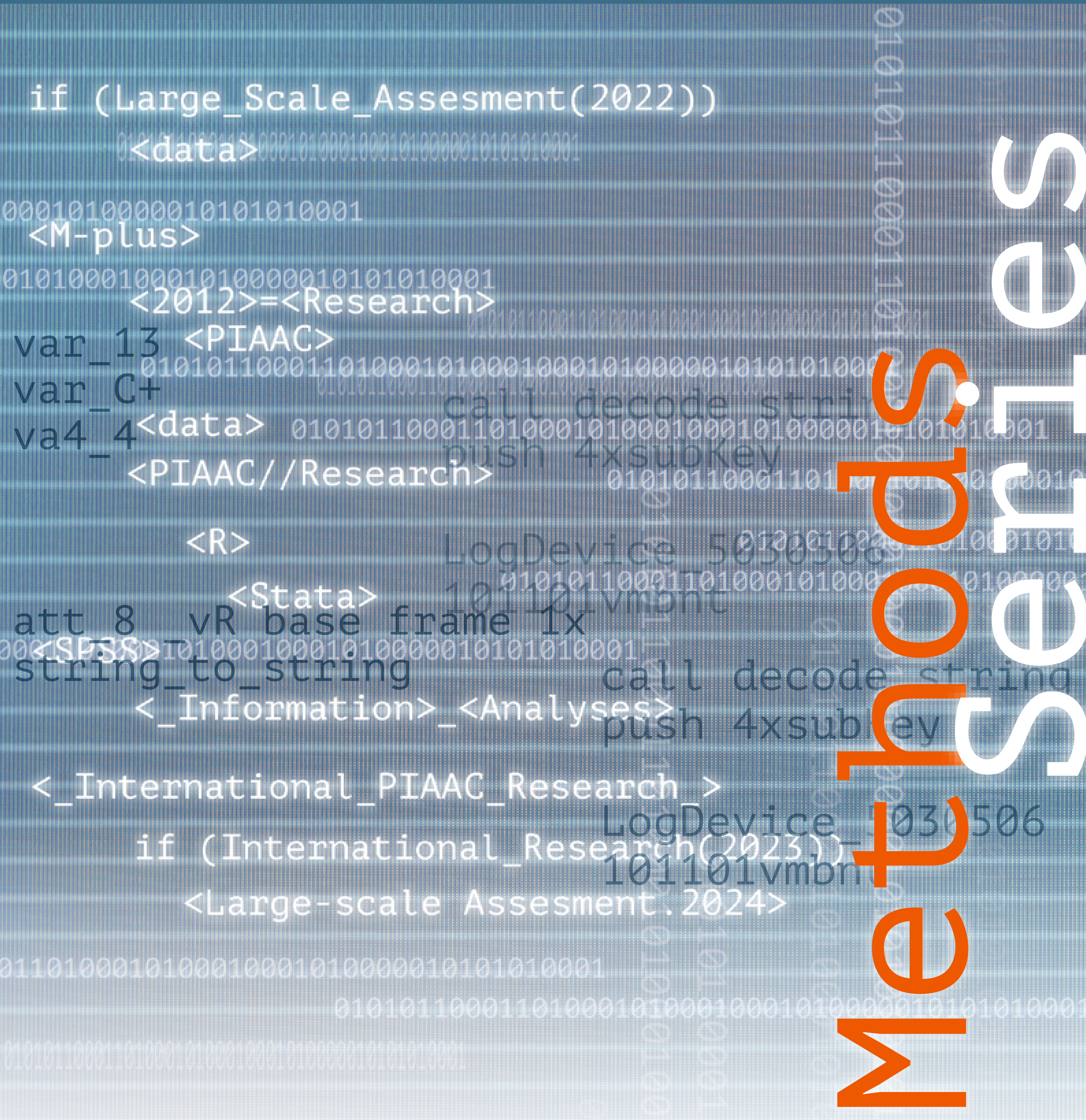
Analysis Scripts in Large-Scale Assessments in Education

Maehler, Débora B. (Ed.)



Methods Series

Analysis Scripts in Large-Scale Assessments in Education

SPONSORED BY THE

Federal Ministry
of Education
and Research

gesis
Leibniz Institute
for the Social Sciences

Leibniz Institute
for the Social Sciences

Methods Series

Analysis Scripts in Large-Scale Assessments in Education

**Research Data Center PIAAC
(RDC PIAAC) at GESIS**

Contact: fdz-piaac@gesis.org
Webpage: https://www.gesis.org/en/piaac/rdc

Scientific Advisory Board

The Scientific Advisory Board of the Methods Series will review scripts submitted for inclusion in future volumes of the series. Made up of researchers and experts in the field with a methodological focus and/or expertise in PIAAC data analyses, the board currently comprises the following researchers (alphabetical order):

» Content

Content

1 PIAAC Methods Series: An Introduction

Débora B. Maehler, Robin-Kiara Braun, Daria Morozova, Jennifer Dickson & Dennis Schüle (GESIS – Leibniz-Institute for the Social Sciences, Germany)

1.1 PIAAC Analysis Scripts

The Programme for the International Assessment of Adult Competencies (PIAAC) is an international large-scale study initiated by the Organisation for Economic Co-operation and Development (OECD). PIAAC assesses key cognitive skills of the adult population in more than 40 countries. The skills assessed are literacy (the ability to understand, use, and interpret written texts; Jones et al., 2009), numeracy (the ability to retrieve, interpret, and use mathematical information; Gal et al., 2009), and problem solving in technology-rich environments (PSTRE; the ability to use technology to access and process information; Rouet et al., 2009). These skills are considered essential to successfully navigate demands in everyday life and in the workplace (OECD, 2013; OECD, 2021). Besides assessing cognitive skills, PIAAC also collects extensive background and job-related information, for example, gender; age; language most often spoken at home; number of people living in the household; number of books at home; parental information; children; education (highest school qualification, highest professional qualification, continuing education and training); work (employment status, occupation and industry, information on current job, information on last job, job search, years of paid work during lifetime, earnings); learning strategies; political efficacy; social trust; cultural engagement; skills mismatch; and skill use (e.g., literacy, numeracy, computer skills). An overview of the extent to which the data have been used in research to date can be found in the PIAAC bibliography (Maehler & Konradt, 2022).

Compared with other social science data, the large-scale PIAAC data are very complex, which makes them difficult to analyze without prior knowledge. For example, they contain multiple competence estimates per person (10 plausible values) and a different number of weighting factors per country, which must be taken into account in the analyses. In this context, applying the appropriate analytical method and the available calculation procedures is a challenge, especially for early career researchers, as it is time-consuming and can be a significant source of error in published results. Furthermore, the growing interdisciplinarity of research has changed the research landscape: The methods used are not solely discipline-specific, and the accessibility of the software and the analysis spectrum (i.e., the extent to which a question can be processed with discipline-specific methods and analysis software) are becoming increasingly relevant.

The aims of the present Methods Series launched by the Research Data Center PIAAC at GESIS are (a) to improve the accessibility of knowledge in keeping with the principle of open science (see, e.g., the Open Science Framework/OSF or the German Data Forum [RatSWD]); (b) to increase the sustainability of scientific work by documenting processes, thereby enabling them to be replicated by other researchers; and (c) to guide (early-career) researchers in their data analyses. Collecting and making available existing analysis scripts based on previous research with PIAAC data is one way of achieving these aims. A digital platform—the PIAAC-scripts—is being made available as an accompaniment to the Methods Series. It contains analysis scripts for analyzing PIAAC data and other educational data in the adult research filed. This will facilitate the subsequent use of the analytical methods, and thus simplify and improve the scientific use of PIAAC data. Open access is an important asset to ensure transparency of data and methods, to give every researcher an equal chance, and to make replication studies easier. Only with sufficient insight into research data and methods is it possible to learn from each other and deliver correct results. The Methods Series establishes a guideline and provides examples of different methods and statistics programs (e.g., Stata, M*plus*, and R). It also serves as quality assurance by providing simplified possibilities for replicating results and facilitating the reproduction of analyses.

The present chapter provides an overview of the available data sets and tools for the analysis of PIAAC data. In addition, it presents an example of differences in outcomes when using correct versus incorrect analyses procedures. Furthermore, it provides a brief introduction to PIAAC Discovery, a Shiny web application (app) for visualizing PIAAC data (Parker, n.d.). Chapter 2 to Chapter 4 present scripts from PIAAC workshops that took place online in 2022. These scripts show how to analyze PIAAC data with the software programs Stata (**Chapter 2**), R (**Chapter 3**), and M*plus* (**Chapter 4**). **Chapter 5** introduce scripts implemented in the International Database Analyzer (IDB Analyzer) to analyze PIAAC data. And finally, **Chapter 6** presents scripts from online tutorials on PIAAC data analysis with Base R.

If you are interested in having your own script published in the Methods Series, or in helping us to keep the **PIAAC scripts digital plattform** up to date, please send us your research for suitability assessment. We would be happy to receive your submissions to support open data and to make it possible to present in this series the latest techniques for analyzing PIAAC data. The concept of openly sharing possible ways of analyzing PIAAC data is of great importance for future research, also in view of the new waves of the data sets coming in the future. It can lead to simpler, more accurate, and faster research results.

1.2 Availability of PIAAC Data

PIAAC is designed as a cross-sectional study to be repeated at regular intervals. Cycle 1 of PIAAC started in 2008 and comprised three rounds, in which a total of 38 countries participated (see **Table 1.1**). Round 1 took place in 2011–2012, and data were collected from a total of 24 countries. A further nine countries were added in Round 2 (2014–2015). In Round 3 of Cycle 1, in 2017, data for Ecuador, Hungary, Kazakhstan, Mexico, and Peru were collected. As Goldhammer et al. (2020) noted, PIAAC “was the first computer-based large-scale assessment to provide anonymised log file data from the cognitive assessment together with extensive online documentation and a data analysis support tool” (p. 239). PIAAC Cycle 1 provides log files from 17 countries, as well as scientific use files from four countries. The available data sets can be found on the **OECD** website or on the website of **the Research Data Center PIAAC** at GESIS.

An exemplary overview of data from PIAAC Germany and its longitudinal follow-up, PIAAC-L, and of how these data can be used, for example, in sociology or psychology can be found in Martin, Zabal et al. (2022) and Martin, Maehler et al. (2022).

Table 1.1

Overview of PIAAC Cycle 1 Countries and Available Data Sets

Country	Available data sets (provider)	Year of assessment (Cycle 1)
Australia	Public Use File (Australian Bureau of Statistics/OECD—*available only in the OECD version of the analysis tool PIAAC International Data Explorer [OECD IDE]*)	2011–2012
Austria	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) Scientific Use Files (Statistics Austria)	2011–2012 2011–2012 2011–2012
Belgium[1]	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012
Canada	Public Use File (OECD/Statistics Canada) Scientific Use File (Statistic Canada) Longitudinal and International Study of Adults (LISA) linked to register data (Canadian Research Data Centers)	2011–2012 2011–2012 2011–2012
Chile	Public Use File (OECD)	2014–2015
Cyprus	Public Use File (RDC PIAAC at GESIS)	2011–2012
Czech Republic	Public Use File (OECD)	2011–2012
Denmark	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) Nordic PIAAC Database linked to register data (Nordic NSIs[2])	2011–2012 2011–2012 2011–2012
Ecuador	Public Use File (OECD)	2017
Estonia	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS Nordic PIAAC Database linked to register data (Nordic NSIs)	2011–2012 2011–2012 2011–2012
Finland	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) Nordic PIAAC Database linked to register data (Nordic NSIs)	2011–2012 2011–2012 2011–2012
France	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012 2017

Country	Available data sets (provider)	Year of assessment (Cycle 1)
Germany	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) Scientific Use Files (RDC PIAAC at GESIS) German PIAAC National Supplement: Prime Age (RDC PIAAC at GESIS) German PIAAC National Supplement: Competencies in Later Life/CiLL (RDC PIAAC at GESIS) PIAAC Germany Scientific Use File: Regional Data (RDC PIAAC at GESIS) PIAAC-L, Longitudinal Scientific Use File (RDC PIAAC at GESIS) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012 2011–2012 2011–2012 2011–2012 2011–2012 2012–2016 2017
Greece	Public Use File (OECD)	2014–2015
Hungary	Public Use File (OECD)	2017
Indonesia	*Not available*	2014–2015
Ireland	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012
Israel	Public Use File (OECD)	2014–2015
Italy	Public Use File (OECD) Public Use File – Extended (INAPP[3]) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012 2011–2012
Japan	Public Use File (OECD) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2017
Kazakhstan	Public Use File (OECD)	2017
Korea	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012
Lithuania	Public Use File (OECD)	2014–2015
Mexico	Public Use File (OECD)	2017
Netherlands	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012
New Zealand	Public Use File (OECD) Public Use File – Extended (New Zealand Ministry of Education)	2014–2015 2014–2015

Country	Available data sets (provider)	Year of assessment (Cycle 1)
Norway	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) Norwegian PIAAC data linked to register data (NSD[4]) Nordic PIAAC Database linked to register data (Nordic NSIs)	2011–2012 2011–2012 2011–2012 2011–2012
Peru	Public Use File (OECD)	2017
Poland	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012
Russian Federation	Public Use File (OECD)	2011–2012
Singapore	Public Use File (OECD)	2014–2015
Slovak Republic	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS)	2011–2012 2011–2012
Slovenia	Public Use File (OECD)	2014–2015
Spain	Public Use File (OECD) PIAAC Log Files (RDC PIAAC at GESIS) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012 2017
Sweden	Public Use File (OECD) Swedish PIAAC data linked to register data (Statistics Sweden) Nordic PIAAC Database linked to register data (Nordic NSIs)	2011–2012 2011–2012 2011–2012
Turkey	Public Use File (OECD)	2014–2015
United Kingdom[5]	Public Use File (OECD) PIAAC Log Files (RDC PIAAC by GESIS) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012 2016

Country	Available data sets (provider)	Year of assessment (Cycle 1)
United States	Public Use File (OECD/NCES[6]) PIAAC 2012/2014 US National Supplement Public Use Data File – Household (NCES) PIAAC Log Files (RDC PIAAC at GESIS) US PIAAC Restricted Use File (NCES) PIAAC 2012/2014 US National Supplement Restricted Use Data File – Household (NCES) PIAAC 2014 US National Supplement Public Use Data Files -Prison (NCES) PIAAC 2014 US National Supplement Restricted Use Data Files -Prison (NCES) PIAAC Data Files on Non-Cognitive Skills (RDC PIAAC at GESIS)	2011–2012 2011–2012; 2014 2011–2012; 2011–2012 2011–2012; 2014 2014 2014 2016

Note. Adapted from Maehler & Konradt (2020) and https://www.oecd.org/skills/piaac/data/.

[1] Only Flanders; [2] Nordic National Statistical Institutions – Denmark, Estonia, Finland, Norway, Sweden; [3] Istituto Nazionale per l'Analisi delle Politiche Pubbliche, Italy; [4] Norwegian Centre for Research Data, Norway; [5] Only England and Northern Ireland; [6] National Center for Education Statistics, United States.

1.3 PIAAC Methodology: Analyzing PIAAC Data

Table 1.2 provides an overview of existing tools and packages and helpful commands to analyze PIAAC data using different software programs (e.g., Stata, R, and M*plus*). The tools that can be used to perform correct analyses using public use files (PUFs), scientific use files (SUFs), or log file data are: (a) the OECD version of the PIAAC International Data Explorer (OECD IDE) and the United States version of the PIAAC International Data Explorer (US IDE; for a description of the two versions, see Pawlowski & Soroui, 2020); (b) the International Association for the Evaluation of Educational Achievement (IEA) International Database Analyzer (IDB Analyzer; for a description, see Sandoval-Hernandez & Carrasco, 2020); and (c) the PIAAC Log Data Analyzer (LDA; for a description, see Goldhammer et al., 2020).

Table 1.2

Overview of Tools for the Analysis of PIAAC Data

Software program	Package	Source	Data used	Analysis/ Commands
Stata	PIAACTOOLS	Pokropek & Jakubowski (2019) Available at: https://www.oecd.org/skills/piaac/PIACTOOLS_16OCT_for_web.pdf	Public Use Files	Command *piaacdes* for descriptive statistics (variance, mean, percentiles); *piaactab* for tables and crosstables, and *piaacreg* for linear and logistic regressions.
Stata	REPEST	Avvisati & Keslair (2014); Keslair (2020)	Public Use Files	Descriptive statistics (e.g., mean, variance, percentiles); tables and cross tables; regression analyses (e.g., linear, logistic)
R	EdSurvey	Bailey et al. (2020) See also: https://www.air.org/project/nces-data-r-project-edsurvey	Public Use Files	Descriptive statistics (mean, percentile analysis); gap analysis; proficiency levels; correlations, regression analyses (e.g., linear, logistic, multivariate)
R	intsvy	Caro & Biecek (2022) Available at: https://cran.r-project.org/web/packages/intsvy/intsvy.pdf https://github.com/eldafani/intsvy	Public Use Files	Descriptive statistics (mean, percentile analysis); proficiency levels; correlation, regression (e.g., logistic)
R	svyPVpack	Peterbauer & Reif (2014) Available at: https://github.com/manuelreif/svyPVpack	Public Use Files	Descriptive statistics (mean, percentile analysis); proficiency levels; correlation

Software program	Package	Source	Data used	Analysis/ Commands
Mplus		Scherer (2020) Available at: https://osf.io/hgbfk/	Public Use Files	Confirmatory factor analysis (CFA); structural equation modeling (SEM; e.g., path models, multigroup versions)
OECD PIAAC International Data Explorer (OECD IDE)	Data Interface	Pawlowski & Soroui (2020) Available at: https://piaac-dataexplorer.oecd.org/ide/idepiaac/	Public Use Files	Descriptive statistics (mean, percentiles); proficiency levels
US PIAAC International Data Explorer (US IDE)	Data Interface	Pawlowski & Soroui (2020) Available at: https://nces.ed.gov/surveys/piaac/ideuspiaac/	Public Use Files	Descriptive statistics (mean, percentiles); proficiency levels; gap analyses; linear regression
IEA International Database Analyzer (IDB Analyzer)	Windows-based tool with macro output in SPSS and SAS	Sandoval-Hernandez & Carrasco (2020); International Association for the Evaluation of Educational Achievement (IEA; n.d.) Available at: https://www.iea.nl/data-tools/tools#section-308	Public Use Files; Scientific Use Files	Descriptive statistics (mean, percentiles); proficiency levels; correlations; regression analyses (logistic regression, linear regression)
PIAAC LogData Analyzer (LDA)	Data Interface	Goldhammer et al. (2020) Available at: https://piaac-logdata.tba-hosting.de/download/	Public Use Files; PIAAC Log Files	Tool to extract predefined aggregated variables from XML files and raw log file data from XML files for creating user-defined aggregated variables.

