for reading scores fall within the range of 374 to 420 (386.8, 397.2, 413.2, 420.1, 374.2, 405.4, 396.6, respectively for the seven cycles), the third quartile values fall within the range of 478 to 531 (496.5, 510.9, 521.6, 531.8, 478.7, 523.6, 515.5, respectively for the seven cycles), and the mean values fall within the range of 426 to 476 (444, 453, 466, 476, 426, 465, 455, respectively for the seven cycles). The first quartile range for science scores falls between 367 and 411 (374.6, 370.6, 403.2, 409.5, 367.6, 411.2, 410.8, respectively for the seven cycles), the third quartile values range from 473 to 537 (487, 477.8, 508.2, 517.2, 473.9, 522.6, 537.5, respectively for the seven cycles), and the mean values range from 422 to 475 (436, 428, 456, 464, 422, 468, 475, respectively for the seven cycles). Moreover, when comparing domains, it is evident that, except for 2018 and 2022, the reading domain yields the highest mean scores, while the math domain yields the lowest mean scores.

In addition to ESCS, the descriptive statistics for the components of ESCS are presented in Figure 2 below to provide information about the components.

Figure 2.
Boxplots of ESCS and Its Components by Year



When analyzing the ESCS variable values across seven cycles, it is observed that the minimum values fall between -4.4 and -5.34, the first quartile values between -1.7 and -2.3, the median values between -1 and -1.5, the third quartile values between -0.2 and -0.7 and the maximum values between 1.9 and 3.12. The year with the highest median value was 2003 with -0.96, while the year with the lowest median value was 2012 with -1.46.

When analyzing the HISEI values over seven cycles, it is evident that the minimum values range from 11 to 16, the first quartile values range from 17 to 30, the median values range from 28 to 45, the third quartile values range from 43 to 49, and the maximum values range from 88 to 90. The year 2003 shows the highest median value of 45, while the year 2012 displays the lowest median value of 28.

When analyzing the values of PAREDINT across seven cycles, it is evident that the minimum values ranged from 0 in 2003 to 3 between 2006-2022. Additionally, the first quartile values ranged from 4 in 2015 to 9 in 2018 and 2022, with a median value of 8 between 2003 and 2015 and 12 in 2018 and 2022. The third quartile values were 11 between 2003 and 2012, 14 in 2015, and 14.5 in 2018 and 2022. The maximum values were 16 in 2003, 2015, and 2018, and 15 in all other years. Notably, the highest median value occurred in 2018 and 2022, with a score of 12; all other years had a median value of 8.

When analyzing the HOMEPOS values for seven cycles, it is evident that the minimum values fall between -3.35 and -7.39, the first quartile values range from -1.08 to -2.12, the median values range from -0.56 to -1.39, the third quartile values range from 0.23 to -0.68, and the maximum values range from 2.04 to 5.76. Notably, the highest median value occurred in 2003 with -0.56, while the lowest was in 2015, with -1.39.

Using Classification and Regression Trees

Classification and Regression Trees (CART) is the common name for tree-based algorithms (Breiman et al., 1984). When the outcome variable is at the classification level, the primary goal of CART is to categorize all units in the study using factors that are thought to be predictors, or to perform a point estimation when the outcome variable is continuous (Orrù et al., 2020). A multi-stage approach is used to determine the class or value of each unit in the outcome variable. A dichotomization with regard to a predictor variable is carried out at each stage. This process continues according to a predetermined statistical reference value and finally the value of each unit in the outcome variable or its class in this variable is estimated. The first phase starts with a single node and is, therefore, called the root node. Since two new nodes are formed from each node, the number of nodes keeps growing in each stage. Since the number of nodes formed in each stage is more than the previous one, and the process continues by dividing each node into two, the final shape resembles a tree (De'ath & Fanricious, 2000; Loh, 2014).

In the context of this research, the CART was utilized solely to identify the most suitable cut-off score for ESCS based on the root node. As the principal philosophy of CART uses the best predictive variable and the optimal value for the relevant variable for the root node, it has been assessed that taking advantage of this approach would allow the most accurate classification of low-high SES by determining the best cut-off score for ESCS.

Analysis Process

Accordingly, in the data analysis process, it was first determined whether there was a significant difference between plausible values for any value of ESCS, by using the CART algorithm in each cycle of PISA Türkiye data. The values which indicated difference were marked as cut-off points. Upper and lower groups of ESCS were formed by using the cut-offs. Then, for each domain in each PISA cycle, the relationship between ESCS and PV score in lower and upper groups was examined using linear regression analysis. Lastly, the variability of the regression equations obtained through multi-group regression analysis has been examined at low and high ESCS levels. Data analysis was carried out with the "rpart" (Therneau et al., 2013) and "rattle" (Williams, 2011) packages included in the R software (R Core Team, 2022).

FINDINGS

The ESCS cut-off values for various years and domains were established using the CART algorithm. Table 2 presents the frequency tables of the lower and upper groups based on the first cut-off values.

The first cut-off values for the ESCS for all years and domains are displayed in Table 2. Examining these numbers reveals that, except for 2003 science and mathematics and 2018 mathematics, all first cut-off points have negative ESCS. Table 2 also shows that the upper group rate decreases when the cut-off point is positive.

The study analyzed the correlation between PV and ESCS within upper and lower groups for each year and domain, using regression equations based on cut-off values. The invariance of the regression equations between these groups was tested by fixing the slope and intercept coefficients. Results showed that invariance was not achieved in any year or domain. Therefore, this study compared the coefficients' relative sizes and the variance proportions. Table 3 shows the regression equations and explained variance ratios (R^2) for each domain in all years, separated by socioeconomic groups. For a more comprehensive analysis, please refer to the scatter plots of Appendix 1 scatter plots for each domain in all years.

Table 2.
Groups Created by Classification and Regression Trees Algorithm

Year	Domain	Cut-off	Group	n (%)	Year	Domain	Cut-off	Group	n (%)
2003	Math	0.19	Lower	4092 (84.5)	2015	Math	-0.35	Lower	4764 (81.3)
			Upper	753 (15.5)				Upper	1095 (18.7)
	Reading	-0.31	Lower	3597 (74.2)		Reading	-0.52	Lower	4557 (77.8)
			Upper	1248 (25.8)				Upper	1302 (22.2)
	Science	0.19	Lower	4092 (84.5)		Science	-0.50	Lower	4587 (78.2)
			Upper	753 (15.5)				Upper	1277 (21.8)
2006	Math	-0.54	Lower	3678 (74.5)	2018	Math	0.05	Lower	5593 (81.6)
			Upper	1256 (25.5)				Upper	1262 (18.4)
	Reading	-0.57	Lower	3643 (73.8)		Reading	-0.07	Lower	5437 (79.3)
			Upper	1291 (26.2)				Upper	1418 (20.7)
	Science	-0.57	Lower	3643 (73.8)		Science	-0.15	Lower	5348 (78)
			Upper	1291 (26.2)				Upper	1507 (22)
2009	Math	-0.41	Lower	3647 (73.4)	2022	Math	-0.23	Lower	5675 (78.2)
			Upper	1320 (26.6)				Upper	1580 (21.8)
	Reading	-0.56	Lower	3460 (69.7)		Reading	-0.22	Lower	5698 (78.5)
			Upper	1507 (30.3)				Upper	1557 (21.5)
	Science	-0.62	Lower	3389 (68.2)		Science	-0.23	Lower	5675 (78.5)
			Upper	1578 (31.8)				Upper	1580 (21.5)
2012	Math	-0.62	Lower	3689 (76.8)					
			Upper	1117 (23.2)					
	Reading	-0.62	Lower	3689 (76.8)					
			Upper	1117 (23.2)					
	Science	-0.62	Lower	3689 (76.8)					
			Upper	1117 (23.2)					

