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# Exploratory Analysis Procedures

Introduction.....	36
Weights.....	36
Replicates for computing the standard error.....	39
Plausible values.....	43
Conclusion.....	46



## INTRODUCTION

PISA surveys use complex methodologies that condition the way data should be analysed. As this is not yet included in standard procedures included in the statistical software packages such as SAS® or SPSS®, this manual describes the methodologies in detail and also presents syntax and macros developed specially for analysing the PISA data.

First of all, PISA does not draw simple random samples of students from exhaustive lists of 15-year-olds. The sampling design applied in PISA, its rationale and its consequences on how data should be analysed are mainly presented in Chapters 3 and 4. Briefly, PISA usually samples students in two stages: schools are first sampled and then students are sampled in the participating schools. Such sampling design increases the standard errors of any population estimates. As most of the statistical packages assume the data were collected on a simple random sample, analysing the PISA data with such software would systematically underestimate the standard errors and therefore lead to reporting non-significant results as significant. This would jeopardise the credibility of the programme.

Secondly, PISA uses imputation methods, denoted plausible values, for reporting student performance. From a theoretical point of view, any analysis that involves student performance estimates should be analysed five times and results should be aggregated to obtain: (i) the final estimate; and (ii) the imputation error that will be combined with the sampling error in order to reflect the test unreliability on the standard error. The detailed description of plausible values and its use are presented in Chapters 6 and 8.

All results published in the OECD initial and thematic reports have been computed accordingly to these methodologies, which means that the reporting of a country mean estimate and its respective standard error requires the computation of 405 means as described in detail in the next sections.

This chapter discusses the importance and usefulness of applying these recommended procedures, depending on the circumstances and on the stage of the data analysis process. Alternatives that shorten the procedures will be also presented, as well as the potential bias associated with such shortcuts.

The chapter is structured according to the three methodological issues that affect the way data should be analysed:

- weights,
- replicates for computing the standard errors,
- plausible values.

## WEIGHTS

Weights are associated to each student and to each school because:

- students and schools in a particular country did not necessarily have the same probability of selection;
- differential participation rates according to certain types of school or student characteristics required various non-response adjustments;
- some explicit strata were over-sampled for national reporting purposes.

Weighting data is a straightforward process in SPSS®. Box 2.1 presents the syntax for weighting, while `w_fstuwt` is the variable name of the student final weights.

All the analyses with the syntax of Box 2.1 will provide unbiased estimates of population parameters.



### Box 2.1 WEIGHT statement in SPSS®

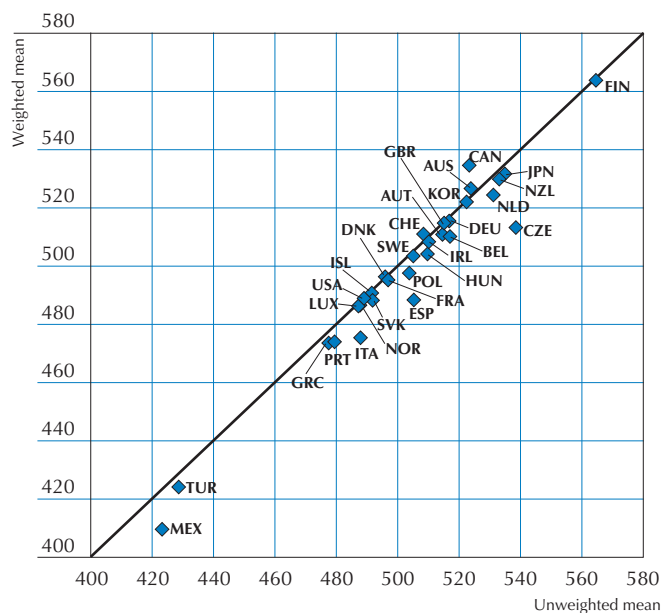
```
WEIGHT BY W_FSTUWT.
```

It is, however, worth noting that SPSS® will consider the sum of the weights as the sample size for the computation of standard errors. When analysts are interested in computing rough estimates of standard errors for provisional exploratory analysis, this becomes an issue. One way of obtaining realistic rough estimates of a standard error,<sup>1</sup> without using replicates, is to normalise the weights. The weight included in the database should be multiplied by a ratio of the number of observations to the sum of the weights. In other words, the weights should be multiplied by the total number of students and divided by the weighted total number of students. This linear transformation will ensure that the sum of the weights is equal to the number of observations.

Can analyses be conducted without weighting the data? Figure 2.1 represents the unweighted and weighted mean proficiency estimates in science for OECD countries in PISA 2006. In most countries, the difference is negligible. However, for some countries, the difference is quite substantial. Large differences between weighted and unweighted means usually result from over-sampling some strata in the population for national reporting purposes.

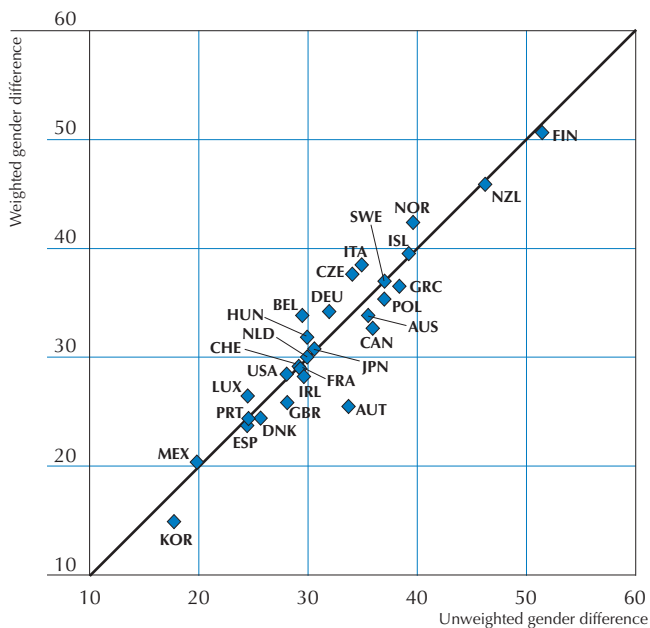
Figure 2.2 compares the unweighted and weighted gender differences in reading in PISA 2000. In most countries, the difference is negligible, but in Austria, for instance, the unweighted and weighted gender differences are equal to 33.5 and 25.4 respectively. Uneven distribution of males and females per type of schools (vocational versus academic) and differential participation rates per type of schools might explain such gaps between unweighted and weighted gender differences.

**Figure 2.1**  
Science mean performance in OECD countries (PISA 2006)

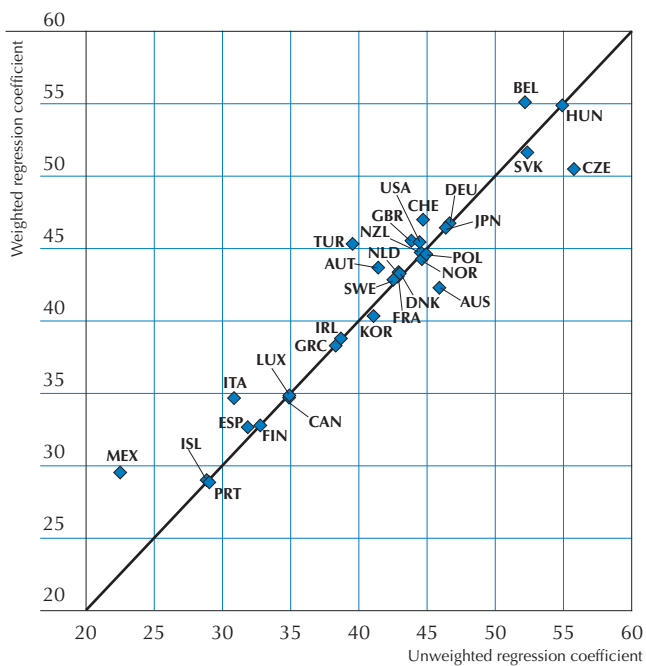




**Figure 2.2**  
Gender differences in reading in OECD countries (PISA 2000)



**Figure 2.3**  
Regression coefficient of ESCS on mathematic performance in OECD countries (PISA 2003)





Finally, Figure 2.3 presents the unweighted and weighted regression coefficient of student socio-economic background (ESCS) on mathematic performance in PISA 2003. As shown by the figure, differences between unweighted and weighted coefficient are sometimes not negligible.

