A CLOSER LOOK TO TURKISH STUDENTS' SCIENTIFIC LITERACY: WHAT DO PISA 2015 RESULTS TELL US?

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
STATISTICS

OCTOBER 2018

Approval of the thesis:

A CLOSER LOOK TO TURKISH STUDENTS' SCIENTIFIC LITERACY: WHAT DO PISA 2015 RESULTS TELL US?

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ABSTRACT

A CLOSER LOOK TO TURKISH STUDENTS' SCIENTIFIC LITERACY: WHAT DO PISA 2015 RESULTS TELL US?

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October 2018, 100 pages

PISA is one of the international large-scale surveys to assess the level of knowledge and skills of the 15-year-old students. In PISA 2015, the main theme was scientific literacy. Correspondingly, this study aims to determine factors that might affect the degree of scientific literacy of the Turkish students. Elastic net regression, which is one of the shrinkage methods was used to select a subset of variables. Then, these variables were modelled by using backward elimination technique manually in multiple linear regression. Based on the analysis, the study revealed that test anxiety, environmental awareness, interest in broad topics in science, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills were the factors that contributed most to the degree of scientific literacy.

Keywords: Elastic net regression, Shrinkage methods, PISA 2015, Scientific Literacy, Multiple Linear Regression

ÖZ

TÜRK ÖĞRENCİLERİN BİLİMSEL OKURYAZARLIKLARINA YAKINDAN BİR BAKIŞ: PISA 2015 SONUÇLARI BİZE NELER SÖYLÜYOR?

Demirci, Sinem
Yüksek Lisans, İstatistik
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Ekim 2018, 100 sayfa

PISA, ülkeler arası yapılan, 15 yaş öğrencilerinin belirli konularda bilgi ve beceri seviyelerini ölçen bir test olarak 2000 yılından beri uygulanmaktadır. Her üç yılda bir uygulanan bu test, her uygulandığı zaman aralığında bir konuyu ana tema olarak belirlemektedir. 2015 yılında PISA'nın ana teması olarak bilimsel okuryazarlık belirlenmiştir. Bu sebeple mevcut çalışmanın amacı, PISA 2015'e katılan Türk öğrencilerinin bilimsel okuryazarlık seviyelerini etki eden faktörleri belirlenmiştir. Büzüşme regresyonlarından biri olan elastik net regresyonu, çalışmanın amacı kapsamında analiz yöntemi olarak seçilmiştir. Elastik net regresyonu sonucunda elde edilen değişkenler, çoklu doğrusal regresyon analizi kullanılarak modellenmiştir. Adımsal yöntemlerden biri olan geriye doğru seçim yöntemi kullanılarak anlamlı bulunan değişkenler ile modelin son hali belirlenmiştir. Çalışma sonucunda sınav kaygısı, çevresel farkındalık, bilim konularına ilgi, okuldan sonra bilgisayar oyunu oynama, matematik okuryazarlığı, okuma becerisi ve ortaklaşa problem çözme becerisinin fen okuryazarlığının belirlenmesinde en önemli değişkenler olduğu gözlenmiştir.

Anahtar Kelimeler: Büzüşme tahminleyicisi, Elastik net regresyonu, PISA 2015, Bilimsel okuryazarlık, Çoklu doğrusal regresyon

To Uncle Yakup

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my supervisor Assoc. Prof. Dr. Özlem İlk Dağ for her guidance, advice, criticism, encouragements and insight throughout the research. Without her endless support, I would not be able to finish this thesis. I would also like to thank committee members for their valuable feedbacks and suggestions. Thank you sincerely.

My husband, Levent, and my mother, Nalan, have supported me throughout my graduate school journey. I would not be standing here today without their endless emotional, financial, and nutritional support. Thank you so much for always encouraging me to follow my dreams even if they are fantastic, surrealistic, or impossible.

Without the existence of my daughter, Yağmur Eylül, I would not be able to complete to write this thesis. Since the day I learned my pregnancy, I accelerated all my academic works so that I will be able to spend more time with her. I am so grateful to have you in my life, honey.

I would also like to thank my office mates, Gözde, Mehmet, and Seçil for their support. Their friendship, creative ideas and questions -and sometimes jokes- helped me improve myself throughout the graduate school years. In addition, I would like to thank Hakan and Oğuz who helped me remember / learn the basics of Calculus, Linear Algebra, and Probability before starting this Master's Degree Program. Studying with them enable me to grasp better the concepts of statistics. Thanks a lot!

Last but not least, I will forever be grateful to Uncle Yakup for always believing in me. Memories with him pushed me to apply this program and it really breaks my heart to not celebrate this graduation with him. But I know he'll be right here watching over me until the day we're together again.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

OECD: The Organisation for Economic Co-operation and Development

PISA: The Programme for International Student Assessment

PV: Plausible Values

VIF: Variance Inflation Factor

WLE: Weighted Likelihood Estimate

CHAPTER 1

INTRODUCTION

The Programme for International Student Assessment (PISA) is an international education survey, which is done at once in every three years. OECD launched this initiative in 1997 (OECD, 2016), and sixth cycle of PISA test were administered in 2015. The purpose of this test is to assess different educational systems of the countries by measuring some skills and knowledge of 15-year-old students.

PISA has a framework shaped by cooperative works of experts from the countries/economies where their students take this test (OECD, 2016). By having international expert groups, it is intended to increase the validity of the test in a way that this test can be used in different cultural and curricular context and allow countries and researchers to compare the test results. In addition to these expert groups, PISA framework is also reviewed by local expert groups in every participating countries/economies and the test framework is finalized in each PISA cycle (OECD,2016).

The areas that students are tested in PISA 2015 are related to science, mathematics, reading, collaborative problem solving and financial literacy (OECD, 2016). In every cycle, PISA choose a focal point to its test. In PISA 2015, this focal point was determined as scientific literacy. Although there are different definitions for scientific literacy, OECD (2017) described scientific literacy in PISA 2015 following:

> Scientific literacy is the ability to engage with science-related issues, and with the ideas of science, as a reflective citizen.
>
> A scientifically literate person is willing to engage in reasoned discourse about science and technology, which requires the competencies to:
>
> - Explain phenomena scientifically – recognise, offer and evaluate explanations for a range of natural and technological phenomena.
> - Evaluate and design scientific enquiry – describe and appraise scientific investigations and propose ways of addressing questions scientifically.
> - Interpret data and evidence scientifically – analyse and evaluate data, claims and arguments in a variety of representations and draw appropriate scientific conclusions (p.22).

Besides assessing skills and knowledge of the students in these literacy frameworks, additional information is collected from students, teachers, parents, and school principals about students' home possessions, some individual characteristics of the students, and their learning environment in their school. After testing is completed, data is shared online in OECD website to enable countries and researchers to conduct several statistical analyses. In this way, policy makers of the countries acquire an opportunity (1) to examine the level of skills and knowledge of their students; (2) to assess how these levels of skills and knowledge might be related to different variables in their home, classroom, and school as well as individual differences (OECD, 2009)

In this thesis, it was aimed to determine what factors affect Turkish students' scientific literacy. Correspondingly, one of the shrinkage methods, elastic net regression, was used to determine which factors may affect the level of scientific literacy of Turkish students. Shrinkage method (also known as penalized regression) is one of the classes of methods in linear model selection and regularization including all *p* predictors by shrinking their coefficients towards zero compared with least squares estimates providing a decrease in variance (James, Witten, Hastie, & Tibshirani, 2013). There are three kinds of shrinkage methods as *ridge regression*, *lasso regression*, and *elastic net regression* (Zou & Hastie, 2003). Based on the shrinkage method that is chosen, some of the coefficients can be valued as zero so that this method may also be used as variable selection (James, Witten, Hastie, & Tibshirani, 2013)

Elastic net regression is one of the shrinkage methods created by Zou and Hastie (2003). This method was proposed to overcome some limitations in lasso regression such as improving prediction accuracy and acquiring better results. Zou and Hastie described this method by making an analogy as (Zou & Hastie, 2003, p.3) "…*It is like a stretchable fishing net that retains 'all' the large 'fish'"*. This method is specifically chosen since the aim of this study is to choose the variables that may affect most the degree of scientific literacy of Turkish students according to PISA 2015 results. The data of this study has more than 200 variables and by using elastic net regression, the number of variables were reduced so that the variables that explain the variance in scientific literacy most were intended to be remained in the model.

After determining the variables by using elastic net regression, the model was also tested in another program called IDB Analyzer. The IEA International Database Analyzer (IDB Analyzer) was created by IEA Data Processing and Research Center (2018) to analyze large-scale surveys mostly in educational context. The reason to test the model with IDB Analyzer is that it enables researchers to construct models using plausible values (PV) both as exploratory and explanatory variables as well as replicate weights in a linear model. The concept of plausible values and replicate weights will be introduced under the section of "Background of the study". IDB Analyzer helped eliminate non-significant variables from the model. A comparison of this model was made finally through ordinary least square regression (OLS) by using R Programming Language because it allows checking if there is multicollinearity between explanatory variables, which IDB Analyzer does not.

The chapters of this thesis contain following: Chapter 1 gives general information about PISA tests and its framework. Chapter 2 includes a review of literature about international key results of previous PISA cycles, studies related to our national PISA results in historical order and shrinkage methods used in statistics. On the other hand, Chapter 3 involves methodology of the study with the description of the variables and participants; data collection and data analysis procedure. In Chapter 4, the results of the study are given in detail by means of data preparation, handling missing data, conducting penalized regression, determining the number of variables, testing the model in IDB analyzer and checking the appropriateness of the model in OLS by using R Programming language. In the last section, a discussions and conclusions are made and implications and limitations of this study is presented.

1.1 Background of the Study

Before introducing the problem, analysis and results of this study, it might be useful to give some background information about PISA data. Unlike other measures, psychological or educational measures involve considerable amount of measurement errors due to several reasons. OECD (2009) outlined these reasons as (1) the concept of theories in social sciences are too comprehensive to be gauged; (2) they might be influenced by several unknown factors such as emotional and / or physical states of the students during the administration of the test; and (3) the environment that students participated in the study might influence their performance. Consequently, there may be large overlaps in the posterior distributions. PISA applies a rotated booklet design which students take subset of the items to overcome these challenges listed above. By using the answers given for the subset of the items, students' ability and their degree of literacy are determined by using plausible values and weighted likelihood estimate (WLE).

Nationwide and international educational tests like PISA generally evaluate the knowledge and/or skill of a population rather than individuals. Hence, reducing error for interpreting the results of a population is focal point rather than concentrating on individuals. Correspondingly, they give students' results via plausible values rather than single-point estimate (OECD, 2009).

Plausible values are used in large educational surveys. Wu and Adams (2002) defined the concept of plausible values as they are random values obtained from the probability distribution of the abilities that an individual might have. In other words, it is an imputation method which have random draws from a distribution rather than estimating a single point estimate for a student. In PISA 2015, students have 10 plausible values for each types of literacy. For instance, they have 10 plausible values for their degree of scientific literacy, 10 plausible values for mathematics literacy etc.

The PISA database also contains WLE estimated from other constructs such as student-level or school-level questions. Warm (1989) indicated that maximum likelihood estimates (MLE) can be biased in individuals' ability estimates and suggested to introduce weights based on the level of information that every questionnaire item has. Using WLE can adjust the small bias by taking into account weights while estimating MLE.

The last concept is replicate weights. In general, educational research involves two-stage sample design in a way that schools are chosen randomly first and then students draw from the schools at random as well. This two-stage random sampling result in an underestimation of the sampling variances. Therefore, IEA used replication methods to calculate sampling variances (OECD, 2009). PISA uses Fay method for replicate weights.

The plausible values, accompanied with the replicates, entails that any parameter like a mean, a standard deviation or a correlation, should be calculated 810 times (i.e. 10 plausible values by one student final weights and 80 replicates) to acquire the final estimate of any parameter and its standard error. Hence, it can be sometimes complex to use different statistical methods and analysis programs for researchers. Therefore, two programs as IDB analyzer and R programming language was used in this study to try different analysis technique to acquire a suitable model to explain the factors that might affect the degree of scientific literacy of Turkish students.

1.2 Statement of the Problem

The statements of the problems of this study are following:

1. What are the factors that affect the level of scientific literacy of Turkish students most?

2. Is there any congruency between the variables emerged in penalized regression and multiple linear regression?

1.3 Significance of the Study

International large-scale assessments have a key role for countries in terms of educational, economical, and political aspects. In terms of educational perspective, countries have an opportunity to explore level of knowledge and skills of the students in different educational areas such as science, mathematics, reading as well as psychological constructs such as motivation and attitudes of the students towards a specific content. Moreover, countries are also informed by other variables that might interfere with students' knowledge and skills like the role of teachers, schools, classroom environments, parents, home belongings etc. By using the data of large-scale assessments, they are able to analyze, infer the relationships among these variables and draw conclusions about their national educational systems. At this point, this study may provide useful information to educational policy makers as well as educators, parents and students themselves about how Turkish students' degree of scientific literacy might be related to various demographic, social, economic and educational variables in Turkey. Moreover, examining the degree of Turkish students may also give some clues about how to enhance our students' scientific literacy by using these variables. In the long run, it may provide an insight for establishing improvements in our national educational systems and for understanding the relative strengths and weaknesses of our own education systems. On the other hand, as OECD (2009) highlighted, economic and social welfare of the nations are largely correlated with their citizens' level of knowledge and skills. Therefore, participating in international tests like PISA enable them to evaluate how their young population is ready for the future. Accordingly, the results of this study may give information and allow doing some projections about our national economy and social welfare in the long run.

As accessible literature on PISA indicated, no study was found using shrinkage methods to analyze PISA data. In terms of statistics perspective, this study may be considered as an initial point to use these types of statistical methods to analyze PISA data to explore which factors may affect the students' level of knowledge and skills mostly among the variables. Moreover, this study may also contribute to the literature in terms of exemplifying how penalized regression works in these types of national and international survey data. Last, working with plausible values, WLEs and replicate weights was not clearly described in most of the studies within the context of education in the accessible national literature. Therefore, this study is also intended to provide some information about how these methods works and how they can be applied in educational statistical analysis.

CHAPTER 2

LITERATURE REVIEW

This chapter summarized the related literature on both elastic net regression and PISA studies. Some studies related to elastic net regression were briefly summarized. Then, literature based on PISA 2015 data were presented. Last, Turkish national literature on PISA results were given.

2.1 Literature Review on Elastic Net Regression

Elastic net regression is relatively newest shrinkage method compared with ridge regression. It was firstly introduced by Zou and Hastie (2003) to gain benefits both from ridge and lasso. Since it is a relatively new area in the literature on shrinkage methods, the number of studies that used elastic net regression are limited (e.g. Lenters, et al., 2016; Ogutu, Schulz-Streeck, & Piepho, 2012; Zou & Hastie, 2005). These studies were conducted in biology and medicine areas. However, no studies were found using shrinkage methods in the educational area in the accessible literature.

2.2 Literature Review on PISA 2015

The data of PISA 2015 were released in 2016 by OECD. After that, studies were conducted to see nations' level of literacy based on the several variables. Besides, some studies were conducted by comparing two or more countries. In general, the range of scientific literacy scores was from 332 to 556. Top ten scorers in PISA 2015 in the area of science are Singapore, Japan, Estonia, Chinese Taipei, Finland, Macao (China), Canada, Viet Nam, Hong Kong (China), B-S-J-G (China). The ranking of Turkey was 54th among 72 other participants. In this section, the results of some other countries available in the literature was summarized.

Thomson, Bortoli and Underwood (2017) published a report related to Australian students PISA 2015 performance. In terms of scientific literacy, their students have higher scores than the OECD average which was 419 even though their score decreased by 17 points since PISA 2006. Gender difference was not statistically significant for their country.

Kastberg, Chan, and Murray (2016) reported U.S. performance in science literacy. Their students' average score in scientific literacy was very close to OECD average. Moreover, they reported that their average scores in scientific literacy were not significantly changed over time.

2.3 National Literature Review of PISA Results in the Context of Scientific Literacy

In our national literature, when the frequencies of the studies in literacy domains were reviewed, limited number of studies concerning the degree of scientific literacy was reported compared to mathematics literacy and reading literacy. Even though different analyses were performed in PISA studies in Turkey, no detailed information about dealing with plausible values were given in all studies. In addition, no shrinkage method was used in our national literature as well. The table summarizing the results of national studies were given in Table 1.

Table 1 Summary of National Studies in PISA

Aim of the Study	*Variables*	*Statistical Methods*	*Results*
• To determine significant factors explaining reading skills in PISA 2015 (Ataş & Karadağ, 2017)	Gender, the social economic cultural index, the education level of the parents, and student-based reading skills = student level variables School type, number of students, number of teachers = school level variables	Two-level hierarchical modeling	• Economic social cultural index, education level of father, the school type and geographical region are statistically significant.
• To explore the relationships among students' level of literacy, income distributions and education costs in OECD countries. (Yorulmaz, Çolak & Ekinci, 2017)	-	Literature review, no statistical method was conducted	• Student achievements of OECD countries in PISA was related to the just and efficient use of educational resources rather than the amount of educational resource allocated.
• To compare PISA 2012 2015 results of Turkey, Estonia, and Finland. Karamustafaoğlu, İleri & Ahisha (2017)	-	Document analysis and interview methods	• Finland and Estonia (1) offer educational facilities to the students with the same quality and the duration, (2) have student-centered teaching, (3) offer science courses in primary school, and (4) provide compulsory examination in every grade level.
• To determine personal and environmental elements that influence students' achievement in PISA 2012. (Kahraman & Çelik, 2017)	Attendance in pre-school, age to start school, mother education status, father education status, number of computers and books in the house.	Binary logistic regression	• Attendance in pre-school, age to start school, mother and father education status, number of computers and books in the house, age to start school and mother's work status are significant

Aim of the Study	*Variables*	*Statistical Methods*	*Results*
• to explore the multilevel latent classes for reading, mathematics, and science achievement in PISA 2012 • to examine predictive ability of students' perseverance, their openness to problem solving, their economic, social, and cultural status, and resources of school. Yalçın, 2017)	perseverance, openness to problem solving, economic, social, and cultural status (ESCS), learning environment at school, school's educational resources, and teacher shortage reading, mathematics, and science achievements	Multilevel latent class analysis	• Approximately half of the successful students were not affected by their parents' ESCS, parents' jobs, home possessions related to educational context, school's facilities, and teacher qualifications.
• to determine the predictive roles of perseverance and openness to problem solving on achievement in the lower and upper quartiles in three domains in PISA 2012. (Kutlu, Kula-Kartal & Şimşek, 2017)	Explanatory variables = Perseverance and openness to problem solving Response variables = Achievement in three domains	Quantile regression analysis	• There is positive, medium, and significant relationship between perseverance and openness to problem solving. • Perseverance predicts achievement better in the lower quartile of score distribution. • Openness to problem solving predicts achievement better in the upper quartile of score distribution in all domains
• To show relationships between students' characteristics and their level of scientific literacy in PISA 2012 (Demir, 2016)	12 variables were defined under 3 factors by using PCA = Socio-economic status, opinions for teachers, attitudes for school Secondary level latent variable = scientific literacy	Secondary level structural equation modelling	• Socioeconomic status is the best predictor of scientific literacy skills. • Opinions for teacher is negatively correlated with scientific literacy. • Attitude is positively correlated. • Home possessions is the best predictor.

Aim of the Study	*Variables*	*Statistical Methods*	*Results*
1. To what extent do the new literacy skills predict reading performance of the students in PISA 2012? 2. To what extent does the reading performance associated with new literacy skills predict mathematics and science performance of the students in PISA 2012? (Arıkan, Yıldırım & Erbilgin, 2016)	17 items for new literacy skills (using technology at school and outside school as two factor), reading scores, math scores, and science scores	Confirmatory factor analysis + path analysis	• Two-factor model emerged by CFA (at school and outside school) • 11% of the variance in reading performance is predicted by new literacy skills. • Reading performance predicts both math (%65 of the variance) and science performance (72% of the variance) • Outside of the school literacy predict science and math positively, whereas at school literacy predict both of them negatively (7% and 8% respectively).
• To find out whether there is any difference between school types in terms of reading enjoyment time, reading attitude, and learning strategies based on PISA 2009 cycle Kır , 2016)	School type Reading enjoyment time, reading attitude, and learning strategies	ANOVA	• The reading enjoyment differs between vocational high school and Anatolian, general high schools • While Anatolian high school students got higher mean scores, vocational high school students got lower mean scores in terms of reading attitude. • Learning strategies differs across all school types to some extent and while maximum difference was found between Anatolian high school and vocational high school, minimum difference was found between Anatolian high school and science high school.

Aim of the Study	*Variables*	*Statistical Methods*	*Results*
To determine the parental variables that explain the reading skills success scores of the students in PISA 2009. (The parent questionnaire was not implemented in Turkey, so researchers use some items in Ankara) (Avşar & Yalçın, 2015)	Explanatory variables: parental variables DV: reading scores of the students	CHAID analysis	• The students whose parents think that most of the teachers in their school are qualified in their field and devoted to their work have higher scores in terms of reading success.
To investigate relations between the factors related to Turkish students' reading abilities and the factors related to facilities that both students and families had in PISA 2009 (Özdemir & Gelbal, 2014)	*Predictor variables:* facilities, socioeconomic status, and info-tech *Criterion variables:* reading score, self-confidence	Canonical Commonality Analysis	- Predictor and criterion variable sets explained 31.7% of variance in students' academic success. - Utilizing information technologies while preparing homework variable was a suppressor and there was a great multicollinearity between facilities that students had at home and socio-economic status of families variables.
To explore factors affecting reading, mathematics, and science literacy in PISA 2009. (Gürsakal, 2012)	Reading literacy, math literacy, science literacy Gender, parental education levels, school starting age	t test, F test and logistic regression	• Students' performances are varying between gender (girls are better in science and reading while boys are better in math), school starting age (negative association between age and achievement) and parent's education level.
To determine the best predictors of reading literacy by the variables of parental education, family wealth possessions, cultural possessions, home education resources for PISA 2003, 2006, 2009. (Gülleroğlu, Bilican Demir & Demirtaşlı, 2014)	Predictive variables: parental education, family wealth possessions, cultural possessions, and home educational resources	Multiple regression analysis (stepwise) for each three year	• Best predictors for each term are respectively, home educational resources, parental education and cultural possessions.

CHAPTER 3

METHODOLOGY

In this chapter, shrinkage methods are briefly introduced. Then, elastic net regression is given in detail. In the next part of this chapter, a summary of multiple linear regression is presented.