Table 3.
Relationship Between ESCS and PV by Year

Year	Domain	Group	Equation	R^2	Adj. R^2	Year	Domain	Group	Equation	R^2	Adj. R^2
2003	Math	Lower	y=470+27x	.94	.93	2015	Math	Lower	y=430+11x	.75	.72
		Upper	y=460+70x	.88	.87			Upper	y=450+42x	.87	.86
	Reading	Lower	y=470+28x	.95	.94		Reading	Lower	y=430+8x	.80	.78
		Upper	y=470+54x	.90	.90			Upper	y=460+36x	.86	.86
	Science	Lower	y=450+24x	.90	.89		Science	Lower	y=430+8.6x	.84	.82
		Upper	y=460+66x	.93	.93			Upper	y=450+33x	.76	.75
2006	Math	Lower	y=450+24x	.94	.93	2018	Math	Lower	y=470+17x	.88	.87
		Upper	y=470+54x	.88	.87			Upper	y=490+40x	.83	.81
	Reading	Lower	y=470+21x	.94	.94		Reading	Lower	y=480+15x	.89	.88
		Upper	y=480+46x	.90	89			Upper	y=500+34x	.76	.74
	Science	Lower	y=450+20x	.95	.94		Science	Lower	y=470+12x	.84	.83
		Upper	y=460+56x	.91	.91			Upper	y=500+33x	.68	.65
2009	Math	Lower	y=470+27x	.96	.96	2022	Math	Lower	y=470+20x	.91	.90
		Upper	y=490+39x	.88	.88			Upper	y=490+43x	.92	.91
	Reading	Lower	y=500+28x	.94	.93		Reading	Lower	y=470+16x	.86	.85
		Upper	y=500+36x	.91	.90			Upper	y=490+33x	.87	.86
	Science	Lower	y=480+23x	.95	.94		Science	Lower	y=490+18x	.93	.92
		Upper	y=490+35x	.93	.92			Upper	y=510+26x	.85	.83
2012	Math	Lower	y=470+20x	.94	.93						
		Upper	y=500+20x	.83	.82						
	Reading	Lower	y=490+15x	.82	.80						
		Upper	y=520+42x	.81	.80						
	Science	Lower	y=480+12x	.79	.77						
		Upper	y=500+47x	.88	.88						

The regression equations for the lower and upper groups, totaling 21 cases, are presented in Table 2. When analyzing the intercepts of the equations, only the intercept for 2003 Mathematics, in the lower group is greater than that in the upper group. Moreover, the intercepts in the upper and lower groups are equal for reading in 2003 and 2009. The intercept in the lower group, except for the three mentioned cases, is lower than that in the upper group, which is expected given the presence of fifteen cases. Examining the slopes, except for mathematics in 2012, reveals that the slope coefficient is higher in the upper group. In comparison to previous years, the difference in slope between the lowest and upper categories in 2009 is smaller. 2015 stands out as having the most significant difference. To clarify, the slope coefficient for the upper group in mathematics in 2015 was 4.5 times higher than that of the lower group.

When examining the R^2 values, it was observed that R^2 was higher in the lower group, except for six cases (2003 and 2012 Science; 2015 and 2022 Reading and Mathematics). The difference between the R^2 values ranged from .01 to .16. The minimum difference was in 2012 Reading, while the maximum difference was in 2018 Science. The R^2 values ranged between .68 and .96. The lowest R^2 value occurred in the upper ESCS group for science in 2018, whereas the highest R^2 value was found in the lower ESCS group for science in 2009. With the exception of the upper ESCS groups for science in 2015 and 2018, as well as the 2018 Reading domains, all R^2 values exceeded 0.80.

DISCUSSION AND CONCLUSION

Numerous studies in the field of education have reported that ESCS plays an important role in determining student literacy and educational equity in a variety of contexts (Chi et al., 2018; Chmielewski, 2019; Gorard, 2006; Perry et al., 2022; Tang et al., 2021). This study analyzed PISA data from 2003-2022 to assess the ability of ESCS to predict student performance in three key academic areas in lower and upper ESCS groups. The first step involved using the CART approach to classify ESCS levels in the lower-upper group. The approach involved identifying the precise value obtained from the CART that segmented the continuous ESCS variable, a crucial factor in predicting academic performance for each domain. This value sets the threshold for the classification of lower-upper. Using the identified thresholds as a framework, we conducted multiple group regression analysis to predict literacy based on ESCS within each domain. We evaluated the constancy of the regression equation within the lower-upper groups. However, we noticed a lack of invariance across all datasets. Thus, we performed simple linear regression analyses for the lower-upper subgroups to ensure accurate results.

Based on the results, an investigation of the lower and upper SES groups separately revealed that the R^2 values were equal to or greater than 0.80 in 37 of the 42 analyses conducted. Furthermore, the R^2 values were discovered to be equal to or greater than 0.90 in 19 analyses. These findings are similar to previous research highlighting the importance of ESCS as a predictor of literacy (e.g., Jehangir et al., 2015; Kim, 2019; Lee & Borgonovi, 2022; Perry et al., 2022; Sirin, 2005). However, the findings of this study suggest that this relationship is stronger for the lower group. The results of this study coincide with Özdemir (2016) finding that the effect of socioeconomic status on mathematics literacy is higher in low socioeconomic levels.

Another notable aspect is that in 2003, 2006, and 2009, the R^2 values in both groups were significantly high, while there has been a notable decline in R^2's in subsequent periods. The year 2009 stood out as the year with the highest explained variance values in both the lower and upper groups across all domains. This trend may be interpreted as a relative decrease in the predictive power of ESCS for both the lower and upper groups in the years 2012, 2015, and 2018. The change in this trend, especially after 2012, can be attributed to the change in the profile of students and the enrollment rate with the change in the compulsory education law in 2012. This finding is consistent with the finding of Aydogdu (2023) that the increased schooling rate with the effect of the compulsory education law led to the SES achievement gaps decline in Türkiye.

It is important to emphasize a specific point regarding 2015 when interpreting the findings. Specifically, this year had the lowest literacy scores in all domains and also the lowest R^2. In three out of six analyses for 2015, the R^2 by ESCS was .80 or below. Interestingly, the relationship between ESCS and literacy scores in the lower-upper group differed from other years. The only year that showed a higher correlation in the upper group for mathematics and reading and in the lower group for science was 2015. This information suggests that the differences observed in predicting academic performance in 2015 need to be investigated further.

This study deviates from many similar studies in its use of lower-upper group classification. Therefore, the classification process did not utilize values from the distribution, such as median or standard deviation. Instead, the cut-offs were determined at the root node, where the CART algorithm separates the continuous predictor variable at its strongest point. Thus, the categorization of the lower-upper group was not based on equally dividing the distribution, but rather on the point with the greatest predictive power for the outcome variable. According to the graphs, notable differences in the outcomes would have arisen if the categorization relied on median values, which consistently sat at around -1.5 for ESCS in all years. The cut-off values for the ESCS lower-upper groups demonstrated variations across different years, as identified in this study. Additionally, these cut-offs were impacted significantly by the chosen methodology. In all analyses conducted, the lower group consistently comprised a larger proportion, ranging from approximately 70% to 85%, with the most frequent proportion being around 75%.

