



UiO • University of Oslo

# Identifying School Climate Variables Associated with Financial Literacy Outcomes in PISA 2018 Data

*A Multilevel Structural Equation Modelling  
Approach*

Tony C. A. Tan

Master of Science (Assessment, Measurement and Evaluation)  
30 credits

Centre for Educational Measurement  
Faculty of Educational Sciences

Spring 2021



# Identifying School Climate Variables Associated with Financial Literacy Outcomes in PISA 2018 Data

*A Multilevel Structural Equation Modelling  
Approach*

Tony C. A. Tan

© 2021 Tony C. A. Tan

Identifying School Climate Variables Associated with Financial Literacy Outcomes in PISA  
2018 Data

<http://www.duo.uio.no/>

Printed: Reprosentralen, University of Oslo

# 敬致父母

To my parents

*Study hard what interests you the most in the  
most undisciplined, irreverent and original manner  
possible.*

*Richard P. Feynman*

# Contents

<b>Contents</b>	<b>i</b>
<b>List of Tables</b>	<b>iii</b>
<b>List of Figures</b>	<b>v</b>
<b>1 Introduction</b>	<b>1</b>
<b>2 Conceptual Framework</b>	<b>5</b>
2.1 In-depth definitions of “financial literacy”	5
2.1.1 Every term my readers need in order to understand my research question	5
2.1.2 Survey not only PISA but also alternative definitions, even critiques of such definitions	5
2.1.3 Any practices that are common in maths/literature but uncommon in financial literacy? Meaning? Implies?	5
2.2 Country-level Financial Knowledge Index	6
<b>3 Methods</b>	<b>11</b>
3.1 Sample	11
3.2 Measures	11
3.2.1 School Climate Variables	11
3.2.2 Financial Literacy Measures	12
3.2.3 Multilevel Latent Covariate Approach to School-level Aggregation	12
3.2.4 Control Variables	12
3.3 Model	13
3.4 Missing Data Treatment	14
3.5 Analysis	14
3.5.1 Weights	14
3.5.2 Plausible Values and Rubin’s Rule	15
3.6 Estimators	15
3.7 Model Comparison	15
<b>4 Results</b>	<b>17</b>
4.1 Descriptive statistics	17
4.2 Correlation matrices	19
4.2.1 Across countries	19
4.2.2 Across levels: Country   School   Students	19
4.3 Examination of measurement models	19
4.4 Address the research question	22
<b>5 Discussion</b>	<b>27</b>
5.1 Brief summary	27
5.1.1 Remind readers what my research questions are	27
5.2 The implication of this study	27
5.3 Limitation and future directions	27
5.3.1 Word in positive form	27
5.4 Bird-eye view	27
5.4.1 What conclusion I can draw from this paper/study	27

<b>Appendices</b>	<b>33</b>
<b>A GDPR Documentation and Ethical Approval</b>	<b>35</b>
<b>B Analysis Code, Additional Tables and Figures</b>	<b>39</b>
B.1 Chapter 1 Introduction . . . . .	39
B.2 Chapter 2 Conceptual Framework . . . . .	39
B.3 Chapter 3 Method . . . . .	39
B.3.1 Data Merging . . . . .	39
<b>C Multilevel Multiple Imputation</b>	<b>43</b>
C.1 Mplus Input Code . . . . .	43
C.2 Selected Mplus Output . . . . .	44
C.3 Diagnostic Plots . . . . .	45



# List of Tables

2.1 Percentages of Missing Values . . . . .	7
3.1 Summary of Measures and Variables . . . . .	12
4.1 Descriptive Statistics . . . . .	18
4.2 Model Parameters and Fit Indices for Multilevel Regressions . . . . .	20
B.1 Summary of Participating Countries . . . . .	41
B.2 Scale Reliabilities (Cronbach's alphas) and Item Parameter References for Derived Variables based on IRT Scaling . . . . .	42
C.1 Summary of Diagnostic Plots of Multilevel Multiple Imputation . . . . .	46



# List of Figures

2.1	Path Diagram . . . . .	8
2.2	Path Diagram . . . . .	9
2.3	Path Diagram . . . . .	10
4.1	Total, Direct and Indirect Effects of School Intervention (FLSCHOOL) . . . . .	23
4.2	Total, Direct and Indirect Effects of Financial Socialisation (FLFAMILY) . . . . .	24
4.3	School-Family Effect Decomposition by Country . . . . .	25



# Acknowledgement

Thank-you goes to



# Popular Abstract

Preparing youth for life-long success with numeracy, literacy and science capability has been the foundation for all schooling. The post-global financial crises and post-COVID era, in addition, imposes increasing demand on financial literacy for school leavers. Since 2012, OECD has been a pioneer in measuring 15-year-olds' financial literacy through its triennial Programme for International Student Assessment (PISA) cycles. Subsequent analyses using PISA data, however, reported paradoxical results that more classroom interventions tend to be associated with either no differences or even lower scores in students' financial literacy measures. It is in educators' interest therefore to carefully examine the relationship between school climate variables, including the academic, safety, community and institutional environment aspects of students' lives, and their financial literacy outcomes.

[Project summary]

The motivation for this project originates from my confusion over the current stock of literature, which states that school efforts do not matter, even harmful, in bringing about students' financial literacy while homes are better suited for this purpose. This claim is worrisome because if school are committing something wrong, school leaders and policy makers genuinely want to know what, which and where so that harmful pedagogies can be reverted into good practices. Alternatively, it could also be the measurement instrument researchers employed so far that led to such underwhelming results. A closer examination of how school effectiveness is measured would also promote research practice and the resultant policy advice.

Using 2018 PISA financial literacy data, including all 20 participating countries, I was able to examine how school climate variables, namely ACADEMIC, SAFETY, COMMUNITY and INSTITUTIONAL ENVIRONMENT each explained the total variation in students' financial literacy outcomes. Using a multilevel SEM with students' finance-related affective variables as mediators, my random intercept model shows that schools' academic practices do matter in advancing students' financial literacy outcomes but only through affective pathways. Cognitive pathways, however, were shown to correlate negatively with financial literacy scores. Since schools' cognitive and affective pathways are similar in size but opposite in signs, combining the two into total effects would have inadvertently resulted in the nonfindings as reported

by prior literature. In addition to this methodological insight, countries that overly focused on accountability through standard testing, tracking and measuring students' financial skills (e.g., the USA) fell prey to this cognitive trap while countries that placed more emphases on cultivating students' affective affinity such as confidence in, and familiarity with, financial matters (e.g., Finland) delivered impressive education outcome in financial literacy.



# Abstract

Repeated economic crises in recent memory have exposed the harsh consequences of financial *illiteracy* shared by high proportions of the general population. Policy makers experienced little resistance when identifying youth as the most effective group for bringing about improvement in citizens' ability to engage with economic and financial matters, but opinions quickly diverge over the optimal approaches for achieving such targeted outcome. Existing literature frequently reports the importance of family environment in cultivating students' financial literacy through the process of "financial socialisation" – [definition goes here] (reference). Such practice, however, encounters interrogation by educators over equity concerns should families remain the main arena for financial literacy development. Schools play vital roles in alleviating inequality in accessing education and training in general but scarce research so far has been devoted into identifying the specific classroom factors that are most effective in advancing students' financial literacy outcomes. The current study therefore attempts to contribute to this enquiry by investigating the relationship between school climate variables and students' financial literacy achievement with an aim of stimulating policy debate about the levers and instruments available to education interventionists for the purpose of improving young people's financial literacy and preparedness as they step into an increasingly uncertain world. Using the 2018 PISA dataset, this paper employs a three-level hierarchical model to conduct cross-country comparisons to highlight school climate variables that are most strongly associated with high financial literacy outcomes.



# Chapter 1 Introduction

Repeated economic crises in recent memory have exposed the harsh consequences of financial *illiteracy* shared by high proportions of the general population. Low levels of financial literacy are observed not only in less developed countries such as India and Indonesia (Cole et al., 2009) but also in advanced economies such as the USA (Huston, 2012), Germany (Bucher-Koenen et al., 2017) and OECD countries (Lusardi, 2015). Amongst the many redress schemes aimed at promoting citizens' financial capability, the return on investment is the highest when intervention is applied early in life. Lusardi and Mitchell (2014) have shown that providing financial knowledge to the least educated before they enter the labour market increases their well-being by approximately 82% of their initial wealth, while the rate of return is around 56% for college graduates—results that are significant both statistically and economically.

Research efforts aiming at advancing youth's financial literacy over the years evolved into two strands: on the design and evaluation of school financial education programs, and on the influence of home environment through the process of financial socialisation—the intentional or involuntary transmission of financial concepts which are required to functioning successfully in society (Bowen, 2002). A recent meta-analysis conducted by Kaiser and Menkhoff (2020) found that while school financial education programs had sizeable impacts on *financial knowledge* (+0.33 *SD*) similar to education interventions in other domains, their effect on students' *financial behaviour* is quite small (+0.07 *SD*). This conclusion added to a list of weak or non-findings regarding the long-term behavioural effect brought about by school financial education programs. Brown et al. (2016), for instance, reported mixed outcome in students' long-term financial well-being depending on the programs received; whereas Cole et al. (2016) observed that traditional personal finance courses lacked any explanatory power in accounting for graduates' financial outcome once the additional mathematics training in which finance topics were packaged has been controlled for. Despite careful controls and thoughtful study designs, correlating classroom interventions and young people's financial literacy outcomes has repeatedly yielded paradoxical results of non-significant or even negative relationship; any positive findings remain small in magnitudes and/or are sensitive to robust analyses.

Optimism, fortunately, runs higher at the financial socialisation camp. Building on the

acknowledgement that families serve as information filters from the outside world (Danes & Haberman, 2007) as well as the foundation for youth's continued financial concept formation, Gudmunson and Danes (2011) put forward a family financial socialisation theory to accommodate both the *process* and the *outcome* for variations in young people's financial capabilities. Using structural equation modelling, Jorgensen and Savla (2010) was able to show that perceived parental influence had a direct and moderately significant influence on financial attitude, did *not* have an effect on *financial knowledge*, and had an indirect and moderately significant influence on financial behaviour, mediated through financial attitude. This attitude(A)–behaviour(B)–cognition(C) conceptualisation of financial literacy (Potrich et al., 2015) continues to influence subsequent research effort. More recently, Moreno-Herrero et al. (2018) continued this line of enquiry by applying multilevel regression analyses to 2015 PISA data and reported that students' financial literacy was associated mainly with understanding the value of saving and discussing money matters with parents. In addition, exposure and use of financial products, in particular holding a bank account, improved students' financial knowledge as well.

One chief concern for every research project is the quality of its data source. Amongst competing inventories, PISA stands out as a comprehensive and reliable source of data for measuring 15-year-olds' financial literacy outcomes thanks to OECD's careful sampling procedure and attention to construct validity of measurement. Four technical features of PISA are crucial for the architecture of this study. First, following statistical theory, PISA designers acknowledged the hierarchical nature of education research data such that students are nested in schools, and schools are further nested in countries. Second, one student weight is assigned to each observation in order to account for the fact that not all schools in a country are equally likely to be sampled by the PISA organiser; and given a particular school that has been chosen, not every student in this school is equally likely to be asked to participate in the test (Rust, 2014). A third complication arises from the "planned missingness" in students' responses because each participant is only given a small number of questions relative to the entire test bank in order to ensure their responses are not undermined by tiredness (von Davier, 2014), leading to the outcome variables being represented by ten plausible values. Fourthly, PISA consulted and synthesised multiple schools of thoughts (OECD, 2019a) before constructing financial literacy as

the knowledge and understanding of financial concepts and risks, and the skills, motivation and confidence to apply such knowledge and understanding in order

to make effective decisions across a range of financial contexts, to improve the financial well-being of individuals and society, and to enable participation in economic life. (p. 128)

As a result, 2018 PISA data set (OECD, [2020a](#)) provides not only variables measuring *cognitive* outcomes but also *affective* factors such as familiarity with concepts of finance and confidence about financial matters, enabling a nuanced study design involving decomposing the total effect of financial literacy development into its “brain” (cognitive) and “heart” (affective) pathways.

The current study wishes to take advantage of the latest wave of 2018 PISA results and investigate the covariation financial literacy outcomes share with the following four aspects of young people’s daily lives, inspired by school climate literature (Wang & Degol, [2016](#)):

(a) academic training, including any financial education programs received at schools; (b) safety perception about their schools; (c) financial socialisation experienced at home; and (d) their schools’ resource endowment. More specifically, this project aims to answer these two research questions:

- RQ1. To what extent can the variation in students’ financial literacy outcomes be accounted for by each of the school climate variables?
- RQ2. How do cognitive and affective pathways interact during classroom financial literacy interventions?