As Arikan et al. (2020) noted, “international large-scale assessments … play a key role in determining educational policies besides their primary objectives of measuring, evaluating and monitoring the educational process” (p. 43). They stressed that it was therefore “critical to analyze the data … using scientifically accurate statistical methods as the results have the potential to influence millions of stakeholders through major policy changes” (p. 43).

In their study, Arikan et al. (2020) illustrated exemplarily what happens if basic methodological issues are not considered correctly when analyzing data from large-scale international assessments such as PIAAC. To raise awareness of the correct way to analyze these data, and to show that there is a high probability of getting incorrect results if sample weights and plausible values (PVs) are not used, the authors ran analyses with and without sample weights and plausible values.

Arikan et al. (2020) conducted *t*-test and multiple regression analyses using the IDB Analyzer (an interface from the International Data Explorer [IDE] for handling analyses of data from large-scale assessments such as PIAAC; for more information see Sandoval-Hernandez & Carrasco, 2020) and multilevel regression analysis using M*plus*. For example, the results of the research question “Is there a statistically significant difference between mean PIAAC 2015 reading scores of adults who looked for a job last month and who did not look for a job last month in Turkey?” (Arikan et al., 2020, p. 51) revealed that when sample weights and plausible values were used, there was no statistically significant difference between the mean PIAAC 2015 literacy of adults in Turkey who looked for a job in the past month and those who did not (see results based on the IDB Analyzer in the first line of Table 1.3).

As Table 1.3 shows, among the 11 analyses, there were contradictory results. The correct results in this case were those of the analyses based on the IDB Analyzer. Three of the analyses using only one PV showed significant differences—deviating from the correct result. The standard errors were higher when sample weights and PVs were used, than when this was not the case. As Arikan et al. (2020) noted, the change in the standard error directly affected the *t* value and the ultimate decision.

Table 1.3

Exemplary Analyses of Literacy Among Adults in Turkey Who Looked for a Job in the Past Month and Those Who Did Not

Method	Looked for a job (*SE*)	Did not look for a job (*SE*)	Mean difference (*SE*)	*t*
IDB Analyzer PV1–PV10	226.11 (4.16)	221.05 (1.45)	5.06 (4.36)	1.16
SPSS PV1	229.06 (2.51)	223.90 (.83)	5.16 (2.73)	1.89
SPSS PV2	229.40 (2.59)	223.23 (.83)	6.17 (2.75)	2.25*
SPSS PV3	227.01 (2.57)	224.33 (.83)	2.67 (2.73)	.98
SPSS PV4	226.87 (2.45)	224.12 (.84)	2.76 (2.74)	1.01
SPSS PV5	226.52 (2.55)	222.94 (.83)	3.58 (2.71)	1.32

Method	Looked for a job (*SE*)	Did not look for a job (*SE*)	Mean difference (*SE*)	*t*
SPSS PV6	231.42 (2.58)	224.81 (.84)	6.61 (2.75)	2.40*
SPSS PV7	226.62 (2.55)	223.93 (.82)	2.70 (2.71)	1.00
SPSS PV8	226.73 (2.56)	223.70 (.83)	3.03 (2.72)	1.11
SPSS PV9	227.88 (2.51)	222.49 (.84)	5.39 (2.76)	1.95
SPSS PV10	231.14 (2.63)	222.82 (.84)	8.32 (2.75)	3.02**
SPSS PVmean	228.27 (2.34)	223.63 (.76)	4.64 (2.51)	1.85

Note: Adapted from Arikan et al. (2020, p. 52). PV = plausible value.
*p < .05. **p <. 01. *** p < . 001.

For a correct way to analyze the PIAAC data using different software and disciplinary approaches, see the methodological handbook by Maehler & Rammstedt (2020).

1.4 PIAAC Discovery: A Shiny App for Visualizing PIAAC Data

PIAAC Discovery is a Shiny app that offers a playful way to visualize and explore PIAAC data on an interactive map. Designed by Daniel R. Parker (n.d.), it allows a preliminary look at the numeracy and literacy skills scores of 22 countries that participated in Cycle 1, Round 1 of PIAAC (for a list of these countries, see Table 1.1).

Users of the app can apply different filters (e.g., age, gender, parents' education, earnings) to take variables into account. By clicking on the individual countries, the mean score is displayed. Countries and sample size are displayed on the right-hand side of the map (see the exemplary map in Figure 1.1).

Parker (n.d.) stresses that "the application is not associated with PIAAC or the OECD," and that its purpose "is to guide research interest rather than test hypotheses" (Information page). To date, only one PV has been taken into consideration, which makes the results unreliable. Additionally, the data have not been weighted for analysis, and "any standard errors produced from the data are biased" (Parker, n.d., Information page).

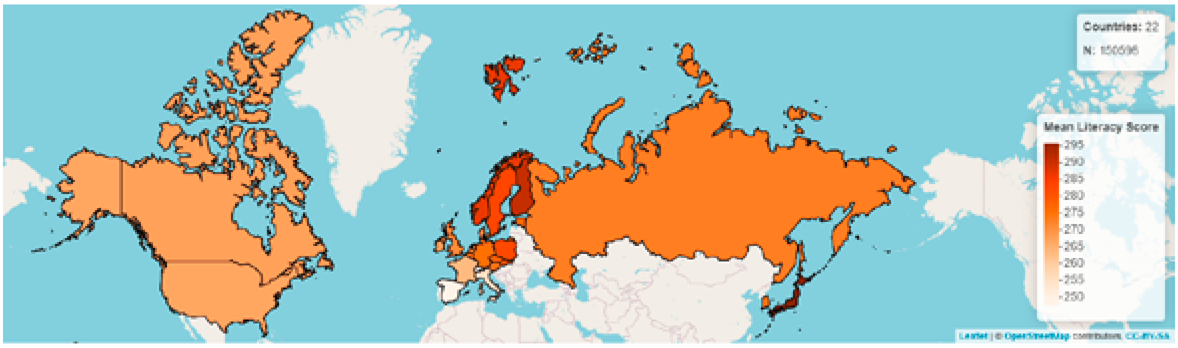


Figure 1.1 *Literacy by country displayed by the Shiny app PIAAC Discovery (Parker, n.d.)*
Source of underlying data: https://www.oecd.org/skills/piaac/data/

1.5 References

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

Avvisati, F., & Keslair, F. (2014). *REPEST: Stata module to run estimations with weighted replicate samples and plausible values* (Revised January 6, 2020) [Computer software]. Boston College, Department of Economics. https://econpapers.repec.org/software/bocbocode/s457918.htm

Bailey, P., Lee, M., Nguyen, T., & Zhang, T. (2020). Using EdSurvey to analyse PIAAC data. In D. B. Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment* (pp. 209–237). Springer. https://doi.org/10.1007/978-3-030-47515-4_9

Caro, D., & Biecek, P. (2022). *Package ‘intsvy’* [Computer software]. CRAN. https://cran.r-project.org/web/packages/intsvy/intsvy.pdf

Gal, I., Alatorre, S., Close, S., Evans, J., Johansen, L., Maguire, T., Manly, M., & Tout, D. (2009). *PIAAC numeracy: A conceptual framework* (OECD Education Working Papers, No. 35). OECD Publishing. https://doi.org/10.1787/220337421165

Goldhammer, F., Hahnel, C., & Kroehne, U. (2020). Analysing log file data from PIAAC. In D. B. Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment* (pp. 239–269). Springer. https://doi.org/10.1007/978-3-030-47515-4_10

International Association for the Evaluation of Educational Achievement (IEA). (n.d.). *IDB Analyzer* [Computer software]. IEA. https://www.iea.nl/data-tools/tools#section-308

Keslair, F. (2020). Analysing PIAAC data with Stata. In D. B Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment* (pp. 149–164). Springer. https://doi.org/10.1007/978-3-030-47515-4_7

Jones, S., Gabrielsen, E., Hagston, J., Linnakylä, P., Megherbi, H., Sabatini, J., Tröster, M., & Vidal-Abarca, E. (2009). *PIAAC literacy: A conceptual framework* (OECD Education Working Papers, No. 34). OECD Publishing. http://doi.org/10.1787/220348414075

Maehler, D. B., & Konradt, I. (2022). *PIAAC bibliography 2008–2021* (GESIS Papers, 2022/02). GESIS – Leibniz Institute for the Social Sciences. https://doi.org/10.21241/ssoar.77833

Maehler, D. B., & Konradt, I. (2020). Adult cognitive and non-cognitive skills: An overview of existing PIAAC data. In D. B. Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment* (pp. 49–92). Springer. https://doi.org/10.1007/978-3-030-47515-4_4

Maehler, D. B, & Rammstedt, B. (Eds.). (2020). *Large-scale cognitive assessment*. Springer.

Martin, S., Maehler, D. B., Zabal, A., & Rammstedt, B. (2022). PIAAC-L: The longitudinal follow-up to PIAAC in Germany. *Soziale Welt – Zeitschrift für sozialwissenschaftliche Forschung und Praxis, 73*(1), 169–199. https://doi.org/10.5771/0038-6073-2022-1-169

Martin, S., Zabal, A., Maehler, D. B., & Rammstedt, B. (2022). Data from PIAAC Germany and its longitudinal follow-up, PIAAC-L. *Journal of Open Psychology Data, 10*(1), 20. https://doi.org/10.5334/jopd.74

Organisation for Economic Co-operation and Development (OECD). (2013). *OECD skills outlook 2013: First results from the Survey of Adult Skills*. OECD Publishing. http://dx.doi.org/10.1787/9789264204256-en

Organisation for Economic Co-operation and Development (OECD). (2021). *The assessment frameworks for Cycle 2 of the Programme for the International Assessment of Adult Competencies.* OECD Publishing. https://doi.org/10.1787/4bc2342d-en

Parker, D. R. (n.d.). *PIAAC Discovery* [Web application]. https://danielallenparker.shinyapps.io/PIAAC_Discovery/

Pawlowski, E., & Soroui, J. (2020). Analysing PIAAC data with the International Data Explorer (IDE). In D. B. Maehler & B. Rammstedt (Eds), *Large-scale cognitive assessment* (pp. 93–115). Springer. https://doi.org/10.1007/978-3-030-47515-4_5

Peterbauer, J., & Reif, M. (2014). *svyPVpack* [Computer software]. GitHub. https://github.com/manuelreif/svyPVpack

Pokropek, A., & Jakubowski, M. (2019). *PIAACTOOLS: Stata® programs for statistical computing using PIAAC data*. OECD Publishing. https://www.oecd.org/skills/piaac/PIACTOOLS_16OCT_for_web.pdf

Rouet, J.-F., Bétrancourt, M., Britt, M. A., Bromme, R., Graesser, A. C., Kulikowich, J. M., Leu, D. J., Ueno, N., & van Oostendorp, H. (2009). *PIAAC problem solving in technology-rich environments: A conceptual framework* (OECD Education Working Papers, No. 36). OECD Publishing. http://dx.doi.org/10.1787/220262483674

Sandoval-Hernandez, A., & Carrasco, D. (2020). Analysing PIAAC data with the IDB Analyzer (SPSS and SAS). In D. B. Maehler & B. Rammstedt (Eds), *Large-scale cognitive assessment* (pp. 117–148). Springer. https://doi.org/10.1007/978-3-030-47515-4_6

Scherer, R. (2019, June 21). *PIAAC structural equation modeling with Mplus* [Project]. https://doi.org/10.17605/OSF.IO/HGBFK

2 Analyzing PIAAC Data With Stata

Britta Gauly
(GESIS – Leibniz-Institute for the Social Sciences, Germany)

2.1 Introduction

The scripts presented in this section are based on the online tutorial “PIAAC Data Analysis in Stata”. They provide a practical guide to performing simple analyses of data from the Programme for the International Assessment of Adult Competencies (PIAAC) in Stata. The tutorial is available on the website of the Research Data Center PIAAC (RDC PIAAC) at GESIS (RDC PIAAC 2021a, 2021b, 2021c, 2021d). The target audience of the tutorial are researchers with at least some experience in data analysis in Stata, who have little or no experience with the analysis of PIAAC data, and who are interested in finding out whether the PIAAC data are suitable for answering their research questions. The tutorial provides several simple example analysis tasks that can be performed with PIAAC data.

Section 2.2 provides information on how to obtain access to the international PIAAC data. Sections 2.3 and 2.4 show how different analysis tools work, what types of analyses they provide, and the advantages and disadvantages of these tools.

2.2 Data Access and First Steps in Stata

The public use files (PUFs) for most countries participating in PIAAC can be accessed via the OECD’s “PIAAC Data” webpage. As these data are not in Stata format (.dta) by default, they have to be converted. By clicking on “Download the datasets (Public Use Files)” under the header “PIAAC Data,” you can download the data in SAS, SPSS, or CSV format.

First, you have to download the data set for each country in CSV format (see OECD, 2016b to OECD, 2016jj), and save all files in one folder on your computer. In the second step, you have to download the do-file in order to import the CSV data into Stata and save it on your computer. This do-file will import and append all PUFs into a unique Stata data set. Third, you can run the do-file by clicking on the “Execute” or “Do” button in the upper left-hand corner. While running, Stata will request the file path where you saved all CSV files. Type the path in the command window and click on “Enter.” You will receive the message: “Your PIAAC dataset is now ready to be used in Stata. Please consider saving this file.” To save the file, type “save” and the path where you want to store your data and a file name in the command window, and click on “Enter.”

This procedure will provide you with the PIAAC PUFs, which are freely available on the OECD website. As data may be updated, it is worth checking the OECD website from time to time.

The suggested folder structure for the data analysis presented below is as follows:

- `orig` includes the original data, comprising the CSV files and the original Stata data set you received when you ran the do-file;
- `data` contains all user-generated data sets, for example, comprising only a subset of countries or respondents;
- `log` includes all log files produced during data analysis;
- `prog` includes all do files;
- `out` contains the result files.

```
/* Load data with all countries */
use “${orig}PIAAC_All_PUFs.dta”

/* Tabulate countries in the data set */
tab cntryid

/* Some countries do not have a label yet --> change label of variable
“cntryid” */
label define CNTRYID 152 “Chile” 218 “Ecuador” ///
300 “Greece” 348 “Hungary” 376 “Indonesia” ///
398 “Kazakhstan” 440 “Lithuania” ///
484 “Mexico” 554 “New Zealand” 604 “Peru” ///
702 “Singapore” 705 “Slovenia” 792 “Turkey”, add
label val cntryid CNTRYID

tab cntryid

/* To get a first look at the skill variables (plausible values), type pvlit,
pvnum, pvpsl in the variable search window or display summary statistics */
sum pvlit1

/* To get a first look at the weighting variables, type spfwt in the variable
search window or display summary statistics */

/* Save small data set including Germany, Greece, Singapore, Sweden, US --> we
will use this data set in the following sample analyses */
preserve
keep if cntryid == 276 | cntryid == 300 | cntryid == 702 | cntryid == 752 |
cntryid == 840
save “${data}PIAAC_5Countries.dta”, replace
restore
```

2.3 Analyzing PIAAC Data Using the Package PIAACTOOLS

The package PIAACTOOLS was developed by Jakubowksi and Pokropek (2019).

```
/* Install piaaltools */
ssc install piaactools, replace

/* Help function */
help piaacdes
help piaactab
help piaacreg

/* Define global paths */
global data “...\2_data\”
global log “...\3_log\”
global out “...\5_out\”

/* Use log file */
log using “${log}Examples_piaactools.log”, replace

/* Load data */
use “${data}PIAAC_5Countries.dta”

/* Tabulate countries in the dataset */
tab cntryid
```

2.3.1 Examples *piaacdes*

```
/* Example 1: Average years of education */
piaacdes yrsqual, countryid(cntryid) stats(mean) round(2) save(“${out}
piaacdes_Ex1”)

/* Example 2: Average literacy skills, overall and by gender */
piaacdes, pv(pvlit) countryid(cntryid) stats(mean) round(2) save(“${out}
piaacdes_Ex2a”)

piaacdes, pv(pvlit) countryid(cntryid) stats(mean) over(gender_r) round(2)
save(“${out}piaacdes_Ex2b”)

/* Example 3: Literacy skill dispersion (5th, 25th, 75th, 95th quantile);
overall and for men between 16 and 34 years */
piaacdes, pv(pvlit) countryid(cntryid) centile(5 25 75 95) round(2)
save(“${out}piaacdes_Ex3a”)

piaacdes if gender_r == 1 & ageg10lfs < 3, pv(pvlit) countryid(cntryid)
centile(5 25 75 95) round(2) save(“${out}piaacdes_Ex3b”)
```