Due to the methodology used (i.e. CART), the mean values for the dependent variable (PVs) were used. Also, the data were analyzed at a single-level because the analysis requires a relatively large data set to provide consistent results. However, the use of the mean values and the single-level analysis of the hierarchical data can be stated as the limitations of this study. In order to improve the research in the future, it would be advisable to use PVs with sample weights, to analyze the data hierarchically and to divide the groups into further divisions in addition to lower-upper, depending on the cut-offs obtained in subsequent nodes. World Bank Report (2023) based on PISA data emphasizes the influence of family background and school type. This report emphasize that secondary schools in Türkiye are clustered according to socioeconomic status. Considering the findings from PISA data that highlight the significant impact of a school's socioeconomic structure on students' academic performance (Perry & McConney, 2010; Neuman, 2022), it can be inferred that this situation holds particular importance in the Turkish context. Therefore, it can be suggested that further research, especially for lower SES, is necessary to explore the relationship between academic achievement and SES in Türkiye.

Both the World Bank report (2023) and the OECD (2019b) report a significant improvement in Türkiye in terms of simultaneous and sustained increase in student performance and reduction in inequality. However, in the OECD (2019b) report, the inequality in the probability of reaching the highest levels of the reading performance index, which is an indicator of the link between top performance and socioeconomic status, the highest level of the index, 0.56, was observed in Türkiye (OECD, 2019c). The higher this index is, the more prevalent the most socioeconomically advantaged students are among the high performers. These findings suggest that although educational inequalities in Türkiye have improved over the years, further attention should continue to be paid to this issue.

As mentioned earlier, student performance scores increase as SES increases. However, the strength of this relationship may differ between low and high SES levels. At low SES levels, even small improvements can significantly improve academic performance (Duncan & Murnane, 2011; Reardon, 2011). In contrast, this relationship may weaken or plateau at higher SES levels (Caro et al., 2009; OECD, 2018).

The quality of schools and educational resources are critical in maintaining or reducing the gap between SES and student performance. In areas with high concentrations of low SES individuals, schools often lack adequate resources, which negatively impacts students' academic progress (Thomson, 2018). These schools often have fewer library materials (American Psychological Association [APA], 2017).

Research shows that school conditions contribute more to SES-related differences in learning rates than family background (Thomson, 2018).

Research in Türkiye has also revealed a strong link between the academic performance of students from low-income backgrounds and their SES. Çıngı et al. (2009) found that family income and parental education levels are closely linked to the achievement of students from lower SES backgrounds. In Yayan and Berberoğlu's (2004) study on mathematics achievement, it was reported that the effect of SES was generally stronger for lower achieving students than for higher achieving students from higher SES backgrounds. Akar (2009) found that although socioeconomic factors still strongly influence outcomes, school-level factors become more important for students from higher SES backgrounds. Heyneman and Loxley (1983) argue that school factors have become more important than family background in determining student achievement in more developed countries, especially for students from higher socioeconomic backgrounds.

In sum, both international and Turkish literature show that the relationship between achievement and socioeconomic status varies across different SES levels. While the link is stronger and more direct at lower levels, it tends to weaken or plateau at higher levels. This understanding is critical in developing targeted educational policies and interventions to effectively address achievement gaps.

Acknowledgement

The manuscript has been orally presented at 8th Congress of Measurement and Evaluation in Education and Psychology on 21-23 September 2022, in Ege University, İzmir.

REFERENCES

Akar, H. (2009). Challenges for schools in communities with internal migration flows: evidence from Turkey. *International Journal of Educational Development, 30*(3), 263–276. https://doi.org/10.1016/j.ijedudev.2009.11.003

American Psychological Association. (2017, July 21). *Education and socioeconomic status*. https://www.apa.org/pi/ses/resources/publications/education

American Psychological Association. (2019). *Definition of socioeconomic status*. https://www.apa.org/topics/socioeconomic-status/

Arıkan, S., Özer, F., Şeker, V. & Ertaş, G. (2020). The importance of sample weights and plausible values in large-scale assessments. *Journal of Measurement and Evaluation in Education and Psychology*, *11*(1), 43-60. https://doi.org/10.21031/epod.602765

Avvisati, F. (2020). The measure of socio-economic status in PISA: a review and some suggested improvements, *Large-scale Assessments in Education*, *8*(8). https://doi.org/10.1186/s40536-020-00086-x

Aydogdu, F. (2023). *The Relationship between Compulsory Schooling Policy, Educational Equity and Student Achievement in Turkey and Portugal* (Publication No. 30687189) [Doctoral dissertation, University of Toronto]. ProQuest Dissertations and Theses Global.

Banerjee, P., & Eryilmaz, N. (2024). A critical evaluation of the validity of socioeconomic measures used in PISA. *International Journal of Comparative Education and Development.* https://doi.org/10.1108/IJCED-02-2023-0011

Berliner, D. C. (2013). Effects of inequality and poverty vs. teachers and schooling on America's youth. *Teachers College Record*, *115*(12), 1-26. https://doi.org/10.1177/016146811311501203

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone C. J. (1984). *Classification and Regression Trees*. CRC Press.

Bukodi, E., & Goldthorpe, J. H. (2013). Decomposing ‘social origins’: The effects of parents’ class, status, and education on the educational attainment of their children. *European Sociological Review, 29*(5), 1024–1039. https://doi.org/10.1093/esr/jcs079

Caro, D. H., McDonald, J. T., & Willms, J. D. (2009). Socio-economic status and academic achievement trajectories from childhood to adolescence. *Canadian Journal of Education, 32*(3), 558-590.

Chi, S., Liu, X., Wang, Z., & Won Han, S. (2018). Moderation of the effects of scientific inquiry activities on low SES students’ PISA 2015 science achievement by school teacher support and disciplinary climate in science classroom across gender. *International Journal of Science Education, 40*(11), 1284-1304. https://doi.org/10.1080/09500693.2018.1476742

Chmielewski, A.K. (2019). The global increase in the socioeconomic achievement gap, 1964 to 2015. *American Sociological Review, 84*(3), 517-544. https://doi.org/10.1177/0003122419847165

Coleman, J. S. (1968). Equality of educational opportunity. *Integrated Education, 6*(5), 19-28. https://doi.org/10.1080/0020486680060504

Coşkun, B., & Karadağ, E. (2023). The effect of student and school characteristics on TIMSS 2015 science and mathematics achievement: The case of Türkiye. *Journal of Pedagogical Research, 7*(1), 203-227. https://doi.org/10.33902/JPR.202318875

Çıngı, H., Kadılar, C., & Koçberber, G. (2009). A statistical approach for identifying the requirements of public primary and secondary schools based on districts in Turkey. *Hacettepe University Journal of Education, 28*(1), 105-116.