# Chapter 2 Conceptual Framework

## 2.1 In-depth definitions of “financial literacy”

2.1.1 Every term my readers need in order to understand my research question

2.1.2 Survey not only PISA but also alternative definitions, even critiques of such definitions

2.1.3 Any practices that are common in maths/literature but uncommon in financial literacy? Meaning? Implies?

## 2.2 Country-level Financial Knowledge Index

PISA 2018 financial literacy dataset (OECD, 2020a) provides rich information about students and schools. For the purpose of cross-country comparison, however, the country-level financial literacy information must be addressed separately by the researchers. Earlier attempts such as Moreno-Herrero et al. (2018) approximated this information using a variable “quality of math and science education” to control for country-level differences since consensus is yet to emerge about the most appropriate measure for countries’ financial knowledge. Inspired by the UN’s approach to forming Human Development Indices, a recent publication by Oliver-Márquez et al. (2020) proposed a macroeconomic measure for countries’ general financial knowledge levels by examining their economic capability, educational training, existing practices in the financial markets as well as incentives to interact with financial products. More specifically, the authors considered a country’s economic capability, represented by its GDP per capita, to be a key dimension in bringing about its financial knowledge index (FKI). Secondly, literature converges on the importance of educational training for a country’s financial knowledge capability (OECD, 2005). Thirdly, countries with regular engagement with sophisticated financial products and financial markets should possess higher FKI. Lastly, countries with higher aggregate consumption levels and with ageing populations are likely to possess higher FKI due to more frequent exposure and pressure in retirement provision, respectively. Macroeconomic data needed for these computations can be sourced from the World Bank (World Bank, 2020) and the United Nations’ *Human Development Reports* (United Nations, 2020).

Combining individual and institutional data sources can be a productive approach in international large-scale assessment (ILSA) research. According to the framework for comparative education analyses (Bray & Thomas, 1995), this project extends education outcome measures to a country level, addresses the aspect of society and labour market, and relates countries’ entire populations to ILSA research (Strietholt & Scherer, 2018). By combining education outcome data with countries’ economic performance indicators, this project remains most comparable to Hanushek and Woessmann (2012)—while these authors looked into the relationship between countries’ education achievement and their GDP growth, the current investigation highlights how countries’ GDP, along with other macroeconomic practices, in turn systematically impacts on their youth’s educational performance.



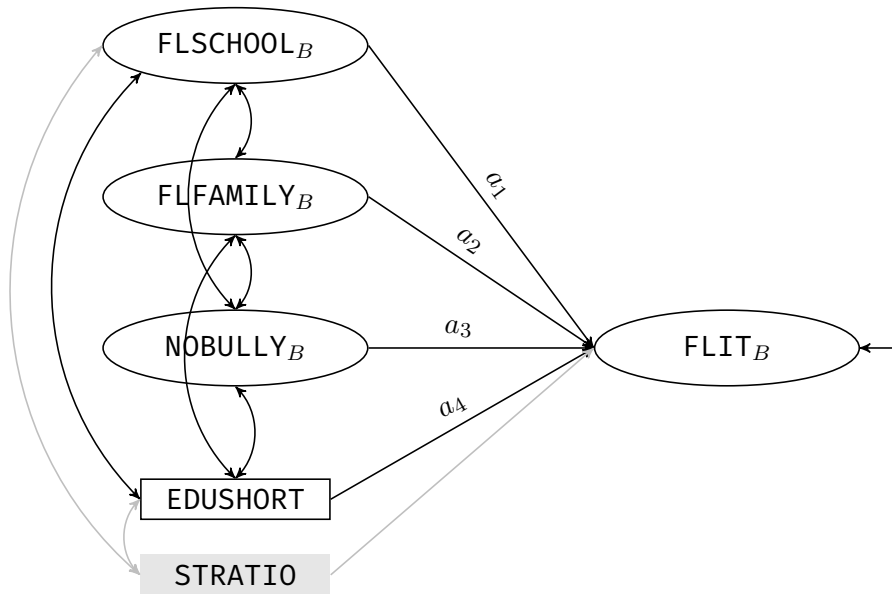
**Table 2.1**  
*Percentages of Missing Values*

CNT	MALE	IMMI1GEN	IMMI2GEN	ESCS	FCFMLRTY	FLCONFIN	PERFEED	TEACHINT	FLSCH00L	DISCRIM <sup>†</sup>	BELONG	BULLY	FLFAMILY	CURSUPP <sup>†</sup>	PASCHPOL <sup>†</sup>	STRATIO	EDUSHT	STAFFSHT
BGR	0	6	6	3	12	27	10	10	21	28	19	31	22	100	100	8	3	3
BRA	0	5	5	2	12	34	9	8	21	36	23	40	24	17	19	12	6	7
CAN <sup>†</sup>	0	7	7	5	11	15	100	100	13	100	8	14	14	100	100	100	2	2
CHL	0	4	4	3	10	24	5	4	13	30	15	34	15	9	8	18	9	9
ESP	0	3	3	2	5	21	3	2	7	25	9	29	8	100	100	11	5	6
EST	0	3	3	3	4	8	3	3	6	9	5	11	6	100	100	0	0	0
FIN	0	2	2	2	4	10	3	3	6	100	6	11	7	100	100	2	7	7
GEO	0	5	5	2	9	26	9	9	17	100	15	22	21	4	5	1	2	2
IDN	0	3	3	1	3	6	3	2	5	3	2	5	5	100	100	23	14	14
ITA	0	4	4	3	7	17	4	4	10	23	10	27	12	16	17	9	3	3
LTU	0	3	3	3	4	12	3	3	5	17	8	20	7	100	100	0	0	0
LVA	0	2	2	2	5	9	3	3	6	14	6	15	7	100	100	6	3	4
NLD	0	3	3	2	3	5	3	2	4	100	4	8	4	100	100	11	5	5
PER	0	2	2	1	2	11	5	4	4	56	31	65	5	100	100	2	0	0
POL	0	1	1	1	3	7	2	1	5	9	3	11	5	100	100	0	0	0
PRT	0	6	6	5	8	11	6	6	10	15	8	17	10	10	10	11	1	1
RUS	0	3	3	2	8	13	5	4	11	13	8	15	11	100	100	3	3	3
SRB	0	3	3	1	10	25	8	7	18	25	15	27	19	100	100	8	1	1
SVK	0	2	2	1	4	12	4	3	7	14	6	17	8	100	100	6	6	7
USA	0	3	3	2	3	6	2	1	4	100	4	6	4	100	100	16	10	10

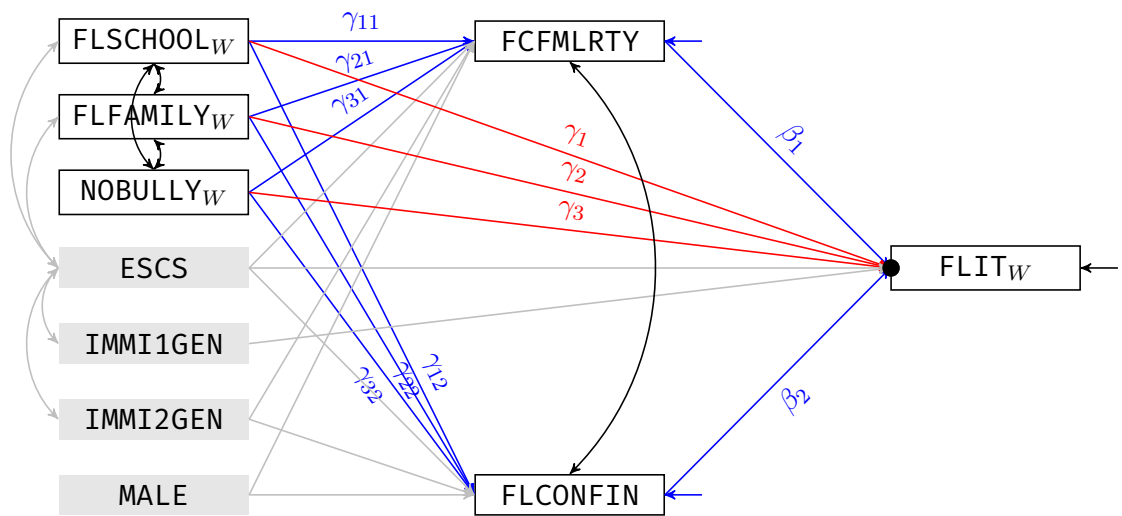
*Note.* Using shades of red in addition to numbers (measured in %), this table visualises the missing percentages by variable and by country. Variables **DISCRIM**, **CURSUPP** and **PASCHPOL** are no longer pursued in the model because too many countries chose not to respond to these questions. Canada (CAN) is not included due to 100 percent missings on multiple variables. <sup>†</sup> marks the country and variables that are excluded from subsequent analyses.

**Figure 2.1**  
Path Diagram

**L2: School**



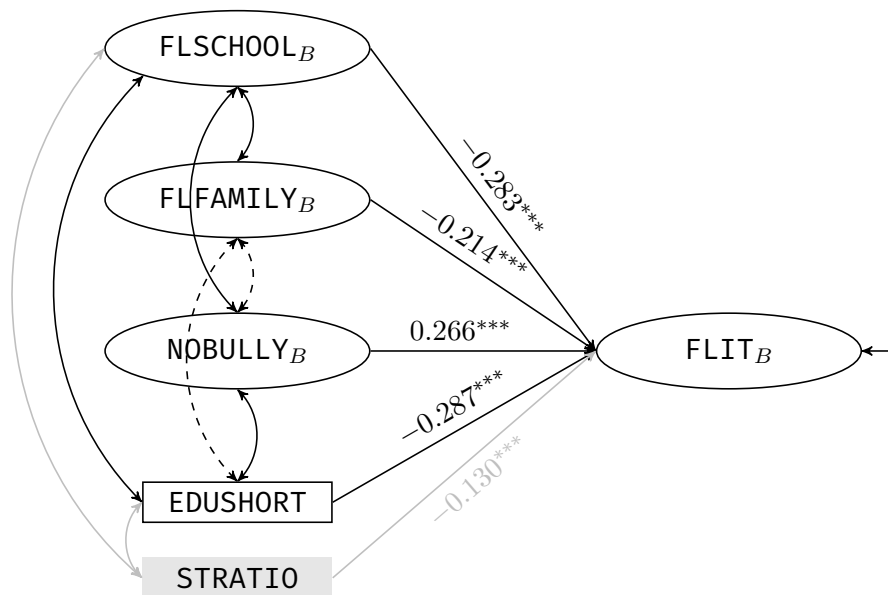
**L1: Student**



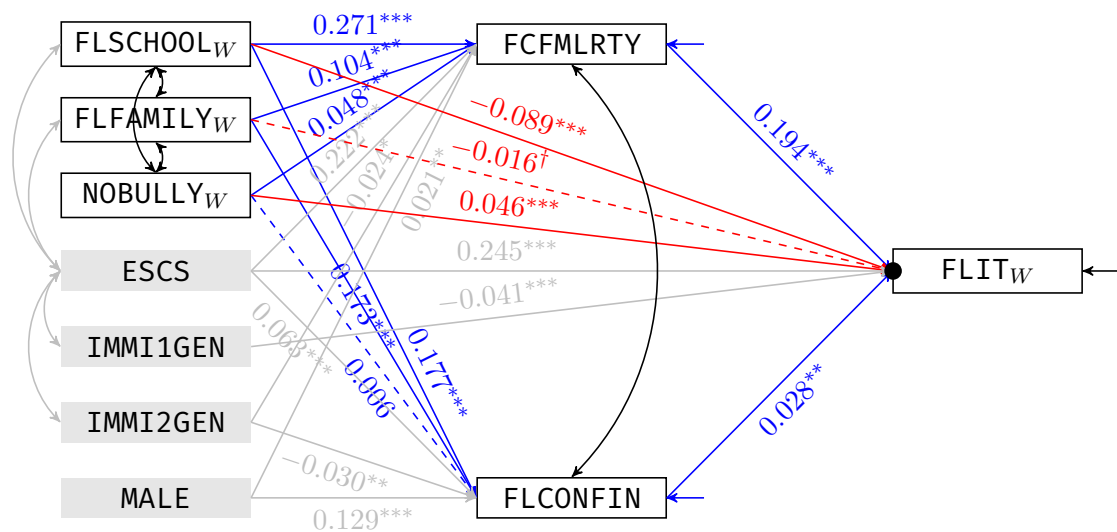
Note. [Insert notes here.]