2.3.2 Examples *piaactab*

```
/* Example 1: Percentages of educational qualifications of respondents' 
mothers */
piaactab j_q06b, countryid(cntryid) round(1) save(“${out}piaactab_Ex1”)

/* Example 2: Percentages of respondents at each numeracy level, overall and 
for the employed population */
piaactab pvnum, countryid(cntryid) round(1) save(“${out}piaactab_Ex2a”)

piaactab pvnum if c_d05 == 1, countryid(cntryid) round(1) save(“${out}
piaactab_Ex2b”)

/* Example 3: Crosstable of numeracy skills and native language */
piaactab pvnum, over(nativelang) countryid(cntryid) round(1) save(“${out}
piaactab_Ex3”)

/* Declare missing values in variable “nativelang” */
tab nativelang
mvdecode nativelang, mv(8, 9)

piaactab pvnum, over(nativelang) countryid(cntryid) round(1) save(“${out}
piaactab_Ex3new”)
```

2.3.3 Examples *piaacreg*

```
/* Example 1: How are age, gender, formal education, and computer experience 
in the job related to PS-TRE skills? */

/* Recode the variable “computer experience” to ease interpretation */
recode g_q04 (1=1) (2=0)

/* Create dummy variables for the categorical variables “age” and “education” 
and include all but the reference categories (here: youngest age group and low 
education) to the regression */
tab ageg10lfs, gen(age10dum)
tab1 age10dum*

tab edcat6, gen(ed6dum)
tab1 ed6dum*

piaacreg age10dum2 age10dum3 age10dum4 age10dum5 gender_r ed6dum2 ed6dum3 
ed6dum4 ed6dum5 ed6dum6 g_q04, pvdep(pvpsl) countryid(cntryid) round(2) 
save(“${out}piaacreg_Ex1b“)

/* Example 2: Do literacy skills and formal education determine participation 
in adult education for women between 35 and 54 years? */

/* First step: check whether the dependent variable is a binary variable */
```

```
tab nfe12

piaacreg nfe12 ed6dum2 ed6dum3 ed6dum4 ed6dum5 ed6dum6 , pvindep1(pvlit)
cmd(“logit”) countryid(cntryid) round(2) save(“${out}piaacreg_Ex2a”)

/* The coefficient on literacy is rather small as literacy is measured on a
scale from 0-500. Standardize literacy skills to get the relationship between
a one standard deviation increase in literacy skills and participation in
training */
forv i = 1/10 {
qui egen pvlit_std`i’ = std(pvlit`i’)
}

piaacreg nfe12 ed6dum2 ed6dum3 ed6dum4 ed6dum5 ed6dum6 , pvindep1(pvlit_std)
cmd(“logit”) countryid(cntryid) round(2) save(“${out}piaacreg_Ex2b”)

log close
```

2.4 Analyzing PIAAC Data Using the REPEST Macro

The REPEST macro was developed by Avvisati and Keslair (2014; Keslair, 2020).

```
/* Install piaaltools */
ssc install repest, replace

/* Help function */
help repest

/* Define global paths */
global data “...\2_data\”
global log “...\3_log\”
global out “...\5_out\”

/* Use log file */
log using “${log}Examples_repest.log”, replace

/* Load data */
use “${data}PIAAC_5Countries.dta”

/* Tabulate countries in the dataset */
tab cntryid
```

2.4.1 Examples Descriptive Statistics

```
/* Example 1: Average years of education and literacy skills; overall and by
gender */

/* The @ character indicates variables with plausible values and initiates a
loop over the correct number of plausible values (here: 10) */
```

```
repest PIAAC, estimate(means yrsqual pvlit@) by(cntryid, average(276 300 702
752 840))

repest PIAAC, estimate(means yrsqual pvlit@) by(cntryid, average(276 300 702
752 840)) over(gender_r)

/* Example 2: Literacy skill dispersion (5th, 25th, 75th, 95th quantile);
overall and for men between 16 and 34 years */
repest PIAAC, estimate(summarize pvlit@, stats(p5 p25 p75 p90)) by(cntryid,
levels(276 752))

repest PIAAC if gender_r == 1 & ageg10lfs == 1, estimate(summarize pvlit@,
stats(p5 p25 p75 p90)) by(cntryid, levels(276 752))

/* Example 3: Percentages of respondents at each numeracy level, overall and
for the employed population */

/* Create levels of numeracy skills according to the OECD (2016a, p.71)
definition */
forv i = 1/10 {
     gen         numlevel`i’ = .
     qui replace numlevel`i’ = 1 if pvnum`i’ <= 225
     qui replace numlevel`i’ = 2 if pvnum`i’ > 225 & pvnum`i’ <= 275
     qui replace numlevel`i’ = 3 if pvnum`i’ > 275 & pvnum`i’ <= 325
     qui replace numlevel`i’ = 4 if pvnum`i’ > 325
     qui replace numlevel`i’ = . if pvnum`i’ == .
     }

repest PIAAC, estimate(freq numlevel@) by(cntryid) outfile(“${out}
repest_Ex3a”)

repest PIAAC if c_d05 == 1, estimate(freq numlevel@) by(cntryid)
outfile(“${out}repest_Ex3b”)

/* Example 4: Crosstable of numeracy skills and native language */

/* Declare missing values in variable “nativelang” */
tab nativelang
mvdecode nativelang, mv(8, 9)

repest PIAAC, estimate(freq numlevel@) over(nativelang)
repest PIAAC, estimate(means pvnum@) over(nativelang, test)

/* Example 5: Correlations between literacy, numeracy, and problem-solving
skills */
repest PIAAC, estimate(corr pvlit@ pvnum@ pvpsl@) by(cntryid, average(276 300
702 752 840))
```

2.4.2 Examples Regression Analysis

```
/* Example 1: How are age, gender, formal education, and computer experience
in the job related to PS-TRE skills? */

/* Recode the variable "computer experience" to ease interpretation */
recode g_q04 (1=1) (2=0)

repest PIAAC, estimate(stata: reg pvpsl@ i.ageg10lfs gender_r i.edcat6 g_q04)
by(cntryid) results(add(N r2))

/* Default: The youngest age group and the lowest education category are the
reference groups */

/* Example 2: Do literacy skills and formal education determine participation
in adult education for women between 35 and 54 years? */

/* First step: check whether the dependent variable is a binary variable */
tab nfe12

repest PIAAC, estimate(stata: logistic nfe12 i.edcat6 pvlit@) by(cntryid,
levels(276 840)) results(add(N r2))

log close
```

2.5 References

Avvisati, F. & Keslair, F. (2014). *REPEST: Stata module to run estimations with weighted replicate samples and plausible values* (Revised January 6, 2020) [Computer software]. Boston College Department of Economics. https://econpapers.repec.org/software/bocbocode/s457918.htm

Jakubowski, M., & Pokropek, A. (2019). PIAACTOOLS: A program for data analysis with PIAAC data. *The Stata Journal*, *19*(1), 112–128. https://doi.org/10.1177/1536867X19830909

Keslair, F. (2020). Analysing PIAAC data with Stata. In D. B. Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment* (pp. 149–164). Springer. https://doi.org/10.1007/978-3-030-47515-4_7

Organisation for Economic Cooperation and Development (OECD). (2016a). The Survey of Adult Skills: Reader's companion (2nd ed.) OECD Publishing. http://dx.doi.org/10.1787/9789264258075-en

Organisation for Economic Cooperation and Development (OECD). (2016b). *Programme for the International Assessment of Adult Competencies (PIAAC), Austria Public Use File* [Version: 17343010, prgautp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016c). *Programme for the International Assessment of Adult Competencies (PIAAC), Belgium Public Use File* [Version: 18224205, prgbelp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016d). *Programme for the International Assessment of Adult Competencies (PIAAC), Canada Public Use File* [Version: 88830378, prgcanp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016e). *Programme for the International Assessment of Adult Competencies (PIAAC), Chile Public Use File* [Version: 17135698, prgchlp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016f). *Programme for the International Assessment of Adult Competencies (PIAAC), Czech Republic Public Use File* [Version: 20736629, prgczep1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016g). *Programme for the International Assessment of Adult Competencies (PIAAC), Denmark Public Use File* [Version: 24972525, prgdnkp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016h). *Programme for the International Assessment of Adult Competencies (PIAAC), Ecuador Public Use File* [Version: 16788347, prgecup1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016i). *Programme for the International Assessment of Adult Competencies (PIAAC), Estonia Public Use File* [Version: 25276973, prgestp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016j). *Programme for the International Assessment of Adult Competencies (PIAAC), Finland Public Use File* [Version: 18842845, prgfinp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016k). *Programme for the International Assessment of Adult Competencies (PIAAC), France Public Use File* [Version: 23516989, prgfrap1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016l). *Programme for the International Assessment of Adult Competencies (PIAAC), Germany Public Use File* (Version: 18834098, prgdeup1.csv). OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016m). *Programme for the International Assessment of Adult Competencies (PIAAC), Greece Public Use File* [Version: 15965250, prggrcp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016n). *Programme for the International Assessment of Adult Competencies (PIAAC), Hungary Public Use File* [Version: 20439451, prghunp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016o). *Programme for the International Assessment of Adult Competencies (PIAAC), Ireland Public Use File* [Version: 19982813, prgirlp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016p). *Programme for the International Assessment of Adult Competencies (PIAAC), Israel Public Use File* [Version: 18069090, prgisrp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016q). *Programme for the International Assessment of Adult Competencies (PIAAC), Italy Public Use File* [Version: 15433181, prgitap1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development ((OECD). (2016r). *Programme for the International Assessment of Adult Competencies (PIAAC), Japan Public Use File* [Version: 17505957, prgjpnp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016s). *Programme for the International Assessment of Adult Competencies (PIAAC), Kazakhstan Public Use File* [Version: 20450859, prgkazp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016t). *Programme for the International Assessment of Adult Competencies (PIAAC), Korea Public Use File* [Version: 22217045, prgkorp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016u). *Programme for the International Assessment of Adult Competencies (PIAAC), Lithuania Public Use File* [Version: 17305986, prgltup1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016v). *Programme for the International Assessment of Adult Competencies (PIAAC), Mexico Public Use File* [Version: 19760643, prgmexp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016w). *Programme for the International Assessment of Adult Competencies (PIAAC), Netherlands Public Use File* [Version: 18028845, prgnldp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016x). *Programme for the International Assessment of Adult Competencies (PIAAC), New Zealand Public Use File* [Version: 21235362, prgnzlp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016y). *Programme for the International Assessment of Adult Competencies (PIAAC), Norway Public Use File* [Version: 17723269, prgnorp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016z). *Programme for the International Assessment of Adult Competencies (PIAAC), Peru Public Use File* [Version: 22883339, prgperp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016aa). *Programme for the International Assessment of Adult Competencies (PIAAC), Poland Public Use File* [Version: 30634733, prgpolp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016bb). *Programme for the International Assessment of Adult Competencies (PIAAC), Russian Federation Public Use File* [Version: 13378965, prgrusp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016cc). *Programme for the International Assessment of Adult Competencies (PIAAC), Singapore Public Use File* [Version: 18353722, prgsgpp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016dd). *Programme for the International Assessment of Adult Competencies (PIAAC), Slovak Republic Public Use* File [Version: 18921861, prgsvkp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016ee). *Programme for the International Assessment of Adult Competencies (PIAAC), Slovenia Public Use File* [Version: 18125930, prgsvnp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016ff). *Programme for the International Assessment of Adult Competencies (PIAAC), Spain Public Use File* [Version: 20201797, prgespp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016gg). *Programme for the International Assessment of Adult Competencies (PIAAC), Sweden Public Use File* [Version: 15716978, prgswep1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016hh). *Programme for the International Assessment of Adult Competencies (PIAAC), Turkey Public Use File* [Version: 16765802, prgturp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016ii). *Programme for the International Assessment of Adult Competencies (PIAAC), United Kingdom Public Use File* [Version: 30110173, prggbrp1.csv]. OECD Publishing.

Organisation for Economic Cooperation and Development (OECD). (2016jj). *Programme for the International Assessment of Adult Competencies (PIAAC), United States Public Use File* [Version: 17016050, prgusap1_2012.csv]. OECD Publishing.

Research Data Center PIAAC (RDC PIAAC). (2021a). *PIAAC data analysis in Stata: A practical guide. Online tutorial, Video 1 – Introduction to PIAAC data*. GESIS –Leibniz Institute for the Social Sciences. **https://www.gesis.org/en/piaac/rdc/**

Research Data Center PIAAC (RDC PIAAC). (2021b). *PIAAC data analysis in Stata: A practical guide Online tutorial, Video 2 – Data access and first steps in Stata*. GESIS –Leibniz Institute for the Social Sciences. **https://www.gesis.org/en/piaac/rdc/**

Research Data Center PIAAC (RDC PIAAC). (2021c). *PIAAC data analysis in Stata: A practical guide. Online tutorial, Video 3 – Stata-Ado piaactools*. GESIS –Leibniz Institute for the Social Sciences. **https://www.gesis.org/en/piaac/rdc/**

Research Data Center PIAAC (2021d). *PIAAC data analysis in Stata: A practical guide. Online tutorial, Video 4 – Stata-Ado repest macro*. GESIS –Leibniz Institute for the Social Sciences. **https://www.gesis.org/en/piaac/rdc/**

3 Analyzing PIAAC Data With R Using EdSurvey

Ting Zhang, Paul Bailey & Emmanuel Sikali
(American Institutes for Research, United States)

3.1 Introduction

This section explains how to use EdSurvey, an R package for large-scale assessment data, to analyze data from the Programme for the International Assessment of Adult Competencies (PIAAC). To analyze these data efficiently, taking into account their complex sample survey design and use of plausible values, the package uses procedures that follow PIAAC methodology.

The following subsections present scripts for essential PIAAC data analysis, from loading the data to data preparation, descriptive statistics, and statistical models (for detailed information see the PIAAC scripts digital plattform).

3.2 Data Preparation and First Steps in R

3.2.1 Loading and Reading in Data

This example shows how to download PIAAC Cycle 1 data all at once and use the `readPIAAC` command, which enables loading selected countries' PIAAC data into R as an `edsurvey.data.frame` (e.g., `ita;` OECD, 2016). To help users manage their system memory efficiently, EdSurvey loads data when needed, and otherwise does not use the memory. Only some metadata and results are maintained in the computer's random-access memory, including the file layout, missing value and special response codes, and assessment design attributes such as plausible values, achievement levels, weights, the primary sampling unit, and stratum variables.

```
library(EdSurvey)
# download data from the first cycle
downloadPIAAC(root = “~”, cycle = 1)
# to read a selection of countries (e.g., Italy)
ita <- readPIAAC(‘~/PIAAC/Cycle 1/’, countries = ‘ITA’)
```

To explore survey design attributes from an `edsurvey.data.frame`:

```
showPlausibleValues(ita, verbose = TRUE)
showWeights(ita)
getAttributes(ita, ‘omittedLevels’)
# by default, EdSurvey will show results from the analyses after listwise
# deletion of respondents with any special values, which are referred as
‘omitted levels’ in EdSurvey; for any data, the omitted levels can be seen
with the omittedLevels command
ita # see all this information at once
```

3.2.2 Data Exploration Using EdSurvey

EdSurvey provides functions for data exploration and variables searching, including `showCodebook`, `searchSDF`, `levelsSDF`.

```
# show codebook
View(showCodebook(ita))

# search variables
searchSDF(‘income’, data = ita)
searchSDF(c(‘income’, ‘annual’), data = ita) # search for an interview
question that includes given words
searchSDF(c(‘income’, ‘annual’), data = ita, levels=TRUE) # same + look at the
answers

# display variable levels
levelsSDF(‘d_q18a_t’, data = ita)
```

3.3 Descriptive Statistics

The `summary2` function produces both weighted and unweighted descriptive statistics for a variable (e.g., ‘d_q18a_t’).

```
summary2(ita, ‘d_q18a_t’) # produce weighted for a variable “ANNUAL NET INCOME”
summary2(ita, ‘d_q18a_t’, weightVar = NULL) # produce unweighted descriptive
statistics
summary2(ita, “d_q18a_t”, omittedLevels = TRUE) # exclude missing
summary2(ita, ‘lit’)
```

`edsurveyTable` creates a summary table of an outcome variable by selected categorical variables.

```
edsurveyTable(lit ~ ageg10lfs, data = ita) # table with literacy score by age
group
edsurveyTable(lit ~ ageg10lfs + c_d05, data = ita) # table with literacy score
by age and employment status
```

In its default setting, EdSurvey applies the sampling weights (e.g., ‘spfwt0’), the 10 plausible values of every scale or subscale of interest, and the jackknife method to compute the variance. It deals with special response codes and missing values by using listwise deletion. The reader can change these default settings using the list of arguments in the EdSurvey documentation.

In general, to find more information about any EdSurvey command, use “?command”; for example:

```
?edsurveyTable
```

3.3.1 Correlation

EdSurvey features multiple correlation methods for data exploration and analysis that fully account for the complex sample design of PIAAC by using the cor.sdf function. The following example displays how to conduct weighted polyserial correction between the literacy scale scores and “ANNUAL NET INCOME”.

```
cor.sdf(‘lit’, ‘d_q18a_t’, data = ita, method = ‘Polyserial’)
```

3.4 Data Manipulation

EdSurvey allows for rudimentary data manipulation and analysis with both EdSurvey and base R functions to edit data before processing. Below are examples for some essential data manipulations using EdSurvey. See the EdSurvey User Guide (Lee et al., 2022) for more advanced data manipulations.