De'ath, G. & Fabricius, K. (2000). Classification and regression trees: A powerful yet simple technique for ecological data analysis. *Ecology, 8*(11), 3178-3192. https://doi.org/10.1890/0012-9658(2000)081[3178:CARTAP]2.0.CO;2

Duncan, G. J., & Murnane, R. J. (Eds.). (2011). *Whither opportunity?: Rising inequality, schools, and children's life chances*. Russell Sage Foundation.

Erdem, C., & Kaya, M. (2021). Socioeconomic status and wellbeing as predictors of students' academic achievement: evidence from a developing country. *Journal of Psychologists and Counsellors in Schools, 33*(2), 1-19. https://doi.org/10.1017/jgc.2021.10

Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2012). *How to design and evaluate research in education* (8th ed.). McGraw-Hill.

Gamazo, A., & Martínez-Abad, F. (2020). An exploration of factors linked to academic performance in PISA 2018 through data mining techniques. *Frontiers in Psychology, 11* Article 575167. https://doi.org/10.3389/fpsyg.2020.575167

Ganzeboom, H. B. G. & Treiman, D. J. (2003). Three internationally standardised measures for comparative research on occupational status. In J. H. P. Hoffmeyer-Zlotnik & C. Wolf (Eds.), *Advances in cross-national comparison* (pp. 159-193). https://doi.org/10.1007/978-1-4419-9186-7_9

Gorard, S. (2006). The true impact of school diversity? In M. Hewlett, R. Pring, & M. Tulloch (Eds.), *Comprehensive education: Evolution, achievement and new directions.* University of Northampton Press.

Hair, N. L., Hanson, J. L., Wolfe, B. L., & Pollak, S. D. (2015). Association of child poverty, brain development, and academic achievement. *JAMA Pediatrics, 169*(9), 822-829.

Heyneman, S. P., & Loxley, W. A. (1983). The effect of primary-school quality on academic achievement across twenty-nine high-and low-income countries. *American Journal of Sociology, 88*(6), 1162-1194. https://doi.org/10.1086/227799

International Labour Organization (2007). *International Standard Classification of Occupations (ISCO) – 08.* https://www.ilo.org/publications/international-standard-classification-occupations-isco-08

Jehangir, K., Glas, C. A., & van den Berg, S. (2015). Exploring the relation between socio-economic status and reading achievement in PISA 2009 through an intercepts-and-slopes-as-outcomes paradigm. *International Journal of Educational Research, 71*, 1-15. https://doi.org/10.1016/j.ijer.2015.02.002

Kim, S. W. (2019). Is socioeconomic status less predictive of achievement in east Asian countries? A systematic and meta-analytic review. *International Journal of Educational Research, 97*, 29–42. https://doi.org/10.1016/j.ijer.2019.05.009

Lam, G. (2014). A theoretical framework of the relation between socioeconomic status and academic achievement of students. *Education, 134*(3), 326-331.

Loh, W. Y. (2014). Fifty Years of Classification and Regression Trees. *International Statistical Review, 82*(3), 329–348. https://doi.org/10.1111/insr.12016

Lee, J., & Borgonovi, F. (2022). Relationships between family socioeconomic status and mathematics achievement in OECD and non-OECD countries. *Comparative Education Review, 66*, 199–227. https://doi.org/10.1086/718930

Ministry of National Education (2012). *12 Yıl Zorunlu Eğitim: Sorular-Cevaplar [12-years Compulsory Education: Questions and Answers]*. Ankara. http://www.meb.gov.tr/duyurular/duyurular2012/12Yil_Soru_Cevaplar.pdf

Neuman, M. (2022). PISA data clusters reveal student and school inequality that affects results. *PLoS ONE 17*(5): Article e0267040. https://doi.org/10.1371/journal.pone.0267040

O'Connell, M. (2019). Is the impact of SES on educational performance overestimated? Evidence from the PISA survey. *Intelligence, 75*, 41-47. https://doi.org/10.1016/j.intell.2019.04.005

OECD (2012). *PISA 2009 Technical Report*. https://www.oecd.org/pisa/pisaproducts/50036771.pdf

OECD. (2018). *Equity in Education: Breaking Down Barriers to Social Mobility*. OECD Publishing. https://doi.org/10.1787/9789264073234-en

OECD (2017). *PISA 2015 Technical Report*. https://www.oecd.org/pisa/data/2015-technical-report/PISA2015_TechRep_Final.pdf

OECD (2019a). *PISA 2018 Results (Volume III): What School Life Means for Students' Lives*. OECD Publishing. https://doi.org/10.1787/acd78851-en

OECD (2019b). *PISA 2018 Results (Volume I): What Students Know and Can Do.* OECD Publishing. https://doi.org/10.1787/5f07c754-en

OECD (2019c). *PISA 2018 Results (Volume II): Where All Students Can Succeed*. OECD Publishing. https://doi.org/10.1787/b5fd1b8f-en

OECD (2020). *PISA 2018 Technical Report*. https://www.oecd.org/pisa/data/pisa2018technicalreport/

OECD (2023). *PISA 2022 Results (Volume II): Learning during – and from – disruption.* https://doi.org/10.1787/a97db61c-en

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., & Sartori, G. (2020). Machine learning in psychometrics and psychological research. *Frontiers in Psychology*, 10, Article 2970. https://doi.org/10.3389/fpsyg.2019.02970

Özdemir, C. (2016). Equity in the Turkish education system: A multilevel analysis of social background influences on the mathematics performance of 15-year-old students. *European Educational Research Journal, 15*(2), 193-217. https://doi.org/10.1177/1474904115627159

Özer Özkan, Y. & Acar Güvendir, M. (2014). Socioeconomic factors of students' relation to mathematic achievement: Comparison of PISA and ÖBBS. *International Online Journal of Educational Sciences, 6*(3), 776-789. http://dx.doi.org/10.15345/iojes.2014.03.020

Perry, L. B., & McConney, A. (2010). Does the SES of the school matter? An examination of socioeconomic status and student achievement using PISA 2003. *Teachers College Record, 112*(4), 1137-1162. https://doi.org/10.1177/016146811011200401

Perry, L. B., Saatcioglu, A., & Mickelson, R. A. (2022). Does school SES matter less for high-performing students than for their lower-performing peers? A quantile regression analysis of PISA 2018 Australia. *Large-scale Assessments in Education, 10*(1), 1-29. https://doi.org/10.1186/s40536-022-00137-5

R Core Team (2022). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*, Vienna, Austria. https://www.R-project.org/

Reardon, R. M. (2011). Elementary school principals' learning-centered leadership and educational outcomes: Implications for principals' professional development. *Leadership and Policy in Schools*, *10*(1), 63-83. https://doi.org/10.1080/15700760903511798

Schulz, W. (2005, April 7-11). *Measuring the Socio-Economic Background of Students and Its Effect on Achievement on PISA 2000 and PISA 2003*. Annual Meeting of the American Educational Research Association.