**Figure 2.2**  
Path Diagram

**L2: School**



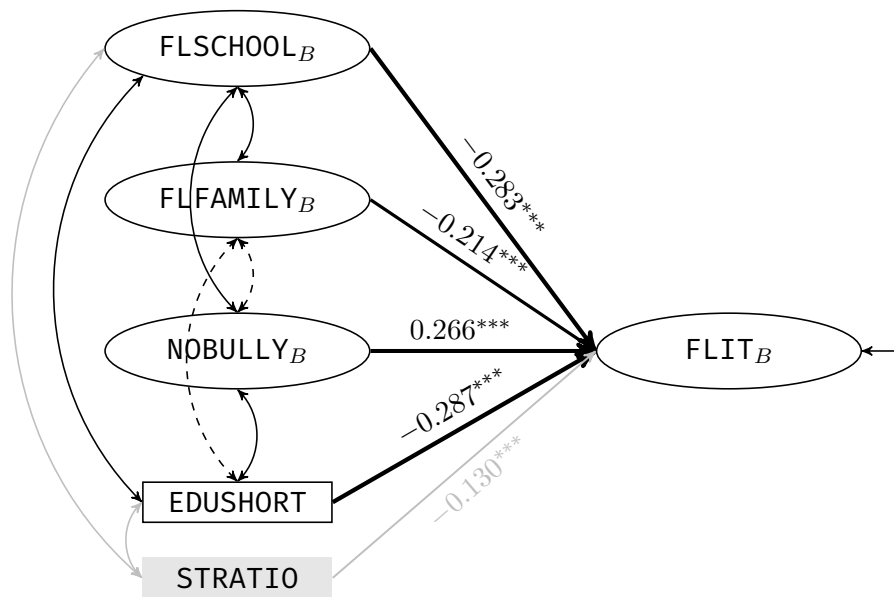
**L1: Student**



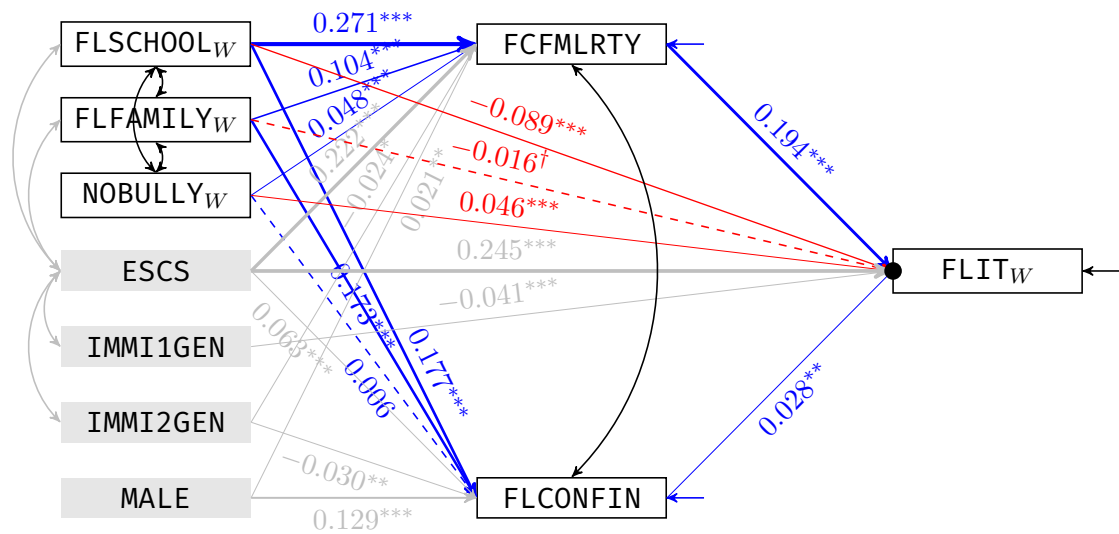
Note. [Insert notes here.]

**Figure 2.3**  
Path Diagram

**L2: School**



**L1: Student**



Note. [Insert notes here.]

# Chapter 3 Methods

## 3.1 Sample

This study drew its primary data source from OECD’s PISA 2018 database. Responses from both student (OECD, 2020a) and school questionnaires (OECD, 2020c) were captured and merged into a master data file using R’s (Version 4.0.5, R Core Team, 2021) `intsvy` package (Version 2.5, Caro & Biecek, 2017) (see Section B.3.1 for analysis code), covering the following 20 participating countries<sup>1</sup>: Brazil, Bulgaria, Canada, Chile, Estonia, Finland, Georgia, Indonesia, Italy, Latvia, Lithuania, the Netherlands, Peru, Poland, Portugal, Russian Federation<sup>2</sup>, Serbia, Slovak Republic, Spain, and the USA. Due to clerical error concerns, twelve observations without school weights were dropped, leading to a sample size of 107162 students nested in 6631 schools (see Table B.1 for detailed sample profile).

## 3.2 Measures

### 3.2.1 School Climate Variables

Wang and Degol’s (2016) catalogue of school climate into academic, community, safety, and institutional environment has been operationalised using variables `FLSCHOOL` (financial education in school lessons), `FLFAMILY` (parental involvement in matters of financial literacy, i.e., “financial socialisation”), `NOBULLY` (reverse coding of `BEINGBULLIED` such that larger numbers implies safer schools) and `EDUSHORT` (shortage of educational material), respectively. All four measures were derived variables based on IRT scaling, with good scale reliabilities for most countries and constructs (see Table B.2 for Cronbach’s alphas). In addition, the PISA organiser has applied multi-group concurrent calibrations to all latent constructs using the root mean square deviance below 0.3 criterion (for a technical discussion on RMSD, see Buchholz & Hartig, 2019, p. 244) in order to ensure cross-country measurement invariance (see Chapter 9 of *PISA 2018 Technical Report* (OECD, 2020b, pp. 14–15) for analytical details).

---

<sup>1</sup>Australia also participated in 2018 PISA financial literacy but chose to withhold its data from public release and is therefore excluded in the current study.

<sup>2</sup>Moscow Region (CNTRYID = 982) and Tatarstan (983) have been merged into Russian Federation (643).

**Table 3.1**  
*Summary of Measures and Variables*

Analysis level	Exogenous variable		Endogenous variable	
	School climate	Demographic control	Financial literacy Affective	Cognitive
School-level ( $L2$ )	FLSCH00L <sub>B</sub> FLFAMILY <sub>B</sub> NOBULLY <sub>B</sub> EDUSHORT	STRAIO		FLIT <sub>B</sub>
Student-level ( $L1$ )	FLSCH00L <sub>W</sub> FLFAMILY <sub>W</sub> NOBULLY <sub>W</sub>	ESCS IMMI1GEN IMMI2GEN MALE	FCFMLRTY FLCONFIN	FLIT <sub>W</sub>

*Note.* Notes go here.

### 3.2.2 Financial Literacy Measures

The OECD has constructed two variables to measure 15-year-old students' affects towards financial matters: **FCFMLRTY** (familiarity with concepts of finance) and **FLCONFIN** (confidence about financial matters). The former was a non-sclaed derived variable by summing up all 18 items from financial literacy questionnaire **FL164**, whereas the latter was derived based on IRT scaling with good reliability properties (see [Table B.2](#) for Cronbach's alphas for **FLCONFIN**).

Similar to the treatment for reading and mathematics capabilities, ten plausible values (**PV1FLIT** to **PV10FLIT**, collectively written as **FLIT** form here on) were generated as indicators of students' financial literacy cognition capability. All ten plausible values have been used in this study following procedures prescribed by Rubin ([1987](#)).

### 3.2.3 Multilevel Latent Covariate Approach to School-level Aggregation

Student-level school climate variables were aggregated into school-level using multilevel latent covariate (MLC) approach (Lüdtke et al., [2008](#); Marsh et al., [2009](#)).

### 3.2.4 Control Variables

The PISA organiser computed students' economic, social and cultural status (**ESCS**) index by taking the arithmetic mean of three indicators: **PARED** (parental education), **HISEI** (parental occupational status) and **HOMEPOS** (home possessions). Figure 16.4 of *PISA 2018 Technical Report* (OECD, [2020b](#)) visualised the procedure for the **ESCS** computation and Avvisati ([2020](#)) interrogated its validity.

Students' immigration status were determined by sythesising responses from student questionnaire items ST019 (parents' country of birth) and ST021 (students' age of arrival in test country) (OECD, 2019b, pp. 212–213). The source dataset (OECD, 2020a) recorded students' immigration status as a categorical variable with levels 1 = Native, 2 = Second-Generation and 3 = First-Generation. This study derived two binary variables from this information **IMMI1GEN** and **IMMI2GEN** for first- and second-generation migrants respectively, with natives receiving zero entries for both markers.

The 2018 PISA financial literacy assessment was conducted as a one-hour computer-based session in addition to the mathematics, reading and science components. Students responded to questions about their familiarity with concepts of finance (**FCFMLRTY**), confidence about financial matters (**FLCONFIN**), their classroom (**FLSCHOOL**) as well as parental (**FLFAMILY**) involvement in matters of financial literacy. Due to a rotation Ten plausible values were subsequently generated by PISA organisers as measures of students' financial literacy outcomes and were used as the dependent variable (**FLIT**).

### 3.3 Model

Student-level ( $L_1$ ):

$$\begin{aligned}
\text{FCFMLRTY}_{ij} &= \alpha_j^{M_1} + \gamma_{11}\text{FLSCHOOL}_{ij} + \gamma_{21}\text{FLFAMILY}_{ij} + \gamma_{31}\text{NOBULLY}_{ij} \\
&\quad + \gamma_{41}\text{ESCS}_{ij} + \gamma_{61}\text{IMMI2GEN}_{ij} + \gamma_{71}\text{MALE}_{ij} + r_{ij}^{M_1} \\
\text{FLCONFIN}_{ij} &= \alpha_j^{M_2} + \gamma_{12}\text{FLSCHOOL}_{ij} + \gamma_{22}\text{FLFAMILY}_{ij} + \gamma_{32}\text{NOBULLY}_{ij} \\
&\quad + \gamma_{42}\text{ESCS}_{ij} + \gamma_{62}\text{IMMI2GEN}_{ij} + \gamma_{72}\text{MALE}_{ij} + r_{ij}^{M_2} \\
\text{FLIT}_{ij} &= \alpha_j^Y + \beta_1\text{FCFMLRTY}_{ij} + \beta_2\text{FLCONFIN}_{ij} \\
&\quad + \gamma_1\text{FLSCHOOL}_{ij} + \gamma_2\text{FLFAMILY}_{ij} + \gamma_3\text{NOBULLY}_{ij} \\
&\quad + \gamma_4\text{ESCS}_{ij} + \gamma_5\text{IMMI1GEN}_{ij} + r_{ij}^Y
\end{aligned} \tag{3.1}$$

School-level ( $L_2$ ):

$$\begin{aligned}
\alpha_j^Y &= \alpha_{00}^Y + a_1\text{FLSCHOOL}_j + a_2\text{NOBULLY}_j + a_3\text{FLFAMILY}_j + a_4\text{EDUSHTG}_j \\
&\quad + a_5\text{STRATIO}_j + \varepsilon_j^Y
\end{aligned} \tag{3.2}$$

Using Kaplan's (2009) notation  $\mathbf{y}_{ij} = \boldsymbol{\alpha}_j + \mathbf{B}_j\mathbf{y}_{ij} + \mathbf{\Gamma}_j\mathbf{x}_{ij} + \mathbf{r}_{ij}$  for student-level ( $L_1$ ) and random intercept  $\boldsymbol{\alpha}_j = \boldsymbol{\alpha}_{00} + \mathbf{A}\mathbf{w}_j + \boldsymbol{\varepsilon}_j$  for school-level ( $L_2$ ):

$$\begin{aligned}
\begin{bmatrix} \text{FCFMLRTY}_{ij} \\ \text{FLCONFIN}_{ij} \\ \text{FLIT}_{ij} \end{bmatrix} &= \begin{pmatrix} \alpha_j^{M_1} \\ \alpha_j^{M_2} \\ \alpha_j^{Y_W} \end{pmatrix} + \begin{pmatrix} 0 & 0 & \beta_1 \\ 0 & 0 & \beta_2 \\ 0 & 0 & 0 \end{pmatrix}^\top \begin{bmatrix} \text{FCFMLRTY}_{ij} \\ \text{FLCONFIN}_{ij} \\ \text{FLIT}_{ij} \end{bmatrix} \\
&+ \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_1 \\ \gamma_{21} & \gamma_{22} & \gamma_2 \\ \gamma_{31} & \gamma_{32} & \gamma_3 \\ \gamma_{41} & \gamma_{42} & \gamma_4 \\ 0 & 0 & \gamma_5 \\ \gamma_{61} & \gamma_{62} & 0 \\ \gamma_{71} & \gamma_{72} & 0 \end{pmatrix}^\top \begin{bmatrix} \text{FLSCHOOL}_{ij} \\ \text{FLFAMILY}_{ij} \\ \text{NOBULLY}_{ij} \\ \text{ESCS}_{ij} \\ \text{IMMI1GEN}_{ij} \\ \text{IMMI2GEN}_{ij} \\ \text{MALE}_{ij} \end{bmatrix} + \begin{pmatrix} r_{ij}^{M_1} \\ r_{ij}^{M_2} \\ r_{ij}^{Y_W} \end{pmatrix}, \quad (3.3) \\
\begin{pmatrix} \alpha_j^{M_1} \\ \alpha_j^{M_2} \\ \alpha_j^{Y_W} \end{pmatrix} &= \begin{pmatrix} \alpha_{00}^{M_1} \\ \alpha_{00}^{M_2} \\ \alpha_{00}^Y \end{pmatrix} + \begin{pmatrix} 0 & 0 & a_1 \\ 0 & 0 & a_2 \\ 0 & 0 & a_3 \\ 0 & 0 & a_4 \\ 0 & 0 & a_5 \end{pmatrix}^\top \begin{bmatrix} \text{FLSCHOOL}_j \\ \text{FLFAMILY}_j \\ \text{NOBULLY}_j \\ \text{EDUSHTG}_j \\ \text{STRATIO}_j \end{bmatrix} + \begin{pmatrix} 0 \\ 0 \\ \varepsilon_j^{Y_B} \end{pmatrix}.
\end{aligned}$$

### 3.4 Missing Data Treatment

Missing data impose great potential for biased estimation. This study addressed the missing data issue through multilevel multiple imputation under the assumption that data were missing at random (Little & Rubin, 2019). Since 2018 PISA financial literacy datasets contain missing data at both student- and school-levels and in both continuous and categorical variables, the joint modelling approach is adopted under the advisory of Grund et al. (2018). More specifically, ten sets of imputed data were ordered through Mplus’s unrestricted variance-covariance model (“JM-AM H1”, Asparouhov & Muthén, 2010) using Bayes estimation procedure with uninformative priors and 4-chain Gibbs sampler to verify convergence as per suggestion by Little and Rubin (2019, p. 230) and Lambert (2018, p. 314). Additionally, the first 50000 MCMC iterations were discarded to ensure stability and any two draws were separated with 5000 iterations to avoid autocorrelation (see Section C.1 for input file)—a safe setting even for moderate to high percentage missings (Grund et al., 2016). Diagnostic plots in Section C.3 presented visual evidence for convergence with imputation results summarised in Table C.1.