Subset

```
itaM <- subset(ita, gender_r %in% ‘MALE’) # subset males
summary2(itaM, ‘lit’) # look for the literacy levels for males
```

Recode

```
summary2(ita, ‘c_d05’) # look at the employment variable
ita$c_d05_recode <- ifelse(ita$c_d05 %in% c(‘OUT OF THE LABOUR FORCE’,
                                             ‘UNEMPLOYED’), ‘NOT EMPLOYED’,
                                           as.character(ita$c_d05))
edsurveyTable(lit ~ c_d05_recode, data = ita) # table literacy by recoded
employment status
```

Rename

```
ita$emp <- ita$c_d05_recode
edsurveyTable(lit ~ emp, data = ita)
itaRaw <- getData(data = ita, varnames = c(‘lit’, ‘spfwt0’, ‘gender_r’, ‘c_
d05’), addAttributes = FALSE, omittedLevels = TRUE)
# extract two variables: gender and annual income + 10 plausible values
associated with lit + the weight for this data frame: spfwt0

itaRaw[1:5,1:15]
itaRaw$c_d05 <- gsub(pattern = ‘OUT OF THE LABOUR FORCE|UNEMPLOYED’,
                     replacement = ‘not employed’,
                     x = itaRaw$c_d05)
# gsub (base R function) uses pattern matching to replace values in a
variable, recodes the values in the variable c_d05
itaRaw <- subset(itaRaw, !c_d05 %in% ‘NOT KNOWN’) # removes the level ‘NOT
KNOWN’
itaRawRebinded <- rebindAttributes(itaRaw, ita) # reassign survey attributes
for EdSurvey package
edsurveyTable(lit ~ c_d05, data = itaRawRebinded) # now we can apply EdSurvey
functions on the cleaned data
```

3.5 Data Analysis

EdSurvey offers various analytical functions that take account of the complex design of PIAAC data and its plausible values. This section showcases five of these functions: linear regression, logistic regression, gap analysis, percentile analysis, and proficiency level analysis. See the EdSurvey User Guide (Lee et al., 2022) for more analytical functions, including mixed models, multivariate regression, and quantile regression.

3.5.1 Linear Regression

The data are read in and analyzed by the `lm.sdf` function. In the example, income quintile and age are regressed on the 10 plausible values for the literacy scale. By default, full sample weight “spfwt0” is applied, and variance is estimated using the jackknife method.

```
lm1 <- lm.sdf(lit ~ d_q18a_t + age_r, data = ita)
# literacy score (lit), which is described as a function of income quintile
(d_q18a_t) and age (age_r)
summary(lm1)
# note that there is no need to generate dummy codes for discrete variables
like d_q18a_t
```

3.5.2 Logistic Regression

The `logit.sdf` function predicts binary outcomes from a set of predictors. Although some variables might already be binary, the function `I()` and a rule such as `lit > 300` will dichotomize a nonbinary variable and specify the desired outcome level. The following example dichotomizes the literacy with the level over 300 as the outcome level. The outcome variable could also be a contextual variable.

```
logit1 <- logit.sdf(I(lit> 300) ~ ageg10lfs + j_q06b, data = ita)
summary(logit1)$coefmat
# omitted values are excluded
oddsRatio(logit1) # works only for results from the logit.sdf function
waldTest(model = logit1, coef = ‘j_q06b’)
# this is a test of both coefficients in j_q06b being zero; two test results
are shown: the chi-square test and the F-test
```

3.5.3 Gap Analysis

In the following example, using the `gap` function, we compare literacy scores of self-employed persons with those of employees.

```
gap(variable = ‘lit’, data = ita, groupA = d_q04 %in% ‘SELF-EMPLOYED’,
     groupB= d_q04 %in% ‘EMPLOYEE’)
```

3.5.4 Percentile Analysis

The `percentile` function compares a numeric vector of percentiles in the range 0 to 100 for a data year. This function can display percentiles of scores for a selected group (e.g., males or females) in the examples below.

```
percentile(variable = ‘lit’, percentiles = c(10, 25, 50, 75, 90), data = ita)
percentile(variable = ‘lit’, percentiles = c(25, 50, 75), data = subset(ita,
gender_r %in% ‘MALE’))
percentile(variable = ‘lit’, percentiles = c(25, 50, 75), data = subset(ita,
gender_r %in% ‘FEMALE’))
```

3.5.5 Proficiency Level Analysis

The `achievementLevels` function computes the percentages of students’ proficiency levels defined by an assessment. The arguments in the function provide user options to

- choose to generate the percentage of individuals performing at each proficiency level (discrete) or at or above each proficiency level (cumulative), and
- calculate the percentage distribution of individuals by proficiency level (discrete or cumulative) and selected characteristics (specified in `aggregateBy`).

```
showCutPoints(ita) # see the proficiency level cut points

# generate the percentage of individuals performing at or above each
proficiency level (cumulative)
achievementLevels(c(‘lit’), data = ita, returnDiscrete = FALSE,
                  returnCumulative = TRUE)

# calculate the percentage distribution of individuals by proficiency level
(discrete or cumulative) and selected characteristics (specified in
aggregateBy)
achievementLevels(c(‘lit’, ‘gender_r’), data = ita,
                  aggregateBy = ‘gender_r’,
                  returnDiscrete = FALSE,
                  returnCumulative = TRUE)
```

3.6 Notes

1. `getData()`: reads in selected variables and sampling weights from the EdSurvey database and returns a `light.edsurvey.data.frame`. This allows users to work with PIAAC data from other R packages.
2. addAttributes is set to the default value of FALSE. Setting `addAttributes = TRUE` is one method by which the resultant data object (e.g., `ita`) can be passed to other EdSurvey package functions.
3. All the jackknife replicate weights are returned automatically (spfwt1 to spfwt80) when a weight is requested.

4. `omittedLevels` is set to TRUE, the default, so that variables with special values, such as multiple entries or NAs, are removed by `getData`. This setting listwise deletes these values from factors that are not typically included in regression analysis and cross-tabulation. Alternatively, `omittedLevels` can be set to FALSE to allow more control by the user.
5. Proficiency levels (PLs) provide an external benchmark against which scale scores can be compared. Six levels—below PL1 to PL5—are defined for each literacy and numeracy, with cut scores for each level determined through a standard-setting process.
6. The `achievementLevels` function applies appropriate weights and the variance estimation method for each `edsurvey.data.frame`, with several arguments for customizing the aggregation and output of the analysis results. By using these optional arguments, users can (a) choose to generate the percentage of individuals performing at each proficiency level (discrete) or at or above each proficiency level (cumulative); (b) calculate the percentage distribution of individuals by proficiency level (discrete or cumulative) and selected characteristics (specified in `aggregateBy`); and (c) compute the percentage distribution of individuals by selected characteristics within a specific proficiency level.

3.7 References

Bailey, P., Lee, M., Nguyen, T., & Zhang, T. (2020). Using EdSurvey to analyse PIAAC data. In D. B. Maehler & B. Rammstedt (Eds.), *Large-scale cognitive assessment: Analyzing PIAAC data.* Springer. https://doi.org/10.1007/978-3-030-47515-4_9

Lee, M., Zhang, T., Bailey, P., Buehler, E., Fink, T., Huo, H., Lee, S., Liao Y., & Sikali, E. (2022). *Analyzing NCES data using EdSurvey: A user's guide*. American Institutes for Research. https://naep-research.airprojects.org/Portals/0/EdSurvey_A_Users_Guide/_book/index.html

Organisation for Economic Cooperation and Development (OECD). (2016). *Programme for the International Assessment of Adult Competencies (PIAAC), Italy Public Use File* [Version: 15433181, prgitap1.sav]. OECD Publishing.

4 Analyzing PIAAC Data With M*plus*

Ronny Scherer
(Centre for Educational Measurement at the University of Oslo, Norway)

4.1 Introduction

PIAAC data files can be analyzed with the statistical software M*plus* to perform structural equation modeling (SEM), for example. SEM represents a statistical approach to disentangle the relations among latent and/or manifest variables, across groups, over time, and at different analytic levels. This section provides a selection of structural equation models (SEMs) in M*plus*, including path models with indirect effects, multi-group path models, SEMs with indirect effects, and multi-group SEMs with several invariance constraints (for more information see the PIAAC scripts digital plattform).

4.2 Structural Models With PIAAC Data

4.2.1 Path Model CURIOUS-LIFE-PSTRE

The following path model describes the structural relation between participants' curiosity (CURIOUS) and their performance on the PIAAC problem solving in technology-rich environments (PSTRE) items for the Norwegian data from PIAAC Cycle 1 (OECD, 2016). Researchers may hypothesize that this relation is at least partially mediated via the participants' use of skills in everyday life (LIFE). Both curiosity and life skills use are represented as average scale scores, and performance on PSTRE items is represented by the full set of plausible values (PVs).

```
DATA:
FILE IS piaac1-nor_pvlist.dat;
! The file contains the list of names of datasets with one PV each

     TYPE = IMPUTATION;
     ! Needed here as the model contains PVs

VARIABLE:
     NAMES ARE
            AGE FEMALE B_Q01a
            D_Q11a D_Q11b D_Q11c D_Q11d
            F_Q03a F_Q03c F_Q05a F_Q05b
            G_Q01a G_Q01b G_Q01c G_Q01d
            G_Q01e G_Q01f G_Q01g G_Q01h
            G_Q02a G_Q02b G_Q02c G_Q02d
            G_Q03b G_Q03c G_Q03d G_Q03f G_Q03g G_Q03h
            G_Q05a G_Q05c G_Q05d G_Q05e
            G_Q05f G_Q05g G_Q05h
            H_Q01a H_Q01b H_Q01c H_Q01d
            H_Q01e H_Q01f H_Q01g H_Q01h
            H_Q02a H_Q02b H_Q02c H_Q02d
            H_Q03b H_Q03c H_Q03d H_Q03f H_Q03g H_Q03h
            H_Q05a H_Q05c H_Q05d H_Q05e
            H_Q05f H_Q05g H_Q05h
            I_Q04b I_Q04d I_Q04h I_Q04j I_Q04l I_Q04m
            I_Q06a
            I_Q07a I_Q07b
            HOMLANG IMGEN
            PVLIT PVNUM PVPSL
            SPFWT0
            SPFWT1-SPFWT80
            VARSTRAT VARUNIT;

     ! Variables to be used
     ! Newly defined variable appear at the end of this list
     USEVARIABLES ARE
            PSTRE
            CURIOUS
            LIFE;

     ! Missing data were coded as -99
     MISSING ARE ALL(-99);

     ! Final participant weight
     WEIGHT = SPFWT0;

     ! Clustering in sampling units
     CLUSTER = VARUNIT;

     ! Stratification
     STRATIFICATION = VARSTRAT;

DEFINE:
     ! Scale down the achievement scores to avoid possible convergence issues
     PSTRE = PVPSL/100;
     LIT = PVLIT/100;

     ! Create scale means as composite scores
     CURIOUS = (I_Q04b+
     I_Q04d+
     I_Q04h+
     I_Q04j+
     I_Q04l+
     I_Q04m)/6;

     LIFE = (H_Q05a+
     H_Q05c+
     H_Q05e+
     H_Q05f)/4;
```

```
ANALYSIS:
      ! Account for the complex sampling design
      TYPE = COMPLEX;

! Robust maximum-likelihood estimation
      ESTIMATOR = MLR;
      H1ITERATIONS = 10000;

MODEL:
      ! STRUCTURAL MODEL
      ! Direct effects with labels a, b, and c
      PSTRE ON
              CURIOUS(c)
              LIFE(b);

      LIFE ON
              CURIOUS(a);

      ! Variance of the exogenous variable
      CURIOUS;

MODEL INDIRECT:
      ! Indirect effect
      PSTRE IND CURIOUS;

MODEL CONSTRAINT:
      ! Estimate indirect and total effects by hand (for comparison)
      new(ind tot);
      ind = a*b;
      tot = ind+c;

OUTPUT:
              STDYX;        ! Fully standardized parameters requested
              STDY;         ! Standardized parameter estimates requested
              SAMPSTAT;     ! Sample statistics
              CINTERVAL;    ! Confidence intervals
```

4.2.2 Multi-Group Path Model CURIOUS-LIFE-PSTRE

The code is prepared in the same way as described in Section 4.2.1 (data, variables, definition, and analysis). To extend the path model to a multi-group path model, a grouping-by-gender command is added to the VARIABLE section.

```
VARIABLE:
              […]
      ! Grouping by gender
      ! Binary coding as 1=Woman and 0=Man
      GROUPING = FEMALE (0=Men 1=Women);

MODEL:
      ! STRUCTURAL MODEL
      ! Direct effects
      ! Note: No more labels here; otherwise, these effects would
      ! be set equal across groups.
      PSTRE ON
            CURIOUS
            LIFE;

      LIFE ON
            CURIOUS;

      ! Variance of the exogenous variable
      CURIOUS;

MODEL INDIRECT:
      ! Indirect effects
      PSTRE IND CURIOUS;

OUTPUT:
            STDYX;         ! Fully standardized parameters requested
            STDY;          ! Standardized parameter estimates requested
            SAMPSTAT;      ! Sample statistics
            CINTERVAL;     ! Confidence intervals
```

4.2.3 Multi-Group Path Model CURIOUS-LIFE-PSTRE With Equal *a*- and *b*-Paths Across Gender

The code is prepared in the same way as described in Section 4.2.2 (data, variables, definition, and analysis). This model assumes that the *a*- and *b*-paths in the multi-group path model are the same across gender. Such a model can be compared with a model with the freely estimated paths to test the hypothesis of equal paths.

```
MODEL:
      ! STRUCTURAL MODEL
      ! Direct effects
      ! Labels here to set parameters equal across groups.
      PSTRE ON
            CURIOUS(b)
            LIFE;

      LIFE ON
            CURIOUS(a);

      ! Variance of the exogenous variable
      CURIOUS;

MODEL INDIRECT:
      ! Indirect effects
      PSTRE IND CURIOUS;
```

```
OUTPUT:
            STDYX;        ! Fully standardized parameters requested
            STDY;         ! Standardized parameter estimates requested
            SAMPSTAT;     ! Sample statistics
            CINTERVAL;    ! Confidence intervals
```

4.2.4 Multi-Group Path Model CURIOUS-LIFE-PSTRE With Equal Indirect Effect Across Gender

The code is prepared in the same way as described in Section 4.2.2 (data, variables, definition, and analysis). This model assumes that the indirect effect (*ab*) in the multi-group path model is the same across gender. Such a model can be compared with a model with the freely estimated effect to test the hypothesis of equal effects.

```
MODEL:
     ! STRUCTURAL MODEL
     ! Direct effects
     ! Note: No more labels in here; otherwise, these effects would
     ! be set equal across groups.
     PSTRE ON
            CURIOUS
            LIFE;

     LIFE ON
            CURIOUS;

     ! Variance of the exogenous variable
     CURIOUS;

MODEL Men:
     ! Model with group-specific labels of paths
     PSTRE ON
            CURIOUS
            LIFE(bM);

     LIFE ON
            CURIOUS(aM);

     ! Variance of the exogenous variable
     CURIOUS;

MODEL Women:
     ! Model with group-specific labels of paths
     PSTRE ON
            CURIOUS
            LIFE(bW);

     LIFE ON
            CURIOUS(aW);
     ! Variance of the exogenous variable
     CURIOUS;

MODEL INDIRECT:
     ! Indirect effects
     PSTRE IND CURIOUS;

MODEL CONSTRAINT:
     ! Set the indirect effects equal across gender
     0 = aM*bM-aW*bW;


OUTPUT:
            STDYX;       ! Fully standardized parameters requested
            STDY;        ! Standardized parameter estimates requested
             SAMPSTAT;   ! Sample statistics
            CINTERVAL;   ! Confidence intervals
```

4.3 Structural Equation Models With PIAAC Data

Except for the inclusion of latent variables, the structural part of these SEMs is identical with that of the path model with manifest variables. As a result, the model syntax is modified by adding the measurement models of curiosity and skills use.