3.1 Shrinkage Methods

Shrinkage method (also known as penalized regression) is one of the classes of methods in linear model selection and regularization including all p predictors by shrinking their coefficients towards zero compared with least squares estimates providing a decrease in variance (James, Witten, Hastie, & Tibshirani, 2013). There are three kinds of shrinkage methods as *ridge regression*, *lasso regression*, and *elastic net regression* (Zou & Hastie, 2003). Even though elastic net regression is used in this study, some general information about ridge regression and lasso regression is presented since elastic net regression combines some of the features of them.

3.1.1 Ridge Regression

As James, Witten, Hastie, and Tibshirani, (2013) defined, least squares regression is one of the techniques that estimates $\beta_0, \beta_1, \beta_2, \ldots \beta_p$ by choosing the values which minimizes residual sum of squares (RSS) as

$$\text{RSS} = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}(\beta_j x_{ij}))^2 \qquad (3.1)$$

Ridge regression have some shared characteristics with least squares. They both minimize RSS. However, one distinctive feature of ridge regression is that it additionally uses second term which includes a *tuning parameter*, λ, being equal to or greater than zero as following:

$$\text{RSS} + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{3.2}$$

where second term is a *shrinkage penalty*. In the case of $\beta_1, \beta_2, \ldots \beta_p$ are close to zero, this penalty term becomes smaller leading to shrinking the estimates of β_j close to zero as well. On the other hand, the tuning parameter λ provide balance the relative effects of terms on the regression coefficient estimates. As it can be easily observed, the shrinkage penalty drops in the case of $\lambda = 0$, and ridge regression becomes the conventional least squares estimates. Nevertheless, the effect of the penalty term increases when $\lambda \rightarrow \infty$, and the ridge regression coefficient estimates becomes closer to the values of zero. Different from least squares technique, ridge regression generates various sets of coefficient estimates for every different λ. Hence, choosing an appropriate value for λ is essential.

One of the benefits of ridge regression compared to least squares is that as tuning parameter increases, variance tend to reduce but accompanied with larger bias compared to least squares (James, Witten, Hastie, & Tibshirani, 2013; Zou & Hastie, 2003). Even though this *bias-variance trade-off* improves prediction, ridge regression includes all the explanatory variables in the model (Zou & Hastie, 2003). In other words, it does not select a subset of the variables, which can be considered as a drawback for building a model. This situation may become complex when the number of variables in dataset is very large.

3.1.2 Lasso Regression

Lasso regression proposed by Tibshirani (1996) is another shrinkage method. This method is designed to improve the drawback of ridge regression summarized in the former section. Lasso regression can be written by the following:

$$\text{RSS} + \lambda \sum_{j=1}^{p} \left|\beta_j\right| \tag{3.3}$$

The difference between (3.2) and (3.3) is the penalty terms. While the penalty term in (3.2) is called as ridge regression penalty in the literature, the latter one is called as lasso penalty.

Similar with ridge regression, lasso regression also apply shrinkage to coefficient estimates near to zero except for compelling some coefficients to have a value of zero in the case of λ is necessarily large. These compelling results in variable selection in the model, which is not the case in ridge regression. Hence, choosing an appropriate value for λ is also essential in lasso regression. Removing some of the irrelevant variables makes a model more interpretable compared to ridge regression (James, Witten, Hastie, & Tibshirani, 2013).

Even though it seems that lasso regression is a better approach than ridge regression, it also has some drawbacks. These drawbacks were listed by Zou and Hastie (2003) as following: (1) if the number of explanatory variables p is larger than number of observations n in a dataset, lasso regression may not be useful; (2) In the case of existing highly correlated variables, lasso regression choses occasionally one of the variables and ignore the other even though removed one may be a better predictor than the other; and (3) In the conventional $n > p$ cases, in the case of highly correlated variables, the lasso regression can be outweighed by ridge regression performance.

3.1.3 Elastic Net Regression

Zou and Hastie (2003) propose elastic net regression to overcome the limitations of lasso and benefit from the advantages of it such as selection of subset among the variables and shrinkage as well. Zou and Hastie described this method by making an analogy as (Zou & Hastie, 2003, p.3) "*…It is like a stretchable fishing net that retains 'all' the large 'fish''*". This means that elastic net regression removes unimportant variables, and this leads to improve prediction accuracy. They proposed both naïve elastic and elastic net and compare the characteristics of them. The naïve elastic net were following:

$$\mathrm{L}\ (\lambda_1, \lambda_2, \beta) = \mathrm{RSS} + \lambda_2 \sum_{j=1}^{p} \beta_j^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| \qquad (3.4)$$

In (3.4) both the ridge penalty and the lasso penalty are used together since the aim of this combination is that Zou and Hastie (2003) intended to use the strengths of the lasso and ridge regression to attain their goals. Nevertheless, even though naïve elastic net penalty gives the impression of combining both strengths of ridge regression and lasso regression, simulation studies and applications in real data does not meet the expectations of them. Based on the results of their study, naïve elastic net tends to be like either ridge regression or lasso regression. That is to say, it does not either eliminate some irrelevant variables or behaves like lasso regression. Moreover, it introduced double amount of shrinkage due to be combination of both shrinkage methods.

In order to improve naïve elastic net, Zou and Hastie (2003) revised it. This rescaling factor improves the performance and allow borrowing strengths of both of ridge regression and lasso regression. This shrinkage method is chosen for this study since the data of this study have more than 200 variables with 5895 number of observations. Hence, we need to have a parsimonious model that can explain the degree of scientific literacy of the students with fewer parameters.

3.2 Model Selection in Elastic Net Regression

In order to select a suitable model in elastic net regression, some criteria are considered such as mean squared error (MSE), mean prediction error, and deviance ratio.

Mean squared error refers to a value that indicates how well the prediction performance of the model is compatible with the observed data (James, Witten, Hastie, & Tibshirani, 2013). The formula of MSE can be written following:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}(x_i))^2 \tag{3.5}$$

where $\hat{f}(x_i)$ can be considered predicted value for i^{th} observation. Based on (3.5), one can conclude that choosing a model having lower MSE values would be better since it indicates how predicted response values is closed to observational values. Therefore, having a relatively lower MSE value was one of the criteria for this study. In both cross-validation and modelling of full data processes, MSE values were examined. In cross-validation, MSE values were calculated based on train data.

Mean prediction error is another criterion that is considered in model selection of this study. Mean prediction error indicated how model constructed by using train data behaves on the test data which is a new data introduced to the model. As in MSE values, having relatively lower mean prediction error is preferred.

Deviance ratio means the fraction of null deviance explained by the model. For elastic net regression, this value can be regarded as R-square (Friedman, Hastie, & Tibshirani, Simon, Narasimhan, & Qian, 2018). Therefore, the having highest deviance ratio was one of the criteria in this study.

CHAPTER 4

APPLICATION

The aim of this study was to determine the factors that might affect the degree of scientific literacy of Turkish students in PISA 2015. Correspondingly, this chapter includes the research design of the study, information of the data set, participants of the study, description of the variables used in PISA 2015 was given. Next, data preparation and data cleaning processes including missing data was reported. Then, brief information about data collection instruments and data analysis procedure was presented.

4.1 Research Design of the Study

One of the quantitative research methodologies is examining the relationships among variables without manipulating them. This methodology is either describe phenomena by exploring the relationships of some variables that might affect the variability in these phenomena or predict possible outcomes based on the nature of the relationships between response and explanatory variables (Fraenkel, Wallen & Hyun, 2012). Within the context of this study, determining the factors that might affect Turkish students' scientific literacy is determined as a purpose. Prediction based on the results of this study may not be possible since some of the explanatory variables such as math literacy, reading literacy and collaborative problem-solving are collected in every PISA cycle. Hence, predicting them may not be possible.

4.2 Population and Sample

PISA 2015 was administered to over half a million 15-year-olds students participating the survey. It is assumed that the population of 15-year-old children in 72 countries and economies is about 29 million (OECD, 2017).

In the context of this study, whole sample of Turkish students in PISA 2015 were chosen as sample. As Ministry of National Education (MONE) reported (2018), the actual population was 1,324,089 students. The accessible population was determined as 925,366 students. The schools are determined by using stratified random sampling technique. The strata in Turkey were determined as statistical regions, types of schools (public or private), types of education (vocational and technical secondary, general secondary and basic education) location of the schools, and types of administrations in schools. After determining the schools, students within each school were selected by using simple random sampling technique. As a result, 5,895 students from 187 schools representing 61 cities from 12 statistical regions was selected as sample for PISA 2015. The detailed information was presented in Table 2.

Table 2 Descriptive Statistics of PISA 2015 Sample According to Regions

Region Code	*Name of the Region*	*Frequency (n)*	*Percentage (%)*
TR1	Istanbul	1070	18.15
TR2	West Marmara	245	4.16
TR3	Aegean	707	11.99
TR4	East Marmara	510	8.65
TR5	West Anatolia	553	9.38
TR6	Mediterranean	817	13.86
TR7	Middle Anatolia	334	5.67
TR8	West Blacksea	303	5.14
TR9	East Blacksea	194	3.29
TRA	Northeast Anatolia	199	3.38
TRB	Middle East Anatolia	276	4.68
TRC	Southeast Anatolia	687	11.65
	TOTAL	5895	100

4.3 Information on the Full Data Set

In PISA 2015, a total of 72 countries /economies administered PISA test to their students. The duration of the test was two-hour long. In every cycle, one of the literacy contexts is chosen as a main subject for that cycle. In this cycle, scientific literacy was the main theme of PISA test. Some of the specific questions, which will be given later in this section, was related to scientific literacy. Students were evaluated in science, mathematics, reading, collaborative problem solving and financial literacy. Besides, some additional information was collected from students, teachers, school principals, and parents. Turkey did not take options of financial literacy questionnaire, ICT literacy questionnaire, educational career questionnaire, parent questionnaire and teacher questionnaire. The language of the PISA test was Turkish. The data set and some descriptive results were published on December 2016 on the following website http://www.oecd.org/pisa/data/2015database/

4.4 Data Preparation and Data Cleaning Processes

Data set published by OECD included whole data of 72 countries in a single data file. Moreover, students data file, bullying questionnaire data file, collaborative problem solving data file and school questionnaire data file were released as different data files on the website. In data preparation part, four data files namely students' data file, bullying questionnaire, collaborative problem-solving data file and school questionnaire merged into a single datafile. Then, data sets firstly were split into country-specific data files to conduct analysis in shorter time interval. The procedure of splitting files was completed in IBM SPSS software program by writing syntax and merging four data files were done by using toolbar of the program. After the data set was formed, descriptive statistics were performed to all variables to obtain some general information about data and determine how missing data will be imputed after examining the descriptive statistics output.

Some variables were deleted from the data set for several reasons. For example, variables that Turkish students did not answer were deleted from the data set. On the other hand, if the percentage of missingness is higher like 50%, these variables were also removed from the data set. Besides, there are some variables that explain the same phenomenon in different types of data. For instance, there are some nominal variables like "*Does your father have this qualification? <ISCED level 6>*" and some ordinal variables such as "*What is the <highest level of schooling> completed by your father?*" which are the same data but entered in different data types. These duplicate variables were also eliminated. Next, there are some variables such as that entered one by one and their total scores or estimates as a factor as well. To overcome this, total scores /estimates were retained in the data file and the others were eliminated as well. Next, the nominal variables that has a lot of categories were removed from the data set to simplify analysis. For example, job occupations of parents have more than 15 categories and generating dummy variables for each job for both mother and father may not be feasible while conducting analysis. Moreover, the variable that has not homogeneously grouped were also eliminated. As an example, a variable dividing into two groups with the percentage 97% and 3% were not included into data set. Last, the variables that are specific to mathematic literacy, reading literacy, and other lectures were also removed from the data set since the response variable of this study was scientific literacy. For these reasons, some items were eliminated from the data set. After data cleaning process was completed, the data set was converted into .csv file to administer imputation methods for missing data in R Project for Statistical Computing (2018).

4.4.1 Handling Missing Data

Missing data were coded in different numbers such as 5, 9, 99, 999 in the data file. In order to apply imputation techniques, they were firstly converted to NA. After converting NA, the results of descriptive statistics were examined. The results of descriptive statistics were given in Appendix A. For the missing data in nominal and ordinal data, mode substitution was used as an imputation method. For continuous variables, mean imputation was carried out as an imputation. The reason to use this imputation method is that the proportion of missing data was quite low in data set. The advantages to use this method is that it enables to use complete case analysis.

4.5 Description of the Variables

After data cleaning and preparation processes were completed, 246 variables remained to be analyzed. The codes and the descriptions of the variables were given in Appendix B.

4.6 Data Collection Instruments

Turkish students were administered PISA 2015 test on computer rather than paper-pencil test. OECD (2016) reported that PISA test is composed of both multiple-choice questions and open-ended questions. The test questions were arranged in groups based on the real-life scenario. Students also take an additional questionnaire related to themselves, facilities at home and at their school as well as learning experiences. For the first time, PISA 2015 included bullying questionnaire and collaborative problem solving questionnaire for the students. Turkey did take these tests as well besides scientific literacy test. Moreover, school principals were administered another questionnaire that is related to their school system and the learning environment.

4.7 Data Collection Procedure

In PISA 2015, students answered the questions on the computer rather than taking paper-pencil test. In the case of answering all the items, students should have spent about 810 minutes of test items for science, reading, mathematics and collaborative problem solving. Due to the fact that it is not possible and feasible as well, different students are administered different subsets of test items. Completing this subset test takes approximately two hours.

When students completed subset of the cognitive PISA items, Rasch model is used to estimate students' performance as if they took the whole test. The principle of Rasch model is summarized by OECD (2005) following: students' ability can be predicted by using item difficulty and probability of the success. In Rasch model, a continuum is generated. Low achievers and easier items were on the left-hand side of the continuum whereas high achievers were on the right-hand side. Rasch model generate a probabilistic function to show the relationship between parameters.

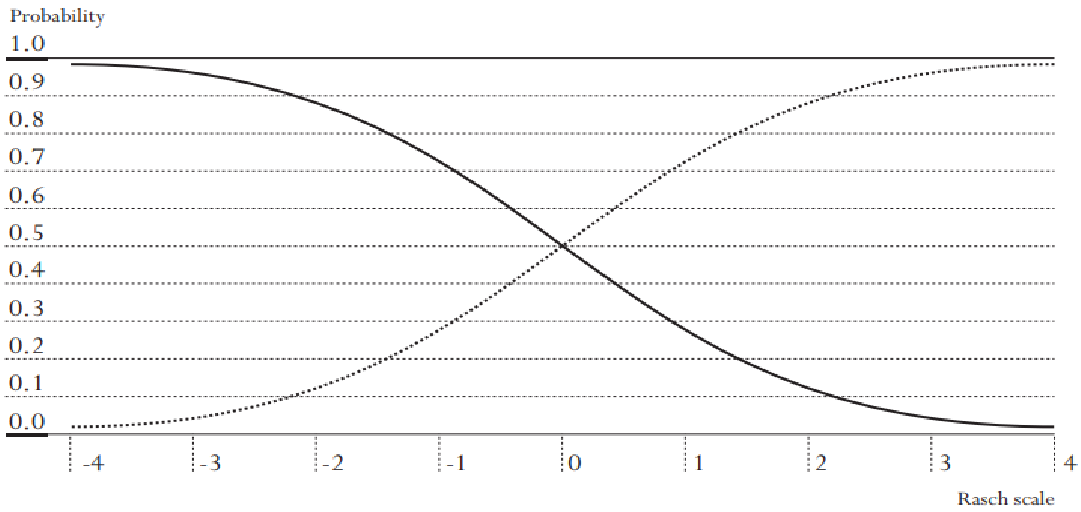

Figure 1. Probability of success to an item of difficulty zero as a function of student ability.
(retrieved http://www.oecd.org/education/school/programmeforinternationalstudentassessmentpisa/35004299.pdf)

Figure 1 indicated the probability of success as dotted curve, whereas probability of failure as a solid curve. This can be also written as a form of logistic function as,

$$P\left(X_{ij} = 1 \middle| \beta_i, \delta_j\right) = \frac{\exp(\beta_i - \delta_j)}{1 + \exp(\beta_i - \delta_j)} \qquad (4.1)$$

where student *i*, with an ability denoted β_i, gives a correct answer to item *j* of difficulty δ_j. By using this function, the probability that a student succeeds on an item can be calculated. With the help of this probabilistic link, solving subset of the items can be sufficient to estimate as if the whole item pool is solved. As long as link items were constructed amongst the subsets, Rasch model can work efficiently. PISA uses a version of generalized Rasch model to polytomous items (correct, partially correct and correct or Likert scale) proposed by Wright and Masters (1982).

There are different kinds of Rasch ability estimators. PISA uses WLE and plausible values which are summarized in the former sections. In the next section, data analysis procedure will be explained.

4.8 Data Analysis Procedure

Data cleaning and data preparation processes were completed in IBM SPSS software program. Descriptive statistics, mean/mode substitution and penalized regression were done by using R Project for Statistical Computing. After selecting variables by using elastic net regression, IDB Analyzer developed by IEA was used to conduct multiple linear regression by using plausible values and replicate weights. Backward elimination technique was used for deciding final model. Last, by using R Project for Statistical Computing program, Variance Inflation Factor (VIF) values were checked if there is a multicollinearity problem which IDB Analyzer does not provide such analysis. In the following chapter, detailed results were presented.

CHAPTER 5

RESULTS

The aim of this study was to determine the factors that might affect the degree of scientific literacy of Turkish students. Based on this purpose, this chapter presents the results of the study. First, cross-validation processes for all 10 plausible values were reported. After choosing the best working plausible value, the analysis related to elastic net regression for the full data were given. There are three different models constructed within the context of the study. The description of the models were summarized in the following sections. After determining the number of variables by using elastic net regression, these three models were tested in IDB Analyzer program since this program enable researcher to use plausible values as both response and explanatory variables. In this program, these three models were tested by using manual backward elimination technique in multiple linear regression. The results and necessary outputs were given. Last, two models were also tested in R Project for Statistical Computing since that function provides more useful outputs, such as *p*-values for the coefficients (James, Witten, Hastie, & Tibshirani, 2013) as well as multicollinearity checks between explanatory variables. After reporting these steps, final model was presented.

5.1 Description of the Data: Exploratory Data Analysis

In this section, some descriptive statistics results were given to portray 15-year-old students in Turkey based on PISA 2015 results in scientific literacy. This section mostly was conducted by using *intsvy* package available in R Project for Statistical Computing Program (Caro & Biecek, 2017). The reason to choose this package is that it enables researchers to conduct analyses by using all plausible values.

Overall, Turkish students had a mean score of 425.49 with a standard deviation of 79.26. In terms of gender, female students had a mean score of 428.65 (*SD*= 78.77) while male students' mean score was 422.33 (*SD*=79.62). As our national report on PISA 2015 declared, this difference between gender was not statistically significant. However, PISA evaluated the scientific literacy of the countries in terms of the level that they determined rather than comparing mean scores. Hence, in the next section, these levels and distribution of the Turkish sample according to these levels were reported.

Level	Lower score limit	Characteristics of tasks
6	708	At Level 6, students can draw on a range of interrelated scientific ideas and concepts from the physical, life and earth and space sciences and use content, procedural and epistemic knowledge in order to offer explanatory hypotheses of novel scientific phenomena, events and processes or to make predictions. In interpreting data and evidence, they are able to discriminate between relevant and irrelevant information and can draw on knowledge external to the normal school curriculum. They can distinguish between arguments that are based on scientific evidence and theory and those based on other considerations. Level 6 students can evaluate competing designs of complex experiments, field studies or simulations and justify their choices.
5	633	At Level 5, students can use abstract scientific ideas or concepts to explain unfamiliar and more complex phenomena, events and processes involving multiple causal links. They are able to apply more sophisticated epistemic knowledge to evaluate alternative experimental designs and justify their choices and use theoretical knowledge to interpret information or make predictions. Level 5 students can evaluate ways of exploring a given question scientifically and identify limitations in interpretations of data sets including sources and the effects of uncertainty in scientific data.
4	559	At Level 4, students can use more complex or more abstract content knowledge, which is either provided or recalled, to construct explanations of more complex or less familiar events and processes. They can conduct experiments involving two or more independent variables in a constrained context. They are able to justify an experimental design, drawing on elements of procedural and epistemic knowledge. Level 4 students can interpret data drawn from a moderately complex data set or less familiar context, draw appropriate conclusions that go beyond the data and provide justifications for their choices.
3	484	At Level 3, students can draw upon moderately complex content knowledge to identify or construct explanations of familiar phenomena. In less familiar or more complex situations, they can construct explanations with relevant cueing or support. They can draw on elements of procedural or epistemic knowledge to carry out a simple experiment in a constrained context. Level 3 students are able to distinguish between scientific and non-scientific issues and identify the evidence supporting a scientific claim.
2	410	At Level 2, students are able to draw on everyday content knowledge and basic procedural knowledge to identify an appropriate scientific explanation, interpret data, and identify the question being addressed in a simple experimental design. They can use basic or everyday scientific knowledge to identify a valid conclusion from a simple data set. Level 2 students demonstrate basic epistemic knowledge by being able to identify questions that can be investigated scientifically.
1a	335	At Level 1a, students are able to use basic or everyday content and procedural knowledge to recognise or identify explanations of simple scientific phenomenon. With support, they can undertake structured scientific enquiries with no more than two variables. They are able to identify simple causal or correlational relationships and interpret graphical and visual data that require a low level of cognitive demand. Level 1a students can select the best scientific explanation for given data in familiar personal, local and global contexts.
1b	261	At Level 1b, students can use basic or everyday scientific knowledge to recognise aspects of familiar or simple phenomenon. They are able to identify simple patterns in data, recognise basic scientific terms and follow explicit instructions to carry out a scientific procedure.

Figure 2. Proficiency level in science *(retrieved from OECD, 2016, p.60)*

5.1.1 Distribution of Percentages for Each Proficiency Level

PISA determined six levels for scientific literacy. These levels were defined as following:

The percentages of the students according to the proficiency levels given in Figure 2 were calculated for both all participants and by grouping the levels according to gender. This procedure was conducted by using *intsvy* package available in R Project for Statistical Computing Program (Caro & Biecek, 2017). The related R-codes were given in Appendix C. The results were given below in Table 3.

Table 3 Percentages and Standard Errors According to Proficiency Level.

Proficiency Levels	*Range of Score Limits*	*All Students*		*Female*		*Male*	
		(%)	*Std. Err.*	*(%)*	*Std. Err.*	*(%)*	*Std. Err.*
6	> 708	0.01	0.02	0.00	0.00	0.02	0.04
5	633-708	0.24	0.12	0.20	0.18	0.28	0.13
4	559-633	4.91	0.87	5.33	1.06	4.50	0.87
3	484-559	19.26	1.40	20.04	1.62	18.48	1.65
2	410-484	30.99	1.28	31.48	1.61	30.50	1.46
1a	335-410	31.82	1.54	31.28	1.65	32.36	1.98
1b	< 335	12.77	1.05	11.67	1.32	13.87	1.46

Based on the Table 3, it can be observed that 75.58% of Turkish students were at or below Level 2. On the other hand, distribution of the percentages among proficiency levels according to the gender have similar patterns. However, almost no female student was located in the highest level in terms of scientific literacy, whereas the percentage of male students was also quite low (0.02%).