### 3.5 Analysis

#### 3.5.1 Weights



### **3.5.2 Plausible Values and Rubin's Rule**

## **3.6 Estimators**

## **3.7 Model Comparison**



# Chapter 4 Results

## 4.1 Descriptive statistics

**Table 4.1***Descriptive Statistics*

Analysis level	Variable label	Non-missing sample size	Missing rate (%) <sup>a</sup>	Median	$M$	$SD$	Variance	Skewness	Excess kurtosis	Minimum	Maximum
Student (within, $L1$ )	FLSCHOOL	96435	10.01	0.126	0.018	1.020	1.040	0.189	-0.343	-1.564	2.317
	FLFAMILY	95133	11.23	0.011	0.064	1.044	1.090	0.121	0.030	-2.042	2.452
	NOBULLY	83499	22.08	0.782	-0.059	1.054	1.110	-1.078	0.664	-3.859	0.782
	FCFMLRTY	99969	6.71	7.000	7.049	5.455	29.752	0.223	-1.039	0.000	18.000
	FLCONFIN	90130	15.89	-0.027	-0.072	1.017	1.034	-0.084	0.355	-2.210	2.322
	ESCS	104784	2.22	-0.158	-0.241	1.088	1.183	-0.533	0.184	-7.711	4.234
	IMMI1GEN	103317	3.59	0.000	0.029	0.167	0.028	5.608	29.446	0.000	1.000
	IMMI2GEN	103317	3.59	0.000	0.042	0.202	0.041	4.542	18.627	0.000	1.000
	MALE	107160	0.00	1.000	0.502	0.500	0.250	-0.007	-2.000	0.000	1.000
School (between, $L2$ )	EDUSHORT	6346	4.30	0.100	0.131	1.036	1.073	0.341	-0.188	-1.421	2.959
	STRATIO	5626	15.16	11.886	13.873	10.171	103.449	4.021	25.425	1.000	100.000

*Note.* <sup>a</sup> Missing rates were computed based on  $N_{L1} = 107162$  students and  $N_{L2} = 6631$  schools.

## **4.2 Correlation matrices**

### **4.2.1 Across countries**

### **4.2.2 Across levels: Country | School | Students**

## **4.3 Examination of measurement models**

**Table 4.2**  
*Model Parameters and Fit Indices for Multilevel Regressions*

Variable — path	Model parameter	Null Model Coef	Null Model SE	One-level Model Coef	One-level Model SE	Two-level Saturated Coef	Two-level Saturated SE	Two-level Structured Coef	Two-level Structured SE
<b>FIXED EFFECTS</b>									
Intercept		454.154	2.690***	451.451	1.449***	445.812	2.578***	486.820	4.500***
<b>Student-level Predictors</b>									
FLSCHOOL (total)	$\gamma_1 + \gamma_{11}\beta_1 + \gamma_{12}\beta_2$			-0.073	0.008***	-0.036	0.011**	-0.036	0.011**
— direct	$\gamma_1$			-0.125	0.008***	-0.088	0.011***	-0.088	0.011***
— total indirect	$\gamma_{11}\beta_1 + \gamma_{12}\beta_2$			0.051	0.003***	0.052	0.003***	0.052	0.003***
— via FCFMLRTY	$\gamma_{11}\beta_1$			0.049	0.002***	0.047	0.003***	0.047	0.003***
— via FLCONFIN	$\gamma_{12}\beta_2$			0.002	0.001	0.005	0.002**	0.005	0.002**
FLFAMILY (total)	$\gamma_2 + \gamma_{21}\beta_1 + \gamma_{22}\beta_2$			0.008	0.007	0.005	0.009	0.005	0.009
— direct	$\gamma_3$			-0.016	0.007*	-0.019	0.009*	-0.019	0.009*
— total indirect	$\gamma_{21}\beta_1 + \gamma_{22}\beta_2$			0.023	0.002***	0.024	0.002***	0.024	0.002***
— via FCFMLRTY	$\gamma_{21}\beta_1$			0.022	0.002***	0.019	0.002***	0.019	0.002***
— via FLCONFIN	$\gamma_{22}\beta_2$			0.002	0.001	0.005	0.002**	0.005	0.002***
NOBULLY (total)	$\gamma_3 + \gamma_{31}\beta_1 + \gamma_{32}\beta_2$			0.075	0.007***	0.053	0.009***	0.053	0.009***
— direct	$\gamma_3$			0.064	0.007***	0.046	0.009***	0.046	0.009***
— total indirect	$\gamma_{31}\beta_1 + \gamma_{32}\beta_2$			0.011	0.002***	0.007	0.002***	0.007	0.002***
— via FCFMLRTY	$\gamma_{31}\beta_1$			0.011	0.002***	0.007	0.002***	0.007	0.002***
— via FLCONFIN	$\gamma_{32}\beta_2$			0.000	0.000	0.000	0.000	0.000	0.000
ESCS (total)	$\gamma_4 + \gamma_{41}\beta_1 + \gamma_{42}\beta_2$			0.497	0.007***	0.289	0.016***	0.289	0.016***
— direct	$\gamma_4$			0.445	0.007***	0.248	0.015***	0.248	0.015***
— total indirect	$\gamma_{41}\beta_1 + \gamma_{42}\beta_2$			0.052	0.003***	0.041	0.003***	0.041	0.003***
— via FCFMLRTY	$\gamma_{41}\beta_1$			0.052	0.002***	0.040	0.003***	0.040	0.003***
— via FLCONFIN	$\gamma_{42}\beta_2$			0.001	0.001	0.001	0.001*	0.001	0.001*
IMMI1GEN (direct)	$\gamma_5$			0.004	0.008	-0.040	0.012**	-0.040	0.012**
IMMI2GEN (total indirect)	$\gamma_{61}\beta_1 + \gamma_{62}\beta_2$			-0.003	0.002†	-0.006	0.002**	-0.006	0.002**
— via FCFMLRTY	$\gamma_{61}\beta_1$			-0.003	0.002†	-0.005	0.002*	-0.005	0.002*
— via FLCONFIN	$\gamma_{62}\beta_2$			0.000	0.000	-0.001	0.000*	-0.001	0.000*
MALE (total indirect)	$\gamma_{71}\beta_1 + \gamma_{72}\beta_2$			0.004	0.002*	0.007	0.002**	0.007	0.002**
— via FCFMLRTY	$\gamma_{71}\beta_1$			0.003	0.002*	0.004	0.002*	0.004	0.002*
— via FLCONFIN	$\gamma_{72}\beta_2$			0.001	0.001	0.003	0.001**	0.003	0.001**

*Continued*

Variable	Model parameter	Null Model		One-level Model		Two-level Saturated		Two-level Structured	
		Coef	<i>SE</i>	Coef	<i>SE</i>	Coef	<i>SE</i>	Coef	<i>SE</i>
<b>School-level Predictors</b>									
FLSCHOOL	$a_1$							-0.295	0.066***
FLFAMILY	$a_2$							-0.225	0.057***
NOBULLY	$a_3$							0.233	0.069***
EDUSHORT	$a_4$							-0.292	0.038***
STRADIO	$a_5$							-0.132	0.026***
<b>RANDOM EFFECTS</b> (residual variances of FLIT)									
Student-level	$\text{var}(r_{ij}^Y)$	6121.904	131.192	7866.408	114.555	5763.677	130.133	5763.690	130.133
School-level	$\text{var}(\varepsilon_j^Y)$	5240.477	202.004			3264.618	193.892	1705.616	135.044
<b>MODEL FIT INDICES</b>		Est	<i>SD</i>	Est	<i>SD</i>	Est	<i>SD</i>	Est	<i>SD</i>
AIC		1253984	1093	3429058	1534	3468075	1661	3468108	1650
BIC		1254013	1093	3429566	1534	3468727	1661	3468740	1650
$\chi^2$ Test of Model Fit		2.193	1.468	304.405	13.167	187.655	10.486	201.645	11.746
RMSEA		0.000	0.000	0.017	0.000	0.009	0.000	0.009	0.000
CFI		0.000	0.000	0.970	0.002	0.970	0.002	0.968	0.002
TLI		1.000	0.000	0.927	0.004	0.899	0.007	0.903	0.007
SRMR <i>L1</i>		0.005	0.003	0.016	0.000	0.015	0.000	0.015	0.000
SRMR <i>L2</i>		0.011	0.005			0.014	0.002	0.030	0.006

*Note.* All  $p$  values in this table are two-tailed.

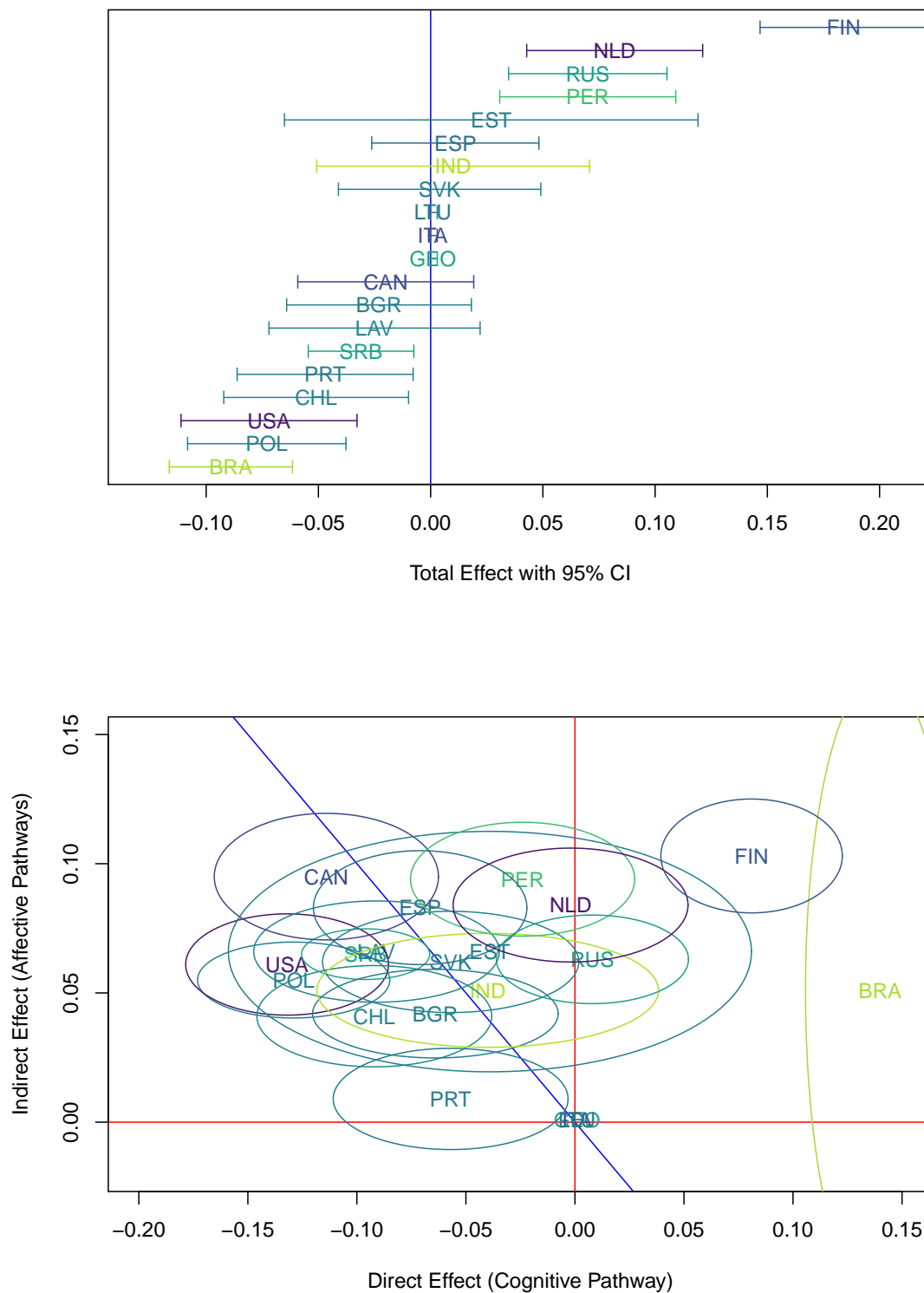
† $p < 0.10$ , \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$