Sirin, S. (2005). Socioeconomic status and academic achievement: a meta-review of research. *Review of Educational Research, 75*, 417–453. https://doi.org/10.3102/00346543075003417

Strietholt, R., Gustafsson, J-E., Hogrebe, N., Rolfe, V., Rosén, M., Steinmann, I. & Yang Hansen, K. (2019). The impact of education policies on socioeconomic inequality in student achievement: a review of comparative studies. In L. Volante, S. Schnepf, J. Jerrim, & D. Klinger (Eds.) *Socioeconomic inequality and student outcomes* (pp 17-38). Springer. https://doi.org/10.1007/978-981-13-9863-6_2

Tang P., Liu H. & Wen, H. (2021) Factors predicting collaborative problem solving: Based on the data from PISA 2015. *Frontiers in Education 6, Article 619450*. https://doi.org/10.3389/feduc.2021.619450

Therneau, T., Atkinson, B., & Ripley, B. (2013). *Rpart: Recursive Partitioning. R Package Version 4.1-3*. http://CRAN.R-project.org/package=rpart

Thomson, S. (2018). Achievement at school and socioeconomic background—an educational perspective. *npj Science of Learning, 3*(1). https://doi.org/10.1038/s41539-018-0022-0

Von Stumm, S., & Plomin, R. (2014). Socioeconomic status and the growth of intelligence from infancy through adolescence. *Intelligence*, *48*, 30–36. https://doi.org/10.1016/j.intell.2014.10.002

Wang, F., King, R.B., & Leung, S.O. (2023). Why do East Asian students do so well in mathematics? A machine learning study. *International Journal of Science and Mathematics Education, 21*, 691–711. https://doi.org/10.1007/s10763-022-10262-w

Williams, G. J. (2011). *Data Mining with Rattle and R: The art of excavating data for knowledge discovery*, series Use R! Springer.

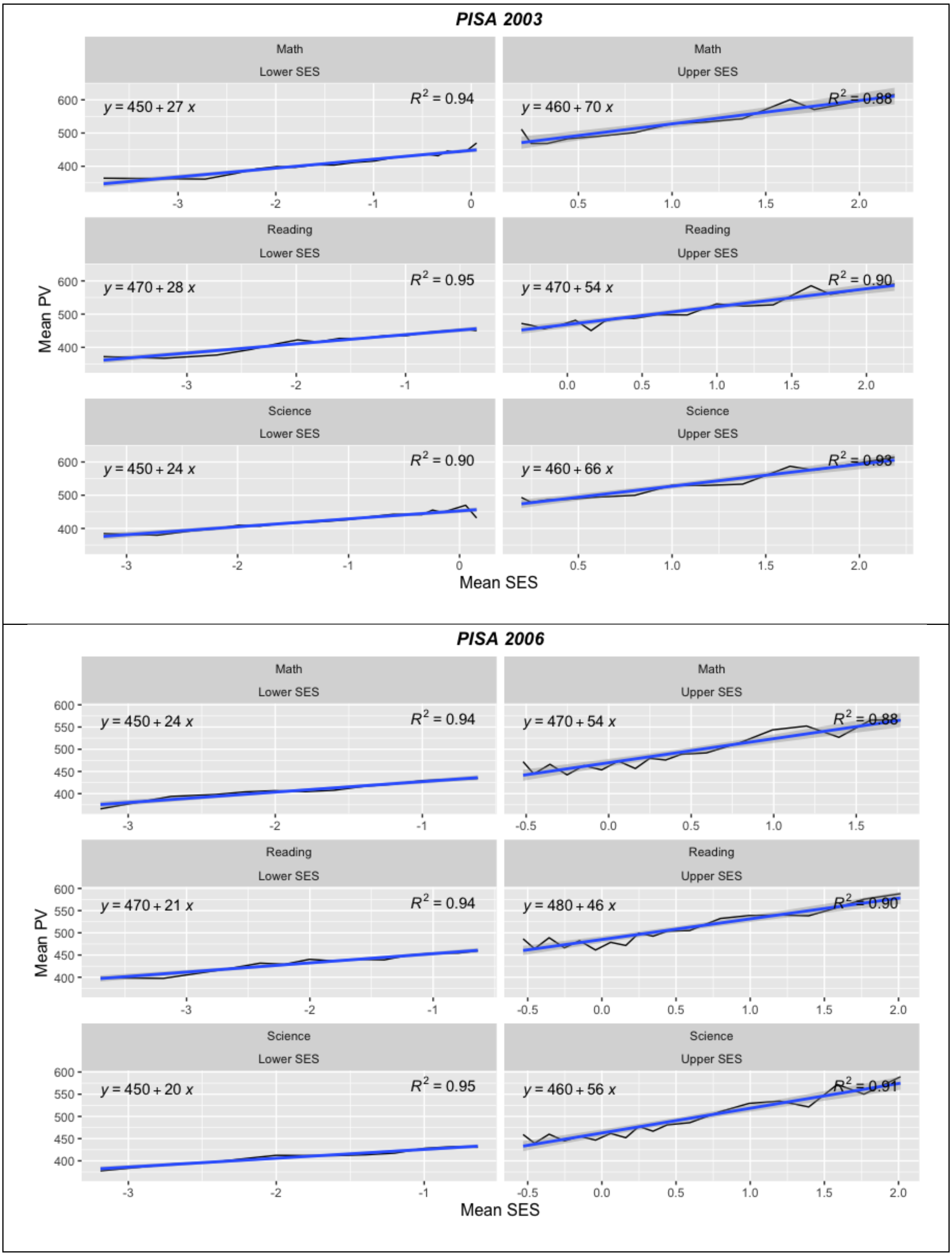
World Bank (2023). *Promoting excellence in Turkey's schools*. (Report No. 77722). World Bank Group. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/944721468110943381/promoting-excellence-in-turkeys-schools

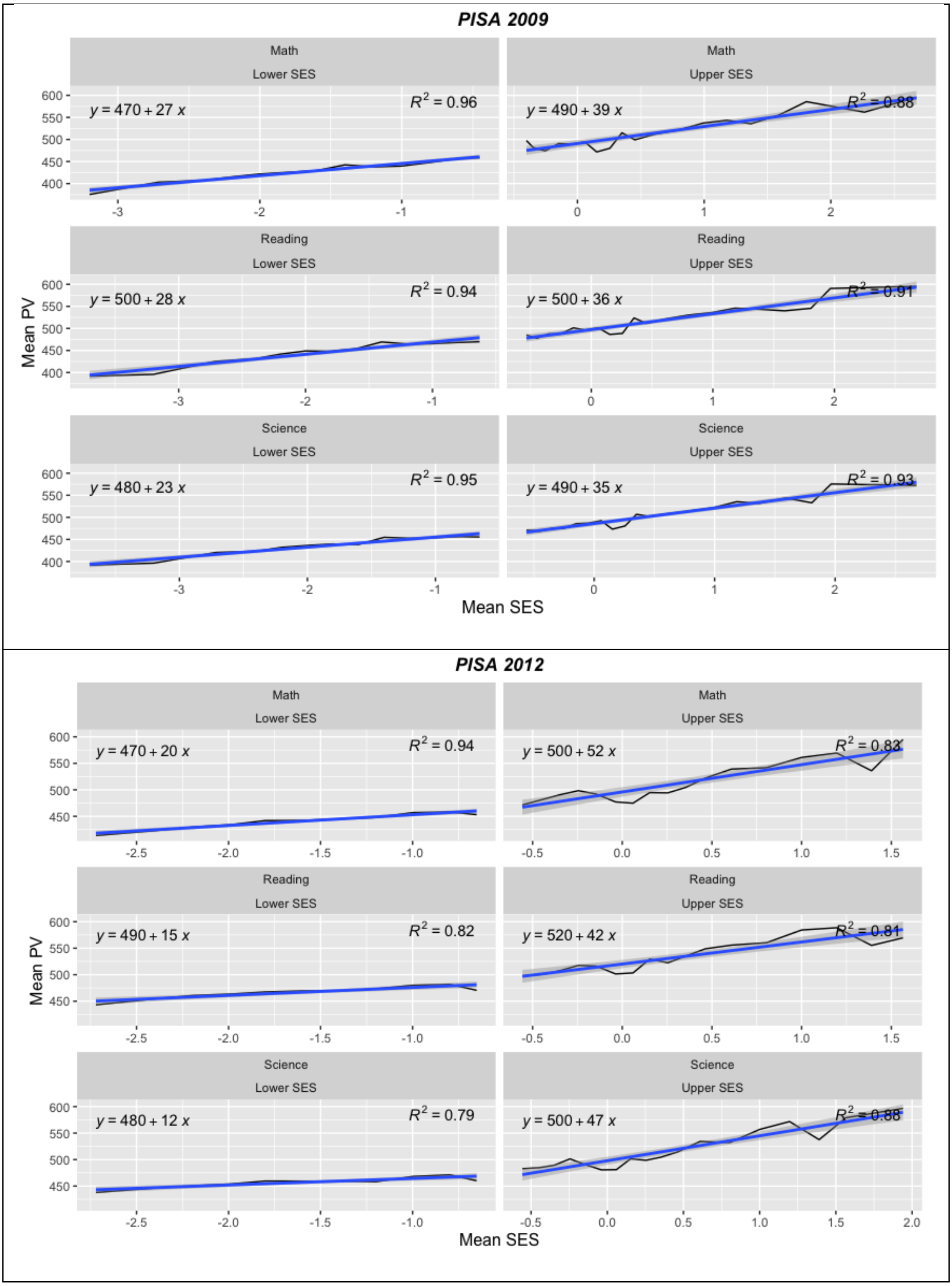
Wu, M. (2005). The role of plausible values in large-scale surveys. *Studies in Educational Evaluation*, 31(2-3), 114-128. https://doi.org/10.1016/j.stueduc.2005.05.005