These three examples clearly demonstrate the impact of the weights on population parameter estimates. The bias of unweighted estimates could be substantial.

In conclusion, the weighting process does not make the analysis procedures more complex and guarantees that population estimates will be unbiased. Analyses should therefore always be weighted, at any stage of the process, whether it is the provisional exploration of the data or the final analyses before reporting.

### REPLICATES FOR COMPUTING THE STANDARD ERROR

PISA applies two-stage sampling instead of simple random sampling. Chapter 3 describes the sampling design of the PISA surveys in detail and why such a design is implemented. This section, however, briefly describes the differences between these two sampling designs in order to provide rationale for using replicate weights. As previously indicated, statistical packages such as SAS® or SPSS® make the assumption that data are collected on a simple random sample of individuals.

One of the differences between simple random sampling and two-stage sampling is that for the latter, selected students attending the same school cannot be considered as independent observations. This is because students within a school usually have more common characteristics than students from different schools. For instance, they would have access to the same school resources, have the same teachers, be taught a common curriculum, and so on. Differences between students from different schools are also greater if different educational programmes are not available in all schools. For example, it would be expected that differences between students from a vocational school and students from an academic school would be bigger than differences between students from two vocational schools.

Furthermore, it is likely that within a country, within subnational entities, and within cities, people tend to live in areas according to their financial resources. As most children tend to attend schools close to their homes, it is assumed that students attending the same school come from similar socio-economic backgrounds.

A simple random sample of 4 000 students is therefore likely to cover the diversity of the population better than a sample of 100 schools with 40 students observed within each school. It follows that the uncertainty associated with any population parameter estimate (*i.e.* standard error) will be greater for a two-stage sample than for a simple random sample of the same size.

Reporting accurate and unbiased standard error estimates is of prime importance, since these estimates could be used for reporting differences that are statistically significant between countries or within countries. Reporting gender differences, for example, might lead to educational reforms aimed to reduce the gap between males and females. It is therefore essential to assure that these differences are indeed statistically significant.

Earlier student assessment surveys used to increase the simple random sample standard errors by the design effect (usually denoted in the statistical literature as DEFF) were roughly estimated on a few key variables for some population estimators, such as means, correlation and regression coefficients. For instance, in the First International Mathematics Study (FIMS) (Husen, 1967):

“four subsamples of each subpopulation were obtained – this meant that instead of having only one sample representing a population, there were four. The purpose of doing this was twofold: (i) the standard errors of sampling could be obtained from the comparison of subsamples and, (ii) the answer sheets for each subsample could be shipped separately; thus if one was lost, three still remained.”<sup>2</sup>



The International Association for the Evaluation of Educational Achievement (IEA) Six Subject Survey extended the FIMS procedure for the estimation of standard errors by integrating the scientific development of John Tukey on the Jackknife replication method. The whole sample for each country was divided into ten subsamples, following the sampling structure, and then ten complementary samples were obtained by leaving out, from the whole sample, each subsample in turn. Population estimates were then computed on each complementary subsample. The variability of these population estimates was used to estimate the standard errors and their respective design effect. The comparison between these design effects and their respective theoretical design effects based on the school variance and the average within school sample size showed quite consistent results, which allowed using the theoretical design effect.

As noted by Peaker (1975), “this evidence was combined with the evidence from the Mathematics Study in 1967, and suggested that appropriate values of DEFF were 2.4 for criterion means, 1.6 for correlations and 1.4 for regression coefficients.”

In the late 1980s, the power of computers allowed the systematic use of replication methods. Standard errors were estimated for the Second International Science Study (SISS) by the Jackknife method for unstratified sample which consists of creating as many complementary samples as the number of schools in the whole sample. Each complementary sample was created by dropping one school at a time. The IEA Reading Literacy Study also used this replication method as well.

This manual presents how these replicates are computed in detail (Chapter 4) and how to estimate a standard error with these replicates (Chapter 7).

This section discusses the consequences of not using the replicates for estimating the standard errors and the appropriateness of using them in all phases of the data analysis process.

The PISA Technical Reports (OECD, 2002c, 2005, 2009) describe the sampling design effects for the performance country mean estimates in the chapter devoted to the sampling outcomes. Mathematically, the design effect corresponds to the ratio between the unbiased estimate of the sampling variance for a particular parameter and the sampling variance for that parameter if the observed sample was considered as a simple random sample.

**Table 2.1**  
**Design effect and type I errors**

Design effect (coefficient of increase)	Type I error	Design effect (coefficient of increase)	Type I error
1.5	0.11	11.0	0.55
2.0	0.17	11.5	0.56
2.5	0.22	12.0	0.57
3.0	0.26	12.5	0.58
3.5	0.29	13.0	0.59
4.0	0.33	13.5	0.59
4.5	0.36	14.0	0.60
5.0	0.38	14.5	0.61
5.5	0.40	15.0	0.61
6.0	0.42	15.5	0.62
6.5	0.44	16.0	0.62
7.0	0.46	16.5	0.63
7.5	0.47	17.0	0.63
8.0	0.49	17.5	0.64
8.5	0.50	18.0	0.64
9.0	0.51	18.5	0.65
9.5	0.52	19.0	0.65
10.0	0.54	19.5	0.66
10.5	0.55	20.0	0.66



In PISA 2000, the sampling design effect for the country mean estimate on the combined reading literacy scale ranged from 2.32 to 19.92. This means that the actual standard error is from 1.5 to 4.4 times larger than the simple random sample standard error. In PISA 2003 and PISA 2006, countries requesting an adjudication of their data at a subnational level had to over-sample. The sampling design was, therefore, less effective and the design effect was higher. For instance, the design effect for the country performance mean estimate of Mexico was higher than 50 in PISA 2003.

Table 2.1 presents the type I error depending on the design effect. For instance, with a design effect of 4, a data analyst using the standard error returned by statistical packages assuming simple random sample will be working with the type I error of 0.33. As 0.01, 0.05 or 0.1 are normally used for the criteria of the significance level, this is a very important difference. Let us suppose an analysis estimates gender difference in science performance. When the gender difference is significantly different from 0 at the significance level of 0.33, the analysis has a 33% chance of being wrong in saying that there is a significant gender difference.

The design effect varies from one country to another, but it also varies from one variable to another within a particular country. Figure 2.4 compares the design effect on the country mean estimates for the science performance and for the student socio-economic background (ESCS) in PISA 2006. The design effect on the mean estimate for the student socio-economic background is usually smaller than the design effect for science performance, since grouping students into different schools is usually based on their academic performance and, to a lesser extent, based on student socio-economic background.