#### **4.4 Address the research question**



**Figure 4.1**

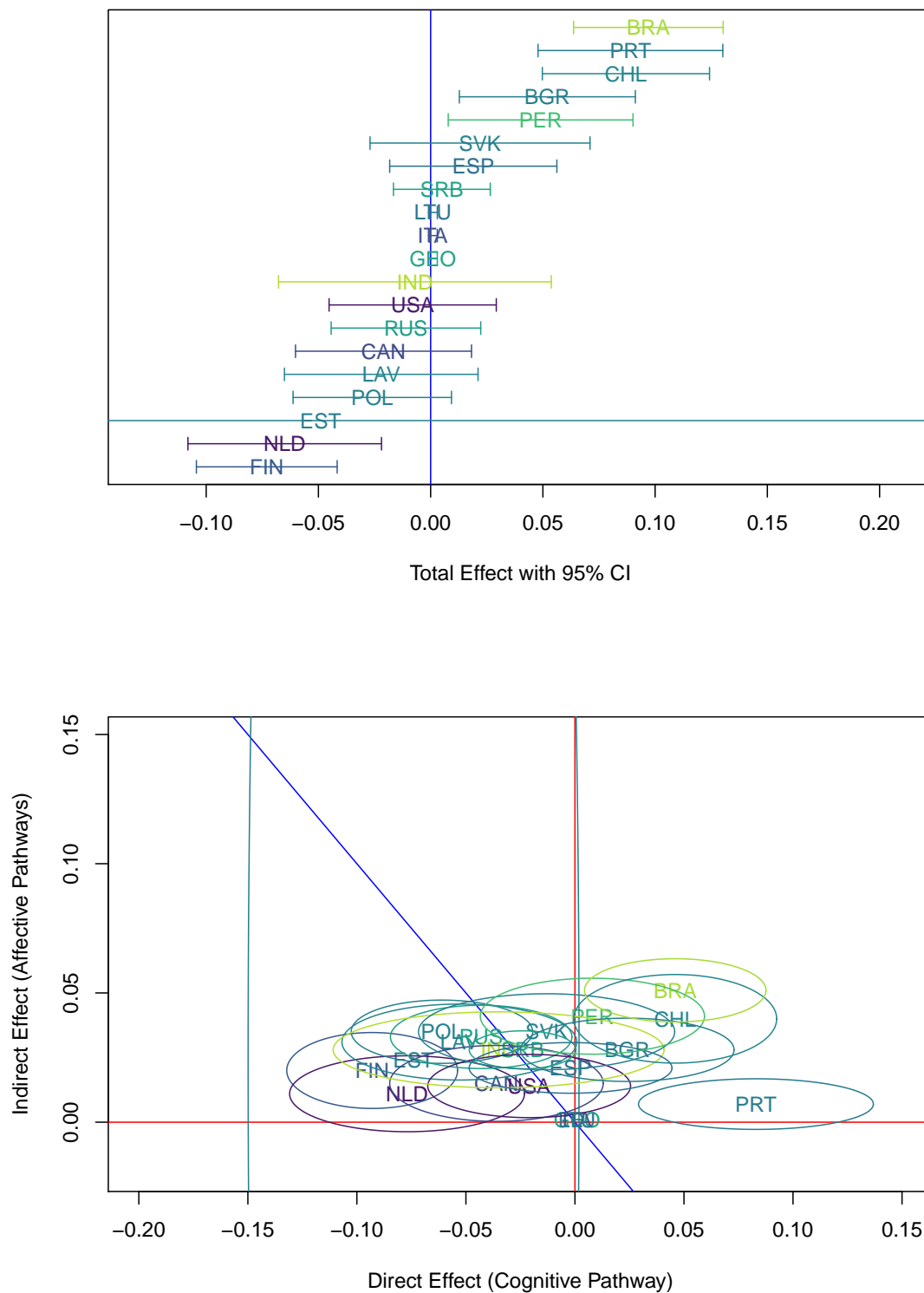
*Total, Direct and Indirect Effects of School Intervention (FLSCHOOL)*



*Note.* Countries with high (low) financial knowledge indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the vertical blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the vertical, horizontal and  $-45^\circ$  lines are not significant for direct, indirect and total effect, respectively.

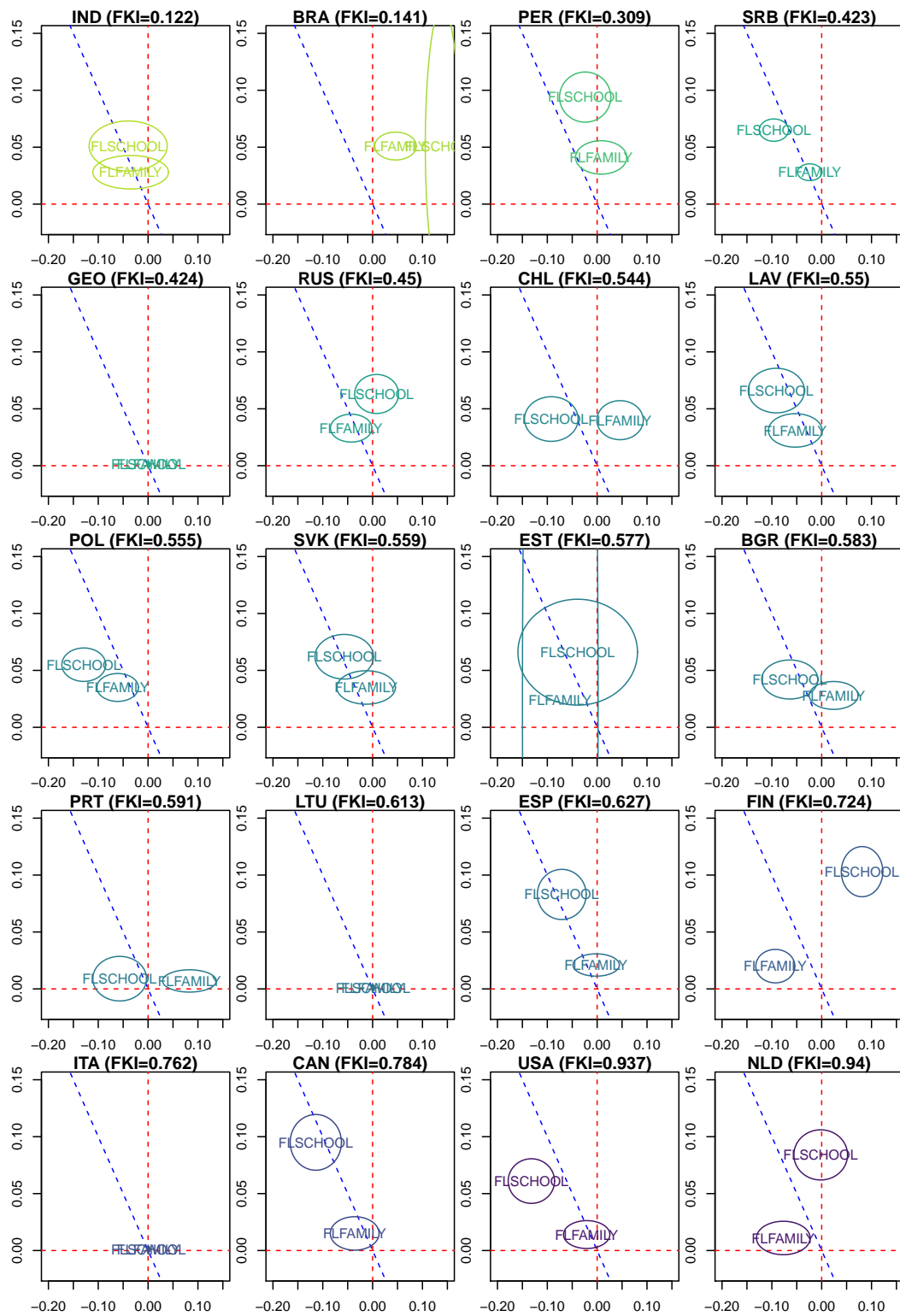
**Figure 4.2**

*Total, Direct and Indirect Effects of Financial Socialisation (FLFAMILY)*



*Note.* Countries with high (low) financial knowledge indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the vertical blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the vertical, horizontal and  $-45^\circ$  lines are not significant for direct, indirect and total effect, respectively.

**Figure 4.3**  
*School-Family Effect Decomposition by Country*



*Note.* Cognitive and affective effects are represented on horizontal and vertical axes respectively.



# Chapter 5 Discussion

## 5.1 Brief summary

### 5.1.1 Remind readers what my research questions are

## 5.2 The implication of this study

## 5.3 Limitation and future directions

### 5.3.1 Word in positive form

## 5.4 Bird-eye view

### 5.4.1 What conclusion I can draw from this paper/study



# References

- Asparouhov, T. & Muthén, B. (2010). *Multiple imputation with Mplus* (2nd ed.). <https://www.statmodel.com/download/Imputations7.pdf>
- Avvisati, F. (2020). The measure of socio-economic status in PISA: A review and some suggested improvements. *Large-scale Assessments in Education*, 8(8), 1–37. <https://doi.org/10.1186/s40536-020-00086-x>
- Bowen, C. F. (2002). Financial knowledge of teens and their parents. *Journal of Financial Counseling and Planning*, 13(2), 93–102. <https://afcpe.buckeyedev.com/wp-content/uploads/2018/10/vol1328.pdf>
- Bray, M. & Thomas, R. M. (1995). Levels of comparison in educational studies: Different insights from different literatures and the value of multilevel analyses. *Harvard Educational Review*, 65(3), 472–491. <https://doi.org/10.17763/haer.65.3.g3228437224v4877>
- Brown, M., Grigsby, J., van der Klaauw, W., Wen, J. & Zafar, B. (2016). Financial education and the debt behavior of the young. *Review of Financial Studies*, 29(9), 2490–2522. <https://doi.org/10.1093/rfs/hhw006>
- Bucher-Koenen, T., Lusardi, A., Alessie, R. & van Rooij, M. (2017). How financially literate are women? An overview and new insights. *Journal of Consumer Affairs*, 51(2), 255–283. <https://doi.org/10.1111/joca.12121>
- Buchholz, J. & Hartig, J. (2019). Comparing attitudes across groups: An IRT-based item-fit statistic for the analysis of measurement invariance. *Applied Psychological Measurement*, 43(3), 241–250. <https://doi.org/10.1177/0146621617748323>
- Caro, D. H. & Biecek, P. (2017). intsvy: An R package for analyzing international large-scale assessment data. *Journal of Statistical Software*, 81(7), 1–44. <https://doi.org/10.18637/jss.v081.i07>
- Cole, S., Paulson, A. & Shastry, G. K. (2016). High school curriculum and financial outcomes: The impact of mandated personal finance and mathematics courses. *Journal of Human Resources*, 51(3), 656–698. <https://doi.org/10.3368/jhr.51.3.0113-5410r1>
- Cole, S., Sampson, T. & Zia, B. (2009). *Financial literacy, financial decisions, and the demand for financial services: Evidence from India and Indonesia* (Working Paper 09-117).

- Harvard Business School. [http://www1.worldbank.org/prem/poverty/ie/dime\\_papers/1107.pdf](http://www1.worldbank.org/prem/poverty/ie/dime_papers/1107.pdf)
- Danes, S. M. & Haberman, H. R. (2007). Teen financial knowledge, self-efficacy, and behavior: A gendered view. *Journal of Financial Counseling and Planning*, 18(2), 48–60. <https://files.eric.ed.gov/fulltext/EJ1104367.pdf>
- von Davier, M. (2014). Imputing proficiency data under planned missingness in population models. In L. Rutkowski, M. von Davier & D. Rutkowski (Eds.), *Handbook of international large-scale assessment: Background, technical issues, and methods of data analysis* (pp. 175–201). CRC Press. <https://doi.org/10.1201/b16061-13>
- Grund, S., Lüdtke, O. & Robitzsch, A. (2016). Multiple imputation of multilevel missing data: An introduction to the R package pan. *SAGE Open*, 1–17. <https://doi.org/10.1177/2158244016668220>
- Grund, S., Lüdtke, O. & Robitzsch, A. (2018). Multiple imputation of missing data for multilevel models: Simulations and recommendations. *Organizational Research Methods*, 21(1), 111–149. <https://doi.org/10.1177/1094428117703686>
- Gudmunson, C. G. & Danes, S. M. (2011). Family financial socialization: Theory and critical review. *Journal of Family and Economic Issues*, 32(4), 644–667. <https://doi.org/10.1007/s10834-011-9275-y>
- Hanushek, E. A. & Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, 17(4), 267–321. <https://doi.org/10.1007/s10887-012-9081-x>
- Huston, S. J. (2012). Financial literacy and the cost of borrowing. *International Journal of Consumer Studies*, 36(5), 566–572. <https://doi.org/10.1111/j.1470-6431.2012.01122.x>
- Jorgensen, B. L. & Savla, J. (2010). Financial literacy of young adults: The importance of parental socialization. *Family Relations*, 59(4), 465–478. <https://doi.org/10.1111/j.1741-3729.2010.00616.x>
- Kaiser, T. & Menkhoff, L. (2020). Financial education in schools: A meta-analysis of experimental studies. *Economics of Education Review*, 78, 1–15. <https://doi.org/10.1016/j.econedurev.2019.101930>
- Kaplan, D. (2009). *Structural equation modeling: Foundations and extensions* (2nd ed.). SAGE. <https://doi.org/10.4135/9781452226576>
- Lambert, B. (2018). *A student's guide to Bayesian statistics*. SAGE.