5.1.2 Distribution of Science Literacy Scores According to Regions and School Types

Turkey is considered as 12 regions in PISA 2015 (please see Table 2). Correspondingly, the mean values of scientific literacy scores according to these 12 regions were calculated. The results were given in Figure 3.

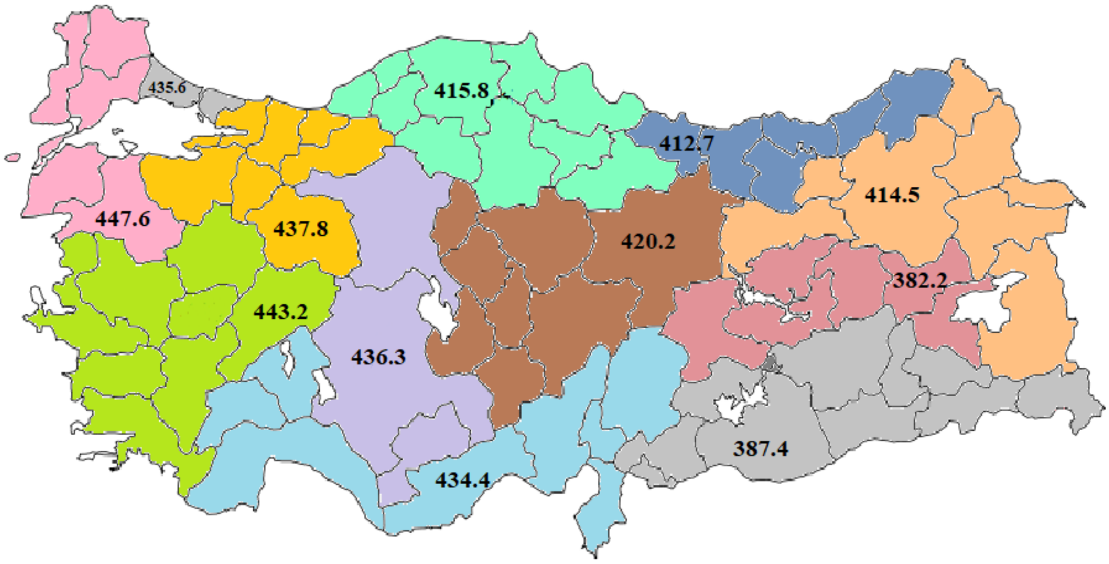

Figure 3. Mean score of scientific literacy according to 12 regions

As indicated in Figure 3, West Marmara had the highest mean value which is 447.6 in scientific literacy, whereas Middle East Anatolia had the mean score of 382.2 which was the lowest.

School typed were determined in PISA 2015 as basic education, general secondary school, and vocational and technical secondary school. The mean values, standard deviations and standard errors according to school types were given in Table 4.

Table 4 Percentages and Standard Errors According to Proficiency Level.

Types of School	*f (n)*	*Mean*	*Std. Err.*	*Standard Deviation*	*Std. Err.*
Basic Education	121	334.53	9.20	55.55	7.84
General Secondary School	3221	457.44	6.09	75.24	2.67
Vocational and Technical Secondary School	2553	389.83	4.15	63.8	2.33

As it can be seen from Table 4, the highest mean value of scientific literacy of Turkish students was from the ones from general secondary school while the lowest score was from the students of basic education (middle school students).

5.1.3 Distribution of Science Literacy Scores According to Playing Video Games after School

Mean scores in scientific literacy according to playing video-games after school were included in exploratory data analysis since it emerged as one of the significant factors in our analysis (please see chapter 5.5). Mean values were calculated whether or not Turkish students play video-games after school. The results were given in Table 5.

Table 5 Percentages and Standard Errors According to Playing Video Games after School

Types of School	*f (n)*	*Mean*	*Std. Err.*	*Standard Deviation*	*Std. Err.*
Not Playing Video Games	2703	431.92	4.30	79.04	2.19
Playing Video Games	2830	424.35	4.12	78.32	2.12
Missing	362	381.70	8.38	74.61	4.61

Table 5 indicated that students who do not play video games after school have a mean score by 7.6 points higher than the others. In terms of statistical significance, it can be concluded there was a significant difference in the scores for playing video games after school (*M* = 424.35, *SD* = 78.32) and not playing video games after school (*M* = 431.91, *SD* =79.04); (*p* value of two-sided test=0.026).

5.1.4 Correlation among Variables

Correlation among variables were calculated and plotted. Figure 4 represents the amount of correlation among variables. White circles represent positive correlation, whereas black circles indicate negative correlation. However, as playing video games after school (ST078Q06NA) were coded as 1 =Yes and 2 = No, the interpretation of the correlation should be done by considering this coding pattern. The size of the circles refers to the strength of the correlation. For the literacy scores, randomly chosen ones were used rather than including all possible 30 plausible values. The reason to choose one random plausible values for each variable will be given in the next sections of this chapter.

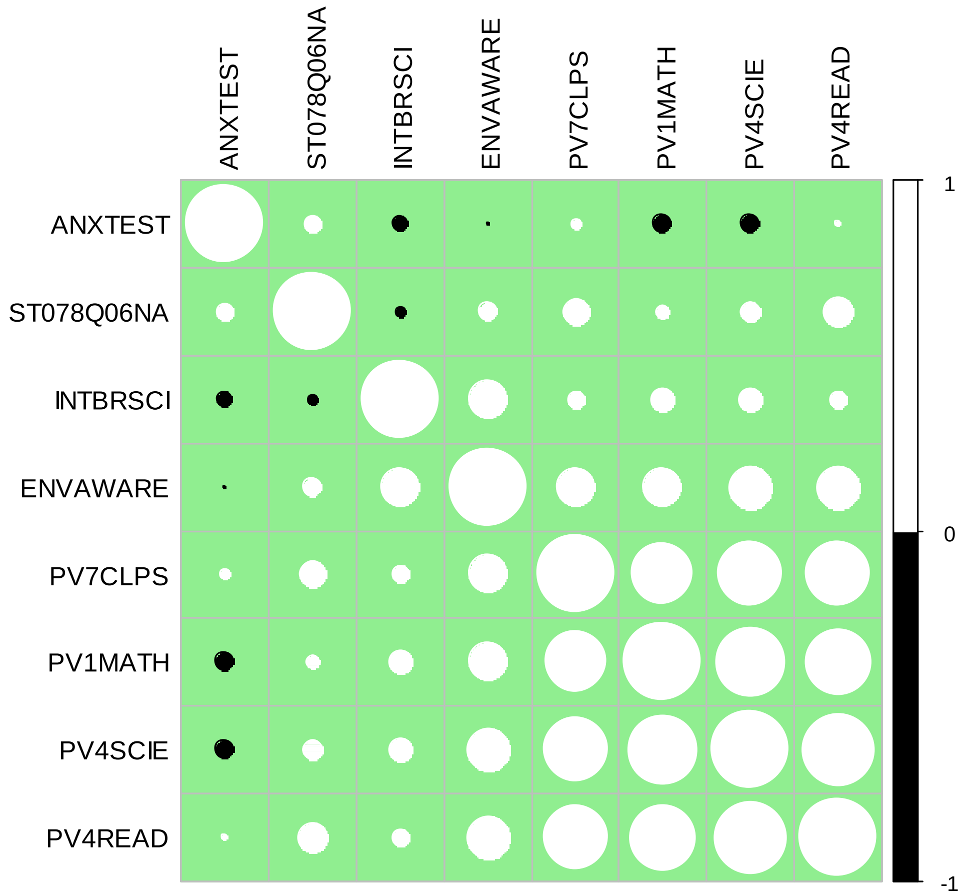

Figure 4. Graphical display of correlation matrix among variables

The correlation values between PV4 Science and other explanatory variables were given in Table 6. Again, the correlation between playing video games and scientific literacy should be interpreted by considering this coding pattern. That is to say, although the correlation seems to be positive, it should be interpreted as negative. Playing video games after school is inversely related to the degree of scientific literacy.

Table 6 Pearson's Correlation Coefficients between PV4 Science and Other Variables

	Environmental Awareness	*Interest in Broad Topics in Science*	*Test Anxiety*	*PV1 Math*	*PV4 READ*	*PV7 CLPS*	*Playing Video Games after School*
PV4 Science	0.31	0.10	-0.06	0.79	0.86	0.69	0.07

To sum up, the exploratory data analysis was conducted and reported in this section. In the following sections, cross-validation, elastic net regression and multiple linear regression was reported.

5.2 Cross-validation

Within the context of this study, scientific literacy was chosen as response variable whereas the other variables were determined as explanatory variables. Since PISA uses one of the Rasch model estimators, plausible values, 10 plausible values for scientific literacy was generated by PISA for each student. Moreover, for each three additional explanatory variables which are namely reading literacy, mathematics literacy, and collaborative problem solving, PISA also provides 10 plausible values. There is no package for including 10 plausible values as one unique response variable as well as other variables having plausible values in R Project for Statistical Computing program. Writing functions in R for overcoming this limitation is not feasible for this study; hence, 20 different data sets was formed for applying elastic net regression in R. In the first scenario, 10 different datasets for every plausible value for science was formed. Within these data sets, all 30 plausible values (10 for math, 10 for reading, and 10 for collaborative problem solving) were included as explanatory variables along with the other variables. In the second scenario, 10 different datasets for each plausible value for science was generated. At this time, three plausible values (1 for math, 1 for reading, and 1 for collaborative problem solving) was selected randomly as explanatory variables along with the other variables.

Each 20 datasets were divided randomly into two datasets as training data and test data to examine the test error of elastic net regression. In this study, a subset of numbers between 1 and *n* was randomly selected as train data (James, Witten, Hastie, & Tibshirani, 2013). Related R-codes were given in Appendix C. A random seed was put before the division of the data set so that the results can be replicable. After splitting the data set, elastic net regression model was fitted on the train data, and some criteria such as MSE, deviance ratio, and number of parameters were compared to choose the best data set for refitting the model on the full data set. Additionally, a grid search with the possible tuning parameters (λ) were done to obtain an interval between 50 and 100 parameters in the model. Among them, tuning parameter that is closer to 50 parameters was selected. The results were given in Table 7.

Based on Table 7, it can be observed that the data set which has *Plausible Value 4 in Science* (PV4) has the lowest MSE, lowest Mean Prediction Error, and highest deviance ratio among all other data sets. Therefore, the data set that has PV4 was decided to be used as full data set to refit the elastic net regression.

5.3 Results of Elastic Net Regression

After deciding which plausible value will be used for refitting, elastic net regression model on the full data set was repeated. Two full data sets were used. The former one has 30 PV within the explanatory variables (Data Set 1) while the latter includes 3 random PV (Data Set 2). Besides, one additional data set was generated by eliminating highly-correlated explanatory variables from Data Set 2 before fitting the model (Data Set 3). The results were reported in Table 8. Residual plots for models emerged from Data Set 1, Data Set 2 and Data Set 3 were given in Figure 5. List of highly correlated variables removed from Data Set 3 were given in Appendix D.

Table 7 Cross-validation of 10 Plausible Science Values

		MSE		*Mean Prediction Error*		*Deviance Ratio*		*Lambda (λ)*		*Number of Parameters*	
		30 PV	*3 PV*	*30 PV*	*3 PV*	*30 PV*	*3 PV*	*30 PV*	*3 PV*	*30 PV*	*3 PV*
PV1	*Train*	841.18	1040.12	-	-	0.863	0.823	2.66	2.01	50	60
	Test	-	-	916.94	1091.86	-	-	-	-	-	-
PV2	*Train*	788.64	1381.70	-	-	0.867	0.768	2.66	2.66	66	52
	Test	-	-	817.10	1446.35	-	-	-	-	-	-
PV3	*Train*	792.58	1406.92	-	-	0.864	0.766	2.66	2.01	58	66
	Test	-	-	831.19	1426.30	-	-	-	-	-	-
PV4	*Train*	753.53	1004.25	-	-	0.877	0.837	2.66	2.01	53	64
	Test	-	-	768.24	1092.29	-	-	-	-	-	-
PV5	*Train*	768.09	1370.12	-	-	0.870	0.764	2.66	2.66	55	53
	Test	-	-	811.51	1444.51	-	-	-	-	-	-
PV6	*Train*	797.97	1442.52	-	-	0.873	0.767	2.01	2.66	64	52
	Test	-	-	817.16	1451.37	-	-	-	-	-	-
PV7	*Train*	784.79	1197.16	-	-	0.863	0.802	2.66	2.01	58	67
	Test	-	-	799.26	1238.49	-	-	-	-	-	-
PV8	*Train*	814.90	1382.09	-	-	0.860	0.760	2.66	2.66	66	54
	Test	-	-	804.48	1514.40	-	-	-	-	-	-
PV9	*Train*	808.57	1424.09	-	-	0.868	0.761	2.66	2.66	55	54
	Test	-	-	793.63	1464.86	-	-	-	-	-	-
PV10	*Train*	771.00	1413.80	-	-	0.869	0.766	2.66	2.66	60	58
	Test	-	-	812.92	1478.65	-	-	-	-	-	-

Table 8 Refitting Elastic Net Regression for the Full Model

	MSE			*Deviance Ratio*			*Lambda*			*Number of Parameters*		
	Data Set 1	*Data Set 2*	*Data Set 3*	*Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 1*	*Data Set 2*	*Data Set 3*	*Data Set 1*	*Data Set 2*	*Data Set 3*
PV4	732.74	1055.02	1061.76	0.879	0.825	0.824	2.01	2.01	2.01	72	61	58

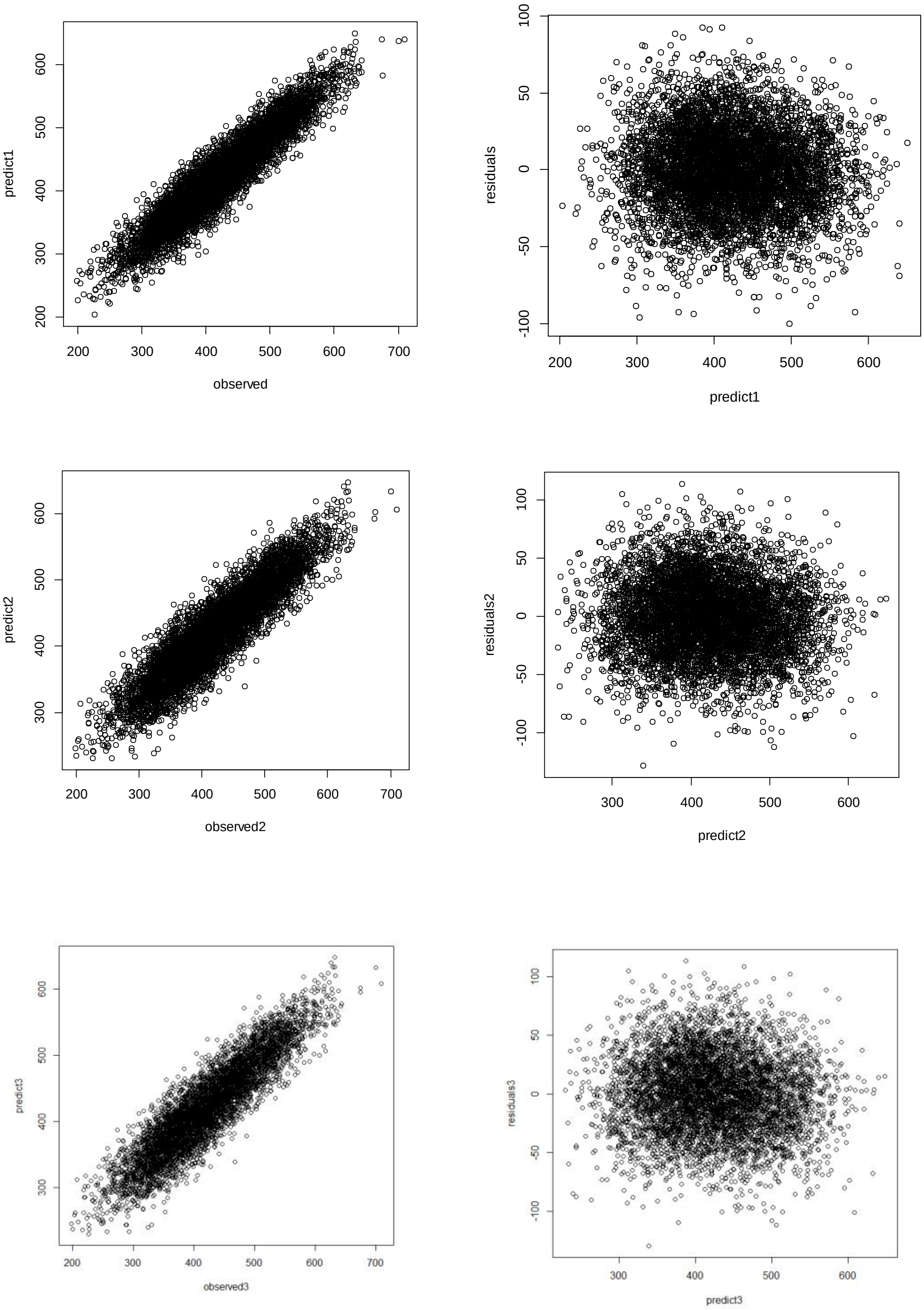

Figure 5. Residual plots emerged from data set 1, data set 2 and data set 3.

When Table 8 is examined, the smallest MSE values, the highest deviance ratio and the highest number of parameters among the three data sets belong to Data Set 1. Even though the other two data sets have high deviance ratio as well, their MSE values are bigger compared to Data Set 1. On the other hand, Figure 5 indicated no serious problem for the fit of these three models emerged from related data sets.

As R Project for Statistical Computing does not provide a multiple linear regression package including the analysis of plausible values, these subsets of variables in three data sets were modelled in IDB Analyzer program by using a manual version of backward stepwise elimination technique. In the next section, detailed results were presented for all three models.

5.4 Results of Multiple Linear Regression in IDB Analyzer

IDB Analyzer is a program developed for large-scale educational assessments. This program allows researchers to conduct some statistical analyses like multiple linear regression by using plausible values, replicate weights, and students' final weights. However, it does not provide an option for shrinkage.

5.4.1 Results of Multiple Linear Regression in IDB Analyzer of Model 1

A total of 72 parameters (please see Table 8) were refitted in another program called IDB Analyzer. This program enables researchers to obtain *R*-square, adjusted *R*-Square, standard error of the estimate and *t*-values. Backward elimination was done manually to decide on the final model. The alpha value (α), the risk of committing Type I Error, was decided as to be 0.05. At first, all values were included in the model by using Data Set 1. Related output was given in Figure 6.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	38.80	21.14	1.83	.	.	.
ANXTEST	-2.34	.88	-2.65	-.03	.01	-2.62
ENVAWARE	1.35	.47	2.86	.02	.01	2.85
ENVOPT	-1.20	.63	-1.91	-.02	.01	-1.90
EPIST	1.01	.71	1.41	.01	.01	1.42
FISCED	-.21	.54	-.39	-.01	.01	-.39
INSTSCIE	1.68	.82	2.05	.02	.01	2.05
INTBRSCI	1.47	.71	2.08	.02	.01	2.07
LEADTCH	1.70	2.77	.61	.02	.04	.61
RESPCUR	1.14	4.00	.29	.00	.02	.29
SC004Q06NA	-.14	.19	-.74	-.01	.01	-.76
SC009Q02TA	-.72	1.09	-.66	-.01	.02	-.65
SC009Q05TA	-1.31	1.16	-1.13	-.02	.02	-1.13
SC009Q10TA	-1.27	2.42	-.52	-.02	.03	-.52
SC009Q11TA	2.23	1.72	1.30	.03	.03	1.29
SC009Q12TA	-2.40	1.47	-1.63	-.03	.02	-1.57
SC027Q04NA	3.15	2.28	1.38	.02	.01	1.38
SC034Q01NA	-2.71	1.40	-1.94	-.03	.01	-1.86
SC034Q04TA	-1.48	1.24	-1.20	-.02	.02	-1.20
SC035Q09NA	-2.70	2.57	-1.05	-.02	.02	-1.05
SC035Q11NA	-1.47	2.19	-.67	-.01	.01	-.67
SC037Q09TA	-1.14	2.02	-.57	-.01	.01	-.57
SC037Q10NA	1.53	2.43	.63	.01	.01	.63
SC040Q11NA	-2.45	3.00	-.81	-.01	.02	-.82
SC040Q15NA	-1.37	3.39	-.40	-.01	.02	-.40
SC052Q01NA	-2.79	2.25	-1.24	-.02	.01	-1.24
SC053Q05NA	.64	2.21	.29	.00	.01	.29
SC064Q03TA	.09	.04	2.11	.03	.02	2.10
SCIEACT	.81	.76	1.06	.01	.01	1.06
ST004D01T	4.79	2.66	1.80	.03	.02	1.80
ST031Q01NA	-.81	.42	-1.96	-.02	.01	-1.96
ST038Q04NA	1.25	.94	1.34	.01	.01	1.34
ST038Q06NA	1.78	1.25	1.42	.01	.01	1.42
ST038Q07NA	1.50	1.39	1.08	.01	.01	1.09
ST064Q01NA	-1.89	1.15	-1.64	-.02	.01	-1.65
ST076Q04NA	-2.56	1.68	-1.52	-.02	.01	-1.52
ST076Q06NA	-1.66	1.88	-.88	-.01	.01	-.89
ST076Q07NA	1.47	1.38	1.07	.01	.01	1.07
ST076Q11NA	-1.28	1.59	-.81	-.01	.01	-.80
ST078Q06NA	-3.23	1.69	-1.91	-.02	.01	-1.92
ST078Q07NA	.72	1.62	.44	.00	.01	.44
ST078Q08NA	4.82	2.16	2.24	.02	.01	2.22
TOTST	.21	.22	.96	.01	.02	.95
STRATUM_D2	.53	3.48	.15	.00	.01	.15
PV_MATH	.39	.02	21.06	.40	.02	22.04
PV_READ	.37	.02	20.18	.38	.02	19.54
PV_CLPS	.21	.02	11.80	.21	.02	11.94

Figure 6. Output including all variables in Model 1.