Figure 2.4

Design effect on the country mean estimates for science performance and for ESCS in OECD countries (PISA 2006)

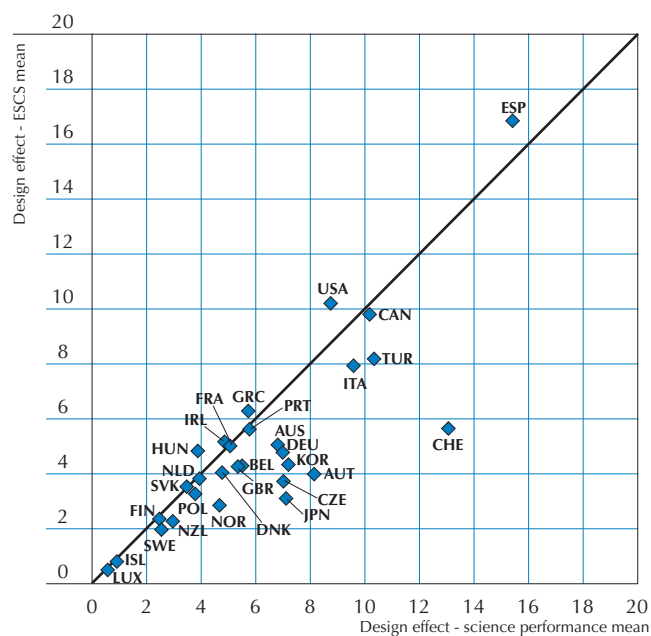


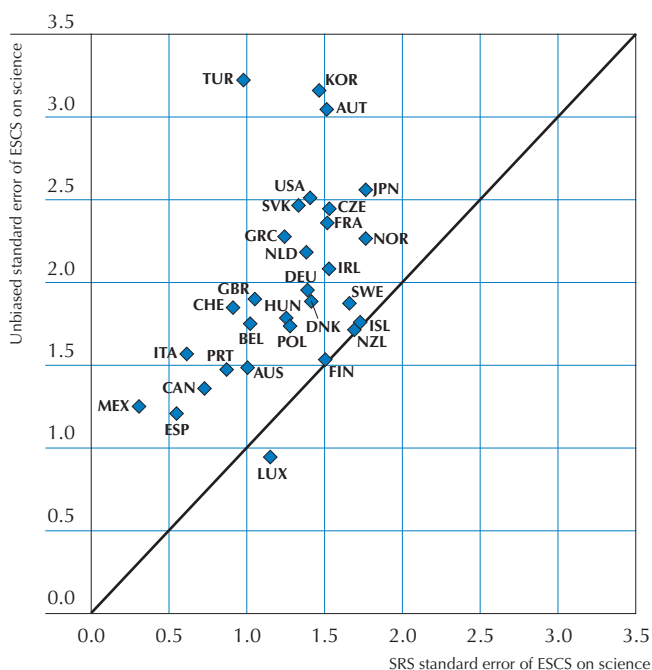


Figure 2.5 compares two different types of standard errors of the regression coefficient of ESCS on science performance: one is computed just as simple random sample (SRS) and the other is computed with replicates (unbiased). In Figure 2.5, the following can be observed:

- For most countries unbiased standard errors are bigger than SRS standard errors (*i.e.* dots are above the diagonal line),<sup>3</sup> but unbiased standard errors are not twice as big as SRS standard errors. This means that design effects are not as big as two in most countries. This result, therefore, supports the notion that design effects for regression coefficients (Figure 2.5) are smaller than design effects for mean estimates (Figure 2.4), as already noted by Peaker (1975).
- No specific patterns between SRS and unbiased standard errors are observed in Figure 2.5. This means that the design effect for regression coefficients varies from one country to another.

Figure 2.5

Simple random sample and unbiased standard errors of ESCS on science performance in OECD countries (PISA 2006)



As illustrated by these few examples, the design effect depends on: (i) the population parameter that needs to be estimated; (ii) the sampling design of the country; (iii) the variables involved in the analyses (in particular the importance of the between-school variance relative to the within-school variance). Therefore, it would be inappropriate to suggest a single design effect for a particular parameter to be used for all countries to obtain a rough estimate of the actual standard error, based on the simple random sample standard error – especially given the increasing number of countries implementing a study design for regional adjudications and the large number of countries implementing international or national options.





In sum, the results that will be reported have to be computed according to the recommended procedures, *i.e.* standard errors have to be estimated by using the replicates. During the exploratory phase, analysts might skip the replicate computations to save time. Instead, analysts could use the normalised weights and apply design effects. But, it is advised not to wait until the last stage of the process to compute unbiased estimates of the standard errors. Indeed, it might change a major outcome that would require rewriting some section of the reports. It is also important to note that analysis with the PISA data for only one country might inflate the standard error by using some fixed design effect values. This would require starting by estimating sensitive values of design effects for parameters such as mean, correlation, regression coefficient and so on. With a little practice, the procedures developed for analysing PISA data are not a constraint anymore. Moreover, with standard computers, these procedures do not take more than a couple of minutes.

## PLAUSIBLE VALUES

This section briefly presents the rationale for using plausible values. The detailed description of plausible values and its use are presented in Chapters 6 and 8.

Since the Third International Mathematics and Science Survey conducted by the IEA in 1995, student proficiency estimates are returned through *plausible values*.

“The simplest way to describe plausible values is to say that plausible values are a representation of the range of abilities that a student might reasonably have. (...). Instead of directly estimating a student’s ability  $\theta$ , a probability distribution for a student’s  $\theta$ , is estimated. That is, instead of obtaining a point estimate for  $\theta$ , (like a WLE<sup>4</sup>), a range of possible values for a student’s  $\theta$ , with an associated probability for each of these values is estimated. Plausible values are random draws from this (estimated) distribution for a student’s  $\theta$ .” (Wu and Adams, 2002)

As will be described in Chapter 6, plausible values present several methodological advantages in comparison with classical Item Response Theory (IRT) estimates such as the Maximum Likelihood Estimates or Weighted Maximum Likelihood Estimates. Indeed, plausible values return unbiased estimates of:

- population performance parameters, such as mean, standard deviation or decomposition of the variance;
- percentages of students per proficiency level as they are on a continuous scale, unlike classical estimates which are on a non-continuous scale;
- bivariate or multivariate indices of relations between performance and background variables as this information is included in the psychometric model.

Usually, five plausible values are allocated to each student on each performance scale. Statistical analyses should be performed independently on each of these five plausible values and results should be aggregated to obtain the final estimates of the statistics and their respective standard errors. It is worth noting that these standard errors will consist of sampling uncertainty and test unreliability.

The plausible value methodology, combined with the replicates, requires that the parameter, such as a mean, a standard deviation, a percentage or a correlation, has to be computed 405 times (*i.e.* 5 plausible values by one student final weights and 80 replicates) to obtain the final estimate of the parameter and its standard error. Chapter 8 describes an unbiased shortcut that requires only 85 computations.

Working with one plausible value instead of five will provide unbiased estimate of population parameters but will not estimate the imputation error that reflects the influence of test unreliability for the parameter estimation. With a large dataset, this imputation error is relatively small. However, the smaller the sample size, the greater the imputation error.



Table 2.2 to Table 2.5 present the differences for four population parameters (*i.e.* mean, standard deviation, correlation and regression coefficient) between the estimates based on one plausible value and the same estimates based on five plausible values. These analyses were computed on the PISA 2006 science performance data in Belgium. Simple random samples of various sizes were selected. Each table shows:

- the estimated statistic based on one plausible value,
- the estimated standard error based on one plausible value,
- the estimated statistic based on five plausible values,
- the estimated standard error based on five plausible values,
- the sampling error based on five plausible values,
- the imputation error based on five plausible values.

With a sample size of 6 400 students, using one plausible value or five plausible values does not make any substantial difference in the two mean estimates (510.56 versus 510.79) as well as in the two standard error estimates (2.64 versus 2.69). In term of type I error, that would correspond to a shift from 0.050 to 0.052.

**Table 2.2**  
Mean estimates and standard errors

Number of cases	Estimate on 1 PV	S.E. on 1 PV	Estimate on 5 PVs	S.E. on 5 PVs	Sampling error	Imputation error
25	500.05	19.47	493.87	21.16	20.57	4.55
50	510.66	17.70	511.48	16.93	16.76	2.18
100	524.63	12.25	518.00	12.42	11.70	3.81
200	509.78	7.52	509.46	7.79	7.56	1.72
400	507.91	6.34	508.31	6.52	6.46	0.86
800	507.92	4.55	508.69	4.58	4.50	0.79
1 600	506.52	3.54	507.25	3.44	3.39	0.52
3 200	511.03	2.77	511.48	2.76	2.70	0.49
6 400	510.56	2.64	510.79	2.69	2.67	0.23

Notes: PV = plausible value; S.E. = standard error.

Table 2.2 also illustrates how the imputation error increases as the sample size decreases. With a sample of 25 students, the imputation error is as big as the sampling error with a sample of 800 students. However, even if the imputation error is quite large with a sample of 25 students, working with one plausible value instead of five would correspond to a small shift in type I error from 0.05 to 0.072.