- Little, R. J. A. & Rubin, D. B. (2019). *Statistical analysis with missing data* (3rd ed.). Wiley.
- Lüdtke, O., Marsh, H. W., Robitzsch, A., Trautwein, U., Asparouhov, T. & Muthén, B. (2008). The multilevel latent covariate model: A new, more reliable approach to group-level effects in contextual studies. *Psychological Methods*, 13(3), 203–229. <https://doi.org/10.1037/a0012869>
- Lusardi, A. (2015). Financial literacy skills for the 21st Century: Evidence from PISA. *Journal of Consumer Affairs*, 49(3), 639–659. <https://doi.org/10.1111/joca.12099>
- Lusardi, A. & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1), 5–44. <https://doi.org/10.1257/jel.52.1.5>
- Marsh, H. W., Lüdtke, O., Robitzsch, A., Trautwein, U., Asparouhov, T., Muthén, B. & Nagengast, B. (2009). Doubly-latent models of school contextual effects: Integrating multilevel and structural equation approaches to control measurement and sampling error. *Multivariate Behavioral Research*, 44(6), 764–802. <https://doi.org/10.1080/00273170903333665>
- Moreno-Herrero, D., Salas-Velasco, M. & Sánchez-Campillo, J. (2018). Factors that influence the level of financial literacy among young people: The role of parental engagement and students' experiences with money matters. *Children and Youth Services Review*, 95, 334–351. <https://doi.org/10.1016/j.childyouth.2018.10.042>
- OECD. (2005). *Improving financial literacy: Analysis of issues and policies*. OECD Publishing. <https://www.oecd-ilibrary.org/docserver/9789264012578-en.pdf>
- OECD. (2019a). PISA 2018 financial literacy framework. *PISA 2018 assessment and analytical framework* (pp. 119–164). OECD Publishing. <https://doi.org/10.1787/alfad77c-en>
- OECD. (2019b). *PISA 2018 results: What school life means for students' lives*. OECD Publishing. <https://doi.org/10.1787/acd78851-en>
- OECD. (2020a). *Financial literacy data file* [Data set]. OECD Publishing. [https://webfs.oecd.org/pisa2018/SPSS\\_STU\\_FLT.zip](https://webfs.oecd.org/pisa2018/SPSS_STU_FLT.zip)
- OECD. (2020b). *PISA 2018 technical report*. OECD Publisher. <https://www.oecd.org/pisa/data/pisa2018technicalreport/>
- OECD. (2020c). *School questionnaire data file* [Data set]. OECD Publisher. [https://webfs.oecd.org/pisa2018/SPSS\\_SCH\\_QQQ.zip](https://webfs.oecd.org/pisa2018/SPSS_SCH_QQQ.zip)

- Oliver-Márquez, F. J., Guarnido-Rueda, A. & Amate-Fortes, I. (2020). Measuring financial knowledge: A macroeconomic perspective. *International Economics and Economic Policy*, 1–46. <https://doi.org/10.1007/s10368-020-00482-2>
- Potrich, A. C. G., Vieira, K. M., Coronel, D. A. & Bender Filho, R. (2015). Financial literacy in Southern Brazil: Modeling and invariance between genders. *Journal of Behavioral and Experimental Finance*, 6, 1–12. <https://doi.org/10.1016/j.jbef.2015.03.002>
- R Core Team. (2021). *R: A language and environment for statistical computing* (Version 4.0.5). R Foundation for Statistical Computing. Vienna, Austria. <https://www.R-project.org/>
- Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. John Wiley & Sons. <https://doi.org/10.1002/9780470316696>
- Rust, K. (2014). Sampling, weighting, and variance estimation in international large-scale assessments. In L. Rutkowski, M. von Davier & D. Rutkowski (Eds.), *Handbook of international large-scale assessment: Background, technical issues, and methods of data analysis* (pp. 117–153). CRC Press. <https://doi.org/10.1201/b16061-11>
- Strietholt, R. & Scherer, R. (2018). The contribution of international large-scale assessments to educational research: Combining individual and institutional data sources. *Scandinavian Journal of Educational Research*, 62(3), 368–385. <https://doi.org/10.1080/00313831.2016.1258729>
- United Nations. (2020). *Human development reports* (Data set). The United Nations. <http://hdr.undp.org/en/data>
- Wang, M.-T. & Degol, J. L. (2016). School climate: A review of the construct, measurement, and impact on student outcomes. *Educational Psychology Review*, 28(2), 315–352. <https://doi.org/10.1007/s10648-015-9319-1>
- World Bank. (2020). *World Bank DataBank* (Data set). The World Bank. <https://databank.worldbank.org/home.aspx>

# Appendices



# Appendix A GDPR Documentation and Ethical Approval

This research project discharges its duty imposed by the EEA's general data protection regulation (GDPR) by following Norwegian Centre for Research Data (NSD)'s [notification test](#) on Friday, 11 September 2020. Both [PISA 2018 Database](#) and the [World Bank Open Data](#) contain only aggregated and de-personalised datasets with no possibility of back-tracing to any particular participant. Resultantly, no identifiable personal data were collected or used at any stage of this research. The NSD's assessment letter outlines the agency's decision of not subjecting this project to the GDPR notification. The NSD decision letter also satisfies University of Oslo's [ethical approval requirement](#) and concludes the approval process.

About us ([/personvernombud/en/about\\_us.html](/personvernombud/en/about_us.html))

Norwegian ([/personvernombud/meld\\_prosjekt/meldeplikttest.html](/personvernombud/meld_prosjekt/meldeplikttest.html))

NSD (</>) > Personvern tjenester (</personvernombud/>) > Data Protection Services (</personvernombud/en/>) > Notify project (</personvernombud/en/notify/>) > Notification Test

Denne siden på norsk ([/personvernombud/meld\\_prosjekt/meldeplikttest.html](/personvernombud/meld_prosjekt/meldeplikttest.html))

## Will you be processing personal data?

Are you unsure whether your project is subject to notification? Feel free to try our informal Notification test. Note that the test is intended as a guidance and is not a formal assessment.

**Will you be collecting/processing directly identifiable personal data?**

☐ Yes

☒ No

A person will be directly identifiable through name, social security number, or other uniquely personal characteristics.

Read more about personal data (</personvernombud/en/help/vocabulary.html?id=8>) and notification (</personvernombud/en/notify/index.html>).

NB! Even though information is to be anonymized in the final thesis/report, check the box if identifying personal data is to be collected/processed in connection with the project.

**Will directly identifiable personal information be linked to the data (e.g. through a reference number which refers to a separate list of names/scrambling key)?**

☐ Yes

☒ No

Note that the project will be subject to notification even if you cannot access the scrambling key (</personvernombud/en/help/vocabulary.html?id=11>), as the procedure often is when using a data processor (</personvernombud/en/help/vocabulary.html?id=3>), or in register-based studies ([/personvernombud/en/help/research\\_methods/register\\_studies.html](/personvernombud/en/help/research_methods/register_studies.html)).

**Will you be collecting/processing background information that may identify individuals (indirectly identifiable personal data)?**

☐ Yes

☒ No

A person will be indirectly identifiable if it is possible to identify him/her through a combination of background information (such as place of residence or workplace/school, combined with information such as age, gender, occupation, etc.).

**Will there be registered personal data (directly/indirectly/via IP or email address, etc.) using online surveys?**

☐ Yes

☒ No

Please note that the project will be subject to notification even if you as a student/researcher cannot access the link to the IP or email address, as the procedure often is when using a data processor.

Read more about online surveys ([/personvernombud/en/help/research\\_methods/online\\_surveys.html](/personvernombud/en/help/research_methods/online_surveys.html)).

**Will there be registered personal data using digital photo or video files?**

☐ Yes

☒ No

Photo/video recordings of faces will be regarded as identifiable personal data. In order for a voice to be considered as identifiable, it must be registered in combination with other background information, in such a way that people can be recognized.

Show results

## Notify project

Do I have to notify my project? (</personvernombud/en/notify/index.html>)

Notification Form ([/personvernombud/en/notify/meldeskjema\\_link](/personvernombud/en/notify/meldeskjema_link))

Notifying changes ([/personvernombud/en/notify/notifying\\_changes.html](/personvernombud/en/notify/notifying_changes.html))

## Get help notifying your project

Processing the notification (</personvernombud/en/help/index.html>)

Frequently asked questions (</personvernombud/en/help/faq.html>)

Vocabulary (</personvernombud/en/help/vocabulary.html>)

Research topics ([/personvernombud/en/help/research\\_topics/](/personvernombud/en/help/research_topics/))

Research methods ([/personvernombud/en/help/research\\_methods/](/personvernombud/en/help/research_methods/))

Information and consent ([/personvernombud/en/help/information\\_consent/](/personvernombud/en/help/information_consent/))

Other approvals ([/personvernombud/en/help/other\\_approvals/](/personvernombud/en/help/other_approvals/))

## Result of Notification Test: Not Subject to Notification

You have indicated that neither directly or indirectly identifiable personal data will be registered in the project.

If no personal data is to be registered, the project will not be subject to notification, and you will not have to submit a notification form.

Please note that this is a guidance based on information that you have given in the notification test and not a formal confirmation.

For your information: *In order for a project not to be subject to notification, we presuppose that all information processed using electronic equipment in the project remains anonymous.*

*Anonymous information is defined as information that cannot identify individuals in the data set in any of the following ways:*

- directly, through uniquely identifiable characteristic (such as name, social security number, email address, etc.)*
- indirectly, through a combination of background variables (such as residence/institution, gender, age, etc.)*
- through a list of names referring to an encryption formula or code, or*
- through recognizable faces on photographs or video recordings.*

*Furthermore, we presuppose that names/consent forms are not linked to sensitive personal data.*

Kind regards,  
NSD Data Protection



# Appendix B Analysis Code, Additional Tables and Figures

## B.1 Chapter 1 Introduction

There is no analysis code in [Chapter 1](#).

## B.2 Chapter 2 Conceptual Framework

There is no analysis code in [Chapter 2](#).

## B.3 Chapter 3 Method

### B.3.1 Data Merging

```
1 | # Import SPSS file into R
  | library(intsvy)
  | finlit <- pisa.select.merge(
  |   student.file = "CY07_MSU_FLT_QQQ.SAV", # file ext in capital
5 |   school.file = "CY07_MSU_SCH_QQQ.sav", # file ext in lower case
  |   student = c(
  |     # Control variables
  |     "ST004D01T", # Student (Standardized) Gender
  |     "IMMIG", # Index Immigration status
10 |     "ESCS", # Index of economic, social and cultural status
  |     # Mediators
  |     "FCFMLRTY", # Familiarity with concepts of finance (Sum)
  |     "FLCONFIN", # Confidence about financial matters (WLE)
  |     # Academic
15 |     "FLSCHOOL", # Financial education in school lessons (WLE)
  |     # Safety
  |     "BEINGBULLIED", # Student's experience of being bullied (WLE)
  |     # Community
  |     "FLFAMILY" # Parental involvement in matters of Financial Literacy (WLE)
20 |   ),
  |   school = c(
  |     "STRATIO", # Student-teacher ratio
  |     "EDUSHORT" # Shortage of educational material (WLE)
  |   ),
25 |   countries = c(
  |     "BRA", "BGR", "CAN", "CHL", "EST",
  |     "FIN", "GEO", "IDN", "ITA", "LVA",
  |     "LTU", "NLD", "PER", "POL", "PRT",
  |     "RUS", "QMR", "QRT", # Russian Federation and other regions
30 |     "SRB", "SVK", "ESP", "USA"
  |   )
  | )
  |
  | names(finlit)
35 | # Throw away columns that I do not need
  | finlit <- finlit[, -c(5, 7:86)] # 5 = BOOKID; 7:86 = resampling weights
  | names(finlit)
  |
  | # Some var need recording
40 | library(car)
  |
  | # Re-code Russian territories to RUS
  | finlit$CNT <- recode(finlit$CNT, "
  |   'QMR' = 'RUS';
```

```

45 |   'QRT' = 'RUS'
   | ")
   |
   | finlit$CNTRYID ← recode(finlit$CNTRYID, "
   |   982 = 643;
50 |   983 = 643
   | ")
   |
   | # Input country-level FKI
   | FKI ← recode(finlit$CNT, "
55 |   'NLD' = 0.940;
   |   'USA' = 0.937;
   |   'CAN' = 0.784;
   |   'ITA' = 0.762;
   |   'FIN' = 0.724;
60 |   'ESP' = 0.627;
   |   'LTU' = 0.613;
   |   'PRT' = 0.591;
   |   'BGR' = 0.583;
   |   'EST' = 0.577;
65 |   'SVK' = 0.559;
   |   'POL' = 0.555;
   |   'LVA' = 0.550;
   |   'CHL' = 0.544;
   |   'RUS' = 0.450;
70 |   'GEO' = 0.424;
   |   'SRB' = 0.423;
   |   'PER' = 0.309;
   |   'BRA' = 0.141;
   |   'IDN' = 0.122
75 | ")
   |
   | # Recode ST004D01T from Sex to Male
   | MALE ← finlit$ST004D01T - 1
   |
80 | # Revert coding direction: bigger number => safer school
   | NOBULLY ← finlit$BEINGBULLIED * (-1)
   |
   | # Recode IMMIG to 1st and 2nd generation
   | IMMI1GEN ← recode(finlit$IMMIG, "
85 |   1 = 0;
   |   2 = 0;
   |   3 = 1
   | ")
   |
90 | IMMI2GEN ← recode(finlit$IMMIG, "
   |   1 = 0;
   |   2 = 1;
   |   3 = 0
   | ")
95 |
   | # Stitch spreadsheet together
   | names(finlit)
   | finlit ← cbind(
   |   FKI, finlit[, c(2:35)], MALE, IMMI1GEN, IMMI2GEN,
100 |   finlit[, c(38:41)], NOBULLY, finlit[, c(43:46)]
   | )
   | head(finlit)
   | names(finlit)
   |
105 | # Remove cases whose school weights (col #45) are NA
   | obs0 ← dim(finlit)[1]
   | finlit ← finlit[complete.cases(finlit$W_FSTUWT_SCH_SUM), ]
   | obs1 ← dim(finlit)[1]
   | obs0 - obs1 # 12 cases contained missing school weights and have been dropped
110 | rm(obs0, obs1)