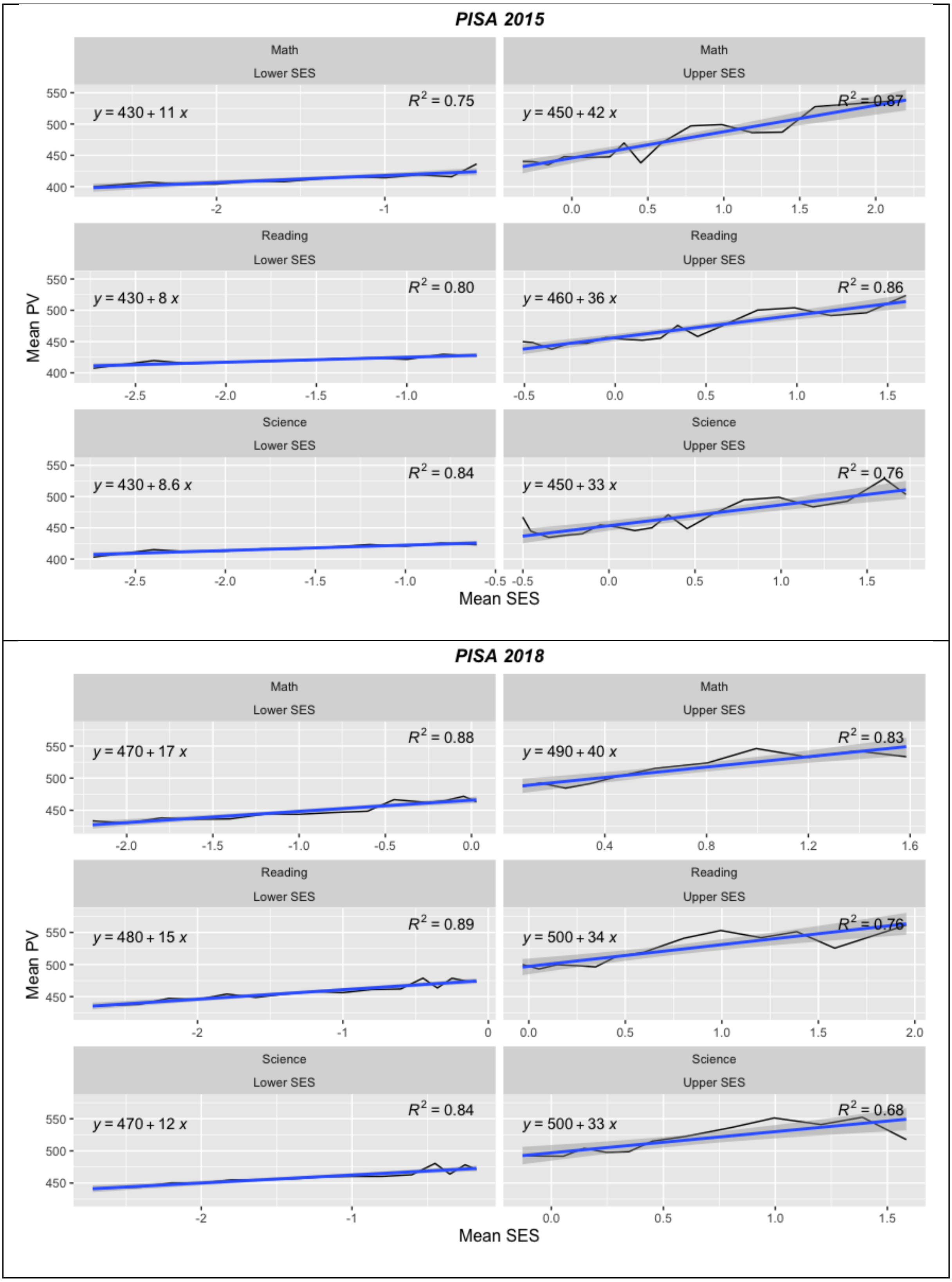
Yayan, B., & Berberoglu, G. (2004). A re-analysis of the TIMSS 1999 mathematics assessment data of the Turkish students. *Studies in Educational Evaluation, 30*(1), 87-104.