When Figure 6 was examined, fewer than 72 items were observed. The reason for this reduction is that R Project for Statistical Computing considered all 30 plausible values in math, literacy, and collaborative problem-solving as 30 separate explanatory variables. On the other hand, IDB Analyzer use replicate weights and students' final weights. Correspondingly, this program treated 30 plausible values as 3 unique explanatory variables (10 PV for math literacy, 10 for reading literacy, and 10 for collaborative problem-solving). The details of this process can be examined in detail PISA Data Analysis Manual through the chapters of 3-8 (OECD, 2009). Moreover, R program allows researcher to construct different nominal variables; however, this is not possible in IDB Analyzer. For the analyses administered in R, the variable of “Stratum” is divided into two nominal variables such as *types of school* and *region*. In the IDB Analyzer, “Stratum” remains as one unique nominal variable. As a result, 72 variables in Data Set 1 decreased to 47 variables in IDB Analyzer.

As a result, a multiple linear regression analysis was conducted to evaluate how well the variables obtained by elastic net regression explain the degree of scientific literacy of Turkish students. Preliminary analyses were conducted to ensure no violation of normality, linearity, and homoscedasticity assumption. According to the results, a total of 10 variables were statistically significant ($| t_{calculated} | > t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, instrumental motivation, interest in broad science topics, proportion of parent involvement in school-related activities, average days attending physical education classes each week, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make a statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 7.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	6.55	7.53	.87	.	.	.
ANXTEST	-2.58	.86	-3.01	-.03	.01	-2.96
ENVAWARE	1.75	.43	4.05	.03	.01	4.04
INSTSCIE	1.49	.79	1.88	.02	.01	1.88
INTBRSCI	2.10	.77	2.73	.03	.01	2.71
SC064Q03TA	.07	.04	1.59	.02	.02	1.60
ST031Q01NA	-.73	.44	-1.65	-.01	.01	-1.65
ST078Q08NA	3.95	2.21	1.79	.02	.01	1.78
PV_MATH	.41	.02	24.66	.43	.02	27.28
PV_READ	.35	.02	22.52	.37	.02	21.55
PV_CLPS	.21	.02	13.19	.20	.02	13.09

Figure 7. Output related to 10 variables.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained first version explain the degree of scientific literacy of Turkish students. According to the results, a total of 6 variables were statistically significant ($|t_{calculated}| > t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 8.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	10.92	6.03	1.81	.	.	.
ANXTEST	-2.58	.85	-3.02	-.03	.01	-2.97
ENVAWARE	1.77	.43	4.09	.03	.01	4.07
INTBRSCI	2.15	.78	2.76	.03	.01	2.75
PV_MATH	.42	.02	23.56	.43	.02	25.96
PV_READ	.36	.02	22.48	.37	.02	21.51
PV_CLPS	.21	.02	13.35	.20	.02	13.22

Figure 8. Final output related to 6 variables.

After setting the final model, the regression equation can be written as following:

$\hat{Y}_{SCILIT}$=10.92-2.58$X_{ANXTEST}$ + 1.77$X_{ENVAWARE}$ + 2.15$X_{INTBRSCIE}$ + .42X_{MATH} + .36X_{READ} + .21X_{CLPS}

5.4.2 Results of Multiple Linear Regression in IDB Analyzer of Model 2

A total of 61 parameters (please see Table 8) were refitted in IDB Analyzer to obtain *R*-square, adjusted *R*-Square, standard error of the estimate and *t*-values. Backward elimination was used manually as a technique to decide on the final model. The alpha value (α), the risk of committing Type I Error, was decided as to be 0.05. At first, all 61 values from Data Set 2 were included in the model named as Model 2. After constructing the model, 10 variables were statistically significant. The nonsignificant variables were removed from the model and multiple linear regression was again performed. At this trial, 7 variables were statistically significant. The variables that were not significant were eliminated and the multiple regression analysis was repeated. At this point, all explanatory variables were observed as statistically significant. Related output for the first trial of multiple linear regression was given in Figure 9.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	-657829.08	1702745.45	-.39	.	.	.
ANXTEST	-2.42	.85	-2.83	-.03	.01	-2.80
ENVAWARE	1.41	.45	3.16	.03	.01	3.15
ENVOPT	-1.13	.62	-1.82	-.02	.01	-1.82
EPIST	1.07	.71	1.50	.02	.01	1.51
IBTEACH	-.07	.86	-.08	.00	.01	-.08
INTBRSCI	1.59	.71	2.23	.02	.01	2.22
LEADCOM	1.07	3.12	.34	.01	.03	.35
RATCMP1	.21	5.73	.04	.00	.02	.04
SC009Q02TA	-1.56	1.93	-.81	-.02	.03	-.80
SC009Q05TA	-1.38	1.24	-1.11	-.02	.02	-1.11
SC009Q11TA	2.53	1.20	2.10	.04	.02	2.08
SC009Q12TA	-2.46	1.49	-1.65	-.03	.02	-1.59
SC016Q01TA	.01	.04	.33	.01	.02	.34
SC019Q01NA01	-.06	2.86	-.02	.00	.20	-.02
SC027Q04NA	4.07	2.30	1.77	.03	.01	1.76
SC034Q01NA	-2.45	1.35	-1.82	-.02	.01	-1.72
SC034Q04TA	-1.90	1.30	-1.46	-.02	.02	-1.46
SC035Q07TA	.16	2.92	.06	.00	.02	.06
SC035Q09NA	-3.28	2.42	-1.36	-.02	.01	-1.35
SC037Q03TA	6.06	4.08	1.49	.02	.02	1.46
SC037Q08TA	-3.49	2.36	-1.48	-.02	.01	-1.48
SC040Q15NA	-1.79	2.76	-.65	-.01	.01	-.65
SC052Q01NA	-2.86	2.29	-1.25	-.02	.01	-1.25
SC053D11TA	.83	2.15	.39	.00	.01	.39
SC059Q01NA	-3.22	3.50	-.92	-.02	.02	-.92
SC059Q06NA	1.16	3.67	.31	.01	.02	.32
SC064Q03TA	.10	.05	2.25	.04	.02	2.24
SCHAUT	2.47	6.96	.35	.01	.02	.35
SCIEACT	1.20	.90	1.34	.02	.01	1.34
SMINS	.01	.01	2.06	.02	.01	2.04
ST004D01T	4.44	2.61	1.70	.03	.02	1.70
ST016Q01NA	-.39	.22	-1.83	-.01	.01	-1.84
ST031Q01NA	-.72	.41	-1.76	-.01	.01	-1.76
ST038Q04NA	.74	.95	.77	.01	.01	.78
ST038Q05NA	.95	1.38	.68	.01	.01	.69
ST038Q06NA	1.24	1.30	.95	.01	.01	.95
ST038Q07NA	.95	1.61	.59	.01	.01	.59
ST063Q06NA	-2.96	1.99	-1.49	-.01	.01	-1.48
ST063Q06NB	2.52	2.37	1.06	.01	.01	1.06
ST064Q01NA	-1.64	1.12	-1.46	-.01	.01	-1.46
ST076Q01NA	2.23	1.79	1.25	.01	.01	1.24
ST076Q06NA	-1.77	1.86	-.95	-.01	.01	-.96
ST076Q07NA	1.13	1.39	.81	.01	.01	.81
ST076Q11NA	-1.92	1.64	-1.17	-.01	.01	-1.16
ST078Q06NA	-3.31	1.63	-2.03	-.02	.01	-2.03
ST078Q07NA	1.04	1.61	.65	.01	.01	.65
ST078Q08NA	3.88	2.17	1.79	.02	.01	1.78
ST078Q09NA	1.08	1.31	.82	.01	.01	.82
ST125Q01NA	.87	1.81	.48	.01	.01	.48
STRATIO	-.06	.22	-.29	.00	.01	-.29
TOTST	.24	2.88	.08	.02	.20	.08
STRATUM_D2	.67	3.25	.21	.00	.01	.21
PV_MATH	.38	.02	18.68	.39	.02	18.50
PV_READ	.37	.02	19.21	.38	.02	18.80
PV_CLPS	.20	.02	11.47	.20	.02	11.67

Figure 9. Output related to model 2.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained by elastic net regression explain the degree of scientific literacy of Turkish students. Preliminary analyses were conducted to ensure no violation of normality, linearity, and homoscedasticity assumption. According to the results, a total of 10 variables were statistically significant (($|t_{calculated|}$ > $t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, participating teachers in reviewing management practices in schools, proportion of parent involvement in school-related activities, learning time of science (minutes per week), playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 10.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	15.10	6.96	2.17	.	.	.
ANXTEST	-2.47	.86	-2.88	-.03	.01	-2.83
ENVAWARE	1.71	.44	3.93	.03	.01	3.93
INTBRSCI	1.98	.78	2.56	.03	.01	2.54
SC009Q11TA	.40	1.02	.39	.01	.02	.39
SC064Q03TA	.07	.04	1.59	.02	.02	1.60
SMINS	.01	.01	1.42	.01	.01	1.42
ST078Q06NA	-5.38	2.47	-2.18	-.03	.02	-2.20
PV_MATH	.40	.02	23.13	.42	.02	24.94
PV_READ	.36	.02	22.63	.37	.02	21.66
PV_CLPS	.21	.02	12.69	.21	.02	12.59

Figure 10. Output related to 10 variables.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained first version explain the degree of scientific literacy of Turkish students. According to the results, a total of 7 variables were statistically significant ($|t_{calculated}|$ > $t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 11.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	17.35	6.10	2.84	.	.	.
ANXTEST	-2.51	.86	-2.94	-.03	.01	-2.89
ENVAWARE	1.74	.44	3.94	.03	.01	3.93
INTBRSCI	2.07	.78	2.66	.03	.01	2.65
ST078Q06NA	-5.32	2.50	-2.13	-.03	.02	-2.15
PV_MATH	.41	.02	22.72	.42	.02	24.49
PV_READ	.36	.02	23.01	.38	.02	22.13
PV_CLPS	.21	.02	12.96	.21	.02	12.89

Figure 11. Output related to 7 variables.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained second version explain the degree of scientific literacy of Turkish students. According to the results, a total of 7 variables were statistically significant ($t_{tabulated} > t_{critical}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make statistically significant contributions to explain the degree of scientific literacy. Contrary to its univariate relation, playing video games after school changed its effect on scientific literacy scores when multiple relations with other variables are introduced.

After setting the final model, the regression equation can be written as following:

$$\hat{Y}_{SCILIT}=17.35-2.51X_{ANXTEST} + 1.74X_{ENVAWARE} + 2.07X_{INTBRSCIE} -5.32\ X_{PLAY} + .41X_{MATH} + .36X_{READ} + .21X_{CLPS}$$

5.4.3 Results of Multiple Linear Regression in IDB Analyzer of Model 3

A total of 58 parameters emerged from Data Set 3 (please see Table 8) were refitted in IDB Analyzer to obtain R-square, adjusted R-Square, standard error of the estimate and *t*-values. Backward elimination was used manually as a technique to decide on the final model. The alpha value (α), the risk of committing Type I Error, was decided as to be 0.05. At first, all 58 values were included in the model named as Model 3. After constructing the model, 10 variables were statistically significant. The nonsignificant variables were removed from the model and multiple linear regression was again performed. At this trial, 7 variables were statistically significant. The variables that were not significant eliminated and the multiple regression analysis was repeated. At this point, all explanatory variables were observed as statistically significant. Related output for the first trial of multiple linear regression was given in Figure 12.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained by elastic net regression explain the degree of scientific literacy of Turkish students. Preliminary analyses were conducted to ensure no violation of normality, linearity, and homoscedasticity assumption. According to the results, a total of 10 variables were statistically significant (($|t_{calculated}| > t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, participating teachers in reviewing management practices in schools, proportion of parent involvement in school-related activities, learning time of science (minutes per week), playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make a statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 13.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	-657829.08	1702745.45	-.39	.	.	.
ANXTEST	-2.42	.85	-2.83	-.03	.01	-2.80
ENVAWARE	1.41	.45	3.16	.03	.01	3.15
ENVOPT	-1.13	.62	-1.82	-.02	.01	-1.82
EPIST	1.07	.71	1.50	.02	.01	1.51
IBTEACH	-.07	.86	-.08	.00	.01	-.08
INTBRSCI	1.59	.71	2.23	.02	.01	2.22
LEADCOM	1.07	3.12	.34	.01	.03	.35
RATCMP1	.21	5.73	.04	.00	.02	.04
SC009Q02TA	-1.56	1.93	-.81	-.02	.03	-.80
SC009Q05TA	-1.38	1.24	-1.11	-.02	.02	-1.11
SC009Q11TA	2.53	1.20	2.10	.04	.02	2.08
SC009Q12TA	-2.46	1.49	-1.65	-.03	.02	-1.59
SC016Q01TA	.01	.04	.33	.01	.02	.34
SC019Q01NA01	-.06	2.86	-.02	.00	.20	-.02
SC027Q04NA	4.07	2.30	1.77	.03	.01	1.76
SC034Q01NA	-2.45	1.35	-1.82	-.02	.01	-1.72
SC034Q04TA	-1.90	1.30	-1.46	-.02	.02	-1.46
SC035Q07TA	.16	2.92	.06	.00	.02	.06
SC035Q09NA	-3.28	2.42	-1.36	-.02	.01	-1.35
SC037Q03TA	6.06	4.08	1.49	.02	.02	1.46
SC037Q08TA	-3.49	2.36	-1.48	-.02	.01	-1.48
SC040Q15NA	-1.79	2.76	-.65	-.01	.01	-.65
SC052Q01NA	-2.86	2.29	-1.25	-.02	.01	-1.25
SC053D11TA	.83	2.15	.39	.00	.01	.39
SC059Q01NA	-3.22	3.50	-.92	-.02	.02	-.92
SC059Q06NA	1.16	3.67	.31	.01	.02	.32
SC064Q03TA	.10	.05	2.25	.04	.02	2.24
SCHAUT	2.47	6.96	.35	.01	.02	.35
SCIEACT	1.20	.90	1.34	.02	.01	1.34
SMINS	.01	.01	2.06	.02	.01	2.04
ST004D01T	4.44	2.61	1.70	.03	.02	1.70
ST016Q01NA	-.39	.22	-1.83	-.01	.01	-1.84
ST031Q01NA	-.72	.41	-1.76	-.01	.01	-1.76
ST038Q04NA	.74	.95	.77	.01	.01	.78
ST038Q05NA	.95	1.38	.68	.01	.01	.69
ST038Q06NA	1.24	1.30	.95	.01	.01	.95
ST038Q07NA	.95	1.61	.59	.01	.01	.59
ST063Q06NA	-2.96	1.99	-1.49	-.01	.01	-1.48
ST063Q06NB	2.52	2.37	1.06	.01	.01	1.06
ST064Q01NA	-1.64	1.12	-1.46	-.01	.01	-1.46
ST076Q01NA	2.23	1.79	1.25	.01	.01	1.24
ST076Q06NA	-1.77	1.86	-.95	-.01	.01	-.96
ST076Q07NA	1.13	1.39	.81	.01	.01	.81
ST076Q11NA	-1.92	1.64	-1.17	-.01	.01	-1.16
ST078Q06NA	-3.31	1.63	-2.03	-.02	.01	-2.03
ST078Q07NA	1.04	1.61	.65	.01	.01	.65
ST078Q08NA	3.88	2.17	1.79	.02	.01	1.78
ST078Q09NA	1.08	1.31	.82	.01	.01	.82
ST125Q01NA	.87	1.81	.48	.01	.01	.48
STRATIO	-.06	.22	-.29	.00	.01	-.29
TOTST	.24	2.88	.08	.02	.20	.08
STRATUM_D2	.67	3.25	.21	.00	.01	.21
PV_MATH	.38	.02	18.68	.39	.02	18.50
PV_READ	.37	.02	19.21	.38	.02	18.80
PV_CLPS	.20	.02	11.47	.20	.02	11.67

Figure 12. Output related to model 3.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	15.10	6.96	2.17	.	.	.
ANXTEST	-2.47	.86	-2.88	-.03	.01	-2.83
ENVAWARE	1.71	.44	3.93	.03	.01	3.93
INTBRSCI	1.98	.78	2.56	.03	.01	2.54
SC009Q11TA	.40	1.02	.39	.01	.02	.39
SC064Q03TA	.07	.04	1.59	.02	.02	1.60
SMINS	.01	.01	1.42	.01	.01	1.42
ST078Q06NA	-5.38	2.47	-2.18	-.03	.02	-2.20
PV_MATH	.40	.02	23.13	.42	.02	24.94
PV_READ	.36	.02	22.63	.37	.02	21.66
PV_CLPS	.21	.02	12.69	.21	.02	12.59

Figure 13. Output related to 10 variables.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained first version explain the degree of scientific literacy of Turkish students. According to the results, a total of 7 variables were statistically significant (($|t_{calculated}| > t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make a statistically significant contributions to explain the degree of scientific literacy.

After eliminating non-significant variables from the model, multiple linear regression was performed again. The related output was given in Figure 14.

Variable	Regression Coefficient	Regression Coefficient (s.e.)	Regression Coefficient (t-value)	Stndrdzd. Coefficient	Stndrdzd. Coefficient (s.e.)	Stndrdzd. Coefficient (t-value)
(CONSTANT)	17.35	6.10	2.84	.	.	.
ANXTEST	-2.51	.86	-2.94	-.03	.01	-2.89
ENVAWARE	1.74	.44	3.94	.03	.01	3.93
INTBRSCI	2.07	.78	2.66	.03	.01	2.65
ST078Q06NA	-5.32	2.50	-2.13	-.03	.02	-2.15
PV_MATH	.41	.02	22.72	.42	.02	24.49
PV_READ	.36	.02	23.01	.38	.02	22.13
PV_CLPS	.21	.02	12.96	.21	.02	12.89

Figure 14. Output related to 7 variables.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained second version explain the degree of scientific literacy of Turkish students. According to the results, a total of 7 variables were statistically significant (($|t_{calculated}|$

$> t_{critical=1.96}$). The sample multiple correlation coefficient was .86. Test anxiety, environmental awareness, interest in broad science topics, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students were found to make a statistically significant contributions to explain the degree of scientific literacy. Contrary to its univariate relation, playing video games after school changed its effect on scientific literacy scores when multiple relations with other variables are introduced.

After setting the final model, the regression equation can be written as following:

$\hat{Y}_{SCILIT}$=17.35-2.51$X_{ANXTEST}$ + 1.74$X_{ENVAWARE}$ + 2.07$X_{INTBRSCIE}$ -5.32 X_{PLAY} + .41X_{MATH} + .36X_{READ} + .21X_{CLPS}

5.5 Deciding on the Final Model

In the former sections of this chapter, all the three models were tested in IDB Analyzer obtained by shrinkage methods since elastic net regression does not include plausible values, replicate weights, and students' final weights. Nevertheless, IDB Analyzer does not contain ANOVA table of the model, VIF values, and *p*-values. Therefore, in order to decide on the final model for this study, *lm* () function in R program were performed for Model 2 to check those values that are not given in IDB Analyzer. Related R-codes were given in Appendix C. Outputs related to the final model and its assumptions were given in Figure 15 and Figure 16 respectively.

A multiple linear regression analysis was conducted to evaluate how well the variables obtained first version explain the degree of scientific literacy of Turkish students. The explanatory variables were test anxiety, environmental awareness, interest in broad science topics, playing video games after school, mathematics literacy, reading literacy, and collaborative problem-solving skills of the students. Preliminary analyses were conducted to ensure no violation of normality, linearity, homoscedasticity, independence of residuals assumptions and multicollinearity assumption. In addition, the data were inspected for outliers and no potential outliers were detected. According to the results, the combination of the predictor variables was significantly related to the dependent variable (F (7, 5887) = 3603, *p-value* < 2.2 x10^{-16}). The sample multiple correlation coefficient was .82. All the coefficients were statistically significant ($p<\alpha$).

```
> summary(model22)

Call:
lm(formula = y ~ z)

Residuals:
     Min       1Q   Median       3Q      Max 
-112.022  -22.792   -0.096   22.741  128.058 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 30.672474   2.950817  10.395  < 2e-16 ***
zENVAWARE    1.797635   0.331430   5.424 6.06e-08 ***
zINTBRSCI    2.063025   0.467632   4.412 1.04e-05 ***
zANXTEST    -3.288669   0.420999  -7.812 6.64e-15 ***
zPV1MATH     0.284320   0.008157  34.856  < 2e-16 ***
zPV4READ     0.520932   0.008735  59.636  < 2e-16 ***
zPV7CLPS     0.145355   0.008099  17.948  < 2e-16 ***
zST078Q06NA -6.259642   0.903059  -6.932 4.61e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 33.82 on 5887 degrees of freedom
Multiple R-squared:  0.8107,	Adjusted R-squared:  0.8105 
F-statistic:  3603 on 7 and 5887 DF,  p-value: < 2.2e-16

> vif(model22)
  zENVAWARE   zINTBRSCI    zANXTEST    zPV1MATH    zPV4READ    zPV7CLPS zST078Q06NA 
     1.1742      1.0706      1.0157      2.2797      2.5717      1.9654      1.0434 
```

Figure 15. Output for Model 2.

To sum up, Model 2 was decided as a final model for this study. The coefficients in IDB Analyzer was used for the regression equation since this program include plausible values, replicate weights, and students' final weights which reduce the bias.