```

**Table B.1**  
*Summary of Participating Countries*

Country	Country	Country	School		Student		Male	
code	ID	name	count	percentage	count	percentage	count	percentage
76	BRA	Brazil	595	8.97%	8310	7.75%	4045	48.68%
100	BGR	Bulgaria	197	2.97%	4110	3.84%	2147	52.24%
124	CAN	Canada	492	7.42%	7762	7.24%	3858	49.70%
152	CHL	Chile	251	3.79%	4482	4.18%	2254	50.29%
233	EST	Estonia	229	3.45%	4166	3.89%	2080	49.93%
246	FIN	Finland	204	3.08%	4328	4.04%	2199	50.81%
268	GEO	Georgia	319	4.81%	4320	4.03%	2239	51.83%
360	IND	Indonesia	395	5.96%	7132	6.66%	3454	48.43%
380	ITA	Italy	539	8.13%	9182	8.57%	4706	51.25%
428	LVA	Latvia	307	4.63%	3151	2.94%	1587	50.36%
440	LTU	Lithuania	349	5.26%	4075	3.80%	2060	50.55%
528	NLD	the Netherlands	151	2.28%	3042	2.84%	1549	50.92%
604	PER	Peru	337	5.08%	4732	4.42%	2390	50.51%
616	POL	Poland	235	3.54%	4294	4.01%	2080	48.44%
620	PRT	Portugal	276	4.16%	4568	4.26%	2320	50.79%
643	RUS	Russian Federation	558	8.42%	9124	8.51%	4601	50.43%
688	SRB	Serbia	186	2.81%	3874	3.62%	1951	50.36%
703	SVK	Slovak Republic	357	5.38%	3411	3.18%	1683	49.34%
724	ESP	Spain	491	7.40%	9361	8.74%	4695	50.15%
840	USA	the USA	163	2.46%	3738	3.49%	1871	50.05%
Total			6631	100%	107162	100%	53769	50.18%
			School		Student		Male	
			$\chi^2_{19}$	$p$ -value	$\chi^2_{19}$	$p$ -value	$\chi^2_{19}$	$p$ -value
$\chi^2$ goodness-of-fit test			1105.8	< .001	16984	< .001	20.9	.34

*Note.* Notes go here.

**Table B.2**

*Scale Reliabilities (Cronbach's alphas) and Item Parameter References for Derived Variables based on IRT Scaling*

Country			School climate variable				Financial literacy
Name	Code	ID	FLSCHOOL	FLFAMILY	NOBULLY	EDUSHORT	FLCONFIN
Brazil	BRA	76	.896	.871	.794	.858	.929
Bulgaria	BGR	100	.912	.836	.851	.814	.927
Canada	CAN	124	.904	.856	.758	.816	.900
Chile	CHL	152	.885	.851	.784	.818	.915
Estonia	EST	233	.865	.833	.709	.752	.872
Finland	FIN	246	.883	.819	.760	.783	.896
Georgia	GEO	268	.891	.834	.846	.862	.920
Indonesia	IND	360	.878	.827	.756	.892	.931
Italy	ITA	380	.857	.798	.795	.840	.898
Latvia	LVA	428	.846	.813	.703	.780	.897
Lithuania	LTU	440	.909	.869	.846	.779	.921
The Netherlands	NLD	528	.849	.792	.638	.792	.874
Peru	PER	604	.847	.813	.758	.882	.903
Poland	POL	616	.878	.830	.771	.839	.913
Portugal	PRT	620	.896	.844	.775	.849	.899
Russian Federation	RUS	643	.892	.855	.726	.874	.911
Serbia	SRB	688	.926	.853	.838	.786	.939
Slovak Republic	SVK	703	.874	.829	.783	.799	.907
Spain	ESP	724	.879	.812	.779	.854	.912
The United States	USA	840	.908	.839	.756	.881	.909
Reference for							
scale reliabilities <sup>a</sup>							
OECD countries			16.89	16.89	16.58	16.63	16.89
Partner countries			16.90	16.90	16.59	16.64	16.90
Reference for item parameters <sup>b</sup>			16.93	16.94	16.61	16.66	16.91

*Note.* <sup>a</sup> <sup>b</sup> Worksheet names in the associated [Excel file](#) accompanying Chapter 16 *PISA 2018 Technical Report* (OECD, 2020b).

# Appendix C Multilevel Multiple Imputation

## C.1 Mplus Input Code

```

1  TITLE:
    Multilevel multiple imputation using JM-AM H1      ! Unrestricted var-cov

5  DATA:
    file = "~/finlit.dat";

10 VARIABLE:
    names =
        FKI CNTRYID CNTSCHID CNTSTUID W_STU           ! Administrative vars
        PV1MATH PV2MATH PV3MATH PV4MATH PV5MATH       ! Plausible values for MATH
        PV6MATH PV7MATH PV8MATH PV9MATH PV10MATH
        PV1READ PV2READ PV3READ PV4READ PV5READ       ! Plausible values for READ
        PV6READ PV7READ PV8READ PV9READ PV10READ
        PV1FLIT PV2FLIT PV3FLIT PV4FLIT PV5FLIT       ! Plausible values for FLIT
        PV6FLIT PV7FLIT PV8FLIT PV9FLIT PV10FLIT
        MALE IMMI1GEN IMMI2GEN ESCS                   ! Demographic info
        FCFMLRTY FLCONFIN                             ! Affects
        FLSCHOOL                                       ! Lat var "Academic"
        NOBULLY                                       ! Lat var "Safety"
        FLFAMILY                                       ! Lat var "Community"
        W_SCH STRATIO                                 ! School characteristics
        EDUSHORT                                       ! Lat var "inst. env."
    ;

    usevar =                                           ! Var to be imputed
        MALE IMMI1GEN IMMI2GEN ESCS
        FCFMLRTY FLCONFIN
        FLSCHOOL NOBULLY FLFAMILY
        STRATIO EDUSHORT
    ;

    within =                                           ! Amongst which, L1 var are
        MALE IMMI1GEN IMMI2GEN ESCS
        FCFMLRTY FLCONFIN
        FLSCHOOL NOBULLY FLFAMILY
    ;

    between =                                         ! L2 are
        STRATIO EDUSHORT
    ;

    auxiliary =                                       ! Var not participating in
        PV1MATH PV2MATH PV3MATH PV4MATH PV5MATH       ! MI but still to be
        PV6MATH PV7MATH PV8MATH PV9MATH PV10MATH       ! included in final output
        PV1READ PV2READ PV3READ PV4READ PV5READ
        PV6READ PV7READ PV8READ PV9READ PV10READ       ! PVs are already "guesses"
        PV1FLIT PV2FLIT PV3FLIT PV4FLIT PV5FLIT       ! themselves so do NOT use
        PV6FLIT PV7FLIT PV8FLIT PV9FLIT PV10FLIT       ! PVs to guess others
        FKI CNTRYID CNTSTUID W_STU
        W_SCH                                           ! Admin vars
    ;

55  cluster = CNTSCHID;

    missing = all (-99);

60 ANALYSIS:
    processors = 64;                                   ! Use all cores of HPC

    type = twolevel;
    estimator = Bayes;

```

```

65      fbiterations = 50000;           ! Number of burn-in
      chains = 4;                     ! Verify convergence
      bseed = 1234;                   ! For replication study

70  DATA IMPUTATION:
      impute =
          MALE (c) IMMI1GEN (c) IMMI2GEN (c) ESCS      ! Categoricals have (c)
          FCFMLRTY FLCONFIN
75      FLSCHOOL NOBULLY FLFAMILY
          STRATIO EDUSHORT
          ;

      ndatasets = 10;                 ! To merge with 10 PVs
80      save = FLIT_MMI_*.dat;
      thin = 5000;                   ! To Avoid autocorrelation

SAVEDATA:
      bpar = bpar.dat;               ! Capture Bayesian paths

85  PLOT:
      type = plot2;                  ! For R's MplusAutomation

```

## C.2 Selected Mplus Output

```

1  MODEL FIT INFORMATION
      Number of Free Parameters                22

5  Bayesian Posterior Predictive Checking using Chi-Square

      95% Confidence Interval for the Difference Between
      the Observed and the Replicated Chi-Square Values

10      28408.938      28906.315

      Posterior Predictive P-Value            0.000

Information Criteria
15      Deviance (DIC)                2100842.641
      Estimated Number of Parameters (pD)    22.054

20  MODEL RESULTS

      Estimate      Posterior      One-Tailed      95% C.I.
      S.D.      P-Value      Lower 2.5%      Upper 2.5%      Significance

25  Within Level

Means
30      MALE      0.502      0.002      0.000      0.499      0.505      *
      IMMI1GEN      0.029      0.001      0.000      0.028      0.030      *
      IMMI2GEN      0.042      0.001      0.000      0.041      0.044      *
      ESCS      -0.241      0.003      0.000      -0.247      -0.234      *
      FCFMLRTY      7.049      0.017      0.000      7.015      7.083      *
      FLCONFIN      -0.072      0.003      0.000      -0.079      -0.065      *
35      FLSCHOOL      0.018      0.003      0.000      0.011      0.024      *
      NOBULLY      -0.059      0.004      0.000      -0.067      -0.052      *
      FLFAMILY      0.064      0.003      0.000      0.057      0.070      *

Variances
40      MALE      0.250      0.001      0.000      0.248      0.252      *
      IMMI1GEN      0.028      0.000      0.000      0.028      0.028      *
      IMMI2GEN      0.041      0.000      0.000      0.040      0.041      *
      ESCS      1.183      0.005      0.000      1.173      1.193      *
      FCFMLRTY      29.753      0.134      0.000      29.494      30.016      *
45      FLCONFIN      1.034      0.005      0.000      1.025      1.044      *

```

	FLSCHOOL	1.040	0.005	0.000	1.031	1.049	*
	NOBULLY	1.110	0.005	0.000	1.100	1.121	*
	FLFAMILY	1.090	0.005	0.000	1.080	1.100	*
50	Between Level						
	Means						
	STRATIO	13.873	0.136	0.000	13.608	14.140	*
55	EDUSHORT	0.131	0.013	0.000	0.106	0.157	*
	Variances						
	STRATIO	103.514	1.948	0.000	99.805	107.425	*
	EDUSHORT	1.074	0.019	0.000	1.038	1.112	*

### C.3 Diagnostic Plots

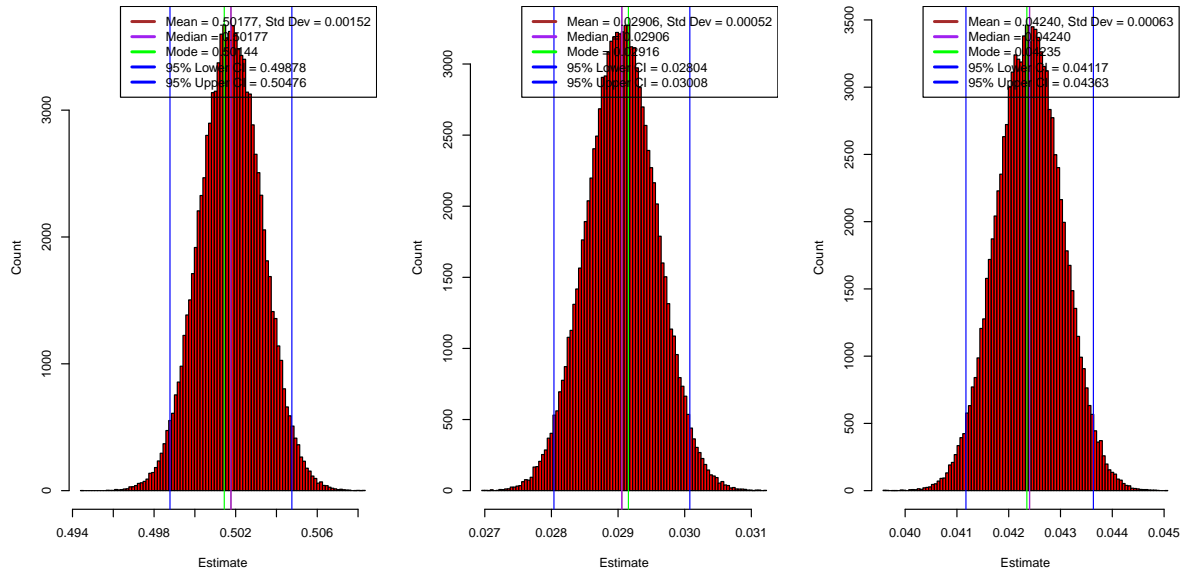
**Table C.1***Summary of Diagnostic Plots of Multilevel Multiple Imputation*