4.3.1 SEM With Measurement Models and Complex Structural Relations

This SEM assumes several structural relations among curiosity, life skills use in everyday life, performance on PSTRE items, and participants' background. Besides the measurement models of life skills and curiosity, the structural model contains the relations between the manifest variables, the latent variables, and the manifest and latent variables. Notably, this example code contains an effect (gender) that describes possible (uniform) differential item functioning (DIF).

```
DATA:
     FILE IS piaac1-nor_pvlist.dat;
     ! The file contains the list of names of datasets with one PV each

     TYPE = IMPUTATION;
     ! Needed here as the model contains PVs

VARIABLE:
     NAMES ARE
            AGE FEMALE B_Q01a
            D_Q11a D_Q11b D_Q11c D_Q11d
            F_Q03a F_Q03c F_Q05a F_Q05b
            G_Q01a G_Q01b G_Q01c G_Q01d
            G_Q01e G_Q01f G_Q01g G_Q01h
            G_Q02a G_Q02b G_Q02c G_Q02d
            G_Q03b G_Q03c G_Q03d G_Q03f G_Q03g G_Q03h
            G_Q05a G_Q05c G_Q05d G_Q05e
```

```
        G_Q05f G_Q05g G_Q05h
        H_Q01a H_Q01b H_Q01c H_Q01d
        H_Q01e H_Q01f H_Q01g H_Q01h
        H_Q02a H_Q02b H_Q02c H_Q02d
        H_Q03b H_Q03c H_Q03d H_Q03f H_Q03g H_Q03h
        H_Q05a H_Q05c H_Q05d H_Q05e
        H_Q05f H_Q05g H_Q05h
        I_Q04b I_Q04d I_Q04h I_Q04j I_Q04l I_Q04m
        I_Q06a
        I_Q07a I_Q07b
        HOMLANG IMGEN
        PVLIT PVNUM PVPSL
        SPFWT0
        SPFWT1-SPFWT80
        VARSTRAT VARUNIT;

    ! Variables to be used
    ! Newly defined variable appear at the end of this list
    USEVARIABLES ARE
        H_Q05a
        H_Q05c
        H_Q05e
        H_Q05f
        I_Q04b
        I_Q04d
        I_Q04h
        I_Q04j
        I_Q04l
        I_Q04m
        HOMLANG
        FEMALE
        LIT
        PSTRE;

    ! Missing data are coded as -99
    MISSING ARE ALL(-99);

    ! Final participant weight
    WEIGHT = SPFWT0;

    ! Clustering in sampling units
    CLUSTER = VARUNIT;

    ! Stratification
    STRATIFICATION = VARSTRAT;

DEFINE:
    ! Scale down the achievement scores to avoid possible convergence issues
    PSTRE = PVPSL/100;
    LIT = PVLIT/100;
```

```
ANALYSIS:
     ! Account for the complex sampling design
     TYPE = COMPLEX;

! Robust maximum-likelihood estimation
     ESTIMATOR = MLR;
     H1ITERATIONS = 10000;

MODEL:
     ! MEASUREMENT MODELS
     ! Life skills use in every-day life
     LIFE BY
            H_Q05a
            H_Q05c
            H_Q05e
            H_Q05f;

     ! Curiosity
     CURIOUS BY
            I_Q04b
            I_Q04d
            I_Q04h
            I_Q04j
            I_Q04l
            I_Q04m;

     ! Covariances between residuals (beyond the latent variable)
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            FEMALE
            HOMLANG
            LIT;

     CURIOUS ON
            FEMALE
            HOMLANG
            LIT;

     LIFE ON
            FEMALE
            HOMLANG
            LIT;

     ! Variances of the exogenous variables and mediator residuals
     CURIOUS;
     LIFE;
     FEMALE;
     HOMLANG;
     LIT;

     ! Covariances among exogenous variables and mediator residuals
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     FEMALE WITH HOMLANG LIT;
     HOMLANG WITH LIT;

     ! Uniform DIF effect
     H_Q05E ON FEMALE;

MODEL INDIRECT:
     ! Indirect effects
     PSTRE IND FEMALE;
     PSTRE IND HOMLANG;
     PSTRE IND LIT;

OUTPUT:
            STDYX;        ! Fully standardized parameters requested
            STDY;         ! Standardized parameter estimates requested
            SAMPSTAT;     ! Sample statistics
            CINTERVAL;    ! Confidence intervals
```

4.3.2 Multi-Group SEM With Measurement Models, Complex Structural Relations, and Configural Measurement and Regression Invariance

Although the basic setup of this code example follows the example in Section 4.3.1 (data, variables, model), it has some extensions. Specifically, gender (FEMALE) is introduced as a grouping variable, and no longer appears as an explicit predictor variable in the MODEL section. In this multi-group SEM, we assume *configural measurement and regression invariance*—that is, all parameters in the measurement and structural model are freely estimated across gender, and the same number of latent variables and loading patterns is assumed.

```
VARIABLE:
     […]

     ! Grouping by gender
     GROUPING IS FEMALE (1=Women 0=Men);

DEFINE:
     ! Scale down the achievement scores to avoid possible convergence issues
     PSTRE = PVPSL/100;
     LIT = PVLIT/100;
```

```
ANALYSIS:
     ! Account for the complex sampling design
     TYPE = COMPLEX;

! Robust maximum-likelihood estimation
     ESTIMATOR = MLR;
     H1ITERATIONS = 10000;

MODEL:
     ! MEASUREMENT MODELS
     ! Everyday life skills
     LIFE BY
            H_Q05a
            H_Q05c
            H_Q05e
            H_Q05f;

     ! Curiosity
     CURIOUS BY
            I_Q04b
            I_Q04d
            I_Q04h
            I_Q04j
            I_Q04l
            I_Q04m;

     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            HOMLANG
            LIT;

     CURIOUS ON
            HOMLANG
            LIT;

     LIFE ON
            HOMLANG
            LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;
     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

MODEL WOMEN:
     ! MEASUREMENT MODELS gender-specific
     ! Everyday life skills
     LIFE BY
           H_Q05a
           H_Q05c
           H_Q05e
           H_Q05f;

     ! Curiosity
     CURIOUS BY
           I_Q04b
           I_Q04d
           I_Q04h
           I_Q04j
           I_Q04l
           I_Q04m;

     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL gender-specific
     ! Direct effects
     PSTRE ON
           CURIOUS
           LIFE
           HOMLANG
           LIT;

     CURIOUS ON
           HOMLANG
           LIT;

     LIFE ON
           HOMLANG
           LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;


MODEL MEN:
     ! MEASUREMENT MODELS gender-specific
     ! Everyday life skills
     LIFE BY
            H_Q05a
            H_Q05c
            H_Q05e
            H_Q05f;

     ! Curiosity
     CURIOUS BY
            I_Q04b
            I_Q04d
            I_Q04h
            I_Q04j
            I_Q04l
            I_Q04m;

     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL gender-specific
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            HOMLANG
            LIT;

     CURIOUS ON
            HOMLANG
            LIT;

     LIFE ON
            HOMLANG
            LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

OUTPUT:
            STDYX;        ! Fully standardized parameters requested
            STDY;         ! Standardized parameter estimates requested
            SAMPSTAT;     ! Sample statistics
            CINTERVAL;    ! Confidence intervals
```

4.3.3 Multi-Group SEM With Measurement Models, Complex Structural Relations, and Metric Measurement and Regression Invariance

The data preparation (data, variables, definition and analysis) is the same as that described in Section 4.3.2. This example adds the assumption of metric invariance to the measurement models (i.e., equal factor loadings across gender).

```
MODEL:
     ! MEASUREMENT MODELS
     ! Everyday life skills
     ! Equality constraints to the model with labels L2-L4
     LIFE BY
            H_Q05a
            H_Q05c(L2)
            H_Q05e(L3)
            H_Q05f(L4);

     ! Curiosity
! Equality constraints to the model with labels L5-L9
     CURIOUS BY
            I_Q04b
            I_Q04d(L5)
            I_Q04h(L6)
            I_Q04j(L7)
            I_Q04l(L8)
            I_Q04m(L9);

     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            HOMLANG
            LIT;
     CURIOUS ON
            HOMLANG
            LIT;

     LIFE ON
            HOMLANG
            LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

MODEL WOMEN:
     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL gender-specific
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            HOMLANG
            LIT;

     CURIOUS ON
            HOMLANG
            LIT;

     LIFE ON
            HOMLANG
            LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

MODEL MEN:
     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL gender-specific
     ! Direct effects
     PSTRE ON
            CURIOUS
            LIFE
            HOMLANG
            LIT;

     CURIOUS ON
            HOMLANG
            LIT;

     LIFE ON
            HOMLANG
            LIT;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

OUTPUT:
            STDYX;       ! Fully standardized parameters requested
            STDY;        ! Standardized parameter estimates requested
            SAMPSTAT;    ! Sample statistics
            CINTERVAL;   ! Confidence intervals
```

4.3.4 Multi-Group SEM With Measurement Models, Complex Structural Relations, and Metric Measurement and Configural Regression Invariance

The data preparation (data, variables, definition and analysis) is the same as that described in Section 4.3.3. This example adds the assumption of regression invariance to the structural models (i.e., equal path coefficients across gender).

```
MODEL:
     ! MEASUREMENT MODELS
     ! Everyday life skills
     ! Equality constraints to the model with labels L2-L4
     LIFE BY
            H_Q05a
            H_Q05c(L2)
            H_Q05e(L3)
            H_Q05f(L4);

     ! Curiosity
     ! Equality constraints to the model with labels L5-L9
     CURIOUS BY
            I_Q04b
            I_Q04d(L5)
            I_Q04h(L6)
            I_Q04j(L7)
            I_Q04l(L8)
            I_Q04m(L9);

     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! STRUCTURAL MODEL
     ! Direct effects
     PSTRE ON
            CURIOUS(R1)
            LIFE(R2)
            HOMLANG(R3)
            LIT(R4);

     CURIOUS ON
            HOMLANG(R5)
            LIT(R6);

     LIFE ON
            HOMLANG(R7)
            LIT(R8);

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;
```

```
MODEL WOMEN:
     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;


MODEL MEN:
     ! Covariances among residuals
     I_Q04B WITH I_Q04H;
     I_Q04B WITH I_Q04J;
     H_Q05E WITH H_Q05F;

     ! Variances of predictors and residuals of mediators
     CURIOUS;
     LIFE;
     HOMLANG;
     LIT;

     ! Covariances among predictors and residuals of mediators
     ! Residuals of mediators
     CURIOUS WITH LIFE;
     ! Predictors
     HOMLANG WITH LIT;

OUTPUT:
            STDYX;       ! Fully standardized parameters requested
            STDY;        ! Standardized parameter estimates requested
            SAMPSTAT;    ! Sample statistics
            CINTERVAL;   ! Confidence intervals
```

4.4 References

Scherer, R. (2020). Analysing PIAAC data with structural equation modelling in Mplus. In D. B. Maehler & B. Rammstedt (Eds.), Large-scale cognitive assessment (pp. 165–208). Springer. https://doi.org/10.1007/978-3-030-47515-4_8

Organisation for Economic Cooperation and Development (OECD). (2016). *Programme for the International Assessment of Adult Competencies (PIAAC), Norway Public Use File* [Version: 17723269, prgnorp1.sav]. OECD Publishing.

5 Using the IDB Analyzer to Analyze PIAAC Data With SPSS, SAS, and R

Umut Atasever & Rolf Strietholt
(IEA – International Association for the Evaluation of Educational Achievement, Germany)

5.1 Introduction

Because PIAAC uses a complex assessment and a clustered sampling design, PIAAC data cannot be analyzed correctly with SPSS, SAS, or R without using specialized packages or macros. Sample statistics and the corresponding standard errors cannot be calculated in a conventional way. Rather, various features of the complex study design must be taken into account (see Gonzalez, 2014, for more information on sampling weights, replication weights, and plausible values). In addition, as sampling designs in PIAAC vary across countries, different methods must be used in each country to estimate sampling variance (see Mohadjer et al., 2013).

The IEA International Database Analyzer (IDB Analyzer) is a software tool developed by the International Association for the Evaluation of Educational Achievement (IEA). It can be used to analyze data from PIAAC and other international large-scale assessments while accounting for sampling and replication weights as well as plausible values. The user-friendly graphical interface generates syntax code for SPSS, SAS, or R to combine data files and conduct analyses with these data. It can be used to compute percentages, means, correlations, and regression analyses while fully taking into account the complex PIAAC design. The software identifies what data are being used and selects appropriate methods and procedures for the data analyses. All procedures correctly use the sampling weights and compute standard errors according to the variance estimation of the corresponding study and country. Analyses that include plausible values for the performance tests—either as dependent or independent variables—consider all plausible values when calculating standard errors. In the following sections, we illustrate the code generated by the IDB Analyzer using mean and regression analyses as examples, and we show code for SPSS, SAS, and R (for detailed information on how the IDB Analyzer works, see the PIAAC scripts digital plattform).

It should be noted that the analyses themselves are not performed using the IDB Analyzer but rather within the respective software package. The analyses must therefore be started within that software package (e.g., by using Ctrl+R in SPSS). After running the analyses, the results are presented in the file formats of the corresponding analysis software, as well as in generic formats such as HTML, CSV or MS Excel XLSX files. The IDB Analyzer can be downloaded free of charge from the IEA website (www.iea.nl), which also offers video tutorials and a regularly updated help manual (IEA, 2022).

5.2 Computing Means With Plausible Values

The following syntaxes were created by the IDB Analyzer to compute means of literacy performance grouped by the grouping variables country (CNTRYID) and migration background (IMGEN). As there are 10 plausible values for performance in literacy (PVLIT1 to PVLIT10), the analyses will be replicated 10 times and then combined (for detailed information see the PIAAC scripts digital plattform).

5.2.1 SPSS

The following code for SPSS was generated using the IDB Analyzer to estimate mean values per group.

```
* Script created using the IEA IDB Analyzer (Version 5.0.16).
* Created on 1/15/2023 at 6:57 PM.
* Press Ctrl+A followed by Ctrl+R to submit this analysis.

include file = “C:\Users\umut.atasever\AppData\Roaming\IEA\IDBAnalyzerV5\bin\
Data\Templates\SPSS_Macros\JB_PV.ieasps”.

JB_PV        infile=”C:\PIAAC_Analysis\00_Data\PIAAC_PRG_merged.sav”/
      cvar=CNTRYID IMGEN/
      almvars=/
      rootpv=PVLIT /
      tailpv=/
      npv=10/
      wgt=SPFWT0/
      nrwgt=80 /
      rwgt=SPFWT/
      jkz=/
      jkr=/
      jk2type=HALF/
      stratvar=/
      nomiss=Y/
      method=PIAAC/
      kfac=0/
      shrtcut=N/
      viewcod=N/
      ndec=2/
      clean = Y/
      strctry = N/
      intavg = Y/
      graphs=Y/
      selcrit = /
      selvar = /
      outdir=”C:\PIAAC_Analysis\01_Syntax”/
      outfile=”Means_IMGEN”.
```

5.2.2 SAS

The following code for SAS was generated using the IDB Analyzer to estimate mean values per group.

```
/* Script created using the IEA IDB Analyzer (Version 5.0.16). */
/* Created on 1/15/2023 at 7:05 PM. */
/* Press F8 to submit this analysis. */

/* This is where the macros are located */
%let mdir = C:\Users\umut.atasever\AppData\Roaming\IEA\IDBAnalyzerV5\bin\Data\
Templates\SAS_Macros;

/* This is where the data will be read from */
%let idir = C:\PIAAC_Analysis\00_Data;

/* This is where the output will be saved */
%let odir = C:\PIAAC_Analysis\01_Syntax;

/* DO NOT EDIT AFTER THIS */
options mrecall sasautos = (sasautos “&mdir”);

%jb_pv ( InDir = &idir ,
      InFile = PIAAC_PRG_merged ,
      SelVar = ,
      SelCrit = ,
      OutDir = &odir ,
      OutFile = Means_IMGEN ,
      CVar = CNTRYID IMGEN  ,
      Almvars =  ,
      NoMiss = Y ,
      strctry = N ,
      rootpv = PVLIT  ,
      tailpv =  ,
      shrtcut = N ,
      npv = 10 ,
      method = PIAAC ,
      kfac = 0 ,
      wgt = SPFWT0 ,
      rwgt = SPFWT ,
      nrwgt = 80 ,
      jkz =  ,
      jkr =  ,
      jk2type = HALF ,
      stratvar =  ,
      newout = Y ,
      qcstats = Y ,
      report = Y ,
      graphs = Y ,
      intavg = Y ,
      viewlbl = Y ,
      ndec = 2 ,
      viewcod = N ,
      ViewPrgs = Y ,
      clean = Y );
```

5.2.3 R

The following code for R was generated using the IDB Analyzer to estimate mean values per group.

```
# Percentages and Means: JB_PV.R

# =================================================================
# Script created using the IEA IDB Analyzer (Version 5.0.16).
# Created on 1/15/2023 at 6:13 PM.
# Press Ctrl+A followed by Ctrl+Enter to submit this analysis.

###################################################

# IEA IDB Analyzer: R Module
# Programmer: IEA Hamburg, please contact idb-analyzer@iea-hamburg.de
##################################################

# Overall function
# Clean workspace and define settings ========================================

rm(list = ls())
# Directory, where the IEA IDB Analyzer macros are stored
include_file <- “C:/Users/umut.atasever/AppData/Roaming/IEA/IDBAnalyzerV5/bin/
Data/Templates/R_Macros”

source(sprintf(“%s/check_packages.R”, include_file), local = TRUE)
source(sprintf(“%s/JB_PV.R”, include_file), local = TRUE)

# Dependencies ===============================================================

library(dplyr)      # version 1.0.10
library(ggplot2)    # version 3.3.6
library(haven)      # version 2.5.1
library(htmltools)  # version 0.5.3
library(kableExtra) # version 1.3.4
library(knitr)      # version 1.40
library(openxlsx)   # version 4.2.5.1
library(rmarkdown)  # version 2.17
library(sjlabelled) # version 1.2.0
library(tidyr)      # version 1.2.1
library(tidyselect) # version 1.2.0

# =================================================================

JB_PV(       infile = “C:/PIAAC_Analysis/00_Data/PIAAC_PRG_MERGED.Rdata”,
      cvar = c(“CNTRYID”,”IMGEN”),
      almvars = NULL,
      rootpv = c(“PVLIT”),
      tailpv = NULL,
      npv = 10,
      wgt = „SPFWT0“,
      nrwgt = 80,
      rwgt = „SPFWT“,
      jkz = NULL,
      jkr = NULL,
      jk2type = “HALF”,
      stratvar = NULL,
      nomiss = “Y”,
      method = “PIAAC”,
      kfac = 0,
      shrtcut = “N”,
      viewcod = “N”,
      ndec = 2,
      clean = “Y”,
      intavg = “Y”,
      graphs = “Y”,
      qcstats = “N”,
      report = “Y”,
      selcrit = NULL,
      selvar = NULL,
      outdir = “C:/PIAAC_Analysis/01_Syntax”,
      outfile = “Means_IMPAR”)
```

5.3 Computing Linear Regression With Plausible Values As An Explanatory Variable

The following syntaxes were created by the IDB Analyzer to conduct ordinary least squares (OLS) regression with plausible values as an independent variable. The dependent variable—use of reading skills at work (READWORK)—was regressed on the independent variables immigration background (IMGEN), social trust (I_Q07a), and literacy performance. As there are 10 plausible values for performance in literacy (PVLIT1 to PVLIT10), the analyses will be replicated 10 times and then combined. The immigration background variable is dummy coded using the first category as the reference category; the social trust variable is effect coded using the third category as the reference category. Regression models were estimated separately for the different countries (for detailed information see the PIAAC scripts digital plattform).