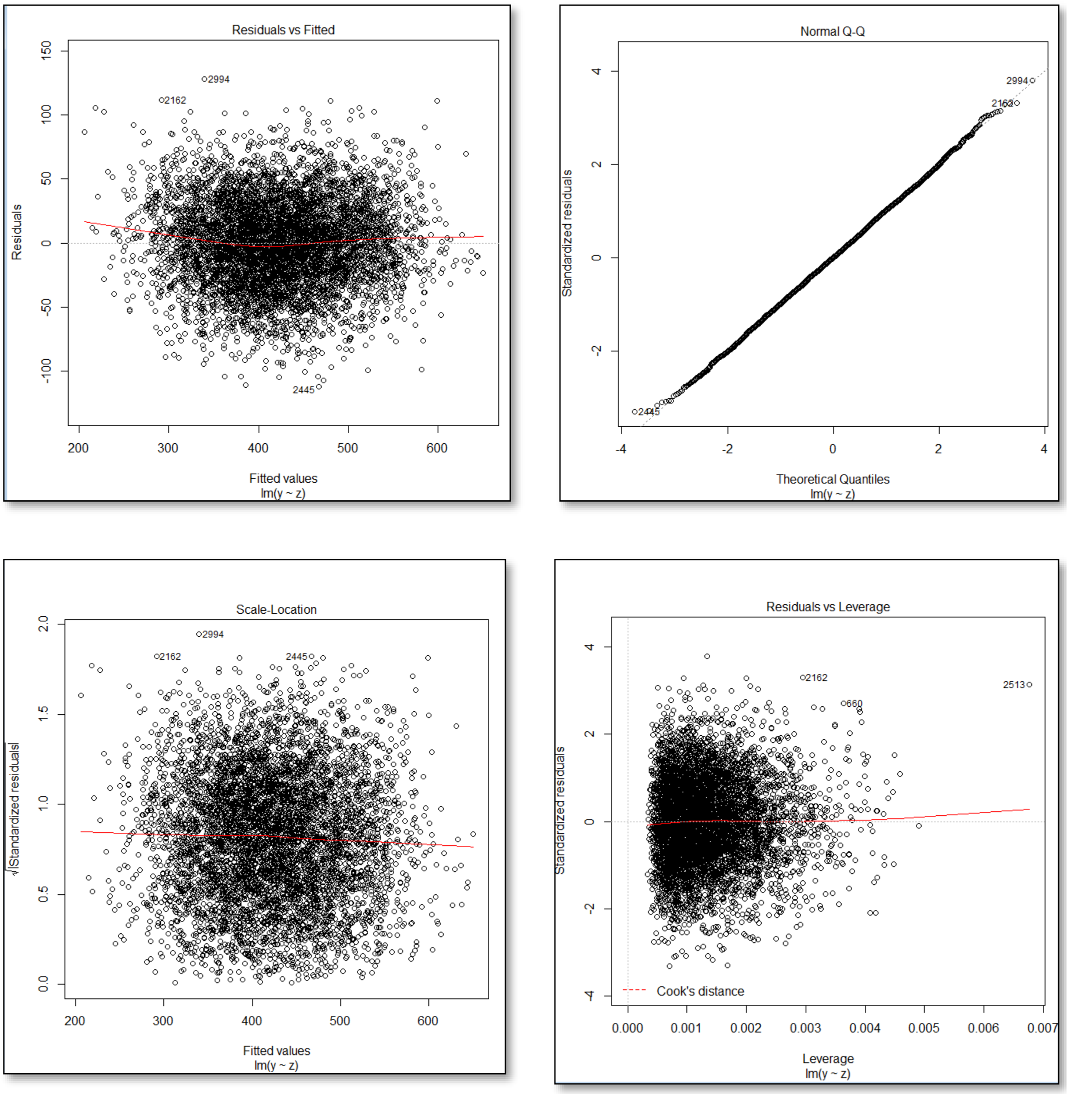

Figure 16. Output for standardized residuals in Model 2.

CHAPTER 6

DISCUSSION AND CONCLUSION

The aim of this study was to determine the factors that might affect the degree of the scientific literacy of Turkish students most and to explore whether there is any congruency between the variables emerged in penalized regression and multiple linear regression. This chapter tried to answer these research problems based on the results reported in the previous chapter.

6.1 Factors That Affect Turkish Students' Level of Scientific Literacy

To answer this research question, one of the newly-developed shrinkage methods was used to obtain subset of 246 variables that might be correlated with the degree of scientific literacy of the students. Before conducting the analysis, cross-validation was done for all 10 plausible values in science. Based on the results given in Table 7, Plausible Value 4 in Science was chosen as a response variable for refitting elastic net regression model in the full data set. Then, these subsets were tested in IDB Analyzer. We have three data sets in this step (please see Table 8 for details). We performed three multiple linear regression for these data sets. Backward elimination procedure was followed manually during these steps. We firstly insert all the variables of subsets obtained by using elastic net regression. Then, non-significant variables were eliminated and the analysis stages were repeated until all explanatory variables were statistically significant.

Even though IDB Analyzer provide analysis for using plausible values, replicate weights, and final students' weights, it does not give an output related to assumptions, ANOVA Table for the full model, and *p*-values for both the model and the parameters. Correspondingly, *lm ()* function in R was performed to obtain these values. Yet, coefficient estimates for the model was determined the ones that emerged from IDB analyzer since its results are unbiased compared to other programs. To conclude, seven variables out of 246 variables were determined as factors that are statistically significant and correlated with the scientific literacy of the students. These variables were explored one by one. The regression equation was following:

$\hat{Y}_{SCILIT}$=17.35-2.51$X_{ANXTEST}$ + 1.74$X_{ENVAWARE}$ + 2.07$X_{INTBRSCIE}$ -5.32 X_{PLAY} + .41X_{MATH} + .36X_{READ} + .21X_{CLPS}

Based on this equation, one can conclude that the degree of scientific literacy is directly proportional to environmental awareness, interest in broad science topics, playing video-games after school (1=YES, 2= NO), the degree of mathematics literacy, the degree of reading literacy and collaborative problem-solving skills of the students. Test anxiety, on the other hand, lead to a decrease in scientific literacy. However, the magnitude of regression coefficients should not be compared directly since the variables are not standardized. That is, it is not reasonable to conclude that test anxiety is more important than mathematics literacy in understanding the scientific literacy. Standardized coefficients are better in such comparisons.

Contrary to other large-scale assessments such as PISA and TIMSS, our final model did not include any variables such as socioeconomic status and homework-related variables. The reason for this result may rooted from including explanatory variables that have plausible values. These variables explained more than 60% of the variability in our model. In other studies, excluding these variables may include socioeconomic status and homework-related variables in their models. In the following sections, these factors were examined in detail.

6.1.1 Test Anxiety and Scientific Literacy

In our study, one unit increase in test anxiety leads to a decrease in scientific literacy about 2.51 unit. Actually, this was an expected result because there are parallel evidences in educational literature between this inverse relation (e.g. Alpert & Haber, 1960; Culler, & Holahan, 1980, Genc, 2017; McDonald, 2001). These studies generally reported that higher level of test anxiety lowers the academic performance of the students. In this study, similar result was also appeared. Turkish students who have higher level of test anxiety have lower level of scientific literacy.

6.1.2 Environmental Awareness and Scientific Literacy

In our study, one unit increase in environmental awareness leads to an increase in scientific literacy about 1.74 unit. This positive correlation was also reported in the literature. For example, Hadzigeorgiou and Skoumios (2013) reported that science education in schools can provide some opportunities to encourage students' about raising environmental awareness. Especially in the last 25 years, science educators focused on environmental issues which create a learning environment that fosters both raising environmental awareness (Wals 2011) and level of knowledge of the students in science (Hadzigeorgiou & Skoumios, 2013). The result of our study also indicated the same positive correlation between environmental awareness and the degree of scientific literacy.

6.1.3 Interest in Broad Science Topics and Scientific Literacy

In our study, one unit increase in interest in broad science topics leads to an increase in scientific literacy about 2.07 unit. There are similar results addressing this relationship (Chang & Cheng, 2008; Grabau & Ma, 2017). For example, Grabau and Ma (2017) use PISA 2006 data to examine the factors including in general interest in learning science on science achievement. The results of their study indicated that there is a positive correlation between interest in science and science achievement. Similarly, we found also the same correlation in Turkey context.

6.1.4 Playing Video Games and Scientific Literacy

In our study, playing video games after school leads to an increase in scientific literacy about 5.32 unit. This was actually an unexpected result since contrary to its univariate result, its relationship with scientific literacy scores was changed. Whereas the univariate results indicated that playing video games after school decreases the scientific literacy scores, our final model implied quite the opposite. The reason for this change can be interpreted as multiple relations with other variables in the regression may contribute to reversing its relationship. Therefore, implications based on this result should be carefully done. Just playing video games itself does not increase the scientific literacy of Turkish students. However, considering other variables of our final model as a whole, we may conclude that playing video games after school can contribute to increase in scientific literacy scores.

When the literature was examined, there is a trend study conducted by Young et al. (2012) related to exploring how games are interacting with academic achievement. They examined more than 300 studies and concluded that playing video games influence language learning, history, and physical education. However, found little support promoting science and mathematics performance of K-12 students. Nevertheless, when the context of Turkey considered, it is recommended that this relationship should be carefully interpreted since it may address something different that it appears. As an example, this can be an indication of the effect of some other variables such as level of socio-economic status which was not appear as a variable in our study. However, there are some studies which reported the statistically significant relationship between PISA results and socio-economic status (e.g. Aydın, Sarıer, & Uysal, 2012; Arıcı & Altıntaş, 2014) in our national literature. Hence, for the further studies, we recommend that the correlation coefficients between playing video games and some other possible variables should be examined. On the other hand, the content of the video-games may have a critical role to be appeared as a factor. The video-games that helps improve cognitive domain the level of knowledge and /skills may have a positive effect on scientific literacy of the students. As a recommendation, qualitative studies can be conducted to explore the relationship between video games and scientific literacy in-depth.

6.1.5 Mathematics Literacy and Scientific Literacy

In our study, one unit increase in test mathematics literacy leads to an increase in scientific literacy about 0.41 unit. Actually, this was an expected result because these two disciplines are inherently correlated with each other (Kullman, 1966). Moreover, a new approach was recently introduced globally named as STEM education. The acronym of STEM is science, technology, engineering, and mathematics. The aim of this strategy is to raise individual as STEM-literate citizens so that they would be able to have a deeper understanding on these subjects and their interrelations as well (Bybee, 2010). Turkey recently changed their national science curriculum so that it enables students to grasp the nature of STEM. Therefore, emerging this correlation is compatible with recent developments in science education.

6.1.6 Reading Literacy and Scientific Literacy

In our study, one unit increase in reading literacy leads to an increase in scientific literacy about 0.36 unit. This was an expected result too since there are some studies supported this result (Arıkan, Yıldırım, & Erbilgin, 2017). They found that reading literacy predicted mathematics literacy and scientific literacy of Turkish students in PISA 2012. As there is a similar result in PISA 2012, our finding related to reading literacy a scientific literacy can be compatible with our national literature.

6.1.7 Collaborative Problem-Solving Skill and Scientific Literacy

In our study, one unit increase in collaborative problem-solving skills leads to an increase in scientific literacy about 0.21 unit. This was an expected result too since there are some studies that support our results (e.g. Coleman, 1998). Additionally, it was reported that problem-solving skill is one of the components of scientific literacy (Palincsar, Anderson, & David, 1993). Therefore, having positive correlation between these two constructs is compatible with the literature.

6.2 Congruency between Elastic Net Regression and Multiple Linear Regression

In cross-validation process for all 10 plausible values in science, PV4 was chosen as response variable for the models constructed in R Project for Statistical Computing. The reason to choose one plausible value is that elastic net regression performed in R Project for Statistical Computing does not include the option to take 10 plausible values into account as a unique response variable. Hence, we decided PV4 as response variable since it has lowest MSE and mean prediction error, highest deviance ratio, and tuning parameter which leads to approximately 50 parameters. Based on the cross-validation results and considering the weighting and PV issues, three full data sets were formed within the context of this study to determine factors that might affect the degree of scientific literacy. Model 1 emerged from Data Set 1 has 30 PV within the explanatory variables, whereas Model 2 from Data Set 2 includes three random PV. Besides, Data Set 3 was generated by eliminating highly-correlated explanatory variables from Data Set 2 before fitting the Model 3.

Elastic net regression was conducted by using all three data sets. The reason to choose this method is that we have 246 variables and we want to select a subset of these variables which might be essential in explaining the degree of scientific literacy of Turkish students. Among them, Data Set 1 has lowest MSE and mean prediction error and highest deviance ratio. From the PISA data analysis manual, we know that using one plausible value without including other plausible values as well as replicate weights and final students' weights result in biased parameter estimates (OECD, 2005). Therefore, we used multiple linear regression technique for all three data sets in IDB Analyzer instead of choosing one of the data sets.

We used IDB Analyzer since it includes students' weights and replicate weights while conducting multiple linear regression to provide unbiased parameter estimates. We used three subsets of the variables emerged form data sets described in the former sections. We obtained three models from three data sets. However, when Model 2 and Model 3 were examined, it can be observed that they yielded the same results. From the theoretical perspective, it was an expected result since elastic net regression removes variables that have potential to create multicollinearity among explanatory variables. In Data Set 2, we have highly-correlated variables ($r \geq .80$) while we eliminate them manually in Data Set 3. If we have, for instance, two highly-correlated variables, we kept one which are highly correlated with all plausible values in science compared to the other. At the end, even though there are different number of parameters in Data Set 2 and Data Set 3, same variables remained in the model in IDB Analyzer. In Data Set 2, elastic net regression removed variables automatically that led to multicollinearity. On the other hand, we removed variables manually that led to multicollinearity in Data Set 3. Hence, it can be reasonable to end up with the same model. This result may also an indicator acquired from educational context that elastic net regression is able to remove one of the variables that are highly-correlated with some other explanatory variables.

Even though IDB Analyzer has some gains like using PV in multiple linear regression both as response and explanatory variable, this program has also drawbacks like not giving ANOVA table of the model, VIF values, and *p*-values. To obtain these values, R Project for Statistical Computing take to the stage. Nevertheless, as it is not possible to use 10 PV as one unique variable, we tested only Model 2 and Model 3 which are, in fact, the same model. We did not test Model 1 since it was obtained from Data Set 1 in which all 30 PV variables were as separate explanatory variables. As it was not the case in IDB Analyzer, it may not be a good idea to check Model 1 by using *lm()* function in R. As a result, all values retained in Model 2 were also statistically significant in multiple linear regression constructed by using *lm()* function. The coefficients were slightly different than the ones in IDB Analyzer. This may not be surprising because *lm()* function did not include replicate weights and students' final weights. What is more, we used 3 random PV explanatory variables. Hence, we accepted the coefficients in IDB Analyzer in our final model. For further studies, we recommend that this final model can be fitted for all proficiency levels defined by OECD (2016) separately to see whether different proficiency levels have the same factors that we found in our final model.

6.3 Limitations of the Study

There are some limitations in this study. They can be outlined as following:

- Working with plausible values in R Project for Statistical Computing was not possible within the context of this study. Even though there are some packages using plausible values as a response variable, including them both as response variable and explanatory variable was not possible in these packages. For the further studies, overcoming this limitation may have unique contribution for the literature.
- Although IDB Analyzer allow researchers especially for those who are non-statisticians have a user-friendly program, it has a limited number of analyses options. Therefore, no shrinkage method was offered in the program. Moreover, IDB Analyzer only accepts the variables already defined in PISA. No additional variable is allowed to introduce for the data set as well as the analysis. In addition,

this program does not offer all the diagnostics that is required to construct a valid multiple regression model. Therefore, we tried to compensate this limitation by using R Project for Statistical Computing. Correspondingly, while we had 2 dummy variables (we divided the variable of stratum into two) in the analysis performed in R, it was not possible in IDB Analyzer.

- For the missing values, Mean/mode substitution were used as imputation methods which is one of the oldest imputation techniques that has many disadvantages. For the further studies, we recommended to use multiple imputation techniques where possible.
- Deleting variables that have comparably higher percentage of missing data was another limitation for this study. Including them may improve the results of these kinds of studies in the future.
- We excluded nominal variables that have too many categories and this resulted in loss of information.
- No interaction term was introduced in this study since IDB analyzer does not have this option. For the further study, it can be fruitful to include interaction terms while performing multiple linear regression.

REFERENCES

Alpert, R., & Haber, R. N. (1960). Anxiety in academic achievement situations. *The Journal of Abnormal and Social Psychology, 61*(2), 207-215.

Arıcı, Ö. & Altıntaş, Ö. (2014). PISA 2009 okuma becerileri yeterliklerinin sosyoekonomik alt yapı ve okul öncesi eğitime katılım açısından incelenmesi "Türkiye Örneği". *Ankara Üniversitesi Eğitim Bilimleri Fakültesi Dergisi*, *47*(1), 423-448.

Arıkan, S., Yıldırım, K., & Erbilgin, E. (2017). Exploring the relationship among new literacies, reading, mathematics and science performance of Turkish students in PISA 2012. *International Electronic Journal of Elementary Education*, *8*(4), 573-588.

Atas, D., & Karadag, O. (2017). An analysis of Turkey's Pisa 2015 results using two-level hierarchical linear modelling. *Journal of Language and Linguistic Studies*, *13*(2), 720.

Aydın, A., Sarıer, Y., & Uysal, Ş. (2012). Sosyoekonomik ve sosyokültürel değişkenler açısından PISA matematik sonuçlarının karşılaştırılması. *Eğitim ve Bilim*, *37*(164).

Bybee, R. W. (2010). What is STEM education?. *Science*, *329*(5995), 996.

Caro, D. & Biecek, P.I. (2017). International Assessment Data Manager, available in R, https://cran.r-project.org/web/packages/intsvy/intsvy.pdf

Chang, C. Y., & Cheng, W. Y. (2008). Science achievement and students' self-confidence and interest in science: A Taiwanese representative sample study. *International Journal of Science Education*, *30*(9), 1183-1200.

Coleman, E. B. (1998). Using explanatory knowledge during collaborative problem solving in science. *Journal of the Learning Sciences*, *7*(3-4), 387-427.

Culler, R. E., & Holahan, C. J. (1980). Test anxiety and academic performance: The effects of study-related behaviors. *Journal of Educational Psychology*, *72*(1), 16-20. http://dx.doi.org/10.1037/0022-0663.72.1.16

Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2012). *How to design and evaluate research in education*. New York: McGraw-Hill Humanities/Social Sciences/Languages.

Friedman, J. Hastie, T., Tibshirani, R., Simon, N., Narasimhan, B. & Qian, J. (2018). Lasso and Elastic-Net Regularized Generalized Linear Models, available at https://cran.r-project.org/web/packages/glmnet/glmnet.pdf

Genc, A. (2017). Coping strategies as mediators in the relationship between test anxiety and academic achievement. *Psihologija*, *50*(1), 51-66.

Grabau, L. J., & Ma, X. (2017). Science engagement and science achievement in the context of science instruction: a multilevel analysis of US students and schools. *International Journal of Science Education*, *39*(8), 1045-1068.

Habacı, İ. (2013). Ortaöğretim 10, 11. ve 12. sınıf öğrencilerinin cinsiyete göre sınav kaygı düzeylerinin belirlenmesi. *Electronic Journal of Education Sciences*, *2*(4), 1-13.

Hadzigeorgiou, Y., & Skoumios, M. (2013). The development of environmental awareness through school science: problems and possibilities. *International Journal of Environmental and Science Education*, *8*(3), 405-426.

IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp. Available at https://www.ibm.com/tr-tr/marketplace/spss-statistics?lnk=STW_TR_SHP_T2_TL&lnk2=trial_SPSSstat

IEA Data Processing and Research Center (2018). New Features and Installation Guide for the IEA's IDB Analyzer (Version 3.2). Retrieved August 15, 2018 from https://www.iea.nl/fileadmin/user_upload/IEA_Software/Help_Manual_for_the_IDB_Analyzer__Version_3_2__-_Features_and_Install_Guide_01.pdf

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). New York: springer.

Kastberg, D., Chan, J. Y., & Murray, G. (2016). Performance of US 15-Year-Old Students in Science, Reading, and Mathematics Literacy in an International Context: First Look at PISA 2015. NCES 2017-048. *National Center for Education Statistics*.

Kullman, D. E. (1966). Correlation of mathematics and science teaching. *School Science and Mathematics*, *66*(7), 645-649.

Ministry of National Education [MONE] (2018). *PISA 2015 Ulusal Raporu*. Retrieved from http://pisa.meb.gov.tr/wp-content/uploads/2014/11/PISA2015_UlusalRapor.pdf

Lenters, V., Portengen, L., Rignell-Hydbom, A., Jönsson, B. A., Lindh, C. H., Piersma, A. H., Toft, G., Bonde, J. P., Heederik, D., Rylander, L, & Vermeulen, R. (2016). Prenatal phthalate, perfluoroalkyl acid, and organochlorine exposures and term birth weight in three birth cohorts: multi-pollutant models based on elastic net regression. *Environmental health perspectives*, *124*(3), 365-372.

McDonald, A. S. (2001). The prevalence and effects of test anxiety in school children. *Educational psychology*, *21*(1), 89-101.

Organisation for Economic Co-Operation and Development [OECD] (2005). *PISA 2003 Technical Report*. Retrieved from https://www.oecd.org/education/school/programmeforinternationalstudentassessmentpisa/35188570.pdf

Organisation for Economic Co-Operation and Development [OECD] (2009). *PISA Data Analysis Manual SPSS, Second Edition*. Retrieved September 17, 2018 from http://archivos.agenciaeducacion.cl/Manual_de_Analisis_de_datos_SPSS_version_ingles.pdf

Organisation for Economic Co-Operation and Development [OECD] (2016). PISA 2015 Results (Volume I) Excellence and Equity in Education, OECD Publishing, Paris. *http://dx.doi.org/10.1787/9789264266490-en*

Organisation for Economic Co-Operation and Development [OECD] (2017). Education at a Glance 2017: OECD Indicators, OECD Publishing, Paris. *http://dx.doi.org/10.1787/eag-2017-en*

Organisation for Economic Co-Operation and Development [OECD] (2017). PISA 2015 Assessment and Analytical Framework: Science, Reading, Mathematic, Financial Literacy and Collaborative Problem Solving, revised edition, PISA, OECD Publishing, Paris. http://dx.doi.org/10.1787/9789264281820-en

Ogutu, J. O., Schulz-Streeck, T., & Piepho, H. P. (2012, December). Genomic selection using regularized linear regression models: ridge regression, lasso, elastic net and their extensions. In *BMC proceedings* (Vol. 6, No. 2, p. S10). BioMed Central.

Palincsar, A. S., Anderson, C., & David, Y. M. (1993). Pursuing scientific literacy in the middle grades through collaborative problem solving. *The elementary school journal*, *93*(5), 643-658.

R Development Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, available at http://www.R-project.org/

Thomson, S. De Bortoli L. & Underwood, C. (2017). *PISA 2015: Reporting Australia's results*. Australian Council for Educational Research Ltd

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 267-288.

Wals, A. (2011). Learning our way to sustainability. *Journal of Education for Sustainable Development*, *5*, 177-186.

Warm, T.A. (1989). Weighted likelihood estimation of ability in ıtem response theory, *Psychometrika*, *54*(3), 427-450.

Wright, B. D., & Masters, G. N. (1982). *Rating scale analysis*. Mesa Press.

Wu, M. & Adams R.J. (2002). Plausible Values – Why They Are Important. Paper presented at the International Objective Measurement Workshop, New Orleans, 6-7 April.

Young, M. F., Slota, S., Cutter, A. B., Jalette, G., Mullin, G., Lai, B., ... & Yukhymenko, M. (2012). Our princess is in another castle: A review of trends in serious gaming for education. *Review of educational research*, *82*(1), 61-89.

Zou, H., & Hastie, T. (2003). Regression shrinkage and selection via the elastic net, with applications to microarrays. *JR Stat Soc Ser B*, *67*, 301-20.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *67*(2), 301-320.