**Table 2.3**  
Standard deviation estimates and standard errors

Number of cases	Estimate on 1 PV	S.E. on 1 PV	Estimate on 5 PVs	S.E. on 5 PVs	Sampling error	Imputation error
25	116.86	14.87	114.99	13.62	11.95	5.97
50	106.53	17.05	104.38	15.32	15.00	2.88
100	90.36	8.79	90.73	8.75	8.19	2.81
200	101.66	6.49	101.18	6.75	6.50	1.65
400	97.52	3.63	97.67	4.39	3.83	1.95
800	100.03	2.66	99.97	3.65	2.92	2.00
1 600	96.82	2.51	96.36	2.41	2.35	0.48
3 200	100.66	2.09	100.29	2.19	2.14	0.42
6 400	98.66	1.97	99.09	2.01	1.94	0.48

Notes: PV = plausible value; S.E. = standard error.



**Table 2.4**  
Correlation estimates and standard errors

Number of cases	Estimate on 1 PV	S.E. on 1 PV	Estimate on 5 PVs	S.E. on 5 PVs	Sampling error	Imputation error
25	0.57	0.13	0.65	0.13	0.11	0.07
50	0.58	0.12	0.58	0.13	0.12	0.05
100	0.47	0.09	0.49	0.09	0.09	0.03
200	0.54	0.05	0.54	0.05	0.04	0.02
400	0.40	0.05	0.40	0.05	0.05	0.01
800	0.39	0.04	0.39	0.04	0.04	0.00
1 600	0.45	0.02	0.45	0.03	0.02	0.01
3 200	0.43	0.02	0.43	0.02	0.02	0.00
6 400	0.43	0.01	0.44	0.02	0.01	0.00

Notes: PV = plausible value; S.E. = standard error.

**Table 2.5**  
ESCS regression coefficient estimates and standard errors

Number of cases	Estimate on 1 PV	S.E. on 1 PV	Estimate on 5 PVs	S.E. on 5 PVs	Sampling error	Imputation error
25	57.76	24.99	51.43	28.32	27.34	6.73
50	34.19	11.20	31.64	11.67	10.90	3.80
100	37.44	12.33	41.19	12.43	11.90	3.28
200	36.43	7.60	41.60	8.65	7.92	3.17
400	53.27	5.43	53.89	5.79	5.61	1.31
800	47.83	4.20	47.98	4.62	4.26	1.64
1 600	47.26	3.12	47.86	3.56	3.17	1.48
3 200	47.98	2.45	48.22	2.54	2.53	0.25
6 400	46.91	1.92	47.23	2.08	1.97	0.63

Notes: PV = plausible value; S.E. = standard error.

Under normal assumptions, the imputation error implies that the average, *i.e.* 493.87 for a sample of 25 students, can vary from 485 to 503. Using one plausible value instead of five for a very small sample may therefore have a considerable impact on the parameter estimates.

Similar conclusions can be drawn from the three tables above that refer respectively to standard deviation, correlation and ESCS regression coefficient.

## CONCLUSION

This chapter briefly described the three methodological components of PISA that condition the data analysis process: weights, replicates and plausible values. It also discussed the consequences of not applying the recommended statistical procedures according to the data analysis phase.

In summary, the recommendations are:

- At any stage of the data analysis process, data should always be weighted. Unweighted data will return biased estimates. The importance of weighting the data is reinforced by the increasing number of countries that request a data adjudication at a subnational level, since such a request requires oversampling in almost all cases. As weighting data does not slow down the data analysis process and can easily be implemented in statistical packages, there is no valid reason for skipping this process.



- Use of replicates for estimating the standard error is certainly the methodological component that slows down the data analysis process the most. During the exploratory phase of the data, it is not of prime importance to estimate the standard error with the replicates. Standard errors returned by statistical software with normalised weight, and inflated by a rough estimate of the design effect, can provide the data analyst with an acceptable indication of the statistical significance of hypotheses. However, any results that will be published or communicated to the scientific community and to policy makers should be computed with replicates.
- Finally, using one plausible value or five plausible values does not really make a substantial difference on large samples. During the exploratory phase of the data, statistical analyses can be based on a single plausible value. It is, however, recommended to base the reported results on five plausible values, even on large samples. This will guarantee consistencies between results published by the OECD and results published in scientific journals or national reports. Further, results based on five plausible values are, from a theoretical point of view, incontestable.

### Notes

1. This rough estimate of standard error is based on the assumption of a simple random sample.
2. In the IEA Six Subject Survey, a box containing answer sheets from Belgium fell out of a boat into the sea.
3. PISA in Luxembourg is not a sample survey but a census. SRS does not take into account the school stratification variables, while PISA does. Therefore, in Luxembourg, SRS standard errors are bigger than unbiased standard errors.
4. Weighted Likelihood Estimates.



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# Table of contents

<b>FOREWORD</b> .....	<b>3</b>
<b>USER'S GUIDE</b> .....	<b>17</b>
<b>CHAPTER 1 THE USEFULNESS OF PISA DATA FOR POLICY MAKERS, RESEARCHERS AND EXPERTS ON METHODOLOGY</b> .....	<b>19</b>
<b>PISA – an overview</b> .....	<b>20</b>
▪ The PISA surveys.....	20
<b>How can PISA contribute to educational policy, practice and research?</b> .....	<b>22</b>
▪ Key results from PISA 2000, PISA 2003 and PISA 2006.....	23
<b>Further analyses of PISA datasets</b> .....	<b>25</b>
▪ Contextual framework of PISA 2006.....	28
▪ Influence of the methodology on outcomes.....	31
<b>CHAPTER 2 EXPLORATORY ANALYSIS PROCEDURES</b> .....	<b>35</b>
<b>Introduction</b> .....	<b>36</b>
<b>Weights</b> .....	<b>36</b>
<b>Replicates for computing the standard error</b> .....	<b>39</b>
<b>Plausible values</b> .....	<b>43</b>
<b>Conclusion</b> .....	<b>45</b>
<b>CHAPTER 3 SAMPLE WEIGHTS</b> .....	<b>47</b>
<b>Introduction</b> .....	<b>48</b>
<b>Weights for simple random samples</b> .....	<b>49</b>
<b>Sampling designs for education surveys</b> .....	<b>51</b>
<b>Why do the PISA weights vary?</b> .....	<b>55</b>
<b>Conclusion</b> .....	<b>56</b>
<b>CHAPTER 4 REPLICATE WEIGHTS</b> .....	<b>57</b>
<b>Introduction</b> .....	<b>58</b>
<b>Sampling variance for simple random sampling</b> .....	<b>58</b>
<b>Sampling variance for two-stage sampling</b> .....	<b>63</b>
<b>Replication methods for simple random samples</b> .....	<b>68</b>
<b>Replication methods for two-stage samples</b> .....	<b>70</b>
▪ The Jackknife for unstratified two-stage sample designs.....	70
▪ The Jackknife for stratified two-stage sample designs.....	71
▪ The Balanced Repeated Replication method.....	72
<b>Other procedures for accounting for clustered samples</b> .....	<b>74</b>
<b>Conclusion</b> .....	<b>74</b>