5.3.1 SPSS

The following code for SPSS was generated using the IDB Analyzer to estimate an OLS regression model.

```
* Script created using the IEA IDB Analyzer (Version 5.0.16).
* Created on 1/24/2023 at 5:50 PM.
* Press Ctrl+A followed by Ctrl+R to submit this analysis.

include file = “C:\Users\umut.atasever\AppData\Roaming\IEA\IDBAnalyzerV5\bin\
Data\Templates\SPSS_Macros\JB_RegGP.ieasps”.

JB_RegGP     infile=”C:\PIAAC_Analysis\00_Data\PIAAC_PRG_merged.sav”/
      cvar=CNTRYID /
```

```
        convar=/
        catvar=IMGEN I_Q07A /
        codings=D E/
        refcats=1 3/
        ncats=3 5/
        PVRoots=PVLIT /
        PVTails=/
        dvar0=READWORK /
        rootpv=/
        tailpv=/
        npv=10/
        wgt=SPFWT0/
        nrwgt=80 /
        rwgt=SPFWT/
        jkz=/
        jkr=/
        jk2type=HALF/
        stratvar=/
        nomiss=Y/
        method=PIAAC/
        missing=listwise/
        kfac=0/
        shrtcut=N/
        viewcod=N/
        ndec=2/
        clean = Y/
        strctry = N/
        viewprgs=Y/
        viewlbl=Y/
        qcstats=Y/
        newout=Y/
        intavg = Y/
        selcrit = /
        selvar = /
        outdir=”C:\PIAAC_Analysis\01_Syntax”/
        outfile=”Regression_IMGEN_TRUST_LITERACY_READWORK”.
```

5.3.2 SAS

The following code for SAS was generated using the IDB Analyzer to estimate an OLS regression model.

```
/* Script created using the IEA IDB Analyzer (Version 5.0.16). */
/* Created on 1/24/2023 at 5:56 PM. */
/* Press F8 to submit this analysis. */

/* This is where the macros are located */
%let mdir = C:\Users\umut.atasever\AppData\Roaming\IEA\IDBAnalyzerV5\bin\Data\
Templates\SAS_Macros;

/* This is where the data will be read from */
```

```
%let idir = C:\PIAAC_Analysis\00_Data;

/* This is where the output will be saved */
%let odir = C:\PIAAC_Analysis\01_Syntax;

/* DO NOT EDIT AFTER THIS */
options mrecall sasautos = (sasautos “&mdir”);

%jb_reggp (
      InDir = &idir ,
      InFile = PIAAC_PRG_merged ,
      SelVar = ,
      SelCrit = ,
      OutDir = &odir ,
      OutFile = Regression_IMGEN_TRUST_LITERACY_READWORK ,
      CVar = CNTRYID  ,
      NoMiss = Y ,
      strctry = N ,
      dvar0 = READWORK  ,
      catvar = IMGEN I_Q07A  ,
      codings = D E ,
      ncats = 3 5 ,
      RefCats = 1 3 ,
      convar =  ,
      PVRoots = PVLIT  ,
      PVTails =  ,
      rootpv =  ,
      tailpv =  ,
      shrtcut = N ,
      npv = 10 ,
      method = PIAAC ,
      kfac = 0 ,
      wgt = SPFWT0 ,
      rwgt = SPFWT ,
      nrwgt = 80 ,
      jkz =  ,
      jkr =  ,
      jk2type = HALF ,
      stratvar =  ,
      missing = listwise ,
      newout = Y ,
      qcstats = Y ,
      Report = Y ,
      intavg = Y ,
      viewlbl = Y ,
      ndec = 2 ,
      viewcod = N ,
      ViewPrgs = Y ,
      clean = Y );
```

5.3.3 R

The following code for R was generated using the IDB Analyzer to estimate an OLS regression model.

```
# Linear Regression: JB_RegGP

# =================================================================

# Script created using the IEA IDB Analyzer (Version 5.0.16).
# Created on 1/24/2023 at 5:58 PM.
# Press Ctrl+A followed by Ctrl+Enter to submit this analysis.

###################################################
#
# IEA IDB Analyzer: R Module
# Programmer: IEA Hamburg, please contact idb-analyzer@iea-hamburg.de
#
##################################################


# Overall function

# Clean workspace and define settings ========================================

rm(list = ls())

# Directory, where the IEA IDB Analyzer macros are stored
include_file <- “C:/Users/umut.atasever/AppData/Roaming/IEA/IDBAnalyzerV5/bin/
Data/Templates/R_Macros”

source(sprintf(“%s/check_packages.R”, include_file), local = TRUE)
source(sprintf(“%s/JB_RegGP.R”, include_file), local = TRUE)

# Dependencies ===============================================================

library(dplyr)      # version 1.0.10
library(ggplot2)    # version 3.3.6
library(haven)      # version 2.5.1
library(htmltools)  # version 0.5.3
library(kableExtra) # version 1.3.4
library(knitr)      # version 1.40
library(openxlsx)   # version 4.2.5.1
library(rmarkdown)  # version 2.17
library(sjlabelled) # version 1.2.0
library(tidyr)      # version 1.2.1
library(tidyselect) # version 1.2.0

# =================================================================

JB_RegGP(    infile = “C:/PIAAC_Analysis/00_Data/PIAAC_PRG_MERGED.Rdata”,
      cvar = c(“CNTRYID”),
      convar = NULL,
      catvar = c(“IMGEN”,”I_Q07A”),
      codings = c(„D“,“E“),
      refcats = c(1,3),
      ncats = c(3,5),
      PVRoots = c(“PVLIT”),
      PVTails = NULL,
      dvar0 = “READWORK”,
      rootpv = NULL,
      tailpv = NULL,
      npv = 10,
      wgt = „SPFWT0“,
      nrwgt = 80,
      rwgt = „SPFWT“,
      jkz = NULL,
      jkr = NULL,
      jk2type = “HALF”,
      stratvar = NULL,
      nomiss = “Y”,
      method = “PIAAC”,
      missing = “listwise”,
      kfac = 0,
      shrtcut = “N”,
      viewcod = “N”,
      ndec = 2,
      clean = “Y”,
      qcstats = “Y”,
      intavg = “Y”,
      selcrit = NULL,
      selvar = NULL,
      outdir = “C:/PIAAC_Analysis/01_Syntax”,
      outfile = “Regression_IMGEN_TRUST_LITERACY_READWORK”)
```

5.4 References

Gonzales, E. J. (2014). Calculating standard errors of sample statistics when using international large-scale assessment data. In R. Strietholt, W. Bos, J. E. Gustafsson, & M. Rosén (Eds.), *Educational policy evaluation through international comparative assessments* (pp. 59–74). Waxmann.

International Association for the Evaluation of Educational Achievement (IEA). (2022). *Help manual for the IEA IDB Analyzer* (Version 5.0). IEA. https://www.iea.nl/sites/default/files/2022-06/IDB-Analyzer-Manual-%28Version-5-0%29.pdf

Mohadjer, L., Krenzke, T., Van de Kerckhove, W., & Hsu, V. (2013). Survey weighting and variance estimation. In OECD (Ed.), *Technical report of the Survey of Adult Skills (PIAAC)* (Chapter 15). Organisation for Economic Co-operation and Development (OECD). https://www.oecd.org/skills/piaac/_Technical%20Report_17OCT13.pdf

6 Analyzing PIAAC Data With Base R

Matthew G. R. Courtney[1] *& Kaidar Nurumov*[2]
([1]Nazarbayev University, Kazakhstan; [2]University of Michigan, USA)

6.1 Introduction

This chapter provides analysts with guidelines for conducting analyses of PIAAC data, predominantly with base R. The chapter is broken into three sections. The first section (6.1) provides an overview of the PIAAC's complex methodology. The second section (6.2) details how to undertake multiple linear regression when the plausible values are the dependent variable in the model. For this section, we replicate the same analysis and results using EdSurvey package *and* base R functions. The third section (6.3) details how to conduct multiple linear regression when the plausible values are the independent variables in the model. Our R code includes quite extensive annotation so that an R user with minimal experience might be guided through the different steps. We have also provided instruction on how to calculate the mean, *SD*, and standard error of the mean (seM) for PV and non-PV PIAAC variables in an associated video, and we encourage readers to make use of these step-by-step instructions for performing these tasks (Courtney & Nurumov, 2023a; 2023b; 2023c).

6.2 PIAAC's Complex Methodology

PIAAC makes use of (a) item-response theory (IRT) as a statistical framework to score and track adult literacy, and (b) complex sampling designs with, for example, groups of participants sampled from geographic localities, and individual participants sampled from households in those pooled localities. Therefore, the use of descriptive and multivariate statistics to analyze PIAAC data should account for both the use of IRT and the application of the complex sampling design.

The associated R script is dedicated to guiding analysts to undertake multiple regression-based analysis that (a) includes IRT-derived, multiply imputed plausible values (i.e., what is considered most plausible in a population) and (b) accounts for PIAAC's complex sampling design.

6.2.1 Accounting for the Application of IRT in PIAAC

PIAAC uses item response theory (IRT) as a framework to score and track adult literacy across different test booklets, population groups, and cycles. The IRT framework is flexible in this way but its application rests on the assumption that adult literacy follows a normal distribution.

The application of the assumed normal distribution, via marginal maximum likelihood estimation (Bock & Aitkin, 1981), to generate estimates of adult literacy introduces some level of distortion when undertaking multivariate statistical analyses. For example, the estimated association between adult literacy and earning power may be consequently inflated if this distortion is not accounted for.

In addition, PIAAC employs a multiple matrix sampling design in which every test taker receives only a subset of items. This methodological feature helps to reduce the length of the test for each and thus, reducing the burden on the test takers. At the same time, due to the reduced number of items, reasonable estimates of adult competencies can only be obtained at the population or a subgroup level and not at the individual level (OECD, 2019).

To account for this, PIAAC, and other large-scale assessment projects, generate “plausible values” (random draws from the computed posterior distribution) that are free from such distortion. In PIAAC, there are 10 plausible values (PVs) for each case (participant): PVLIT1 to PVLIT10 are the plausible values for adult reading literacy. Therefore, to properly account for this distortion, all 10 plausible values should be used in any statistical analysis.

For more details on the derivation of plausible values and variance estimation in complex sampling designs, see Section 4 of the PIAAC Technical Report by the OECD (2019).

6.2.2 Accounting for the Application of Complex Sampling in PIAAC

For many countries (including the example of Kazakhstan, herein), PIAAC makes use of a complex multi-stage sampling design where (a) participant groups are sampled based on pooled geographic localities (residential areas, defined as ‘primary sampling units’) and then (b) dwelling units (apartment numbers or private houses defined as ‘secondary sampling units’) are sampled from the selected PSUs, finally (c) individual participants are sampled from the selected DUs.

To obtain unbiased estimates of the mean, standard error of the mean (SEM), and standard deviation (*SD*), associated with adult literacy (PVs), we should make use of (a) all available plausible values, (b) the final sample weight, and (c) all available jackknife replicate weights. Therefore, any analysis that includes PVs involves 810 estimates for each statistic. To calculate the mean and SD for PV for a country, for example, we use the final full sample weight (10 by 1) to generate 10 estimates of the mean; then, for each of the 10 estimated means, we also use the 80 jackknife replicate weights (10 by 80 = 800) to estimate of the variation in adult literacy due to the complex sampling design. However, we only report a single final mean (and standard error and *SD*) for our results (see the Rubin’s [1987] rule for reporting averages when dealing with PVs). The above principle applies to any statistics of interest, including calculation of regression coefficients and their associated standard errors. The next sections provide detailed descriptions of how to perform multiple regression analysis that includes PVs as dependent and independent variables (see Courtney & Nurumov, 2023a, for calculating the mean, seM, and *SD*).

6.3 Using Plausible Values as Dependent Variable

This section provides a description and script to undertake an analysis of PIAAC data where the plausible values are defined as the dependent variable in a multiple regression model. The first part of the section (6.2.1) provides details as to how to undertake the analysis using the EdSurvey package while the second section (6.2.2) replicates the same analysis using base R.

When applying multiple linear regression with large scale educational assessment studies, such as PIAAC, it is important to follow the same general steps applied for univariate statistics (see section 6.1). More specifically, we should take into consideration (a) the uncertainty associated with PVs, and (b) the application of the complex sampling design.

Overall, for any regression-based analysis using PIAAC data, there are two possible scenarios: (1) when the plausible values are used in the analysis as the dependent (or independent) variable; or, (2) the analysis is run without plausible values. For this section (6.2), we focus on the scenario when plausible values are the dependent variable.

For the purposes of obtaining unbiased estimates of regression coefficients (and their standard errors) associated with adult literacy (as measured via PVs), we should make use of (a) all available plausible values, (b) the final sample weight, and (c) all available jackknife replicate weights (this analysis involves 810 estimates for each statistic). For example, for each unique PV, we use the final full sample weight (10 by 1) to generate 10 estimates for each individual regression coefficient. The average coefficient, in this case, is represented by β_0 in Equation 1. To estimate the variance in the regression coefficient attributable to imputation (i.e., the PVs), we use the full Equation 1. Thereafter, to estimate the variance in the regression coefficient attributable to sampling, we make use of Equation 2. In this instance, for each of the 10 estimated coefficients, we also use the 80 jackknife replicate weights (10 by 80 = 800). However, we only report single final coefficients for each model predictor for our results (see the Rubin's [1987] rule for reporting averages when dealing with PVs) (note Equation 3 for reporting standard errors).

For PIAAC, which includes 10 PVs, the resulting variance components of the standard errors for the coefficients are calculated in accordance with Equations 1, 2, and 3. For the variance attributable to the plausible values (var_{imp}) we use the following formula,

$$var_{imp} = \frac{(10+1)}{10(10-1)} \sum_{pv=1}^{10} (\beta_i - \beta_0) \qquad [1]$$

Where β_i is the regression coefficient calculated with $i\text{-}th$ plausible value and β_0 is the average overall regression coefficients calculated with PV1-PV10. For the variance attributable to the sampling design, we use the following formula,

$$var_{sampl} = \frac{1}{10} \left(\gamma \sum_{jk=1}^{80} (\beta_{ji} - \beta_{0i})\right) \qquad [2]$$

Where β_{ji} is the regression coefficient calculated with $i\text{-}th$ plausible value and $j\text{-}th$ replicate, β_{0i} is the coefficient from $i\text{-}th$ plausible value and the final weight, and γ is the constant, in this case, 1. To calculate the overall variance components of the standard errors, we use the following formula,

$$var_{overall} = var_{imp} + var_{sampl} \qquad [3]$$

Finally, the standard errors of the regression coefficients are obtained by taking the square root of $var_{overall}$. While this describes how the regression coefficients and standard errors are estimated, the associated *t*-value, degrees of freedom, and *p* value for each coefficient also need to be calculated. This chapter provides also provides details as to how this is achieved. Keep in mind that when using *EdSurvey* package and function *lm.sdf*, you need to specify jrrMax=10 otherwise the resulting standard errors will be calculated using only the variance from the first plausible value (*sigma_pv1* in the code).

For more information please see Technical Report of PIAAC and statistical methods vignette of *EdSurvey* (OECD, 2019; Bailey et al, 2023).