APPENDIX A

Descriptive Statistics of the Variables

ST071Q01NA	DISCLISCI	TEACHSUP	IBTEACH
Min. : 0.000	Min. : -2.4162	Min. : -2.7195	Min. : -3.3405
1st Qu.: 2.000	1st Qu.: -0.7224	1st Qu.:-0.4527	1st Qu.:-0.2823
Median : 4.000	Median : 0.0039	Median : 0.0966	Median : 0.2894
Mean : 5.338	Mean :-0.1349	Mean : 0.1962	Mean : 0.3209
3rd Qu.: 7.000	3rd Qu.: 0.3949	3rd Qu.: 1.4475	3rd Qu.: 0.9314
Max. :30.000	Max. : 1.8837	Max. : 1.4475	Max. : 3.1829
NA's :562	NA's :631	NA's :642	NA's :643

TDTEACH	ENVAWARE	ENVOPT	JOYSCIE
Min. :-2.4476	Min. :-3.3765	Min. :-1.7932	Min. :-2.1154
1st Qu.:-0.6102	1st Qu.:-0.3221	1st Qu.:-1.7932	1st Qu.:-0.6306
Median :-0.0087	Median : 0.3836	Median :-0.7797	Median : 0.3262
Mean :-0.0595	Mean : 0.5521	Mean :-0.5347	Mean : 0.1249
3rd Qu.: 0.4505	3rd Qu.: 1.3695	3rd Qu.: 0.5435	3rd Qu.: 0.5426
Max. : 2.0781	Max. : 3.2932	Max. : 3.0127	Max. : 2.1635
NA's :653	NA's :248	NA's :234	NA's :261

INTBRSCI	INSTSCIE	SCIEEFF	EPIST
Min. :-2.5813	Min. :-1.9301	Min. :-3.7565	Min. :-2.7904
1st Qu.:-0.3856	1st Qu.:-0.2152	1st Qu.:-0.3811	1st Qu.:-0.9357
Median : 0.0487	Median : 0.3708	Median : 0.3155	Median :-0.1933
Mean :-0.0656	Mean : 0.3754	Mean : 0.3365	Mean :-0.1923
3rd Qu.: 0.5305	3rd Qu.: 1.0388	3rd Qu.: 0.9360	3rd Qu.: 0.5002
Max. : 2.7303	Max. : 1.7359	Max. : 3.2775	Max. : 2.1552
NA's :502	NA's :300	NA's :299	NA's :285

SCIEACT	OUTHOURS	SMINS	BELONG
Min. :-1.7570	Min. : 0.00	Min. : 0.0	Min. :-3.1297
1st Qu.: 0.1676	1st Qu.:13.00	1st Qu.:120.0	1st Qu.:-1.0795
Median : 0.9725	Median :22.00	Median :240.0	Median :-0.5173
Mean : 0.6873	Mean :24.54	Mean :198.8	Mean :-0.4365
3rd Qu.: 1.3970	3rd Qu.:34.00	3rd Qu.:280.0	3rd Qu.: 0.0951
Max. : 3.3617	Max. :70.00	Max. :800.0	Max. : 2.6127
NA's :310	NA's :516	NA's :276	NA's :91

ANXTEST	MOTIVAT	COOPERATE	CPSVALUE
Min. :-2.5050	Min. :-3.0877	Min. :-3.33200	Min. :-2.82940
1st Qu.:-0.3080	1st Qu.:-0.0676	1st Qu.:-0.84700	1st Qu.:-0.62140
Median : 0.2900	Median : 0.7050	Median :-0.28820	Median :-0.07480
Mean : 0.3185	Mean : 0.6137	Mean : 0.00072	Mean :-0.04272
3rd Qu.: 0.8531	3rd Qu.: 1.3961	3rd Qu.: 0.82420	3rd Qu.: 0.59710
Max. : 2.5493	Max. : 1.8543	Max. : 2.28790	Max. : 2.10170
NA's :78	NA's :88	NA's :96	NA's :108

EMOSUPS	PERFEED	ADINST	unfairteacher
Min. :-3.0789	Min. :-1.5255	Min. :-1.9656	Min. : 1.00
1st Qu.:-0.8890	1st Qu.:-0.1553	1st Qu.:-0.3816	1st Qu.: 7.00
Median :-0.1691	Median : 0.2838	Median : 0.0214	Median : 9.00
Mean :-0.2674	Mean : 0.3510	Mean : 0.1069	Mean :10.25
3rd Qu.: 0.5658	3rd Qu.: 1.0534	3rd Qu.: 0.6524	3rd Qu.:12.00
Max. : 1.0991	Max. : 2.4994	Max. : 2.0469	Max. :24.00
NA's :64	NA's :668	NA's :724	NA's :109

CULTPOSS	HEDRES	HOMEPOS	ICTRES
Min. :-1.7072	Min. :-4.3706	Min. :-6.7115	Min. :-3.2718
1st Qu.:-0.7273	1st Qu.:-1.4432	1st Qu.:-2.1214	1st Qu.:-1.8547
Median :-0.1661	Median :-0.7218	Median :-1.3934	Median :-1.0838
Mean :-0.2597	Mean :-0.5833	Mean :-1.4323	Mean :-1.1906
3rd Qu.: 0.2834	3rd Qu.: 0.0321	3rd Qu.:-0.6786	3rd Qu.:-0.5776
Max. : 2.4613	Max. : 1.1767	Max. : 5.1519	Max. : 3.4968
NA's :180	NA's :90	NA's :35	NA's :69

WEALTH	ESCS	SC004Q02TA	SC004Q03TA
Min. :-6.9639	Min. :-5.131	Min. : 0.00	Min. : 0.00
1st Qu.:-2.1158	1st Qu.:-2.332	1st Qu.: 4.00	1st Qu.: 2.00
Median :-1.4517	Median :-1.522	Median : 17.00	Median : 15.00
Mean :-1.4877	Mean :-1.448	Mean : 26.75	Mean : 21.84
3rd Qu.:-0.8149	3rd Qu.:-0.643	3rd Qu.: 39.00	3rd Qu.: 29.00
Max. : 4.0881	Max. : 3.123	Max. :164.00	Max. :164.00
NA's :51	NA's :36	NA's :95	NA's :95

SC004Q04NA	SC004Q05NA	SC004Q06NA	SC004Q07NA
Min. : 0.000	Min. : 0.00	Min. : 0.000	Min. : 0.000
1st Qu.: 0.000	1st Qu.: 0.00	1st Qu.: 1.000	1st Qu.: 2.000
Median : 0.000	Median :21.00	Median : 3.000	Median : 4.000
Mean : 3.593	Mean :20.87	Mean : 4.397	Mean : 8.012
3rd Qu.: 0.000	3rd Qu.:32.00	3rd Qu.: 5.000	3rd Qu.: 6.000
Max. :164.000	Max. :60.00	Max. :45.000	Max. :70.000
NA's :95	NA's :56	NA's :56	NA's :56

SC016Q01TA	SC016Q02TA	SC016Q03TA	SC019Q01NA01
Min. : 0.00	Min. : 0.000	Min. : 0.000	Min. : 1.000
1st Qu.: 60.00	1st Qu.: 0.000	1st Qu.: 1.000	1st Qu.: 4.000
Median : 80.00	Median : 0.000	Median : 5.000	Median : 6.000
Mean : 73.89	Mean : 6.352	Mean : 9.524	Mean : 7.134
3rd Qu.: 95.00	3rd Qu.: 2.000	3rd Qu.: 11.000	3rd Qu.: 9.000
Max. :100.00	Max. :100.000	Max. :100.000	Max. :53.000
NA's :44	NA's :415	NA's :234	NA's :42

SC019Q02NA01	SC019Q03NA01	SC025Q02NA	SC048Q03NA
Min. : 0.000	Min. : 0.000	Min. : 0.00	Min. : 0.00
1st Qu.: 0.000	1st Qu.: 2.000	1st Qu.: 0.00	1st Qu.: 15.00
Median : 1.000	Median : 4.000	Median : 3.00	Median : 40.00
Mean : 3.515	Mean : 5.506	Mean : 19.84	Mean : 40.68
3rd Qu.: 6.000	3rd Qu.: 7.000	3rd Qu.: 19.00	3rd Qu.: 60.00
Max. :28.000	Max. :49.000	Max. :100.00	Max. :100.00
NA's :35	NA's :71	NA's :751	NA's :328

SC064Q01TA	SC064Q02TA	SC064Q03TA	SC064Q04NA
Min. : 1.00	Min. : 2.00	Min. : 0.00	Min. : 0.00
1st Qu.: 20.00	1st Qu.: 20.00	1st Qu.: 10.00	1st Qu.: 3.00
Median : 40.00	Median : 40.00	Median : 30.00	Median : 8.00
Mean : 41.63	Mean : 42.88	Mean : 34.38	Mean : 15.43
3rd Qu.: 60.00	3rd Qu.: 60.00	3rd Qu.: 51.00	3rd Qu.: 20.00
Max. :100.00	Max. :100.00	Max. :100.00	Max. :100.00
NA's :72	NA's :72	NA's :113	NA's :447

SCHSIZE	CLSIZE	RATCMP1	LEAD
Min. : 59.0	Min. :13.00	Min. :0.0000	Min. :-1.5849
1st Qu.: 432.0	1st Qu.:38.00	1st Qu.:0.0190	1st Qu.:-0.0014
Median : 792.0	Median :53.00	Median :0.0784	Median : 0.4600
Mean : 873.7	Mean :46.93	Mean :0.1593	Mean : 0.6367
3rd Qu.:1137.0	3rd Qu.:53.00	3rd Qu.:0.1770	3rd Qu.: 1.2175
Max. :2836.0	Max. :53.00	Max. :1.2041	Max. : 4.4300
NA's :39	NA's :56	NA's :147	NA's :39

LEADCOM	LEADINST	LEADPD	LEADTCH
Min. :-2.9808	Min. :-1.6791	Min. :-1.2228	Min. :-1.5768
1st Qu.:-0.1461	1st Qu.:-0.1449	1st Qu.:-0.1082	1st Qu.: 0.0278
Median : 0.3440	Median : 0.5085	Median : 0.4295	Median : 0.5820
Mean : 0.3247	Mean : 0.5381	Mean : 0.5817	Mean : 0.7522
3rd Qu.: 0.7709	3rd Qu.: 1.0154	3rd Qu.: 1.8133	3rd Qu.: 1.6883
Max. : 2.9951	Max. : 2.2317	Max. : 1.8133	Max. : 2.3955
NA's :39	NA's :39	NA's :67	NA's :75

RESPCUR	RESPRES	SCHAUT	TEACHPART
Min. :-1.256	Min. :-0.7946	Min. :0.0000	Min. :0.0000
1st Qu.:-1.256	1st Qu.:-0.7820	1st Qu.:0.1700	1st Qu.:0.0000
Median :-1.256	Median :-0.7644	Median :0.2500	Median :0.0000
Mean :-1.126	Mean :-0.6993	Mean :0.2883	Mean :0.5748
3rd Qu.:-1.142	3rd Qu.:-0.6941	3rd Qu.:0.4200	3rd Qu.:1.0000
Max. : 1.481	Max. : 2.2968	Max. :1.0000	Max. :7.0000
NA's :1	NA's :1	NA's :1	NA's :1

EDUSHORT	STAFFSHORT	TOTST	CREACTIV
Min. :-1.2541	Min. :-1.6823	Min. : 1.000	Min. :0.000
1st Qu.:-0.7421	1st Qu.: 0.0156	1st Qu.: 4.000	1st Qu.:1.000
Median : 0.0680	Median : 0.7106	Median : 6.000	Median :1.000
Mean : 0.2079	Mean : 0.5561	Mean : 7.324	Mean :1.464
3rd Qu.: 0.9328	3rd Qu.: 1.2529	3rd Qu.: 9.000	3rd Qu.:2.000
Max. : 3.6096	Max. : 3.7219	Max. :53.000	Max. :3.000
NA's :1	NA's :1	NA's :42	NA's :80

SCIERES	STUBEHA	TEACHBEHA	STRATIO
Min. :0.000	Min. :-2.3872	Min. :-2.1182	Min. : 2.633
1st Qu.:1.000	1st Qu.:-0.3334	1st Qu.:-0.4866	1st Qu.:12.184
Median :2.000	Median : 0.1937	Median : 0.2229	Median :14.704
Mean :2.489	Mean : 0.2644	Mean : 0.1425	Mean :15.213
3rd Qu.:4.000	3rd Qu.: 0.8947	3rd Qu.: 0.7440	3rd Qu.:17.174
Max. :8.000	Max. : 2.5858	Max. : 2.2359	Max. :37.333
NA's :41	NA's :1	NA's :1	NA's :39

PV1MATH	PV2MATH	PV3MATH	PV4MATH
Min. :133.6	Min. : 92.3	Min. :147.7	Min. :155.2
1st Qu.:359.9	1st Qu.:360.5	1st Qu.:360.1	1st Qu.:359.2
Median :413.1	Median :411.6	Median :413.3	Median :411.4
Mean :416.1	Mean :415.9	Mean :416.3	Mean :416.0
3rd Qu.:473.2	3rd Qu.:471.8	3rd Qu.:470.8	3rd Qu.:471.9
Max. :700.8	Max. :699.6	Max. :666.9	Max. :690.2

PV5MATH	PV6MATH	PV7MATH	PV8MATH
Min. :144.3	Min. :142.9	Min. :143.6	Min. :131.0
1st Qu.:360.9	1st Qu.:358.5	1st Qu.:359.5	1st Qu.:357.1
Median :413.8	Median :409.6	Median :412.0	Median :412.0
Mean :416.1	Mean :414.9	Mean :416.1	Mean :414.4
3rd Qu.:470.5	3rd Qu.:467.6	3rd Qu.:471.4	3rd Qu.:470.2
Max. :702.3	Max. :715.6	Max. :696.4	Max. :709.8

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PV9MATH          PV10MATH         PV1READ          PV2READ
Min.   :151.1    Min.   :163.6    Min.   :137.6    Min.   :136.0
1st Qu.:360.8    1st Qu.:361.0    1st Qu.:370.6    1st Qu.:370.5
Median :412.7    Median :411.6    Median :425.9    Median :425.6
Mean   :416.4    Mean   :415.9    Mean   :425.7    Mean   :425.1
3rd Qu.:471.5    3rd Qu.:468.9    3rd Qu.:482.7    3rd Qu.:480.7
Max.   :702.7    Max.   :676.2    Max.   :712.8    Max.   :714.4

PV3READ          PV4READ          PV5READ          PV6READ
Min.   :153.9    Min.   : 99.95   Min.   : 60.11   Min.   :129.2
1st Qu.:370.9    1st Qu.:370.62   1st Qu.:372.60   1st Qu.:370.4
Median :426.3    Median :426.30   Median :425.81   Median :425.9
Mean   :425.3    Mean   :425.28   Mean   :426.40   Mean   :425.6
3rd Qu.:480.9    3rd Qu.:481.72   3rd Qu.:482.58   3rd Qu.:481.9
Max.   :689.0    Max.   :717.78   Max.   :719.73   Max.   :694.1

PV7READ          PV8READ          PV9READ          PV10READ
Min.   :125.6    Min.   :155.1    Min.   :155.7    Min.   :119.9
1st Qu.:371.1    1st Qu.:371.6    1st Qu.:369.5    1st Qu.:369.9
Median :425.1    Median :425.9    Median :424.9    Median :425.8
Mean   :424.7    Mean   :425.5    Mean   :424.9    Mean   :425.6
3rd Qu.:480.7    3rd Qu.:479.8    3rd Qu.:480.8    3rd Qu.:482.6
Max.   :679.4    Max.   :737.9    Max.   :720.6    Max.   :705.4

PV1CLPS          PV2CLPS          PV3CLPS          PV4CLPS
Min.   :132.8    Min.   :140.6    Min.   :145.7    Min.   :138.9
1st Qu.:365.1    1st Qu.:367.4    1st Qu.:366.2    1st Qu.:364.4
Median :418.0    Median :418.6    Median :417.5    Median :417.8
Mean   :420.3    Mean   :420.7    Mean   :419.8    Mean   :419.0
3rd Qu.:474.1    3rd Qu.:473.6    3rd Qu.:473.7    3rd Qu.:471.8
Max.   :682.9    Max.   :668.0    Max.   :671.1    Max.   :686.9

PV5CLPS          PV6CLPS          PV7CLPS          PV8CLPS
Min.   :162.0    Min.   :146.0    Min.   :184.1    Min.   :131.5
1st Qu.:365.5    1st Qu.:363.8    1st Qu.:366.1    1st Qu.:365.5
Median :416.8    Median :417.5    Median :419.1    Median :417.1
Mean   :419.3    Mean   :419.6    Mean   :420.2    Mean   :419.3
3rd Qu.:473.6    3rd Qu.:473.8    3rd Qu.:472.7    3rd Qu.:471.5
Max.   :694.4    Max.   :701.5    Max.   :659.8    Max.   :701.3

PV9CLPS          PV10CLPS         ST001D01T        ST004D01T
Min.   :138.6    Min.   :150.2    Min.   : 7.000   Freq
1st Qu.:365.8    1st Qu.:365.5    1st Qu.:10.000   1: 2938
Median :418.2    Median :417.4    Median :10.000   2: 2957
Mean   :419.9    Mean   :419.2    Mean   : 9.774
3rd Qu.:473.6    3rd Qu.:471.8    3rd Qu.:10.000
Max.   :665.2    Max.   :681.8    Max.   :12.000
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ST125Q01NA	ST062Q01TA	ST062Q02TA	ST062Q03TA
Freq	Min. :1.000	Min. :1.000	Min. :1.000
0: 2620	1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000
1:2662	Median :1.000	Median :1.000	Median :1.000
NA's :613	Mean :1.723	Mean :1.648	Mean :1.738
	3rd Qu.:2.000	3rd Qu.:2.000	3rd Qu.:2.000
	Max. :4.000	Max. :4.000	Max. :4.000
	NA's :147	NA's :183	NA's :177

ST031Q01NA	ST032Q01NA	ST063Q01NB	ST063Q02NB
Min. :1.000	Min. :1.000	Freq	Freq
1st Qu.:2.000	1st Qu.:2.000	0:2685	0:2740
Median :2.000	Median :3.000	1: 3177	1: 3122
Mean :3.076	Mean :3.949	NA's :33	NA's :33
3rd Qu.:3.000	3rd Qu.:6.000		
Max. :6.000	Max. :8.000		
NA's :237	NA's :206		

ST063Q03NB	ST063Q06NA	ST063Q06NB	ST064Q01NA
Freq	Freq	Freq	Min. :1.000
0: 2796	0: 5156	0: 5181	1st Qu.:1.000
1: 3066	1:706	1:681	Median :2.000
NA's :33	NA's :33	NA's :33	Mean :1.765
			3rd Qu.:2.000
			Max. :3.000
			NA's :628

ST064Q02NA	ST064Q03NA	ST076Q01NA	ST076Q02NA	ST076Q03NA
Min. :1.000	Min. :1.000	Freq	Freq	Freq
1st Qu.:1.000	1st Qu.:1.000	1: 4454	1: 4343	1: 4064
Median :2.000	Median :2.000	2: 1183	2: 1269	2: 1527
Mean :1.694	Mean :1.686	NA's :258	NA's :283	NA's :304
3rd Qu.:2.000	3rd Qu.:2.000			
Max. :3.000	Max. :3.000			
NA's :649	NA's :669			

ST076Q04NA	ST076Q05NA	ST076Q06NA	ST076Q07NA
Freq	Freq	Freq	Freq
1:3624	1: 4143	1: 2459	1:4020
2:1960	2: 1464	2: 3120	2:1575
NA's :311	NA's :288	NA's :316	NA's :300

ST076Q08NA	ST076Q09NA	ST076Q10NA	ST076Q11NA
Freq	Freq	Freq	Freq
1:4450	1: 3856	1: 1468	1:3475
2:1129	2: 1713	2: 4086	2:2131
NA's :316	NA's :326	NA's :341	NA's :339

ST078Q01NA	ST078Q02NA	ST078Q03NA	ST078Q04NA
Freq	Freq	Freq	Freq
1:5455	1: 4855	1: 4674	1:3969
2:173	2: 745	2: 897	2:1593
NA's :267	NA's :295	NA's :324	NA's :333

ST078Q05NA	ST078Q06NA	ST078Q07NA	ST078Q08NA
Freq	Freq	Freq	Freq
1:4424	1: 2830	1: 4294	1:3475
2:1156	2: 2703	2: 1277	2:2131
NA's :315	NA's :362	NA's :324	NA's :334

ST078Q09NA	ST078Q10NA	ST078Q11NA	MISCED
Freq	Freq	Freq	Min. :0.000
1:4066	1: 1626	1: 3543	1st Qu.:1.000
2:1463	2: 3877	2: 1987	Median :2.000
NA's :366	NA's :392	NA's :365	Mean :2.863
			3rd Qu.:5.000
			NA's :70

FISCED	REPEAT	ST016Q01NA	ST038Q03NA
Min. :0.000	Freq	Min. : 0.000	Min. :1.0
1st Qu.:1.000	0:5221	1st Qu.: 4.000	1st Qu.:1.0
Median :2.000	1:631	Median : 6.000	Median :1.0
Mean :2.666	NA's :43	Mean : 6.112	Mean :1.3
3rd Qu.:5.000		3rd Qu.: 9.000	3rd Qu.:1.0
Max. :6.000		Max. :10.000	Max. :4.0
NA's :65		NA's :201	NA's :159

ST038Q04NA	ST038Q05NA	ST038Q06NA	ST038Q07NA
Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000
1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000
Median :1.000	Median :1.000	Median :1.000	Median :1.000
Mean :1.326	Mean :1.215	Mean :1.184	Mean :1.163
3rd Qu.:1.000	3rd Qu.:1.000	3rd Qu.:1.000	3rd Qu.:1.000
Max. :4.000	Max. :4.000	Max. :4.000	Max. :4.000
NA's :179	NA's :167	NA's :168	NA's :166

ST038Q08NA	SC001Q01TA	SC003Q01TA	SC053Q01TA	SC053Q02TA
Min. :1.000	Min. :1.000	Min. :1.000	Freq	Freq
1st Qu.:1.000	1st Qu.:3.000	1st Qu.:6.000	1:2330	1:3003
Median :1.000	Median :4.000	Median :9.000	2:3350	2:2682
Mean :1.322	Mean :3.958	Mean :7.786	NA's :215	NA's :210
3rd Qu.:1.000	3rd Qu.:5.000	3rd Qu.:9.000		
Max. :4.000	Max. :5.000	Max. :9.000		
NA's :179	NA's :39	NA's :56		