<b>CHAPTER 5 THE RASCH MODEL</b> .....	<b>77</b>
<b>Introduction</b> .....	78
<b>How can the information be summarised?</b> .....	78
<b>The Rasch Model for dichotomous items</b> .....	79
▪ Introduction to the Rasch Model.....	79
▪ Item calibration.....	83
▪ Computation of a student's score.....	85
▪ Computation of a student's score for incomplete designs.....	89
▪ Optimal conditions for linking items.....	90
▪ Extension of the Rasch Model.....	91
<b>Other item response theory models</b> .....	92
<b>Conclusion</b> .....	92
 <b>CHAPTER 6 PLAUSIBLE VALUES</b> .....	 <b>93</b>
<b>Individual estimates versus population estimates</b> .....	94
<b>The meaning of plausible values (PVs)</b> .....	94
<b>Comparison of the efficiency of WLEs, EAP estimates and PVs for the estimation of some population statistics</b> .....	97
<b>How to perform analyses with plausible values</b> .....	100
<b>Conclusion</b> .....	101
 <b>CHAPTER 7 COMPUTATION OF STANDARD ERRORS</b> .....	 <b>103</b>
<b>Introduction</b> .....	104
<b>The standard error on univariate statistics for numerical variables</b> .....	104
<b>The SPSS® macro for computing the standard error on a mean</b> .....	107
<b>The standard error on percentages</b> .....	110
<b>The standard error on regression coefficients</b> .....	112
<b>The standard error on correlation coefficients</b> .....	114
<b>Conclusion</b> .....	115
 <b>CHAPTER 8 ANALYSES WITH PLAUSIBLE VALUES</b> .....	 <b>117</b>
<b>Introduction</b> .....	118
<b>Univariate statistics on plausible values</b> .....	118
<b>The standard error on percentages with PVs</b> .....	121
<b>The standard error on regression coefficients with PVs</b> .....	121
<b>The standard error on correlation coefficients with PVs</b> .....	124
<b>Correlation between two sets of plausible values</b> .....	124
<b>A fatal error shortcut</b> .....	128
<b>An unbiased shortcut</b> .....	129
<b>Conclusion</b> .....	130
 <b>CHAPTER 9 USE OF PROFICIENCY LEVELS</b> .....	 <b>133</b>
<b>Introduction</b> .....	134
<b>Generation of the proficiency levels</b> .....	134
<b>Other analyses with proficiency levels</b> .....	139
<b>Conclusion</b> .....	141





<b>CHAPTER 10 ANALYSES WITH SCHOOL-LEVEL VARIABLES</b> .....	<b>143</b>
<b>Introduction</b> .....	144
<b>Limits of the PISA school samples</b> .....	145
<b>Merging the school and student data files</b> .....	146
<b>Analyses of the school variables</b> .....	146
<b>Conclusion</b> .....	148
<b>CHAPTER 11 STANDARD ERROR ON A DIFFERENCE</b> .....	<b>149</b>
<b>Introduction</b> .....	150
<b>Statistical issues and computing standard errors on differences</b> .....	150
<b>The standard error on a difference without plausible values</b> .....	152
<b>The standard error on a difference with plausible values</b> .....	157
<b>Multiple comparisons</b> .....	161
<b>Conclusion</b> .....	162
<b>CHAPTER 12 OECD TOTAL AND OECD AVERAGE</b> .....	<b>163</b>
<b>Introduction</b> .....	164
<b>Recoding of the database to estimate the pooled OECD total and the pooled OECD average</b> .....	166
<b>Duplication of the data to avoid running the procedure three times</b> .....	168
<b>Comparisons between the pooled OECD total or pooled OECD average estimates and a country estimate</b> .....	169
<b>Comparisons between the arithmetic OECD total or arithmetic OECD average estimates and a country estimate</b> .....	171
<b>Conclusion</b> .....	171
<b>CHAPTER 13 TRENDS</b> .....	<b>173</b>
<b>Introduction</b> .....	174
<b>The computation of the standard error for trend indicators on variables other than performance</b> .....	175
<b>The computation of the standard error for trend indicators on performance variables</b> .....	177
<b>Conclusion</b> .....	181
<b>CHAPTER 14 STUDYING THE RELATIONSHIP BETWEEN STUDENT PERFORMANCE AND INDICES DERIVED FROM CONTEXTUAL QUESTIONNAIRES</b> .....	<b>183</b>
<b>Introduction</b> .....	184
<b>Analyses by quarters</b> .....	184
<b>The concept of relative risk</b> .....	186
▪ <b>Instability of the relative risk</b> .....	187
▪ <b>Computation of the relative risk</b> .....	188
<b>Effect size</b> .....	191
<b>Linear regression and residual analysis</b> .....	193
▪ <b>Independence of errors</b> .....	193
<b>Statistical procedure</b> .....	196
<b>Conclusion</b> .....	197



<b>CHAPTER 15 MULTILEVEL ANALYSES</b> .....	<b>199</b>
<b>Introduction</b> .....	200
<b>Two-level modelling with SPSS®</b> .....	202
▪ Decomposition of the variance in the empty model.....	202
▪ Models with only random intercepts.....	205
▪ Shrinkage factor.....	207
▪ Models with random intercepts and fixed slopes.....	207
▪ Models with random intercepts and random slopes.....	209
▪ Models with Level 2 independent variables.....	214
▪ Computation of final estimates and their respective standard errors.....	217
<b>Three-level modelling</b> .....	219
<b>Limitations of the multilevel model in the PISA context</b> .....	221
<b>Conclusion</b> .....	222
<b>CHAPTER 16 PISA AND POLICY RELEVANCE – THREE EXAMPLES OF ANALYSES</b> .....	<b>223</b>
<b>Introduction</b> .....	224
<b>Example 1: Gender differences in performance</b> .....	224
<b>Example 2: Promoting socio-economic diversity within school?</b> .....	228
<b>Example 3: The influence of an educational system on the expected occupational status of students at age 30</b> .....	234
<b>Conclusion</b> .....	237
<b>CHAPTER 17 SPSS® MACRO</b> .....	<b>239</b>
<b>Introduction</b> .....	240
<b>Structure of the SPSS® Macro</b> .....	240
<b>REFERENCES</b> .....	<b>321</b>
<b>APPENDICES</b> .....	<b>323</b>
<b>Appendix 1</b> Three-level regression analysis.....	324
<b>Appendix 2</b> PISA 2006 International database.....	332
<b>Appendix 3</b> PISA 2006 Student questionnaire.....	341
<b>Appendix 4</b> PISA 2006 Information communication technology (ICT) Questionnaire.....	350
<b>Appendix 5</b> PISA 2006 School questionnaire.....	352
<b>Appendix 6</b> PISA 2006 Parent questionnaire.....	359
<b>Appendix 7</b> Codebook for PISA 2006 student questionnaire data file.....	363
<b>Appendix 8</b> Codebook for PISA 2006 non-scored cognitive and embedded attitude items.....	407
<b>Appendix 9</b> Codebook for PISA 2006 scored cognitive and embedded attitude items.....	427
<b>Appendix 10</b> Codebook for PISA 2006 school questionnaire data file.....	439
<b>Appendix 11</b> Codebook for PISA 2006 parents questionnaire data file.....	450
<b>Appendix 12</b> PISA 2006 questionnaire indices.....	456