6.3.1 Plausible Values as Dependent Variables (using the EdSurvey Package)

For this example, we are using adult data from Kazakhstan and focusing on predicting literacy of non-post-secondary-school-qualified adults based on (a) highest qualification, (b) gender, (c) age, (d) language of survey in native tongue, and (e) extent of habitual reading. The EdSurvey code to perform this task is as follows. Note that the EdSurvey package saves country-level data as a list of various components necessary for analysis and the package also uses its own functions to manipulate and prepare data, as will be described in the following code.

```
########## 1. Obtain the Data of Interest ##########
# The following files need to be downloaded and placed into the working
directory:
# 1a. All csv files from here: https://webfs.oecd.org/piaac/puf-data/CSV/
# 1b. The international codebook at a link here: https://www.oecd.org/skills/
piaac/data/
# *Codebook name: “International Codebook_PIAAC Public-use File (PUF)
Variables and Values.xlsx”

########## 2. Set the Working Directory ##########
# 2a. Using base R:
setwd(“/Users/user/Desktop/PIAAC”)
# 2b. Manually, using RStudio, as alternative: Session -> Set Working
Directory -> Choose Directory ###

########## 3. Clear the Global Environment in R ##########
rm(list=ls())

########## 4. Install and Load R Package Management Software ##########
if (!require(“pacman”)){install.packages(“pacman”, dependencies = TRUE)
                        library(tidyverse)
                        }

########## 5. Install and load all necessary packages for the analysis in this
script ##########
pacman::p_load(EdSurvey)

########## 6. Read in the Data ##########
kaz <- EdSurvey::readPIAAC(“/Users/user/Desktop/Current Projects/PIAAC
Analysis/PIAAC PV as DV”, countries= ‘KAZ’)
summary(kaz)
# list of 31

########## 7. Subset all participants with ISCED < 5 ##########
# Note that we need to use specialized coding for managing this special
EdSurvey dataset
# I.e., we have to spell out the labels when doing the subset:
# b_q01a is qualification level

kaz <- subset(kaz, b_q01a %in% c(‘NO FORMAL QUALIFICATION OR BELOW ISCED 1’,
                                 ‘ISCED 1’,
                                 ‘ISCED 2’,
                                 ‘ISCED 3A-B’,
                                 ‘ISCED 4A-B’,
                                 ‘ISCED 4 (WITHOUT DISTINCTION A-B-C)’))

########## 8. Standardize the age variable ##########
kaz[,”ageg5lfs”] <- as.numeric(kaz[,”ageg5lfs”])
kaz$ageg5lfs <- scale(kaz$ageg5lfs)
# This is to standardize the variable

########## 9. Standardize the reading at home variable ##########
kaz[,”readhome_wle_ca”]<- as.numeric(kaz[,”readhome_wle_ca”])
kaz$readhome_wle_ca <- scale(kaz$readhome_wle_ca)

########## 10 .Change gender and native language to numeric ##########
kaz[,“gender_r“]<- as.numeric(kaz[,“gender_r“])
kaz[,“nativelang“]<- as.numeric(kaz[,“nativelang“])

table(kaz[,“gender_r“])
table(kaz[,”nativelang”])
# Nine means missing! But, all variables OK

########## 11 .Use EdSurvey recode function to recode 9 as NA for native
language ##########
kaz <- recode.sdf(kaz, recode =
                    list(nativelang =
                           list(from = c(9),
                                to = c(NA))))
table(kaz[,”nativelang”])

########## 12 .Use EdSurvey recode function to recode quals as either low or
moderate ##########
kaz <- recode.sdf(kaz, recode=
                    list(b_q01a=
                           list(from = c(‘NO FORMAL QUALIFICATION OR BELOW
ISCED 1’,
                                       ‘ISCED 1’,
                                       ‘ISCED 2’),
                                to = c(‘low’))))
kaz <- recode.sdf(kaz, recode=
                    list(b_q01a =
                           list(from = c(‘ISCED 3A-B’,
                                       ‘ISCED 4A-B’,
                                       ‘ISCED 4 (WITHOUT DISTINCTION A-B-C)’),
                                to=c(‘moderate’))))
table(kaz[,”b_q01a”])
nrow(kaz)         # 2421

#################### 13. Use the lm.sdf function to run the regression model
#################
lm1 <- lm.sdf(lit ~  gender_r + ageg5lfs + nativelang + b_q01a +
readhome_wle_ca,
                         data=kaz, varMethod = ‘jackknife’, jrrIMax = 10)
# jrrImax = 10 leads to more accurate estimates
summary(lm1, src=TRUE)

########## 14.  Output from EdSurvey ##########
# Formula: lit ~ gender_r + ageg5lfs + nativelang + b_q01a + readhome_wle_ca
# Weight variable: ‘spfwt0’
# Variance method: jackknife
# JK replicates: 80
# Plausible values: 10
# jrrIMax: 10
# full data n: 6050
# n used: 1841

# Coefficients:
#              coef    se    t    dof    Pr(>|t|)    stdCoef      stdSE
#  (Intercept) 236.9124948   4.5912367 51.60102 48.238 0.000000    NA    NA
#  gender_r   1.0268129  2.1396433  0.47990 52.750 0.633283  0.0132 0.02747 *
#  ageg5lfs   -1.8001830  1.3125085 -1.37156 57.165 0.175560 -0.0478 0.03486 *
#  nativelang  0.7745880  2.5494632  0.30382 42.896 0.762731  0.0092 0.03016 *
#  b_q01amoderate 6.4453079  3.0862085 2.08842 38.760 0.043378  0.0770 0.03686
*
#  readhome_wle_ca  3.9320115  1.4956350  2.62899 54.717 0.011095  0.1017
0.03867 *
#   ---
#  Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
# Multiple R-squared: 0.0224

# Note on getting p from t and df?
options(scipen = 9999999)
2*stats::pt(0.47990, 52.750, lower.tail = F) # * this is from the gender_r
output above.
## END ##
```

6.3.2 Plausible Values as Dependent Variables (using base R code)

While the EdSurvey package provides analysts with a highly efficient means to undertaking multiple linear regression analysis of PIAAC data, some analysts may also be interested in using base R to prepare their data (via standard dataframes) and, necessarily, also interested in using non-base R packages to perform the analysis itself. For such cases, the following code provides an option for analysts.

```
########################################################################
#                    A. READING IN AND PREPARING DATA                  #
########################################################################
########## 1. Obtain the Data of Interest ##########
# FYI codebook: https://www.oecd.org/skills/piaac/data/
# PUF data: https://webfs.oecd.org/piaac/puf-data/SPSS/

#* Create folder on your desktop and put the following two files in it:
```

```
# 1. data (prgkazp1.sav)                                                #
Kazakhstan data used as example here
# 2. codebook (International Codebook_PIAAC Public-use File (PUF) Variables
and Values)

########## 2. Set the Working Directory ##########
# 2a. Using base R:
setwd("/Users/user/Desktop/PIAAC")
# 2b. Manually, using RStudio, as alternative: Session -> Set Working
Directory -> Choose Directory ###

########## 3. Clear the Global Environment in R ##########
rm(list=ls())

########## 4. Install and Load R Package Management Software ##########
if (!require("pacman")){install.packages("pacman", dependencies = TRUE)
                        library(tidyverse)
                        }

########## 5. Install and load all necessary packages for the analysis in this
script ##########
pacman::p_load(psych, foreign, dplyr, Hmisc)
# 'psych' for exploring data; 'foreign' for reading in spss files, etc.;
'dplyr' for subsetting datasets; 'Hmisc' for weighted variance.

########## 6. Read in the SPSS .sav Data ##########
dir()
data <- foreign::read.spss('prgkazp1.sav', to.data.frame = T)
# Try the "readxl" package for Excel formatted files!
base::dim(data)                                  # 6050 persons, 1328 columns
for the Kazakh data file

########################################################################
#                            B. DATA PREPARATION                             #
########################################################################
########## 1. Dependent Variables ##########
# PVLIT1 to PVLIT10: Plausible values for adult literacy
summary(data$PVLIT1)                             # Note only 6 NAs
str(data$PVLIT1)                                 # Number (num), so no problem
psych::describe(data$PVLIT1)                     # M = 249.7, SD = 33.4

########## 2. Independent Variables ##########
# B_Q01a: ISCED Levels 1 (no formal qualification) to 8 (doctoral degree) of
Education (highest completed level of education)
summary(data$B_Q01a)                             # Note only 8 NAs
str(data$B_Q01a)                                 # Variable is a 'factor' but
needs to be a number (num)
# We will subset the data on this so let's change later...

# GENDER_R: Gender of the adult, male = 1, female = 2
levels(data$GENDER_R)
print(data$GENDER_R)
```

```
summary(data$GENDER_R)                   # Note no NAs
str(data$GENDER_R)                        # Variable is a ‘factor’ number but
needs to be a numeric
data$GENDER_R <- as.numeric(data$GENDER_R)

# AGEG5LFS: Age-group of adults, 10 levels, pseudo-continuous variable (e.g.,
1 = 16-19,... 10 = 60-65)
summary(data$AGEG5LFS)                    # Note zero NAs
str(data$AGEG5LFS)                        # Variable is a ‘factor’ number but
needs to be a numeric
data$AGEG5LFS <- as.numeric(data$AGEG5LFS)
table(data$AGEG5LFS)

# NATIVELANG: 2 = test lang same as native lang, 1 = test lang not same as
native lang.
print(data$NATIVELANG)
summary(data$NATIVELANG)
# Note 1406 NAs. *When using EdSuvrey, ensure that numercial value of NAs is
correctly
# specificed before any analysis

table(data$NATIVELANG)

str(data$NATIVELANG)                               # Variable is a ‘factor’
number but needs to be a numeric
data$NATIVELANG <- as.numeric(data$NATIVELANG)
table(data$NATIVELANG)
summary(data$NATIVELANG)
data$NATIVELANG <- car::recode(data$NATIVELANG, “1=0; 2=1”)
 # *This coding scheme is used in EdSurvey so we apply the same here.
summary(data$NATIVELANG)

# READHOME_WLE_CA: Extent to which respondent reads at home, 1 = all zero (no
reading), 2 = lowest to 20%, ...6 = more than 80%.
summary(data$READHOME_WLE_CA) # Note 5 NAs
str(data$READHOME_WLE_CA)             # Variable is a ‘factor’ number but
needs to be a numeric
data$READHOME_WLE_CA <- as.numeric(data$READHOME_WLE_CA)
table(data$READHOME_WLE_CA)

########## 3. Weighting and Replicate Variables ##########
# SPFWT0: Final full sample weight
summary(data$SPFWT0)                             # Note, no NAs
str(data$SPFWT0)                                 # Number (num), so no problem
psych::describe(data$SPFWT0)                     # M = 1918.9, SD = 1060.1

# SPFWT1 to SPFWT80: Final replicate weight 1 to 80
summary(data$SPFWT1)
psych::describe(data$SPFWT1)                     # M = 1918.9, SD = 1096.2
str(data$SPFWT1)                                 # Number (num), so no problem
```

```
# Sequence variable
dim(data)
length(unique(data$SEQID))

#######################################################################
#                          C. DATA MANIPULATION                       #
#######################################################################

########## 1. Select the Variables and Weights for the Study ##########
# Subset variables from the ‘data’ df using dplyr’s select function
df <- data %>% dplyr::select(SEQID, B_Q01a, GENDER_R, AGEG5LFS, NATIVELANG,
READHOME_WLE_CA, PVLIT1:PVLIT10, SPFWT0, SPFWT1:SPFWT80)
# PVLIT1:PVLIT10 include all PVs for literacy
colnames(df)                          # Reflect selected columns of interest
dim(df)                               # 6050 columns and 96 variables

########## 2. Select the focal adults for the study ##########
# Subset adults with non-post-secondary education levels (< ISCED 5A)
table(df$B_Q01a)

df <- subset(df, B_Q01a %in% c(‘No formal qualification or below ISCED 1’,
                               ‘ISCED 1’,
                               ‘ISCED 2’,
                               ‘ISCED 3A-B’,
                               ‘ISCED 4A-B’,
                               ‘ISCED 4 (without distinction A-B-C)’))

df$B_Q01a <- ifelse(df$B_Q01a == ‘No formal qualification or below ISCED
1’|df$B_Q01a == ‘ISCED 1’|df$B_Q01a == ‘ISCED 2’, ‘low’, ‘moderate’)
table(df$B_Q01a)

########## 3. Conduct Scaling for READHOME and Age variables ##########
summary(df$READHOME_WLE_CA)
str(df$READHOME_WLE_CA)
READHOME_WLE_CA.SCALED <- scale(df$READHOME_WLE_CA)
df <- cbind.data.frame(df, READHOME_WLE_CA.SCALED)
colnames(df)

summary(df$AGEG5LFS)
table(df$AGEG5LFS)
AGEG5LFS.SCALED <- scale(df$AGEG5LFS)
table(AGEG5LFS.SCALED)
summary(AGEG5LFS.SCALED)

df <- cbind.data.frame(df, AGEG5LFS.SCALED)
colnames(df)

########## 4. Use complete cases only ##########
dim(df)                                                         # 2421 rows
table(df$NATIVELANG)
summary(df$NATIVELANG)                                          # 580 NAs
df <- df[complete.cases(df), ]
```

```
dim(df)                                            # 1841 cases and 98 columns
colnames(df)
summary(df$NATIVELANG)

# predictor variable check
table(df$B_Q01a)                                   # 562   1279
table(df$GENDER_R)                                 # 778  1063
table(df$NATIVELANG)                               # 563   1305
table(df$AGEG5LFS.SCALED)                          # 214, 212, 192,...
summary(df$AGEG5LFS.SCALED)                        # mean: -0.01878
summary(df$READHOME_WLE_CA.SCALED)                 # mean: -0.03497

# DV variable check
apply(df[, c(7:16)], 2, FUN = function(x)mean(x))

#######################################################################
#                         D. RUN MODELS                               #
#######################################################################

########## 1. Check variables ##########
str(df$PVLIT1)
str(df$GENDER_R)
str(df$AGEG5LFS.SCALED)
str(df$NATIVELANG)
str(df$READHOME_WLE_CA.SCALED)

########## 2. Establish series of PVs to Generate Mean Coefficients ##########
which(colnames(df) == “PVLIT1”)
which(colnames(df) == “PVLIT10”)
pv.names <- colnames(df)[7:16]
print(pv.names)                          # the different PVs for each model

########## 3. Run model 10 times for The Average Overall Regression
Coefficients ##########
models <- lapply(pv.names, function(x){reg <-lm(df[,c(x)] ~ GENDER_R +
AGEG5LFS.SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                data = df,
                                weights = SPFWT0)
                                return(c(coef(reg)))
                                }
                       )

final_w <- t(as.data.frame(models))       # Transforms (t) the dataframe into
standard format
rownames(final_w) <- NULL                 # Removes non-useful row names

#### Extract mean Coefficients ####
mu_pvs <- apply(final_w, 2, FUN = function(x)mean(x))
print(mu_pvs)                             # These are the coefficients to be
presented in the final model (all PVs and final sample weight)
```

```
########### 4. Create Functions for Variance Due to Sampling and PVs
(imputations) ###########
colnames(df)
which(colnames(df) == "SPFWT1")
which(colnames(df) == "SPFWT80")
rw.names <- colnames(df)[18:97]
print(rw.names)

##### 4.1 Create Function for Imputation Variance #####
# data set or matrix with regression coefficients estimated with 10 pvs and
final weights
sigma.i <- function(fin.df, mu, M){res <- t(fin.df) - mu
                                   res <- t(res)^2
                                   res <- (M+1)/(M*(M - 1))*res
                                   res <- apply(res, 2, sum)
                                   return(res)
                                   }

##### 4.2 Create Function for Sampling Variance #####
sigma.s <- function(rep.df, pv.set, fin.df){res<-t(rep.df) - fin.df[pv.
set,c(1:ncol(rep.df))]
                                   res<-t(res)^2
                                   res<-apply(res, 2, sum)
                                   return(res)
                                    }

########### 5. Run Models 10 Times to Generate Variance Due to Imputations
(PVs) ############ We also calculate the 10 results for Welch-Satterthwaite DoF
formula for each PV

##### 5.1 Model for PV1 #####
pv1 <- lapply(rw.names, function(x){reg <- lm(PVLIT1 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                       )

pv1 <- t(as.data.frame(pv1))
rownames(pv1) <- NULL
sigma_pv1 <- sigma.s(rep.df=pv1, pv.set=1, fin.df=final_w)

#### DoF of Coef (Welch-Satterthwaite) ####
 # DoF_ws is Equation 4
# Create a function to apply to the PV2, PV3, etc...
x <- pv1                           # 80 jack-knife replicates with
y <- final_w[1,]

# Create the ws_df function:
ws_dof <- function(x, y){(df_v <- (apply(sweep(as.matrix(x), 2, y, "-")^2, 2,
function(x)sum(x))  )^2 ) /
```

```
                                   (apply(sweep(as.matrix(x), 2, y, “-”)^4, 2,
function(x)sum(x)) )
                                   }

pv1_dof <- ws_dof(x = pv1, final_w[1,])
print(pv1_dof)

##### 5.2 Model for PV2 #####
pv2 <- lapply(rw.names, function(x) {reg <- lm(PVLIT2 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                    data = df,
                                    weights = df[,c(x)])
                                    return(coef(reg))
                                    }
                        )

pv2 <- t(as.data.frame(pv2))
rownames(pv2) <- NULL
sigma_pv2 <- sigma.s(rep.df=pv2, pv.set=2, fin.df=final_w)

# DoF
pv2_dof <- ws_dof(x = pv2, final_w[2,])
print(pv2_dof)

##### 5.3 Model for PV3 #####
pv3 <- lapply(rw.names, function(x){reg <- lm(PVLIT3 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                     data = df,
                                     weights = df[,c(x)])
                                     return(coef(reg))
                                     }
                       )

pv3 <- t(as.data.frame(pv3))
rownames(pv3) <- NULL
sigma_pv3 <- sigma.s(rep.df=pv3, pv.set=3, fin.df=final_w)

# DoF
pv3_dof <- ws_dof(x = pv3, final_w[3,])

##### 5.4 Model for PV4 #####
pv4 <- lapply(rw.names, function(x){reg <- lm(PVLIT4 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                        )

pv4 <- t(as.data.frame(pv4))
rownames(pv4) <- NULL
sigma_pv4 <- sigma.s(rep.df=pv4, pv.set=4, fin.df=final_w)
```

```r
# DoF
pv4_dof <- ws_dof(x = pv4, final_w[4,])

#####5.5 Model for PV5 #####
pv5 <- lapply(rw.names, function(x){reg <- lm(PVLIT5 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                      )

pv5 <- t(as.data.frame(pv5))
rownames(pv5) <- NULL
sigma_pv5 <- sigma.s(rep.df=pv5, pv.set=5, fin.df=final_w)

# DoF
pv5_dof <- ws_dof(x = pv5, final_w[5,])

##### 5.6 Model for PV6 #####
pv6 <- lapply(rw.names, function(x){reg <- lm(PVLIT6 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                        )

pv6 <- t(as.data.frame(pv6))
rownames(pv6) <- NULL
sigma_pv6 <- sigma.s(rep.df=pv6, pv.set=6, fin.df=final_w)

# DoF
pv6_dof <- ws_dof(x = pv6, final_w[6,])

##### 5.7 Model for PV7 #####
pv7 <- lapply(rw.names, function(x){reg <- lm(PVLIT7 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                      )

pv7 <- t(as.data.frame(pv7))
rownames(pv7) <- NULL
sigma_pv7 <- sigma.s(rep.df=pv7, pv.set=7, fin.df=final_w)

# DoF
pv7_dof <- ws_dof(x = pv7, final_w[7,])
```

```
##### 5.8 Model for PV8 #####
pv8 <- lapply(rw.names, function(x){reg <- lm(PVLIT8 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                        )

pv8 <- t(as.data.frame(pv8))
rownames(pv8) <- NULL
sigma_pv8 <- sigma.s(rep.df=pv8, pv.set=8, fin.df=final_w)

# DoF
pv8_dof <- ws_dof(x = pv8, final_w[8,])

##### 5.9 Model for PV9 #####
pv9 <- lapply(rw.names, function(x){reg <- lm(PVLIT9 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                      )

pv9 <- t(as.data.frame(pv9))
rownames(pv9) <- NULL
sigma_pv9 <- sigma.s(rep.df=pv9, pv.set=9, fin.df=final_w)

# DoF
pv9_dof <- ws_dof(x = pv9, final_w[9,])

##### 5.10 Model for PV10 #####
pv10 <- lapply(rw.names, function(x){reg <- lm(PVLIT10 ~ GENDER_R + AGEG5LFS.
SCALED + NATIVELANG + B_Q01a + READHOME_WLE_CA.SCALED,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
               )

pv10 <- t(as.data.frame(pv10))
rownames(pv10) <- NULL
sigma_pv10 <- sigma.s(rep.df=pv10, pv.set=10, fin.df=final_w)

# DoF
pv10_dof <- ws_dof(x = pv10, final_w[10,])
```

```
########## 6. Calculate Variance (se) Due to Imputations (PVs) in Accordance
with Equation 1 ##########
sigma_imp <- sigma.i(final_w, mu_pvs, 10)   # mean coefficients for each PV ad

########## 7. Calculate Variance (se) Due to Sampling in Accordance with
Equation 2 ##########
pool.df <- rbind(sigma_pv1, sigma_pv2, sigma_pv3, sigma_pv4, sigma_pv5,
                 sigma_pv6, sigma_pv7, sigma_pv8, sigma_pv9, sigma_pv10)

sigma_final <- colMeans(pool.df)
print(sigma_final)

########## 8. Combine Variance (se) Due to Imputations and Sampling with
Equation 3 ##########
sigma_pv_sample <- sigma_imp + sigma_final             # Equation 3
print(sigma_pv_sample)                                 # Overall variance

s.e. <- sqrt(sigma_pv_sample)
print(s.e.)
# Final standard errors for the coefficients

########## 9. Calculation of t-values for Coefficients ##########
t.values <- mu_pvs/s.e.
print(t.values)                         # Final t-values for each coefficient

########## 10. Find Mean for DoF_sw for all PVs ##########
all_dof_sw <- rbind.data.frame(pv1_dof, pv2_dof, pv3_dof, pv4_dof, pv5_dof,
pv6_dof, pv7_dof, pv8_dof, pv9_dof, pv10_dof)
colnames(all_dof_sw) <- NULL
mu_dof_sw <- apply(all_dof_sw, 2, FUN = function(x)mean(x))
print(mu_dof_sw)

########## 11. Implement Johnson-Rust DoF Correction ##########
#### DoF Johnson-Rust Correction for DoF: DoF_jr function ####
jr_dof <- function(x){(3.16-(2.77/sqrt(length(rw.names))))*x}

# Apply function
dof_jr <- jr_dof(mu_dof_sw)
print(dof_jr)

########## 12. Calculate final adjusted p values for coefficients ##########
print(t.values)
print(dof_jr)

# Build function
p_final <- function(x, y){2*stats::pt(abs(x), y, lower.tail = F)}

# Run function
p_values <- p_final(x = t.values, y = dof_jr)
print(p_values)
```

```
########## 13. Calculate Coefficients and Associated Standard Errors
##########
reg.coef <- cbind(mu_pvs, s.e., t.values, dof_jr, p_values)
colnames(reg.coef) <- c(“Coefficients”, “se”, “t”, “DoF”,”p”)
print(reg.coef)
## END Base R Calculation of the results!
```