SC053Q03TA	SC053Q04TA	SC053Q05NA	SC053Q06NA	SC053Q07TA
Freq	Freq	Freq	Freq	Freq
1:2322	1:4294	1:2358	1:3111	1:4485
2:3374	2:1471	2:3262	2:2616	2:1315
NA's :199	NA's :130	NA's :275	NA's :168	NA's :95

SC053Q08TA	SC053Q09TA	SC053D11TA	SC059Q01NA	SC059Q02NA
Freq	Freq	Freq	Freq	Freq
1:2930	1:3179	1:2122	1:1505	1: 1797
2:2270	2:2519	2:3573	2:4276	2:3916
NA's :195	NA's :197	NA's :200	NA's :114	NA's :182

SC059Q03NA	SC059Q04NA	SC059Q05NA	SC059Q06NA
Freq	Freq	Freq	Freq
1:3478	1:1656	1:2027	1:1603
2:2376	2:4125	2:3795	2:4178
NA's :41	NA's :114	NA's :73	NA's :114

SC059Q07NA	SC059Q08NA	SC052Q01NA	SC052Q02NA
Freq	Freq	Freq	Freq
1:1218	1:1285	1:2945	1:2194
2:4563	2:4460	2:2879	2:3662
NA's :114	NA's :150	NA's :71	NA's :39

SC009Q01TA	SC009Q02TA	SC009Q03TA	SC009Q04TA
Min. :1.000	Min. :1.000	Min. :2.000	Min. :1.000
1st Qu.:2.000	1st Qu.:2.000	1st Qu.:4.000	1st Qu.:3.000
Median :3.000	Median :3.000	Median :4.000	Median :4.000
Mean :3.109	Mean :3.119	Mean :4.426	Mean :3.885
3rd Qu.:4.000	3rd Qu.:4.000	3rd Qu.:6.000	3rd Qu.:5.000
Max. :6.000	Max. :6.000	Max. :6.000	Max. :6.000
NA's :39	NA's :39	NA's :78	NA's :39

SC009Q05TA	SC009Q06TA	SC009Q07TA	SC009Q08TA
Min. :2.000	Min. :2.000	Min. :1.000	Min. :2.000
1st Qu.:3.000	1st Qu.:4.000	1st Qu.:4.000	1st Qu.:5.000
Median :4.000	Median :5.000	Median :5.000	Median :6.000
Mean :4.457	Mean :4.847	Mean :4.516	Mean :5.219
3rd Qu.:6.000	3rd Qu.:6.000	3rd Qu.:6.000	3rd Qu.:6.000
Max. :6.000	Max. :6.000	Max. :6.000	Max. :6.000
NA's :39	NA's :39	NA's :39	NA's :67

SC009Q09TA	SC009Q10TA	SC009Q11TA	SC009Q12TA
Min. :2.000	Min. :2.000	Min. :1.000	Min. :2.000
1st Qu.:4.000	1st Qu.:4.000	1st Qu.:3.000	1st Qu.:4.000
Median :5.000	Median :5.000	Median :4.000	Median :5.000
Mean :4.807	Mean :4.805	Mean :4.414	Mean :5.002
3rd Qu.:6.000	3rd Qu.:6.000	3rd Qu.:6.000	3rd Qu.:6.000
Max. :6.000	Max. :6.000	Max. :6.000	Max. :6.000
NA's :39	NA's :39	NA's :75	NA's :39

SC009Q13TA	SC013Q01TA	SC027Q02NA	SC027Q03NA
Min. :2.000	Min. :1.000	Freq	Freq
1st Qu.:3.000	1st Qu.:1.000	1: 3169	1: 1903
Median :3.000	Median :1.000	2: 2725	2: 3991
Mean :3.787	Mean :1.093	NA's :1	NA's :1
3rd Qu.:5.000	3rd Qu.:1.000		
Max. :6.000	Max. :9.000		
NA's :39	NA's :1		

SC027Q04NA	SC034Q01NA	SC034Q02NA	SC034Q03TA
Freq	Min. :1.000	Min. :1.000	Min. :2.000
1:2731	1st Qu.:1.000	1st Qu.:2.000	1st Qu.:3.000
2:3163	Median :2.000	Median :2.000	Median :3.000
NA's :1	Mean :1.741	Mean :2.504	Mean :3.471
	3rd Qu.:2.000	3rd Qu.:3.000	3rd Qu.:4.000
	Max. :5.000	Max. :5.000	Max. :5.000
	NA's :81	NA's :33	NA's :10

SC034Q04TA	SC035Q01NA	SC035Q02TA	SC035Q03TA	SC035Q03TB
Min. :1.000	Freq	Freq	Freq	Freq
1st Qu.:2.000	1:4058	1:3994	1:1915	1:3858
Median :3.000	2:1565	2:1629	2:3710	2: 1979
Mean :3.135	NA's :272	NA's :272	NA's :270	NA's :58
3rd Qu.:4.000				
Max. :5.000				
NA's :78				

SC035Q04TA	SC035Q04TB	SC035Q05TA	SC035Q05TB	SC035Q06TA
Freq	Freq	Freq	Freq	Freq
1:2178	1:2908	1:3877	1:2128	1:3931
2:3411	2:2862	2:1781	2:3609	2:1691
NA's :306	NA's :125	NA's :237	NA's :158	NA's :273

SC035Q06TB	SC035Q07TA	SC035Q07TB	SC035Q08TA	SC035Q08TB
Freq	Freq	Freq	Freq	Freq
1:3037	1:2697	1:2871	1:3141	1: 3085
2:2700	2:2925	2:2866	2:2481	2:2658
NA's :158	NA's :273	NA's :158	NA's :273	NA's :152

SC035Q09NA	SC035Q09NB	SC035Q10TA	SC035Q10TB	SC035Q11NA
Freq	Freq	Freq	Freq	Freq
1:3371	1:4207	1:3994	1:2371	1: 2706
2:2251	2:1536	2:1705	2:3325	2:2952
NA's :273	NA's :152	NA's :196	NA's :199	NA's :237

SC035Q11NB	SC036Q01TA	SC037Q01TA	SC037Q02TA
Freq	Freq	Min. :1.000	Freq
1:3402	1:3445	1st Qu.:1.000	0:1205
2:2335	2:2449	Median :1.000	1:4650
NA's :158	NA's :1	Mean :1.406	NA's :40
		3rd Qu.:2.000	
		Max. :3.000	
		NA's :1	

SC037Q03TA	SC037Q04TA	SC037Q07TA	SC037Q08TA
Freq	Freq	Freq	Freq
0:539	0:819	0:780	0:2000
1:5355	1:4997	1:5114	1:3855
NA's :1	NA's :79	NA's :1	NA's :40

SC037Q09TA	SC037Q10NA	SC040Q02NA	SC040Q03NA
0:2974	0:1404	0:2483	0:2723
1:2920	1:4490	1:3064	1:2784
NA's :1	NA's :1	NA's :348	NA's :388

SC040Q05NA	SC040Q11NA	SC040Q12NA	SC040Q15NA
0:1854	0:1927	0:2868	0:1196
1:3661	1:3588	1:2674	1:4351
NA's :380	NA's :380	NA's :353	NA's :348

SC040Q16NA	SC040Q17NA	SC041Q01NA	SC041Q03NA
Freq	Freq	Min. :1.000	Min. :1.000
0:3072	0:2314	1st Qu.:1.000	1st Qu.:1.000
1:2475	1:3233	Median :1.000	Median :1.000
NA's :348	NA's :348	Mean :2.119	Mean :2.004
		3rd Qu.:2.000	3rd Qu.:2.000
		Max. :9.000	Max. :9.000
		NA's :1	NA's :1

SC041Q04NA	SC041Q05NA	SC041Q06NA	SC042Q01TA	SC042Q02TA
Min. :1.000	Min. :1.00	Min. :1.000	Min. :1.000	Min. :1.000
1st Qu.:1.000	1st Qu.:1.00	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000
Median :1.000	Median :1.00	Median :2.000	Median :3.000	Median :3.000
Mean :2.045	Mean :1.99	Mean :2.553	Mean :2.638	Mean :2.679
3rd Qu.:2.000	3rd Qu.:2.00	3rd Qu.:2.000	3rd Qu.:3.000	3rd Qu.:3.000
Max. :9.000	Max. :9.00	Max. :9.000	Max. :3.000	Max. :9.000
NA's :1	NA's :1	NA's :1	NA's :42	NA's :1

SCHLTYPE	region	typofsch	PV1SCIE
Min. :1.000	Min. : 1.000	Min. :1.000	Min. :197.7
1st Qu.:3.000	1st Qu.: 3.000	1st Qu.:2.000	1st Qu.:368.6
Median :3.000	Median : 5.000	Median :2.000	Median :418.3
Mean :2.924	Mean : 5.626	Mean :2.413	Mean :422.5
3rd Qu.:3.000	3rd Qu.: 8.000	3rd Qu.:3.000	3rd Qu.:476.6
Max. :3.000	Max. :12.000	Max. :3.000	Max. :707.9
NA's :39			

PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
Min. :186.4	Min. :196.5	Min. :198.7	Min. :171.7
1st Qu.:367.3	1st Qu.:365.0	1st Qu.:365.2	1st Qu.:365.9
Median :418.3	Median :415.8	Median :417.5	Median :417.9
Mean :423.1	Mean :421.4	Mean :422.3	Mean :421.9
3rd Qu.:477.2	3rd Qu.:475.4	3rd Qu.:476.3	3rd Qu.:475.2
Max. :728.6	Max. :686.7	Max. :709.3	Max. :689.7

PV6SCIE	PV7SCIE	PV8SCIE	PV9SCIE	PV10SCIE
Min. :182.2	Min. :175.3	Min. :183.1	Min. :187.3	Min. :192.1
1st Qu.:365.8	1st Qu.:365.3	1st Qu.:366.5	1st Qu.:366.1	1st Qu.:365.2
Median :417.4	Median :416.5	Median :417.0	Median :416.8	Median :416.7
Mean :421.7	Mean :421.3	Mean :421.0	Mean :422.1	Mean :421.7
3rd Qu.:475.4	3rd Qu.:473.8	3rd Qu.:475.0	3rd Qu.:476.6	3rd Qu.:476.5
Max. :667.5	Max. :682.0	Max. :691.2	Max. :698.5	Max. :686.8

APPENDIX B

Names of Variables in PISA 2015

PV1SCIE	Plausible Value 1 in Science
PV2SCIE	Plausible Value 2 in Science
PV3SCIE	Plausible Value 3 in Science
PV4SCIE	Plausible Value 4 in Science
PV5SCIE	Plausible Value 5 in Science
PV6SCIE	Plausible Value 6 in Science
PV7SCIE	Plausible Value 7 in Science
PV8SCIE	Plausible Value 8 in Science
PV9SCIE	Plausible Value 9 in Science
PV10SCIE	Plausible Value 10 in Science
ST001D01T	Student International Grade (Derived)
ST004D01T	Student (Standardized) Gender
ST125Q01NA	How old were you when you started <ISCED 0>? Years
ST062Q01TA	In the last two full weeks of school, how often: I <skipped> a whole school day
ST062Q02TA	In the last two full weeks of school, how often: I <skipped> some classes
ST062Q03TA	In the last two full weeks of school, how often: I arrived late for school
ST071Q01NA	This school year, approximately how many hours per week do you spend learning in addition? <School Science>
ST031Q01NA	On avg, how many days do you attend physical education classes each week?
ST032Q01NA	Moderate physical activities for a total of at least 60 minutes per day
ST063Q01NB	Which <school science> course did you attend? Physics: Last year
ST063Q02NB	Which <school science> course did you attend? Chemistry: Last year
ST063Q03NB	Which <school science> course did you attend? Biology: Last year
ST063Q06NA	Which <school science> course did you attend? <General, integrated, or comprehen science> course: This year
ST063Q06NB	Which <school science> course did you attend? <General, integrated, or comprehen science> course: Last year
ST064Q01NA	<school science> courses? I can choose the <school science> course(s) I study.
ST064Q02NA	<school science> courses? I can choose the level of difficulty.
ST064Q03NA	<school science> courses? I can choose the number of <school science> courses or <class periods>.
ST076Q01NA	Before going to school did you: Eat breakfast
ST076Q02NA	Before going to school did you: Study for school or homework
ST076Q03NA	Before going to school did you: Watch TV\<DVD>\Video
ST076Q04NA	Before going to school did you: Read a book\newspaper\magazine
ST076Q05NA	Before going to school did you: Internet\Chat\Social networks (e.g. <Facebook>, <country-specific social network>)
ST076Q06NA	Before going to school did you: Play video-games
ST076Q07NA	Before going to school did you: Meet friends or talk to friends on the phone

ST076Q08NA	Before going to school did you: Talk to your parents
ST076Q09NA	Before going to school did you: Work in the household or take care
ST076Q10NA	Before going to school did you: Work for pay
ST076Q11NA	Before going to school did you: Exercise or practice a sport
ST078Q01NA	After leaving school did you: Eat dinner
ST078Q02NA	After leaving school did you: Study\school\hmk
ST078Q03NA	After leaving school did you: Watch TV\<DVD>\Video
ST078Q04NA	After leaving school did you: Read a book\newspaper\magazine
ST078Q05NA	After leaving school did you: Internet\Chat\Social net (e.g. <Facebook>)
ST078Q06NA	After leaving school did you: Play video-games
ST078Q07NA	After leaving school did you: Meet friends or talk to friends on the phone
ST078Q08NA	After leaving school did you: Talk to your parents
ST078Q09NA	After leaving school did you: Work in the household or take care of other family members
ST078Q10NA	After leaving school did you: Work for pay
ST078Q11NA	After leaving school did you: Exercise or practice a sport
DISCLISCI	Disciplinary climate in science classes (WLE)
TEACHSUP	Teacher support in a science classes of students choice (WLE)
IBTEACH	Inquiry-based science teaching an learning practices (WLE)
TDTEACH	Teacher-directed science instruction (WLE)
ENVAWARE	Environmental Awareness (WLE)
ENVOPT	Environmental optimism (WLE)
JOYSCIE	Enjoyment of science (WLE)
INTBRSCI	Interest in broad science topics (WLE)
INSTSCIE	Instrumental motivation (WLE)
SCIEEFF	Science self-efficacy (WLE)
EPIST	Epistemological beliefs (WLE)
SCIEACT	Index science activities (WLE)
MISCED	Mother's Education (ISCED)
FISCED	Father's Education (ISCED)
REPEAT	Grade Repetition
OUTHOURS	Out-of-School Study Time per week (Sum)
SMINS	Learning time (minutes per week) - <science>
BELONG	Subjective well-being: Sense of Belonging to School (WLE)
ANXTEST	Personality: Test Anxiety (WLE)
MOTIVAT	Student Atttidudes, Preferences and Self-related beliefs: Achieving motivation (WLE)
COOPERATE	Collaboration and teamwork dispositions: Enjoy cooperation (WLE)
CPSVALUE	Collaboration and teamwork dispositions: Value cooperation (WLE)
EMOSUPS	Parents emotional support (WLE)
PERFEED	Perceived Feedback (WLE)
ADINST	Adaption of instruction (WLE)
unfairteacher	Teacher Fairness (Sum)
CULTPOSS	Cultural possessions at home (WLE)

HEDRES	Home educational resources (WLE)
HOMEPOS	Home possessions (WLE)
ICTRES	ICT Resources (WLE)
WEALTH	Family wealth (WLE)
ESCS	Index of economic, social and cultural status (WLE)
PV1MATH	Plausible Value 1 in Mathematics
PV2MATH	Plausible Value 2 in Mathematics
PV3MATH	Plausible Value 3 in Mathematics
PV4MATH	Plausible Value 4 in Mathematics
PV5MATH	Plausible Value 5 in Mathematics
PV6MATH	Plausible Value 6 in Mathematics
PV7MATH	Plausible Value 7 in Mathematics
PV8MATH	Plausible Value 8 in Mathematics
PV9MATH	Plausible Value 9 in Mathematics
PV10MATH	Plausible Value 10 in Mathematics
PV1READ	Plausible Value 1 in Reading
PV2READ	Plausible Value 2 in Reading
PV3READ	Plausible Value 3 in Reading
PV4READ	Plausible Value 4 in Reading
PV5READ	Plausible Value 5 in Reading
PV6READ	Plausible Value 6 in Reading
PV7READ	Plausible Value 7 in Reading
PV8READ	Plausible Value 8 in Reading
PV9READ	Plausible Value 9 in Reading
PV10READ	Plausible Value 10 in Reading
PV1CLPS	Plausible Value 1 in Collaborative Problem Solving
PV2CLPS	Plausible Value 2 in Collaborative Problem Solving
PV3CLPS	Plausible Value 3 in Collaborative Problem Solving
PV4CLPS	Plausible Value 4 in Collaborative Problem Solving
PV5CLPS	Plausible Value 5 in Collaborative Problem Solving
PV6CLPS	Plausible Value 6 in Collaborative Problem Solving
PV7CLPS	Plausible Value 7 in Collaborative Problem Solving
PV8CLPS	Plausible Value 8 in Collaborative Problem Solving
PV9CLPS	Plausible Value 9 in Collaborative Problem Solving
PV10CLPS	Plausible Value 10 in Collaborative Problem Solving
ST016Q01NA	Overall, how satisfied are you with your life as a whole these days?
ST038Q03NA	Other students left me out of things on purpose.
ST038Q04NA	Other students made fun of me.
ST038Q05NA	I was threatened by other students.
ST038Q06NA	Other students took away or destroyed things that belonged to me.
ST038Q07NA	I got hit or pushed around by other students.
ST038Q08NA	Other students spread nasty rumours about me.
SC001Q01TA	Which of the following definitions best describes the community in which your school is located?

SC003Q01TA	What is the average size of <test language> classes in <national modal grade for 15-year-olds> in your school?
SC004Q02TA	Student-comp ratio in <national modal grade for 15-year-olds>. How many comps are avail for students for ed
SC004Q03TA	Student-comp ratio in <national modal grade for 15-year-olds>. How many comps are connected to Internet\World
SC004Q04NA	Student-comp ratio in <national modal grade for 15-year-olds>. How many comps are portable (e.g. laptop, tablet)?
SC004Q05NA	Total No. of interactive whiteboards in the school altogether
SC004Q06NA	Total No. of data projectors in the school altogether
SC004Q07NA	Total No. of computers with internet connection available for teachers in the school.
SC053Q01TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Band, orchestra\choir
SC053Q02TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? School play\musical
SC053Q03TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? School yrbk, newspaper
SC053Q04TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Volunteering or servic
SC053Q05NA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Science club
SC053Q06NA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Science competitions
SC053Q07TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Chess club
SC053Q08TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Inform\Commun. Tech.
SC053Q09TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? Art club\activities.
SC053D11TA	<This academic year>,follow. activities\school offers<national modal grade for 15-year-olds>? <country specific item>
SC059Q01NA	Compared to other departments, our school's <school science department> is well equipped.
SC059Q02NA	If we ever have some extra funding, a big share goes into improvement of our <school science> teaching.
SC059Q03NA	<School science> teachers are among our best educated staff members.
SC059Q04NA	Compared to similar schools, we have a well equipped laboratory.
SC059Q05NA	The material for hands-on activities in <school science> is in good shape.
SC059Q06NA	We have enough laboratory material that all courses can regularly use it.
SC059Q07NA	We have extra laboratory staff that helps support <school science> teaching.
SC059Q08NA	Our school spends extra money on up-to-date <school science> equipment.
SC052Q01NA	Does your school provide study help? Room(s) where the students can do their homework
SC052Q02NA	Does your school provide the following study help? Staff help with homework
SC009Q01TA	Frequency of <the last academic year>. I use student performance results to develop the school's educational goal
SC009Q02TA	Frequency of <the last academic year>. I make sure that the professional development activities of teachers are in
SC009Q03TA	Frequency of <the last academic year>. I ensure that teachers work according to the school's educational goals.
SC009Q04TA	Frequency of <the last academic year>. I promote teaching practices based on recent educational research.
SC009Q05TA	Frequency of <the last academic year>. I praise teachers whose students are actively participating in learning.