## LIST OF BOXES

Box 2.1	WEIGHT statement in SPSS®.....	37
<hr/>		
Box 7.1	SPSS® syntax for computing 81 means (e.g. PISA 2003).....	104
Box 7.2	SPSS® syntax for computing the mean of HISEI and its standard error (e.g. PISA 2003).....	107
Box 7.3	SPSS® syntax for computing the standard deviation of HISEI and its standard error by gender (e.g. PISA 2003).....	109
Box 7.4	SPSS® syntax for computing the percentages and their standard errors for gender (e.g. PISA 2003).....	110
Box 7.5	SPSS® syntax for computing the percentages and its standard errors for grades by gender (e.g. PISA 2003).....	112
Box 7.6	SPSS® syntax for computing regression coefficients, $R^2$ and its respective standard errors: Model 1 (e.g. PISA 2003).....	113
Box 7.7	SPSS® syntax for computing regression coefficients, $R^2$ and its respective standard errors: Model 2 (e.g. PISA 2003).....	114
Box 7.8	SPSS® syntax for computing correlation coefficients and its standard errors (e.g. PISA 2003).....	114
<hr/>		
Box 8.1	SPSS® syntax for computing the mean on the science scale by using the MCR_SE_UNIV macro (e.g. PISA 2006).....	119
Box 8.2	SPSS® syntax for computing the mean and its standard error on PVs (e.g. PISA 2006).....	120
Box 8.3	SPSS® syntax for computing the standard deviation and its standard error on PVs by gender (e.g. PISA 2006).....	131
Box 8.4	SPSS® syntax for computing regression coefficients and their standard errors on PVs by using the MCR_SE_REG macro (e.g. PISA 2006).....	122
Box 8.5	SPSS® syntax for running the simple linear regression macro with PVs (e.g. PISA 2006).....	123
Box 8.6	SPSS® syntax for running the correlation macro with PVs (e.g. PISA 2006).....	124
Box 8.7	SPSS® syntax for the computation of the correlation between mathematics/quantity and mathematics/space and shape by using the MCR_SE_COR_2PV macro (e.g. PISA 2003).....	126
<hr/>		
Box 9.1	SPSS® syntax for generating the proficiency levels in science (e.g. PISA 2006).....	135
Box 9.2	SPSS® syntax for computing the percentages of students by proficiency level in science and its standard errors (e.g. PISA 2006).....	136
Box 9.3	SPSS® syntax for computing the percentage of students by proficiency level in science and its standard errors (e.g. PISA 2006).....	138
Box 9.4	SPSS® syntax for computing the percentage of students by proficiency level and its standard errors by gender (e.g. PISA 2006).....	138
Box 9.5	SPSS® syntax for generating the proficiency levels in mathematics (e.g. PISA 2003).....	139
Box 9.6	SPSS® syntax for computing the mean of self-efficacy in mathematics and its standard errors by proficiency level (e.g. PISA 2003).....	140
<hr/>		
Box 10.1	SPSS® syntax for merging the student and school data files (e.g. PISA 2006).....	146
Box 10.2	Question on school location in PISA 2006.....	147
Box 10.3	SPSS® syntax for computing the percentage of students and the average performance in science, by school location (e.g. PISA 2006).....	147
<hr/>		
Box 11.1	SPSS® syntax for computing the mean of job expectations by gender (e.g. PISA 2003).....	152
Box 11.2	SPSS® macro for computing standard errors on differences (e.g. PISA 2003).....	155



Box 11.3	Alternative SPSS® macro for computing the standard error on a difference for a dichotomous variable (e.g. PISA 2003).....	156
Box 11.4	SPSS® syntax for computing standard errors on differences which involve PVs (e.g. PISA 2003).....	158
Box 11.5	SPSS® syntax for computing standard errors on differences that involve PVs (e.g. PISA 2006).....	160
<hr/>		
Box 12.1	SPSS® syntax for computing the pooled OECD total for the mathematics performance by gender (e.g. PISA 2003).....	166
Box 12.2	SPSS® syntax for the pooled OECD average for the mathematics performance by gender (e.g. PISA 2003).....	167
Box 12.3	SPSS® syntax for the creation of a larger dataset that will allow the computation of the pooled OECD total and the pooled OECD average in one run (e.g. PISA 2003).....	168
<hr/>		
Box 14.1	SPSS® syntax for the quarter analysis (e.g. PISA 2006).....	185
Box 14.2	SPSS® syntax for computing the relative risk with five antecedent variables and five outcome variables (e.g. PISA 2006).....	189
Box 14.3	SPSS® syntax for computing the relative risk with one antecedent variable and one outcome variable (e.g. PISA 2006).....	190
Box 14.4	SPSS® syntax for computing the relative risk with one antecedent variable and five outcome variables (e.g. PISA 2006).....	190
Box 14.5	SPSS® syntax for computing effect size (e.g. PISA 2006).....	192
Box 14.6	SPSS® syntax for residual analyses (e.g. PISA 2003).....	196
<hr/>		
Box 15.1	Normalisation of the final student weights (e.g. PISA 2006).....	203
Box 15.2	SPSS® syntax for the decomposition of the variance in student performance in science (e.g. PISA 2006).....	203
Box 15.3	SPSS® syntax for normalising PISA 2006 final student weights with deletion of cases with missing values and syntax for variance decomposition (e.g. PISA 2006).....	206
Box 15.4	SPSS® syntax for a multilevel regression model with random intercepts and fixed slopes (e.g. PISA 2006).....	208
Box 15.5	Results for the multilevel model in Box 15.4.....	208
Box 15.6	SPSS® syntax for a multilevel regression model (e.g. PISA 2006).....	210
Box 15.7	Results for the multilevel model in Box 15.6.....	211
Box 15.8	Results for the multilevel model with covariance between random parameters.....	212
Box 15.9	Interpretation of the within-school regression coefficient.....	214
Box 15.10	SPSS® syntax for a multilevel regression model with a school-level variable (e.g. PISA 2006).....	214
Box 15.11	SPSS® syntax for a multilevel regression model with interaction (e.g. PISA 2006).....	215
Box 15.12	Results for the multilevel model in Box 15.11.....	216
Box 15.13	SPSS® syntax for using the multilevel regression macro (e.g. PISA 2006).....	217
Box 15.14	SPSS® syntax for normalising the weights for a three-level model (e.g. PISA 2006).....	219
<hr/>		
Box 16.1	SPSS® syntax for testing the gender difference in standard deviations of reading performance (e.g. PISA 2000).....	225
Box 16.2	SPSS® syntax for computing the 5th percentile of the reading performance by gender (e.g. PISA 2000).....	227
Box 16.3	SPSS® syntax for preparing a data file for the multilevel analysis.....	230



Box 16.4	SPSS® syntax for running a preliminary multilevel analysis with one PV .....	231
Box 16.5	Estimates of fixed parameters in the multilevel model.....	231
Box 16.6	SPSS® syntax for running preliminary analysis with the MCR_ML_PV macro.....	233
Box 17.1	SPSS® macro of MCR_SE_UNI.sps.....	243
Box 17.2	SPSS® macro of MCR_SE_PV.sps.....	247
Box 17.3	SPSS® macro of MCR_SE_PERCENTILES_PV.sps .....	251
Box 17.4	SPSS® macro of MCR_SE_GrpPct.sps.....	254
Box 17.5	SPSS® macro of MCR_SE_PctLev.sps.....	257
Box 17.6	SPSS® macro of MCR_SE_REG.sps .....	261
Box 17.7	SPSS® macro of MCR_SE_REG_PV.sps.....	265
Box 17.8	SPSS® macro of MCR_SE_COR.sps.....	270
Box 17.9	SPSS® macro of MCR_SE_COR_1PV.sps.....	273
Box 17.10	SPSS® macro of MCR_SE_COR_2PV.sps.....	277
Box 17.11	SPSS® macro of MCR_SE_DIFF.sps.....	281
Box 17.12	SPSS® macro of MCR_SE_DIFF_PV.sps.....	285
Box 17.13	SPSS® macro of MCR_SE_PV_WLEQRT.sps.....	290
Box 17.14	SPSS® macro of MCR_SE_RR.sps.....	295
Box 17.15	SPSS® macro of MCR_SE_RR_PV.sps.....	298
Box 17.16	SPSS® macro of MCR_SE_EFFECT.sps.....	302
Box 17.17	SPSS® macro of MCR_SE_EFFECT_PV.sps .....	306
Box 17.18	SPSS® macro of MCR_ML.sps.....	311
Box 17.19	SPSS® macro of MCR_ML_PV.sps .....	315
Box A1.1	Descriptive statistics of background and explanatory variables.....	326
Box A1.2	Background model for student performance.....	327
Box A1.3	Final net combined model for student performance.....	328
Box A1.4	Background model for the impact of socio-economic background.....	329
Box A1.5	Model of the impact of socio-economic background: “school resources” module.....	330
Box A1.6	Model of the impact of socio-economic background: “accountability practices” module .....	331
Box A1.7	Final combined model for the impact of socio-economic background.....	331