6.4 Plausible Values as Independent Variables (using base R code)

As mentioned, this section is devoted to describing how to conduct regression-based analysis when the plausible values are defined as the independent variable in the model. This analysis uses the same variables as section 6.2.2. Therefore, the analyst may use steps A (READING IN AND PREPARING THE DATA), B (DATA PREPARATION), and C (DATA MANIPULATION) in section 6.2.2 prior to undertaking this example analysis.

```
#######################################################################
#                               D. RUN MODELS                         #
#######################################################################

########## 1. Check variables ##########
str(df$PVLIT1)
str(df$GENDER_R)
str(df$AGEG5LFS.SCALED)
str(df$NATIVELANG)
str(df$READHOME_WLE_CA.SCALED)

########## 2. Establish series of PVs to Generate Mean Coefficients ##########
which(colnames(df) == “PVLIT1”)
which(colnames(df) == “PVLIT10”)
pv.names <- colnames(df)[7:16]
print(pv.names)                        # the different PVs for each model

########## 3. Run model 10 times for The Average Overall Regression
Coefficients ##########
models <- lapply(pv.names, function(x){reg <-lm(READHOME_WLE_CA.SCALED ~
df[,c(x)] + GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                   data = df,
                                   weights = SPFWT0)
                                   return(c(coef(reg)))
                                   }
                           )

final_w <- t(as.data.frame(models))          # Transforms (t) the dataframe
into standard format
rownames(final_w) <- NULL                    # Removes non-useful row names
print(final_w)                               # Coefficients for each PV

#### Extract mean Coefficients ####
mu_pvs <- apply(final_w, 2, FUN = function(x)mean(x))
```

```
print(mu_pvs)

##########  4. Create Functions for Variance Due to Sampling and PVs
(imputations) ##########
colnames(df)
which(colnames(df) == “SPFWT1”)
which(colnames(df) == “SPFWT80”)
rw.names <- colnames(df)[18:97]
print(rw.names)

##### 4.1 Create Function for Imputation Variance #####
# data set or matrix with regression coefficients estimated with 10 pvs and
final weights
sigma.i <- function(fin.df, mu, M){res <- t(fin.df) - mu
                                    res <- t(res)^2
                                    res <- (M+1)/(M*(M - 1))*res
                                    res <- apply(res, 2, sum)
                                    return(res)
                                    }

##### 4.2 Create Function for Sampling Variance #####
sigma.s <- function(rep.df, pv.set, fin.df){res<-t(rep.df) - fin.df[pv.
set,c(1:ncol(rep.df))]
                                    res<-t(res)^2
                                    res<-apply(res, 2, sum)
                                    return(res)
                                    }

########## 5. Run Models 10 Times to Generate Variance Due to Imputations
(PVs) ##########  #We also calculate the 10 results for Welch-Satterthwaite
DoF formula for each PV#

##### 5.1 Model for PV1 #####
pv1 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT1
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                     data = df,
                                     weights = df[,c(x)])
                                     return(coef(reg))
                                     }
                        )

pv1 <- t(as.data.frame(pv1))
rownames(pv1) <- NULL
print(pv1)                        # Coefficients using PV1 and each of the 80
jk replicates
sigma_pv1 <- sigma.s(rep.df=pv1, pv.set=1, fin.df=final_w)
# Variance (error) due to sampling from PV1 (right side of Eq 2)

#### DoF of Coef (Welch-Satterthwaite) ####             # DoF_ws is Equation 4
# Create a function to apply to the PV2, PV3, etc...
x <- pv1
y <- final_w[1,]
```

```
# Create the ws_df function:
ws_dof <- function(x, y){(df_v <- (apply(sweep(as.matrix(x), 2, y, “-”)^2, 2,
function(x)sum(x))  )^2 ) /        (apply(sweep(as.matrix(x), 2, y, “-”)^4, 2,
function(x)sum(x)) )
                                           }

pv1_dof <- ws_dof(x = pv1, final_w[1,])
print(pv1_dof)

##### 5.2 Model for PV2 #####
pv2 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT2
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                     data = df,
                                     weights = df[,c(x)])
                                     return(coef(reg))
                                     }
                        )

pv2 <- t(as.data.frame(pv2))
rownames(pv2) <- NULL
sigma_pv2 <- sigma.s(rep.df=pv2, pv.set=2, fin.df=final_w)

# DoF
pv2_dof <- ws_dof(x = pv2, final_w[2,])

##### 5.3 Model for PV3 #####
pv3 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT3
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                      data = df,
                                      weights = df[,c(x)])
                                      return(coef(reg))
                                      }
                        )

pv3 <- t(as.data.frame(pv3))
rownames(pv3) <- NULL
sigma_pv3 <- sigma.s(rep.df=pv3, pv.set=3, fin.df=final_w)

# DoF
pv3_dof <- ws_dof(x = pv3, final_w[3,])

##### 5.4 Model for PV4 #####
pv4 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT4
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                    data = df,
                                    weights = df[,c(x)])
                                    return(coef(reg))
                                    }
                           )

pv4 <- t(as.data.frame(pv4))
```

```
rownames(pv4) <- NULL
sigma_pv4 <- sigma.s(rep.df=pv4, pv.set=4, fin.df=final_w)

# DoF
pv4_dof <- ws_dof(x = pv4, final_w[4,])

##### 5.5 Model for PV5 #####
pv5 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT5
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                    data = df,
                                    weights = df[,c(x)])
                                    return(coef(reg))
                                    }
                           )

pv5 <- t(as.data.frame(pv5))
rownames(pv5) <- NULL
sigma_pv5 <- sigma.s(rep.df=pv5, pv.set=5, fin.df=final_w)

# DoF
pv5_dof <- ws_dof(x = pv5, final_w[5,])

##### 5.6 Model for PV6 #####
pv6 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT6
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                    data = df,
                                    weights = df[,c(x)])
                                    return(coef(reg))
                                    }
                        )

pv6 <- t(as.data.frame(pv6))
rownames(pv6) <- NULL
sigma_pv6 <- sigma.s(rep.df=pv6, pv.set=6, fin.df=final_w)

# DoF
pv6_dof <- ws_dof(x = pv6, final_w[6,])

##### 5.7 Model for PV7 #####
pv7 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT7
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                         )

pv7 <- t(as.data.frame(pv7))
rownames(pv7) <- NULL
sigma_pv7 <- sigma.s(rep.df=pv7, pv.set=7, fin.df=final_w)

# DoF
```

```
pv7_dof <- ws_dof(x = pv7, final_w[7,])

##### 5.8 Model for PV8 #####
pv8 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT8
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                        )

pv8 <- t(as.data.frame(pv8))
rownames(pv8) <- NULL
sigma_pv8 <- sigma.s(rep.df=pv8, pv.set=8, fin.df=final_w)

# DoF
pv8_dof <- ws_dof(x = pv8, final_w[8,])

##### 5.9 Model for PV9 #####
pv9 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~ PVLIT9
+ GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                        )

pv9 <- t(as.data.frame(pv9))
rownames(pv9) <- NULL
sigma_pv9 <- sigma.s(rep.df=pv9, pv.set=9, fin.df=final_w)

# DoF
pv9_dof <- ws_dof(x = pv9, final_w[9,])

##### 5.10 Model for PV10 #####
pv10 <- lapply(rw.names, function(x){reg <- lm(READHOME_WLE_CA.SCALED ~
PVLIT10 + GENDER_R + AGEG5LFS.SCALED + NATIVELANG + B_Q01a,
                                   data = df,
                                   weights = df[,c(x)])
                                   return(coef(reg))
                                   }
                       )

pv10 <- t(as.data.frame(pv10))
rownames(pv10) <- NULL
sigma_pv10 <- sigma.s(rep.df=pv10, pv.set=10, fin.df=final_w)

# DoF
pv10_dof <- ws_dof(x = pv10, final_w[10,])

########## 6. Calculate Variance (se) Due to Imputations (PVs) in Accordance
with Equation 1 ##########
```

```
sigma_imp <- sigma.i(final_w, mu_pvs, 10)          # mean coefficients for
each PV ad

########## 7. Calculate Variance (se) Due to Sampling in Accordance with
Equation 2 ##########
pool.df <- rbind(sigma_pv1, sigma_pv2, sigma_pv3, sigma_pv4, sigma_pv5,
sigma_pv6, sigma_pv7, sigma_pv8, sigma_pv9, sigma_pv10)

sigma_final <- colMeans(pool.df)
print(sigma_final)

########## 8. Combine Variance (se) Due to Imputations and Sampling with
Equation 3 ##########
sigma_pv_sample <- sigma_imp + sigma_final             # Equation 3
print(sigma_pv_sample)                                 # Overall variance

s.e. <- sqrt(sigma_pv_sample)
print(s.e.)                           # Final standard errors for the coefficients

########## 9. Calculation of t-values for Coefficients ##########
t.values <- mu_pvs/s.e.
print(t.values)                       # Final t-values for each coefficient

########## 10. Find Mean for DoF_sw for all PVs ##########
all_dof_sw <- rbind.data.frame(pv1_dof, pv2_dof, pv3_dof, pv4_dof, pv5_dof,
pv6_dof, pv7_dof, pv8_dof, pv9_dof, pv10_dof)
colnames(all_dof_sw) <- NULL
mu_dof_sw <- apply(all_dof_sw, 2, FUN = function(x)mean(x))
print(mu_dof_sw)

########## 11. Implement Johnson-Rust DoF Correction ##########
#### DoF Johnson-Rust Correction for DoF: DoF_jr function ####
jr_dof <- function(x){(3.16-(2.77/sqrt(length(rw.names))))*x}

# Apply function
dof_jr <- jr_dof(mu_dof_sw)
print(dof_jr)

########## 12. Calculate final adjusted p values for coefficients ##########
print(t.values)
print(dof_jr)

# Build function
p_final <- function(x, y){2*stats::pt(abs(x), y, lower.tail = F)}

# Run function
p_values <- p_final(x = t.values, y = dof_jr)
print(p_values)
```

```
########## 13. Calculate Coefficients and Associated Standard Errors
##########
reg.coef <- cbind(mu_pvs, s.e., t.values, dof_jr, p_values)
colnames(reg.coef) <- c("Coefficients", "se", "t", "DoF","p")
rownames(reg.coef)[2] <- "Lit"
print(reg.coef)
```

6.5 Conclusion

This chapter has provided details as to how to conduct multiple regression analysis of PIAAC data predominantly with base R. While the first section provided details as to how to do the analysis using the EdSurvey package, the second section replicates this analysis using base R (well, truth-be-told, we did make use of a few commonly used packages actually!). Finally, our third section provides details as to how to conduct regression analysis when the PVs are independent variables in the model. We provide details as to how exactly the variables were prepared prior to analysis, a key part of statistical modelling of any data. We would also like to note that our code can also be adapted. For example, for the final example where the PV was an IV in the model, the education level could be specified as a dependent variable in the model by changing the main model statement and the model family (i.e., logit/probit). As a final note, we would like to acknowledge all the authors of the open-source R packages that we have used to make this chapter possible.

6.6 References

Bailey, P., Emad, A., Huo, H., Lee, M., Liao, Y., Lishinski, A., ... & Bailey, M. P. (2023). *EdSurvey: Analysis of NCES Education Survey and Assessment Data*. R package version 3.0.1. https://CRAN.R-project.org/package=EdSurvey

Bock, R. D., & Aitkin, M. (1981). Marginal maximum likelihood estimation of item parameters: Application of an EM algorithm. *Psychometrika*, 46, 443 59.

Courtney, M.G.R & Nurumov, K. (2023a). *PIAAC Data Analyses: Examples using R. Online Tutorial, Video 2a - Descriptive Analyses*. GESIS –Leibniz Institute for the Social Sciences, Mannheim. Available at https://www.youtube.com/playlist?list=PLv4AV-dc1b8WKKheCn7IUTLBeJ4TrwCfr.

Courtney, M.G.R & Nurumov, K. (2023b). *PIAAC Data Analyses: Examples using R. Online Tutorial, Video 2b - Regression-based Analysis using R*: Plausible Values as Dependent Variable. GESIS –Leibniz Institute for the Social Sciences, Mannheim. Available at https://www.youtube.com/playlist?list=PLv4AV-dc1b8WKKheCn7IUTLBeJ4TrwCfr.

Courtney, M.G.R & Nurumov, K. (2023c). *PIAAC Data Analyses: Examples using R. Online Tutorial, Video 2c - Regression-based Analysis using R*: Plausible Values as Independent Variable. GESIS –Leibniz Institute for the Social Sciences, Mannheim. Available at https://www.youtube.com/playlist?list=PLv4AV-dc1b8WKKheCn7IUTLBeJ4TrwCfr.

Johnson, E. G., & Rust, K. F. (1992). Population inferences and variance estimation for NAEP data. *Journal of Education Statistics*, 17(2), 175–190.

Organisation for Economic Cooperation and Development (OECD). (2019). *Technical Report of the Survey of Adult Skills*, 3rd Ed. (PIAAC). OECD.

Organisation for Economic Cooperation and Development (OECD). (2016). *Programme for the International Assessment of Adult Competencies (PIAAC), Kazakhstan Public Use File* [Version: 20450859, prgkazp1.sav]. OECD Publishing.

Rubin, D. (1987). *Multiple imputation for non-response in surveys*. New York: John Wiley & Sons.

Satterthwaite, F. E. (1946). An approximate distribution of estimates of variance components. *Biometrics Bulletin*, 2, 110–114.

Welch, B. L. (1947). The generalization of ‘student’s’ problem when several different population variances are involved. *Biometrika*, 34, 28–35.

SPONSORED BY THE

Federal Ministry
of Education
and Research

gesis
Leibniz Institute
for the Social Sciences