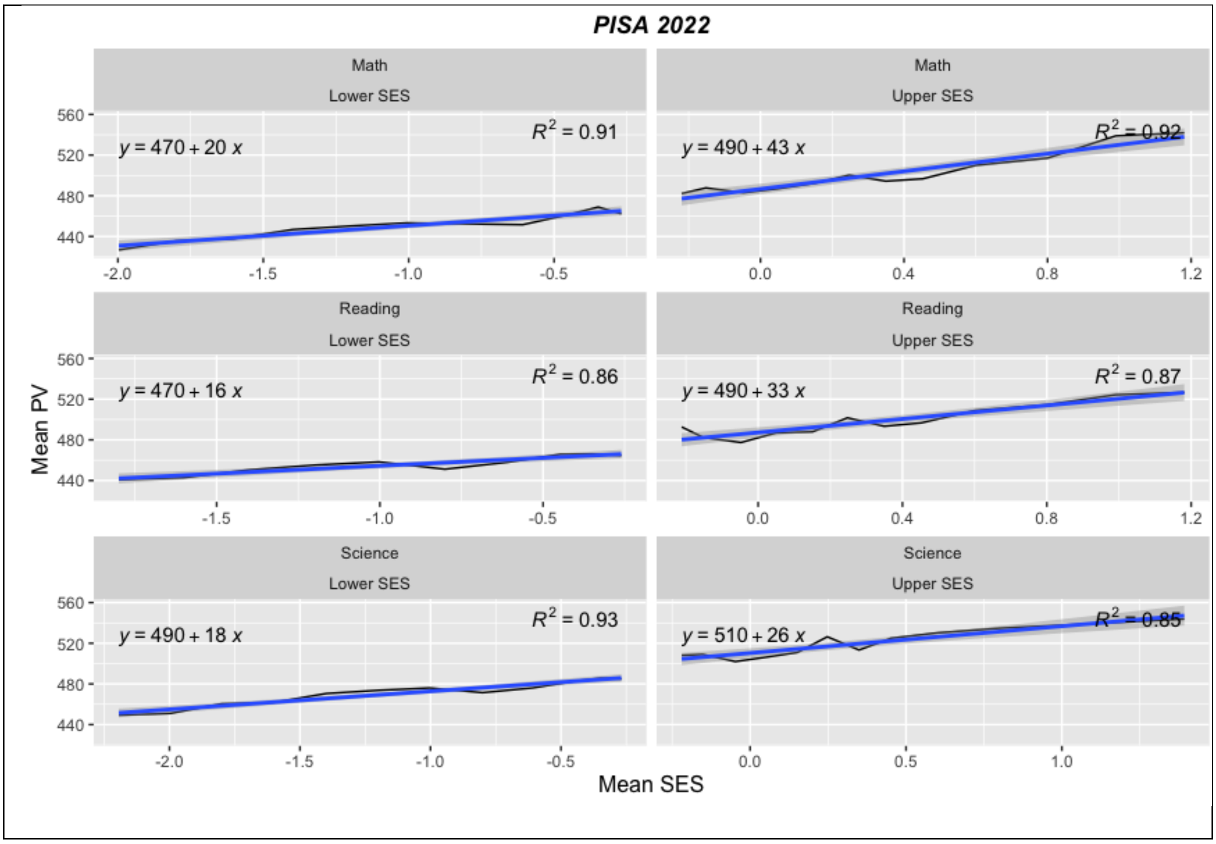
APPENDICES

Appendix 1:




PISA 2009
Math Lower SES
y = 470 + 27 x
R^2 = 0.96
Math Upper SES
y = 490 + 39 x
R^2 = 0.88
Reading Lower SES
y = 500 + 28 x
R^2 = 0.94
Reading Upper SES
y = 500 + 36 x
R^2 = 0.91
Science Lower SES
y = 480 + 23 x
R^2 = 0.95
Science Upper SES
y = 490 + 35 x
R^2 = 0.93
Mean PV
Mean SES
PISA 2012
Math Lower SES
y = 470 + 20 x
R^2 = 0.94
Math Upper SES
y = 500 + 52 x
R^2 = 0.83
Reading Lower SES
y = 490 + 15 x
R^2 = 0.82
Reading Upper SES
y = 520 + 42 x
R^2 = 0.81
Science Lower SES
y = 480 + 12 x
R^2 = 0.79
Science Upper SES
y = 500 + 47 x
R^2 = 0.88
Mean PV
Mean SES


PISA 2015
Math Lower SES
y = 430 + 11 x
R² = 0.75
Math Upper SES
y = 450 + 42 x
R² = 0.87
Reading Lower SES
y = 430 + 8 x
R² = 0.80
Reading Upper SES
y = 460 + 36 x
R² = 0.86
Science Lower SES
y = 430 + 8.6 x
R² = 0.84
Science Upper SES
y = 450 + 33 x
R² = 0.76
Mean PV
Mean SES
PISA 2018
Math Lower SES
y = 470 + 17 x
R² = 0.88
Math Upper SES
y = 490 + 40 x
R² = 0.83
Reading Lower SES
y = 480 + 15 x
R² = 0.89
Reading Upper SES
y = 500 + 34 x
R² = 0.76
Science Lower SES
y = 470 + 12 x
R² = 0.84
Science Upper SES
y = 500 + 33 x
R² = 0.68
Mean PV
Mean SES


PISA 2022
Math
Lower SES
y = 470 + 20 x
R2 = 0.91
Math
Upper SES
y = 490 + 43 x
R2 = 0.92
Reading
Lower SES
y = 470 + 16 x
R2 = 0.86
Reading
Upper SES
y = 490 + 33 x
R2 = 0.87
Science
Lower SES
y = 490 + 18 x
R2 = 0.93
Science
Upper SES
y = 510 + 26 x
R2 = 0.85
Mean PV
Mean SES

TÜRKÇE GENİŞLETİLMİŞ ÖZET

Uluslararası Öğrenci Değerlendirme Programı (PISA) ile her üç yılda bir 70'ten fazla ülkeden 15 yaşındaki yaklaşık 500.000 öğrenciden okuma, matematik ve fen alanlarında başarılarını düzeylerini ölçen testler ve öğrencilerin başarı düzeylerini etkilediği düşünülen değişkenlere ilişkin anketler aracılığıyla veri toplanmaktadır. Bu verilerle öğrencilerin performansları ve performanslarını etkileyen değişkenler analiz edilmekte ve ülkelerin eğitim sistemleri değerlendirilmektedir (OECD, 2020).

Başta PISA olmak üzere geniş ölçekli sınav sonuçları, ülkelere eğitim sistemlerini oluşturan unsurların etkililiği, sistemdeki öğrenci, öğretmen ve yönetici profilleri ile eğitim sistemlerinin genel işleyişi hakkında detaylı bilgi sağlamaktadır (Arıkan vd., 2020). Tüm bu bilgiler ışığında, öğrenci başarısını yordayan faktörlerin belirlenmesinin ülkelerin eğitim politikalarının geliştirilmesi açısından büyük önem taşıdığı söylenebilir (Strietholt vd., 2019). Bu faktörlerin doğru tespit edilmesi ve bunlara yönelik müdahalelerin başarı üzerinde olumlu bir etki yaratacağı öngörülmektedir.

Diğer faktörlerin yanı sıra sosyoekonomik düzeyin (SED) öğrenci başarısının önemli bir yordayıcı olduğunu gösteren çalışmalar mevcuttur (Berliner, 2013; Coşkun & Karadağ, 2023; Erdem & Kaya, 2021; Gamazo & Martínez-Abad, 2020; Perry & McConney, 2010; Schulz, 2005; Wang vd., 2023). Sosyal bilimlerde, SED'in bireylerin önemli yaşam sonuçları üzerinde önemli bir etkisi olduğu kabul edilmektedir. Akademik başarı için önemi de yaygın olarak kabul edilmektedir (O'Connell, 2019). Bu durum, PISA verileri üzerinde yapılan çalışmalarla örneklendirilebilir. Öğrenci başarı puanlarından sonra, ekonomik, sosyal ve kültürel statü (ESKS) muhtemelen PISA'dan elde edilen verilerin raporlarında ve ikincil analizlerinde en sık kullanılan değişkendir (Avvisati, 2020). Bu endeks, öğrencilerin anketlere verdikleri yanıtlara dayalı olarak eğitim fırsatları ve öğrenme çıktılarındaki eşitsizliklerle ilgili kaygıların ele alınmasına yardımcı olmaktadır.