## LIST OF FIGURES

Figure 1.1	Relationship between social and academic segregations.....	27
Figure 1.2	Relationship between social segregation and the correlation between science performance and student HISEI .....	27
Figure 1.3	Conceptual grid of variable types.....	29
Figure 1.4	Two-dimensional matrix with examples of variables collected or available from other sources .....	30
Figure 2.1	Science mean performance in OECD countries (PISA 2006).....	37
Figure 2.2	Gender differences in reading in OECD countries (PISA 2000).....	38
Figure 2.3	Regression coefficient of ESCS on mathematic performance in OECD countries (PISA 2003).....	38
Figure 2.4	Design effect on the country mean estimates for science performance and for ESCS in OECD countries (PISA 2006) .....	41
Figure 2.5	Simple random sample and unbiased standard errors of ESCS on science performance in OECD countries (PISA 2006) .....	42



Figure 4.1	Distribution of the results of 36 students.....	58
Figure 4.2	Sampling variance distribution of the mean.....	60
Figure 5.1	Probability of success for two high jumpers by height (dichotomous).....	80
Figure 5.2	Probability of success for two high jumpers by height (continuous).....	81
Figure 5.3	Probability of success to an item of difficulty zero as a function of student ability.....	81
Figure 5.4	Student score and item difficulty distributions on a Rasch continuum.....	84
Figure 5.5	Response pattern probabilities for the response pattern (1, 1, 0, 0).....	86
Figure 5.6	Response pattern probabilities for a raw score of 1.....	87
Figure 5.7	Response pattern probabilities for a raw score of 2.....	88
Figure 5.8	Response pattern probabilities for a raw score of 3.....	88
Figure 5.9	Response pattern likelihood for an easy test and a difficult test.....	89
Figure 5.10	Rasch item anchoring.....	90
Figure 6.1	Living room length expressed in integers.....	94
Figure 6.2	Real length per reported length.....	95
Figure 6.3	A posterior distribution on a test of six items.....	96
Figure 6.4	EAP estimators.....	97
Figure 8.1	A two-dimensional distribution.....	125
Figure 8.2	Axes for two-dimensional normal distributions.....	125
Figure 13.1	Trend indicators in PISA 2000, PISA 2003 and PISA 2006.....	175
Figure 14.1	Percentage of schools by three school groups (PISA 2003).....	194
Figure 15.1	Simple linear regression analysis versus multilevel regression analysis.....	201
Figure 15.2	Graphical representation of the between-school variance reduction.....	209
Figure 15.3	A random multilevel model.....	210
Figure 15.4	Change in the between-school residual variance for a fixed and a random model.....	212
Figure 16.1	Relationship between the segregation index of students' expected occupational status and the segregation index of student performance in reading (PISA 2000).....	236
Figure 16.2	Relationship between the segregation index of students' expected occupational status and the correlation between HISEI and students' expected occupational status.....	236

**LIST OF TABLES**

Table 1.1	Participating countries/economies in PISA 2000, PISA 2003, PISA 2006 and PISA 2009.....	21
Table 1.2	Assessment domains covered by PISA 2000, PISA 2003 and PISA 2006.....	22
Table 1.3	Correlation between social inequities and segregations at schools for OECD countries.....	28
Table 1.4	Distribution of students per grade and per ISCED level in OECD countries (PISA 2006).....	31
Table 2.1	Design effect and type I errors.....	40
Table 2.2	Mean estimates and standard errors.....	44



Table 2.3	Standard deviation estimates and standard errors.....	44
Table 2.4	Correlation estimates and standard errors.....	45
Table 2.5	ESCS regression coefficient estimates and standard errors.....	45
<hr/>		
Table 3.1	Height and weight of ten persons .....	50
Table 3.2	Weighted and unweighted standard deviation estimate .....	50
Table 3.3	School, within-school, and final probability of selection and corresponding weights for a two-stage, simple random sample with the first-stage units being schools of equal size.....	52
Table 3.4	School, within-school, and final probability of selection and corresponding weights for a two-stage, simple random sample with the first-stage units being schools of unequal size .....	52
Table 3.5	School, within-school, and final probability of selection and corresponding weights for a simple and random sample of schools of unequal size (smaller schools) .....	53
Table 3.6	School, within-school, and final probability of selection and corresponding weights for a simple and random sample of schools of unequal size (larger schools) .....	53
Table 3.7	School, within-school, and final probability of selection and corresponding weights for PPS sample of schools of unequal size .....	54
Table 3.8	Selection of schools according to a PPS and systematic procedure.....	55
<hr/>		
Table 4.1	Description of the 630 possible samples of 2 students selected from 36 students, according to their mean.....	59
Table 4.2	Distribution of all possible samples with a mean between 8.32 and 11.68.....	61
Table 4.3	Distribution of the mean of all possible samples of 4 students out of a population of 36 students.....	62
Table 4.4	Between-school and within-school variances on the mathematics scale in PISA 2003.....	65
Table 4.5	Current status of sampling errors.....	65
Table 4.6	Between-school and within-school variances, number of participating schools and students in Denmark and Germany in PISA 2003 .....	66
Table 4.7	The Jackknives replicates and sample means.....	68
Table 4.8	Values on variables X and Y for a sample of ten students.....	69
Table 4.9	Regression coefficients for each replicate sample.....	69
Table 4.10	The Jackknife replicates for unstratified two-stage sample designs.....	70
Table 4.11	The Jackknife replicates for stratified two-stage sample designs.....	71
Table 4.12	Replicates with the Balanced Repeated Replication method.....	72
Table 4.13	The Fay replicates .....	73
<hr/>		
Table 5.1	Probability of success when student ability equals item difficulty.....	82
Table 5.2	Probability of success when student ability is less than the item difficulty by 1 unit.....	82
Table 5.3	Probability of success when student ability is greater than the item difficulty by 1 unit .....	82
Table 5.4	Probability of success when student ability is less than the item difficulty by 2 units .....	83
Table 5.5	Probability of success when student ability is greater than the item difficulty by 2 units.....	83
Table 5.6	Possible response pattern for a test of four items.....	85
Table 5.7	Probability for the response pattern (1, 1, 0, 0) for three student abilities.....	85
Table 5.8	Probability for the response pattern (1, 0) for two students of different ability in an incomplete test design.....	89
Table 5.9	PISA 2003 test design .....	91

Table 6.1	Structure of the simulated data.....	98
Table 6.2	Means and variances for the latent variables and the different student ability estimators.....	98
Table 6.3	Percentiles for the latent variables and the different student ability estimators.....	99
Table 6.4	Correlation between HISEI, gender and the latent variable, the different student ability estimators.....	99
Table 6.5	Between- and within-school variances.....	100
Table 7.1	HISEI mean estimates .....	105
Table 7.2	Squared differences between replicate estimates and the final estimate.....	106
Table 7.3	Output data file from Box 7.2.....	108
Table 7.4	Available statistics with the UNIVAR macro .....	109
Table 7.5	Output data file from Box 7.3.....	109
Table 7.6	Output data file from Box 7.4.....	110
Table 7.7	Percentage of girls for the final and replicate weights and squared differences.....	111
Table 7.8	Output data file from Box 7.5.....	112
Table 7.9	Output data file from Box 7.6.....	113
Table 7.10	Output data file from Box 7.7.....	114
Table 7.11	Output data file from Box 7.8.....	114
Table 8.1	The 405 mean estimates.....	118
Table 8.2	Mean estimates and their respective sampling variances on the science scale for Belgium (PISA 2006).....	119
Table 8.3	Output data file from Box 8.2.....	121
Table 8.4	Output data file from Box 8.3.....	121
Table 8.5	The 450 regression coefficient estimates.....	123
Table 8.6	HISEI regression coefficient estimates and their respective sampling variance on the science scale in Belgium after accounting for gender (PISA 2006).....	123
Table 8.7	Output data file from Box 8.5.....	123
Table 8.8	Output data file from Box 8.6.....	124
Table 8.9	Correlation between the five plausible values for each domain, mathematics/quantity and mathematics/space and shape.....	126
Table 8.10	The five correlation estimates between mathematics/quantity and mathematics/space and shape and their respective sampling variance.....	127
Table 8.11	Standard deviations for mathematics scale using the correct method (plausible values) and by averaging the plausible values at the student level (pseudo-EAP) (PISA 2003).....	128
Table 8.12	Unbiased shortcut for a population estimate and its standard error .....	129
Table 8.13	Standard errors from the full and shortcut computation (PISA 2006).....	130
Table 9.1	The 405 percentage estimates for a particular proficiency level .....	136
Table 9.2	Estimates and sampling variances per proficiency level in science for Germany (PISA 2006) .....	137
Table 9.3	Final estimates of the percentage of students, per proficiency level, in science and its standard errors for Germany (PISA 2006).....	137
Table 9.4	Output data file from Box 9.3.....	138
Table 9.5	Output data file from Box 9.4.....	138
Table 9.6	Mean estimates and standard errors for self-efficacy in mathematics per proficiency level (PISA 2003).....	141
Table 9.7	Output data file from Box 9.6.....	141