SC009Q06TA	Frequency of <the last academic year>. When a teacher has problems in his\her classroom, I take the initiative to
SC009Q07TA	Frequency of <the last academic year>. I draw teachers' attention to the importance of pupils development of cri
SC009Q08TA	Frequency of <the last academic year>. I pay attention to disruptive behaviour in classrooms.
SC009Q09TA	Frequency of <the last academic year>. I provide staff with opportunities to participate in school decision-making
SC009Q10TA	Frequency of <the last academic year>. I engage teachers to help build a school culture of continuous improvement.
SC009Q11TA	Frequency of <the last academic year>. I ask teachers to participate in reviewing management practices.
SC009Q12TA	Frequency of <the last academic year>. When a teacher brings up a classroom problem, we solve the problem together
SC009Q13TA	Frequency of <the last academic year>. I discuss the school's academic goals with teachers at faculty meetings.
SC013Q01TA	Is your school a public or a private school?
SC016Q01TA	Percent. total funding for school year comes from? Government
SC016Q02TA	Percent. total funding for school year comes from? Student fees or school charges paid by parents
SC016Q03TA	Percent. total funding for school year comes from? Benefactors, donations, bequests, sponsorships, parent funraising
SC019Q01NA01	<School science> teachers in TOTAL: Full-time
SC019Q02NA01	<School science> teachers <fully certified> by <the appropriate authority>: Full-time
SC019Q03NA01	<School science> teachers\<ISCED Level 5A or higher> qualification <with a major> in <school science>: Full-time
SC025Q02NA	Teaching staff in your school has attended a programme of profess dev? Science teaching staff
SC027Q02NA	Our school invites specialists to conduct in-service training for teachers.
SC027Q03NA	Our school organises in-service workshops which deal with specific issues that our school faces.
SC027Q04NA	Our school organises in-service workshops for specific groups of teachers (e.g. newly appointed teachers).
SC034Q01NA	How often are students assessed? Mandatory <standardized tests>
SC034Q02NA	How often are students assessed? Nonmandatory <standardized tests>
SC034Q03TA	How often are students assessed? Teacher-developed tests
SC034Q04TA	How often are students assessed? Teachers judgmental ratings
SC035Q01NA	Are <standardized tests> used in school? Guide student learning
SC035Q02TA	Are <standardized tests> used in school? To inform parents about child's progress
SC035Q03TA	Are <standardized tests> used in school? To make decisions about students' retention or promotion
SC035Q03TB	Are teacher-developed tests used in school? To make decisions about students' retention or promotion
SC035Q04TA	Are <standardized tests> used in school? To group students for instructional purposes
SC035Q04TB	Are teacher-developed tests used in school? To group students for instructional purposes
SC035Q05TA	Are <standardized tests> used in school? To compare the school to <district or national> performance
SC035Q05TB	Are teacher-developed tests used in school? To compare the school to <district or national> performance
SC035Q06TA	Are <standardized tests> used in school? To monitor the school's progress from year to year

SC035Q06TB	Are teacher-developed tests used in school? To monitor the school's progress from year to year
SC035Q07TA	Are <standardized tests> used in school? To make judgements about teachers' effectiveness
SC035Q07TB	Are teacher-developed tests used in school? To make judgements about teachers' effectiveness
SC035Q08TA	Are <standardized tests> used in school? To identify aspects of instruction or curriculum that should be improved
SC035Q08TB	Are teacher-developed tests used in school? To identify aspects of instruction or curriculum that should be improved
SC035Q09NA	Are <standardized tests> used in school? To adapt teaching to the students' needs
SC035Q09NB	Are teacher-developed tests used in school? To adapt teaching to the students' needs
SC035Q10TA	Are <standardized tests> used in school? To compare the school with other schools
SC035Q10TB	Are teacher-developed tests used in school? To compare the school with other schools
SC035Q11NA	Are <standardized tests> used in school? To award certification to students
SC035Q11NB	Are teacher-developed tests used in school? To award certification to students
SC036Q01TA	Achievement data used in any of the following <accountability procedures>? Achievement data are posted publicly
SC037Q01TA	Internal evaluation \ Self-evaluation
SC037Q02TA	Does improvement exist at school? External evaluation
SC037Q03TA	Does improvement exist at school? Written specification of the schools curricular profile and educational goals
SC037Q04TA	Does improvement exist at school? Written specification of student performance standards
SC037Q07TA	Does improvement exist at school? Seeking written feedback from students (e.g. regarding lessons, teachers, resources
SC037Q08TA	Does improvement exist at school? Teacher mentoring
SC037Q09TA	Does improvement exist at school? Consultation aimed at school improvement\experts over a period of six months
SC037Q10NA	Does improvement exist at school? Implementation of a standardised policy for science subjects
SC040Q02NA	Did your school implement any measures in: Educational staff (e.g. workload, personal requirm.)
SC040Q03NA	Did your school implement any measures in: Implementation of the curriculum
SC040Q05NA	Did your school implement any measures in: Quality of teaching and learning
SC040Q11NA	Did your school implement any measures in: Parental engagement in school
SC040Q12NA	Did your school implement any measures in: Teacher professional development
SC040Q15NA	Did your school implement any measures in: Student achievement
SC040Q16NA	Did your school implement any measures in: Students' cross-curricular competencies
SC040Q17NA	Did your school implement any measures in: Equity in school
SC041Q01NA	The results of external evaluations led to changes in school policies.
SC041Q03NA	We used the data to plan specific action for school development.
SC041Q04NA	We used the data to plan specific action for the improvement of teaching.
SC041Q05NA	We put measures derived from the results of external evaluations into practice promptly.
SC041Q06NA	The impetus triggered by the external evaluation "disappeared" very quickly at our school.
SC042Q01TA	School's policy\for students in <national modal grade for 15-year-olds>? Students\group.ability into differ. classes.

SC042Q02TA	School's policy\for students in <national modal grade for 15-year-olds>? Students\group.ability within\classes.
SC048Q03NA	Est. percent. <national modal grade for 15-year-olds>. Students from socioeconomic disadvantaged homes
SC064Q01TA	<the last academic year>, what proport. of parents part. school-related activit? On their own initiative
SC064Q02TA	<the last academic year>, what proport. of parents part. school-related activit? On initiative of child's teachers
SC064Q03TA	<the last academic year>, what proport. of parents part. school-related activit? Partici. in local school government
SC064Q04NA	<the last academic year>, what proport. of parents part. school-related activit? Volun\phys, or extra-curricular act
SCHSIZE	School Size (Sum)
CLSIZE	Class Size
RATCMP1	Number of available computers per student at modal grade
LEAD	Educational leadership (WLE)
LEADCOM	Curricular development (WLE)
LEADINST	Instructional leadership (WLE)
LEADPD	Professional development (WLE)
LEADTCH	Teachers participation (WLE)
RESPCUR	Responsibility for curriculum
RESPRES	Responsibility for ressources
SCHAUT	School autonomy (Mean)
TEACHPART	Teacher participation (Sum)
EDUSHORT	Shortage of educational material (WLE)
STAFFSHORT	Shortage of educational staff (WLE)
TOTST	Total number of science teachers at school
CREACTIV	Creative extra-curricular activities (Sum)
SCIERES	Index science specific ressources (Sum)
STUBEHA	Student behaviour hindering learning (WLE)
TEACHBEHA	Teacher behaviour hindering learning (WLE)
STRATIO	Student-Teacher ratio
SCHLTYPE	School Ownership
STRATUM	

APPENDIX C

R Codes for Elastic Net Regression

```
####### running penalized regression for PV4 for full model (30 PV with correlated explanatory variables)

dataset1=read.csv("CNT_TUR_2607.csv")
dim(dataset1) # 246 variables
summary(dataset1)

# converting some observed values to another possible value, just to set them back to
# the original observed values later, but to deal with missing values

dataset1$SC025Q02NA[dataset1$SC025Q02NA==99.0000]=101
dataset1$SC048Q03NA[dataset1$SC048Q03NA==99.0000]=101
dataset1$SC016Q01TA[dataset1$SC016Q01TA==99.0000]=101
dataset1[dataset1==99.0000]=NA
dataset1[dataset1==99999.0]=NA
dataset1[dataset1==999.000]=NA
dataset1[dataset1==998.00]=NA
dataset1[dataset1==9999999]=NA
dataset1[dataset1==99999999]=NA
dataset1$SC025Q02NA[dataset1$SC025Q02NA==101]=99
dataset1$SC048Q03NA[dataset1$SC048Q03NA==101]=99
dataset1$SC016Q01TA[dataset1$SC016Q01TA==101]=99

#converting missing values to NA
dataset1$ST062Q01TA[dataset1$ST062Q01TA==9]=NA
dataset1$ST062Q02TA[dataset1$ST062Q02TA==9]=NA
…
dataset1$ST071Q01NA[dataset1$ST071Q01NA==999.00]=NA
…
dataset1$SC040Q02NA[dataset1$SC040Q02NA==5]=NA
dataset1$SC040Q15NA[dataset1$SC040Q15NA==5]=NA
…
dataset1$SC016Q01TA[dataset1$SC016Q01TA==998.00]=NA
dataset1$SC016Q02TA[dataset1$SC016Q01TA==998.00]=NA
```

```
dim(dataset1) # to cross-check
colnames(dataset1)[1]="PV1SCIE"

###missing imputation###
#cont. variables#
ST071Q01NA= dataset1[,17]
a=dataset1 [,50:61]
b=dataset1 [,65:81]
c=dataset1 [,121:126]
d=dataset1 [,161:167]
e=dataset1 [,219:243]
z=cbind(ST071Q01NA,a,b,c,d,e)
#head(z)
dim(z)

library(Hmisc)
cont.imp=z
for(i in 1:68)
cont.imp[,i]=impute(cont.imp[,i], mean)

pv=dataset1[,82:111] # adding 30 PVs to dataset1
t=cbind(cont.imp, pv)
#head(t)
dim(t)

###missing imputation###
#nominal and ordinal variables#
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
f=dataset1 [,11:16]
g=dataset1 [,18:49]
h=dataset1 [,62:64]
j=dataset1 [,112:120]
k=dataset1 [,127:160]
m=dataset1 [,168:218]
n= dataset1 [,244:246]
cont=cbind(f,g,h,j,k,m,n)
#head(cont)
dim(cont)
```

```
mode.imp=cont
for(i in 1:138)
mode.imp[,i]=impute(mode.imp[,i], getmode)
head(mode.imp)
x=cbind(t,mode.imp)
summary(x) # to check if all NA's were imputed
dim(x)
class(x)


#####Penalized Regression for 30 PV#########
PV4SCIE <- dataset1[,4]
length(PV4SCIE)
yx=cbind(PV4SCIE,x)
#head(yx)
dim(yx)
class(yx)
yx[,237]=factor(yx[,237])
yx[,236]=factor(yx[,236])

xmatrix=model.matrix(yx[,1]~.,yx)[,-c(1,2)]
y= yx[,1]
#head(xmatrix)
class(yx[,237])

library(glmnet)
set.seed(327)
grid1=10^seq(10,-2, length =100)
grid1
fit1 <- glmnet(xmatrix, y, family="gaussian", alpha=0.5, lambda=grid1)
fit1$df
select=min(which(50<fit1$df&fit1$df<100)) #selecting a tuning parameter that is
#close to 50 parameters
fit1$lambda [select]  #the value of tuning parameter
coef(fit1)[ ,select]  #coefficients of variables
fit1$df[select]
fit1$dev.ratio[select]
```

```
index = which(abs(coef(fit1)[ ,select])>10^-3) # removing variables having
#coefficient smaller than 10^-3
length(index)
coef(fit1)[index,select]

predict1=predict(fit1 ,s=fit1$lambda [select], newx=xmatrix)
mean((predict1 -y)^2) #MSE value

observed = y
residuals = predict1 - observed
plot(observed, predict1)
plot(predict1, residuals)
##################################################

####### running preg for PV4 for full model (3 PV)####

dataset2=read.csv("CNT_TUR_3007.csv")
dim(dataset2)#219 variable
#summary(dataset2)
dataset2$SC025Q02NA[dataset2$SC025Q02NA==99.0000]=101
dataset2$SC048Q03NA[dataset2$SC048Q03NA==99.0000]=101
dataset2$SC016Q01TA[dataset2$SC016Q01TA==99.0000]=101
dataset2[dataset2==99.0000]=NA
dataset2[dataset2==99999.0]=NA
dataset2[dataset2==999.000]=NA
dataset2[dataset2==998.00]=NA
dataset2[dataset2==9999999]=NA
dataset2[dataset2==99999999]=NA
dataset2$SC025Q02NA[dataset2$SC025Q02NA==101]=99
dataset2$SC048Q03NA[dataset2$SC048Q03NA==101]=99
dataset2$SC016Q01TA[dataset2$SC016Q01TA==101]=99
dataset2$ST062Q01TA[dataset2$ST062Q01TA==9]=NA
dataset2$ST062Q02TA[dataset2$ST062Q02TA==9]=NA
dataset2$ST071Q01NA[dataset2$ST071Q01NA==999.00]=NA
…
dataset2$SC040Q15NA[dataset2$SC040Q15NA==5]=NA
dataset2$SC040Q16NA[dataset2$SC040Q16NA==5]=NA
…
dataset2$SC016Q01TA[dataset2$SC016Q01TA==998.00]=NA
dataset2$SC016Q02TA[dataset2$SC016Q01TA==998.00]=NA
…
```

```
dim(dataset2)
colnames(dataset2)[1]="PV1SCIE"

###missing imputation###
ST071Q01NA2= dataset2[,17]
a2=dataset2 [,50:61]
b2=dataset2 [,65:81]
c2=dataset2 [,94:99]
d2=dataset2 [,134:140]
e2=dataset2 [,192:216]
z2=cbind(ST071Q01NA2,a2,b2,c2,d2,e2)
#head(z2)
dim(z2)
#library(Hmisc)
cont.imp2=z2
for(i in 1:68)
cont.imp2[,i]=impute(cont.imp2[,i], mean)
pv2=dataset2[,82:84]
t2=cbind(cont.imp2, pv2)
#head(t2)
dim(t2)
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
f2=dataset2 [,11:16]
g2=dataset2 [,18:49]
h2=dataset2 [,62:64]
j2=dataset2 [,85:93]
k2=dataset2 [,100:133]
m2=dataset2 [,141:191]
n2= dataset2 [,217:219]
cont2=cbind(f2,g2,h2,j2,k2,m2,n2)
#head(cont2)
dim(cont2)
mode.imp2=cont2
for(i in 1:138)
mode.imp2[,i]=impute(mode.imp2[,i], getmode)
#head(mode.imp2)
x2=cbind(t2,mode.imp2)
head(x2)
```

```
dim(x2)
class(x2)

#####Penalized regression for 3 PV####
PV4SCIE <- dataset2[,4]
length(PV4SCIE)
y2x=cbind(PV4SCIE,x2)
#head(y2x)
dim(y2x)
class(y2x)
y2x[,209]=factor(y2x[,209])
y2x[,210]=factor(y2x[,210])

x2matrix=model.matrix(y2x[,1]~.,y2x)[,-c(1,2)]
y2= y2x[,1]
#head(x2matrix)
#library(glmnet)
set.seed(329)
grid2=10^seq(10,-2, length =100)
grid2
fit2 <- glmnet(x2matrix, y2, family="gaussian", alpha=0.5, lambda=grid2)
fit2$df
select2=min(which(50<fit2$df&fit2$df<100))
fit2$lambda [select2]
coef(fit2)[ ,select2]
fit2$df[select2]
fit2$dev.ratio[select2]

index2 = which(abs(coef(fit2)[ ,select2])>10^-3)
length(index2)
coef(fit2)[index2,select2]
predict2=predict(fit2 ,s=fit2$lambda [select2], newx=x2matrix)
mean((predict2 -y2)^2)

observed2 = y2
residuals2 = predict2 - observed2
plot(observed2, predict2)
plot(predict2, residuals2)

##########################################################
```

```
####### running preg for PV4 for full model (3 PV, uncorrelated explanatory variables)

dataset3=read.csv("CNT_TUR_10083PV.csv")
dim(dataset3)
summary(dataset3)

dataset3$SC025Q02NA[dataset3$SC025Q02NA==99.0000]=101
dataset3$SC048Q03NA[dataset3$SC048Q03NA==99.0000]=101
dataset3$SC016Q01TA[dataset3$SC016Q01TA==99.0000]=101
dataset3 [dataset3==99.0000]=NA
dataset3 [dataset3==99999.0]=NA
dataset3 [dataset3==999.000]=NA
dataset3 [dataset3==998.00]=NA
dataset3 [dataset3==9999999]=NA
dataset3 [dataset3==99999999]=NA
dataset3$SC025Q02NA[dataset3$SC025Q02NA==101]=99
dataset3$SC048Q03NA[dataset3$SC048Q03NA==101]=99
dataset3$SC016Q01TA[dataset3$SC016Q01TA==101]=99
dataset3$ST062Q01TA[dataset3$ST062Q01TA==9]=NA
…
dataset3$OUTHOURS[dataset3$OUTHOURS==999.0]=NA
…
dataset3$SC040Q15NA[dataset3$SC040Q15NA==5]=NA
dataset3$SC040Q16NA[dataset3$SC040Q16NA==5]=NA
…
dataset3$SC016Q01TA[dataset3$SC016Q01TA==998.00]=NA
…

###missing imputation###
 ST071Q01NA= dataset3[,17]
a3=dataset3 [,46:57]
b3=dataset3 [,61:75]
c3=dataset3 [,87:91]
d3=dataset3 [,119:125]
e3=dataset3 [,172:190]
z3=cbind(ST071Q01NA,a3,b3,c3,d3,e3)
head(z3)
dim(z3)
```

```
#library(Hmisc)
cont.imp3=z3
for(i in 1:59)
cont.imp3[,i]=impute(cont.imp3[,i], mean)

pv3=dataset3[,76:78]
t3=cbind(cont.imp3, pv3)
#head(t3)
dim(t3)
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
f3=dataset3 [,11:16]
g3=dataset3 [,18:45]
h3=dataset3 [,58:60]
j3=dataset3 [,79:86]
k3=dataset3 [,92:118]
m3=dataset3 [,126:171]
n3= dataset3 [,191:192]
cont3=cbind(f3,g3,h3,j3,k3,m3,n3)
#head(cont3)
dim(cont3)
mode.imp3=cont3
for(i in 1:120)
mode.imp3[,i]=impute(mode.imp3[,i], getmode)
#head(mode.imp3)
x3=cbind(t3,mode.imp3)
#head(x3)
dim(x3)
class(x3)
#########locating highly-correlated variables
cor(x3)
ss<-round(cor(x3),2)
min(ss)
which(0.79<ss, arr.ind=TRUE)
a5= dataset3[,1:10]
b5= x3[,72:74]
CLSIZE= x3[,47]
SC003Q01TA= x[,110]
cor4=cbind(a5,b5,CLSIZE,SC003Q01TA)
```

```
head(cor4)
cor(cor4)

#################################
PV4SCIE <- dataset3[,4]
length(PV4SCIE)
y3x=cbind(PV4SCIE,x3)
#head(y3x)
dim(y3x)
class(y3x)
y3x[,182]=factor(y3x[,182])
y3x[,183]=factor(y3x[,183])

x3matrix=model.matrix(y3x[,1]~.,y3x)[,-c(1,2)]
y3= y3x[,1]
#head(x3matrix)
#class(y3x[,185])

#library(glmnet)
set.seed(31249)
grid2=10^seq(10,-2, length =100)
grid2
fit2 <- glmnet(x3matrix, y3, family="gaussian", alpha=0.5, lambda=grid2)
fit2$df
select2=min(which(50<fit2$df&fit2$df<100))
fit2$lambda [select2]
coef(fit2)[ ,select2]
fit2$df[select2]
fit2$dev.ratio[select2]
index2 = which(abs(coef(fit2)[ ,select2])>10^-3)
length(index2)
coef(fit2)[index2,select2]
predict2=predict(fit2 ,s=fit2$lambda [select2], newx=x3matrix)
mean((predict2 -y3)^2)

observed2 = y2
residuals2 = predict2 - observed2
plot(observed2, predict2)
plot(predict2, residuals2)
```

```
####lm function for MODEL 2###############
model2=read.csv("CNT_TUR_1608.csv")
dim(model2)# 23 variables
summary(model2)
model2[model2==99.0000]=NA
model2[model2==999.0000]=NA
model2$ST078Q06NA [model2$ST078Q06NA==9]=NA
model2$ST078Q08NA[model2$ST078Q08NA==9]=NA
dim(model2)
colnames(model2)[1]="PV1SCIE"
###missing imputation###
a=model2 [,14:17]
SC064Q03TA = model2[,23]
z=cbind(SC064Q03TA,a)
#head(z)
dim(z)

cont.imp=z
for(i in 1:5)
cont.imp[,i]=impute(cont.imp[,i], mean)

pv=model2[,18:20]
t=cbind(cont.imp, pv)
#head(t)
dim(t)

getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

f=model2 [,11:13]
g=model2 [,21:22]
cont=cbind(f,g)
#head(cont)
dim(cont)
mode.imp=cont
for(i in 1:5)
mode.imp[,i]=impute(mode.imp[,i], getmode)
```

```
#head(mode.imp)
x=cbind(t,mode.imp)
#head(x)
#summary(x)
dim(x)
class(x)
x=as.matrix(x)
y=model2$PV4SCIE

##### t= 1.96 regression with VIF values for model 2#####

ENVAWARE= x[,2]
d = x[,4:8]
ST078Q06NA =x[,10]
z=cbind(ENVAWARE ,d,ST078Q06NA)
model22=lm(y~z)
summary(model22)
#library(DAAG)
vif(model22)
######################################################################

## Exploratory Data Analysis

PISA2015=read.csv("a.csv")
dim(PISA2015
summary(PISA2015)

install.packages("intsvy")
library("intsvy")

## calculates means of achievement scores###
pisa2015.mean.pv(pvlabel="SCIE",data = PISA2015)
pisa2015.mean.pv(pvlabel="SCIE",by="ST004D01T",PISA2015 )
pisa2015.mean.pv(pvlabel="SCIE",by="ST078Q06NA",data = PISA2015 )
pisa2015.mean.pv(pvlabel="SCIE",by="SCHLTYPE",data = PISA2015 )
pisa2015.mean.pv(pvlabel="SCIE",by="STRATUM",data = PISA2015 )
pisa2015.mean.pv(pvlabel="SCIE",by="region",data = PISA2015 )
pisa2015.mean.pv(pvlabel="SCIE",by="typofsch",data = PISA2015 )

###calculating percentages of students at each proficiency level###
```

```
pisa2015.ben.pv(pvlabel = "SCIE", cutoff= c(335,410,484,559, 633,708),  data =
PISA2015)
pisa2015.ben.pv(pvlabel = "SCIE", by="ST004D01T", cutoff= c(335,410,484,559,
633,708), data = PISA2015)
pisa2015.ben.pv(pvlabel = "SCIE", by="ST078Q06NA", cutoff= c(335,410,484,559,
633,708), data = PISA2015)
pisa2015.ben.pv(pvlabel = "SCIE", by="STRATUM", cutoff= c(335,410,484,559,
633,708), data = PISA2015)

## correlation matrix
install.packages ("corrplot")
library("corrplot")
a=cbind(
M <- cor(x)
corrplot(M, order = "hclust",col = c("black", "white"), bg = "lightgreen",tl.col =
"black")
```

APPENDIX D

List of Highly Correlated Variables

	row col	
ICTRES	28 27	HOMEPOS
WEALTH	29 27	HOMEPOS
WEALTH	29 28	ICTRES
SC004Q03TA	32 31	SC004Q02TA
LEADCOM	53 52	LEAD
LEADINST	54 52	LEAD
TOTST	63 40	SC019Q01NA01
ST063Q02NB	108 107	ST063Q01NB
ST063Q03NB	109 107	ST063Q01NB
ST063Q03NB	109 108	ST063Q02NB
SC003Q01TA	148 50	CLSIZE
SC059Q04NA	162 159	SC059Q01NA
SC009Q04TA	172 54	LEADINST
SC009Q05TA	173 54	LEADINST
SC009Q07TA	175 54	LEADINST
SC009Q06TA	174 55	LEADPD
SC009Q09TA	177 56	LEADTCH
SC009Q10TA	178 56	LEADTCH
SC009Q11TA	179 56	LEADTCH
SC009Q12TA	180 55	LEADPD
SC041Q03NA	228 227	SC041Q01NA
SC041Q04NA	229 227	SC041Q01NA
SC041Q04NA	229 228	SC041Q03NA
SC041Q05NA	230 227	SC041Q01NA
SC041Q05NA	230 228	SC041Q03NA
SC041Q05NA	230 229	SC041Q04NA
SC041Q06NA	231 227	SC041Q01NA
SC041Q06NA	231 228	SC041Q03NA
SC041Q06NA	231 229	SC041Q04NA
SC041Q06NA	231 230	SC041Q05NA
SCHLTYPE	234 38	SC016Q02TA
SC059Q01NA	159 65	SCIERES
SC059Q04NA	162 65	SCIERES
SC041Q01NA	227 212	SC037Q02TA
SC041Q03NA	228 212	SC037Q02TA
SC041Q04NA	229 212	SC037Q02TA
SC041Q05NA	230 212	SC037Q02TA
SC041Q06NA	231 212	SC037Q02TA

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