Bugüne kadar PISA üzerine yapılan araştırmaların önemli bir bölümü, SED ile başarı arasında orta ile yüksek düzeyde bir ilişki olduğunu bildirmiştir (Chi vd., 2018; Chmielewski, 2019; Gorard, 2006; Perry vd., 2022; Tang vd., 2021). Bir diğer önemli husus, bu ilişkinin farklı SED düzeyleri arasında nasıl değiştiğidir. Alanyazın, SED ile akademik başarı arasındaki ilişkiyi, SED boyunca kademeli olarak artması nedeniyle sosyoekonomik bir gradyan ya da yüksek ve düşük SED'deki öğrenciler arasında akademik başarıda bir eşitsizlik olduğunu öne sürdüğü için sosyoekonomik bir uçurum olarak nitelendirmektedir (Jehangir vd., 2015). Bu açıdan bakıldığında, bu iki değişken arasındaki ilişkinin her düzeyde tutarlı olmayabileceği ve SED açısından özellikle düşük ve yüksek düzeylere odaklanılması gerektiği ileri sürülebilir.

Bu çalışma kapsamında, ESKS ile başarı arasındaki ilişkiye odaklanılırken, bu ilişkinin düşük-yüksek ESKS düzeylerinde nasıl değiştiği belirlenmeye çalışılmıştır. Bu doğrultuda, Türkiye'nin 2003-2022 yılları arasında fen, okuma ve matematik performansına yönelik PISA kapsamında elde edilen verileri kullanılmıştır. Her dönemde, her bir alan için düşük-yüksek ESKS sınıflandırması için regresyon ağaçları yöntemi kullanılmıştır. Çalışma şu araştırma sorusuna odaklanmaktadır: 2003-2022 PISA Türkiye verilerinde, düşük ve yüksek ESKS düzeylerinde, ESKS'nin okuma, fen ve matematik okuryazarlığı puanlarını yordama düzeyi nasıl farklılaşmaktadır?

Çalışma, var olan bir durumu betimlemek için yapıldığından betimsel bir araştırmadır (Fraenkel vd., 2012). Araştırmanın evreni, PISA 2003, 2006, 2009, 2012, 2015, 2018 ve 2022 döngülerine Türkiye'den katılan 15 yaşındaki öğrencilerdir. Altı döngüdeki Türk öğrencilerden elde edilen veriler kullanılmış ve örneklem 39.516 öğrenciden oluşmuştur. Veri analizi sürecinde ilk olarak PISA Türkiye verilerinin her bir döngüsünde Sınıflama ve Regresyon Ağaçları (SRA) algoritması kullanılarak herhangi bir ESKS değeri için başarı puanları arasında anlamlı bir fark olup olmadığı belirlenmiştir. Farklılığa işaret eden değerler kesme noktaları olarak işaretlenmiştir. Kesme noktaları kullanılarak ESKS'nin alt ve üst grupları oluşturulmuştur. Ardından, her bir PISA döngüsündeki her bir alan için, ESKS ile alt ve üst gruplardaki başarı puanları arasındaki ilişki basit doğrusal regresyon analizi kullanılarak incelenmiştir.

Sonuçlara göre, alt ve üst SED grupları ayrı ayrı incelendiğinde, yapılan 42 analizin 37'sinde R2 değerlerinin 0,80'e eşit veya 0,80'den daha yüksek olduğu görülmüştür. Ayrıca, 19 analizde R2 değerlerinin 0,90'a eşit veya 0,90'dan daha yüksek olduğu tespit edilmiştir. Bu bulgular, başarı puanlarının bir yordayıcısı olarak ESKS'nin önemini vurgulayan önceki araştırmalarla benzerlik göstermektedir (örneğin, Jehangir vd., 2015; Kim, 2019; Lee ve Borgonovi, 2022; Perry vd., 2022; Sirin, 2005). Ancak bu çalışmanın bulguları, bu ilişkinin alt grup için daha güçlü olduğunu göstermektedir. Bu çalışmanın sonuçları, Özdemir'in (2016) sosyoekonomik düzeyin matematik okuryazarlığı üzerindeki etkisinin düşük sosyoekonomik düzeylerde daha yüksek olduğu bulgusuyla örtüşmektedir.

Dikkat çeken bir diğer husus, 2003, 2006 ve 2009 yıllarında her iki grupta da R2 değerlerinin önemli ölçüde yüksek olması, sonraki dönemlerde ise R2'lerde belirgin bir düşüş olmasıdır. 2009 yılı tüm alanlarda hem alt hem de üst gruplarda en yüksek açıklanan varyans değerlerine sahip yıl olarak göze çarpmaktadır. Bu eğilim, 2012, 2015 ve 2018 yıllarında hem alt hem de üst gruplar için ESKS'nin yordama gücünde göreceli bir azalma olduğu şeklinde yorumlanabilir. Bu eğilimin özellikle 2012 yılından sonra değişmesi, 2012 yılında zorunlu eğitim yasasında yapılan değişiklikle birlikte öğrenci profilinin ve okullaşma oranının değişmesine bağlanabilir. Bu bulgu, Aydogdu'nun (2023) zorunlu eğitim yasasının etkisiyle artan okullaşma oranının Türkiye'de SED başarı farklarının azalmasını sağladığı bulgusuyla tutarlıdır.

2015 yılı tüm alanlarda en düşük başarı puanlarına ve aynı zamanda en düşük R2 değerine sahiptir. 2015 için yapılan altı analizden üçünde R2 0,80 veya daha düşük çıkmıştır. İlginç bir şekilde, alt-üst grupta ESKS ile başarı puanları arasındaki ilişki diğer yıllara göre farklılık göstermiştir. Matematik ve okuma alanları için üst grupta, fen için ise alt grupta daha yüksek korelasyon gösteren tek yıl 2015'tir. Bu bilgi, 2015 yılında akademik performansın öngörülmesinde gözlenen farklılıkların daha fazla araştırılması gerektiğini göstermektedir.

Bu çalışma, alt-üst grup sınıflandırmasını kullanması bakımından birçok benzer çalışmadan ayrılmaktadır. Bu nedenle, sınıflandırma sürecinde dağılımdaki medyan veya standart sapma gibi değerler kullanılmamıştır. Bunun yerine, kesme noktaları SRA algoritmasının sürekli yordayıcı değişkeni en güçlü noktasında ayırdığı kök düğümde belirlenmiştir. Böylece, alt-üst grubun kategorizasyonu dağılımı eşit olarak bölmeye değil, sonuç değişkeni için en büyük yordama gücüne sahip noktaya dayandırılmıştır. Grafiklere göre, kategorizasyonun medyan değerlere dayanması halinde sonuçlarda kayda değer farklılıklar ortaya çıkacaktı ki bu değerler tüm yıllarda ESKS için sürekli olarak -1,5 civarında seyretmiştir. ESCS alt-üst grupları için kesme değerleri, bu çalışmada tespit edildiği gibi, yıllar arasında farklılıklar göstermiştir. Ayrıca, bu kesme değerleri seçilen yöntemden önemli ölçüde etkilenmiştir. Yapılan tüm analizlerde, alt grup sürekli olarak daha büyük bir oran oluşturmuş, yaklaşık %70 ile %85 arasında değişmiş ve en sık rastlanan oran %75 civarında olmuştur.