Table 10.1	Percentage of students per grade and ISCED level, by country (PISA 2006).....	144
Table 10.2	Output data file from the first model in Box 10.3.....	148
Table 10.3	Output data file from the second model in Box 10.3.....	148
<hr/>		
Table 11.1	Output data file from Box 11.1.....	153
Table 11.2	Mean estimates for the final and 80 replicate weights by gender (PISA 2003).....	153
Table 11.3	Difference in estimates for the final weight and 80 replicate weights between females and males (PISA 2003).....	155
Table 11.4	Output data file from Box 11.2.....	156
Table 11.5	Output data file from Box 11.3.....	157
Table 11.6	Gender difference estimates and their respective sampling variances on the mathematics scale (PISA 2003).....	157
Table 11.7	Output data file from Box 11.4.....	158
Table 11.8	Gender differences on the mathematics scale, unbiased standard errors and biased standard errors (PISA 2003).....	159
Table 11.9	Gender differences in mean science performance and in standard deviation for science performance (PISA 2006).....	159
Table 11.10	Regression coefficient of HISEI on the science performance for different models (PISA 2006).....	160
Table 11.11	Cross tabulation of the different probabilities.....	161
<hr/>		
Table 12.1	Regression coefficients of the index of instrumental motivation in mathematics on mathematic performance in OECD countries (PISA 2003).....	165
Table 12.2	Output data file from Box 12.1.....	166
Table 12.3	Output data file from Box 12.2.....	167
Table 12.4	Difference between the country mean scores in mathematics and the OECD total and average (PISA 2003).....	170
<hr/>		
Table 13.1	Trend indicators between PISA 2000 and PISA 2003 for HISEI, by country.....	176
Table 13.2	Linking error estimates.....	178
Table 13.3	Mean performance in reading by gender in Germany.....	180
<hr/>		
Table 14.1	Distribution of the questionnaire index of cultural possession at home in Luxembourg (PISA 2006).....	184
Table 14.2	Output data file from Box 14.1.....	186
Table 14.3	Labels used in a two-way table.....	186
Table 14.4	Distribution of 100 students by parents' marital status and grade repetition.....	187
Table 14.5	Probabilities by parents' marital status and grade repetition.....	187
Table 14.6	Relative risk for different cutpoints.....	187
Table 14.7	Output data file from Box 14.2.....	189
Table 14.8	Mean and standard deviation for the student performance in reading by gender, gender difference and effect size (PISA 2006).....	191
Table 14.9	Output data file from the first model in Box 14.5.....	197
Table 14.10	Output data file from the second model in Box 14.5.....	197
Table 14.11	Mean of the residuals in mathematics performance for the bottom and top quarters of the PISA index of economic, social and cultural status, by school group (PISA 2003).....	195

Table 15.1	Between- and within-school variance estimates and intraclass correlation (PISA 2006).....	204
Table 15.2	Fixed parameter estimates .....	211
Table 15.3	Variance/covariance estimates before and after centering.....	213
Table 15.4	Output data file of the fixed parameters file.....	215
Table 15.5	Average performance and percentage of students by student immigrant status and by type of school.....	216
Table 15.6	Variables for the four groups of students .....	216
Table 15.7	Comparison of the regression coefficient estimates and their standard errors in Belgium (PISA 2006).....	218
Table 15.8	Comparison of the variance estimates and their respective standard errors in Belgium (PISA 2006) .....	218
Table 15.9	Three-level regression analyses.....	220
<hr/>		
Table 16.1	Differences between males and females in the standard deviation of student performance (PISA 2000).....	226
Table 16.2	Distribution of the gender differences (males – females) in the standard deviation of the student performance .....	226
Table 16.3	Gender difference on the PISA combined reading scale for the 5 <sup>th</sup> , 10 <sup>th</sup> , 90 <sup>th</sup> and 95 <sup>th</sup> percentiles (PISA 2000) .....	227
Table 16.4	Gender difference in the standard deviation for the two different item format scales in reading (PISA 2000) .....	228
Table 16.5	Random and fixed parameters in the multilevel model with student and school socio-economic background.....	229
Table 16.6	Random and fixed parameters in the multilevel model with socio-economic background and grade retention at the student and school levels .....	233
Table 16.7	Segregation indices and correlation coefficients by country (PISA 2000).....	234
Table 16.8	Segregation indices and correlation coefficients by country (PISA 2006).....	235
Table 16.9	Country correlations (PISA 2000).....	237
Table 16.10	Country correlations (PISA 2006).....	237
<hr/>		
Table 17.1	Synthesis of the 19 SPSS® macros.....	241
<hr/>		
Table A2.1	Cluster rotation design used to form test booklets for PISA 2006 .....	332
<hr/>		
Table A12.1	Mapping of ISCED to accumulated years of education .....	457
Table A12.2	ISCO major group white-collar/blue-collar classification .....	459
Table A12.3	ISCO occupation categories classified as science-related occupations .....	459
Table A12.4	Household possessions and home background indices.....	463
Table A12.5	Factor loadings and internal consistency of ESCS 2006 in OECD countries.....	473
Table A12.6	Factor loadings and internal consistency of ESCS 2006 in partner countries/economies.....	474



# User's Guide

## Preparation of data files

All data files (in text format) and the SPSS® control files are available on the PISA website ([www.pisa.oecd.org](http://www.pisa.oecd.org)).

## SPSS® users

By running the SPSS® control files, the PISA data files are created in the SPSS® format. Before starting analysis in the following chapters, save the PISA 2000 data files in the folder of “c:\pisa2000\data\”, the PISA 2003 data files in “c:\pisa2003\data\”, and the PISA 2006 data files in “c:\pisa2006\data\”.

## SPSS® syntax and macros

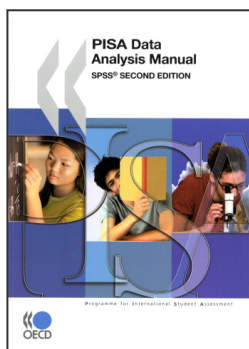
All syntaxes and macros in this manual can be copied from the PISA website ([www.pisa.oecd.org](http://www.pisa.oecd.org)). These macros were developed for SPSS 17.0. The 19 SPSS® macros presented in Chapter 17 need to be saved under “c:\pisa\macro\”, before starting analysis. Each chapter of the manual contains a complete set of syntaxes, which must be done sequentially, for all of them to run correctly, within the chapter.

## Rounding of figures

In the tables and formulas, figures were rounded to a convenient number of decimal places, although calculations were always made with the full number of decimal places.

## Country abbreviations used in this manual

AUS	Australia	FRA	France	MEX	Mexico
AUT	Austria	GBR	United Kingdom	NLD	Netherlands
BEL	Belgium	GRC	Greece	NOR	Norway
CAN	Canada	HUN	Hungary	NZL	New Zealand
CHE	Switzerland	IRL	Ireland	POL	Poland
CZE	Czech Republic	ISL	Iceland	PRT	Portugal
DEU	Germany	ITA	Italy	SVK	Slovak Republic
DNK	Denmark	JPN	Japan	SWE	Sweden
ESP	Spain	KOR	Korea	TUR	Turkey
FIN	Finland	LUX	Luxembourg	USA	United States



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