Parameter number	Parameter label	Modelling level	Brief description	Posterior mean	Posterior variance	95% CI of distribution	Chain converged	AR-free chains
1	MALE	Within	Whether participant is male	0.502		(0.499, 0.505)	Yes	4
2	IMMI1GEN	Within	Whether participant migrated to this country	0.029		(0.028, 0.030)	Yes	4
3	IMMI2GEN	Within	Whether their parent did	0.042		(0.041, 0.044)	Yes	4
4	ESCS	Within	Index of economic, social and cultural status	−0.241		(−0.247, −0.234)	Yes	4
5	FCFMLRTY	Within	Familiarity with concepts of finance	7.049		(7.015, 7.083)	Yes	4
6	FLCONFIN	Within	Confidence about financial matters	−0.072		(−0.079, −0.065)	Yes	4
7	FLSCHOOL	Within	Financial education in school lessons	0.018		(0.011, 0.024)	Yes	4
8	NOBULLY	Within	Participant's experience of being bullied (reverse)	−0.059		(−0.067, −0.052)	Yes	4
9	FLFAMILY	Within	Parental involvement in matters of financial literacy	0.064		(0.057, 0.070)	Yes	4
10	MALE	Within	Whether participant is male		0.250	(0.248, 0.252)	Yes	4
11	IMMI1GEN	Within	Whether participant migrated to this country		0.028	(0.028, 0.028)	Yes	4
12	IMMI2GEN	Within	Whether their parent		0.041	(0.040, 0.041)	Yes	4
13	ESCS	Within	Index of economic, social and cultural status		1.183	(1.173, 1.193)	Yes	4
14	FCFMLRTY	Within	Familiarity with concepts of finance		29.754	(29.495, 30.016)	Yes	4
15	FLCONFIN	Within	Confidence about financial matters		1.034	(1.025, 1.044)	Yes	4
16	FLSCHOOL	Within	Financial education in school lessons		1.040	(1.031, 1.049)	Yes	4
17	NOBULLY	Within	Participant's experience of being bullied (reverse)		1.111	(1.100, 1.121)	Yes	4
18	FLFAMILY	Within	Parental involvement in matters of financial literacy		1.090	(1.080, 1.100)	Yes	4
19	STRAIO	Between	Student–teacher ratio	13.873		(13.607, 14.139)	Yes	4
20	EDUSHORT	Between	Shortage of educational material	0.131		(0.106, 0.157)	Yes	4
21	STRAIO	Between	Student–teacher ratio		103.532	(99.750, 107.430)	Yes	4
22	EDUSHORT	Between	Shortage of educational material		1.074	(1.037, 1.112)	Yes	4

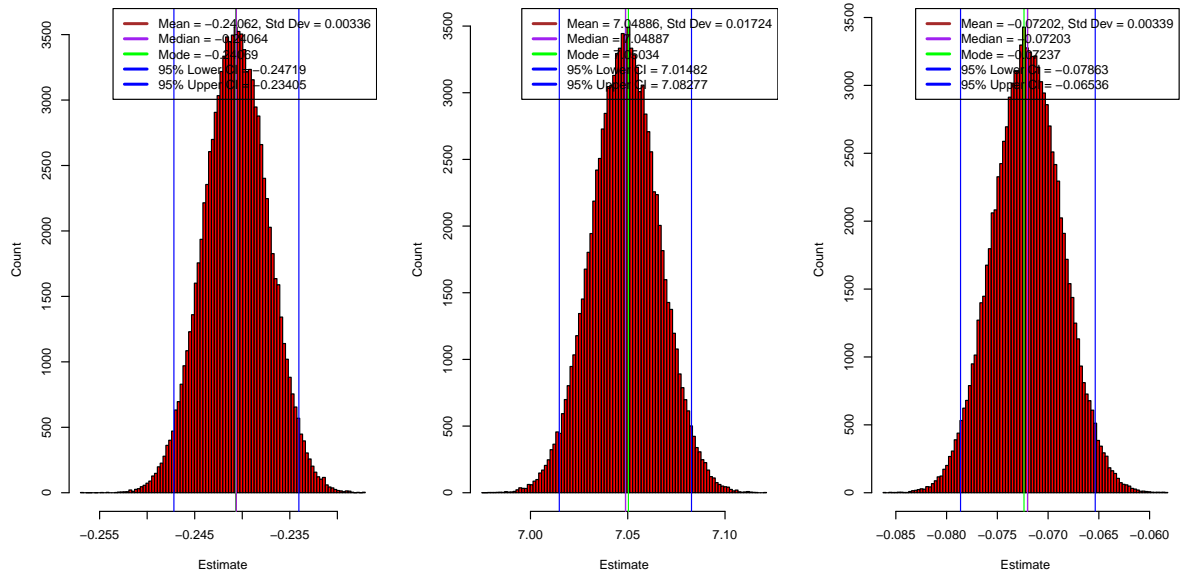
*Note.* Notes go here.



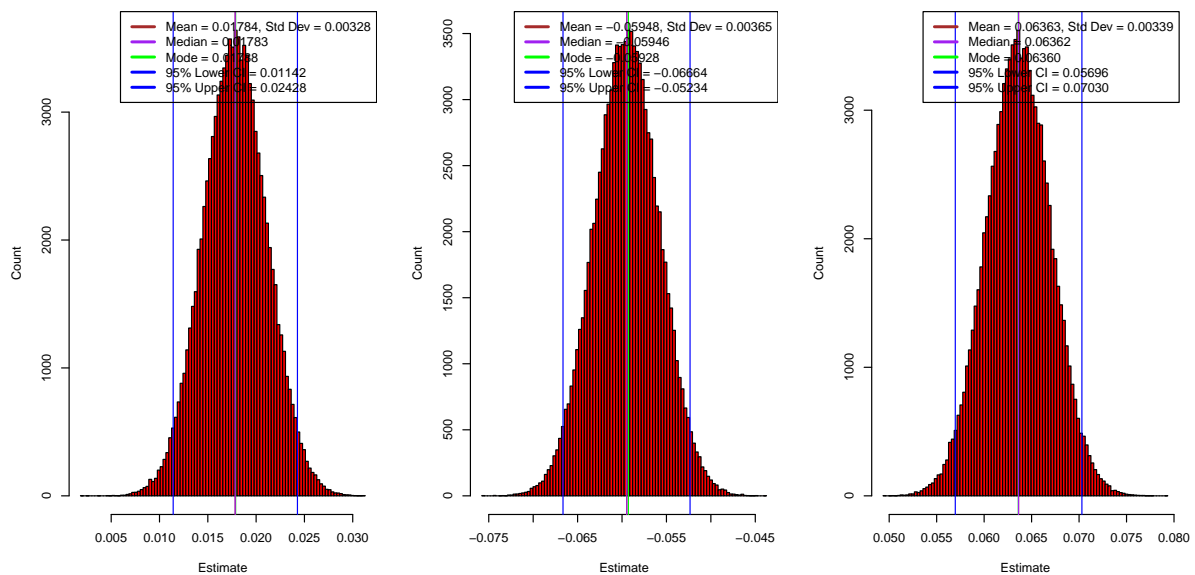
Distribution of: Parameter 1, %WITHIN%: [ MALE ] Distribution of: Parameter 2, %WITHIN%: [ IMMI1GEI ] Distribution of: Parameter 3, %WITHIN%: [ IMMI2GEI ]



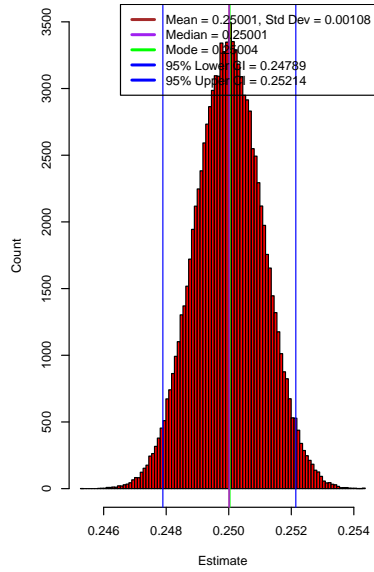
Distribution of: Parameter 4, %WITHIN%: [ ESCS ] Distribution of: Parameter 5, %WITHIN%: [ FCFMLRT ] Distribution of: Parameter 6, %WITHIN%: [ FLCONFI ]



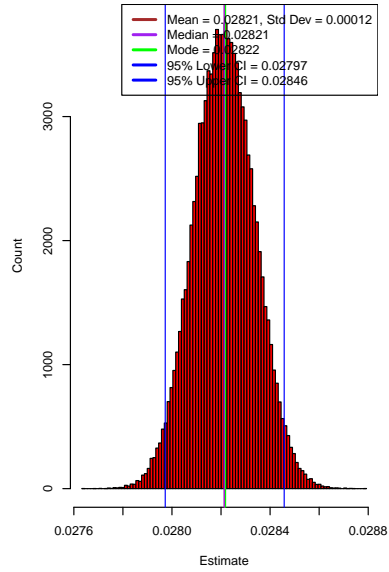
Distribution of: Parameter 7, %WITHIN%: [ FLSCHOC ] Distribution of: Parameter 8, %WITHIN%: [ NOBULL' ] Distribution of: Parameter 9, %WITHIN%: [ FLFAMIL' ]



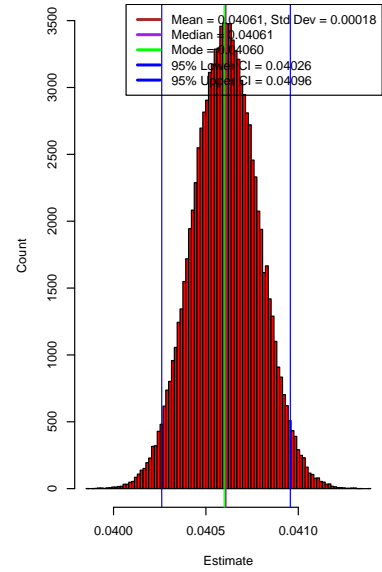
Distribution of: Parameter 10, %WITHIN%: MALE



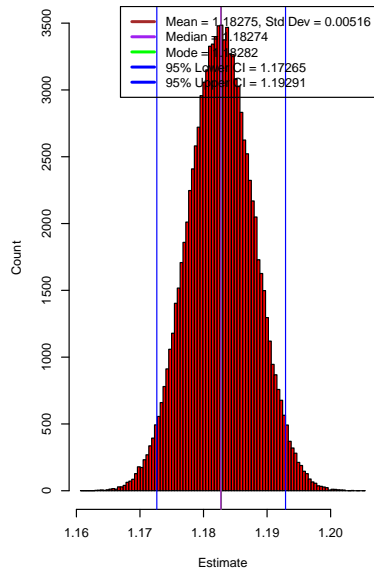
Distribution of: Parameter 11, %WITHIN%: IMMI1GE



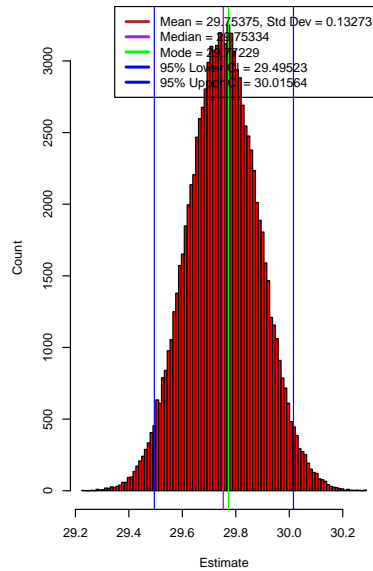
Distribution of: Parameter 12, %WITHIN%: IMMI2GE



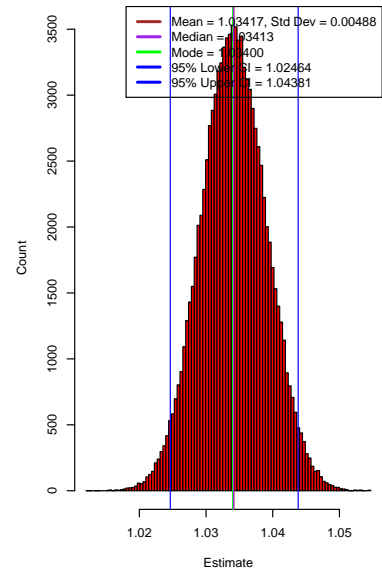
Distribution of: Parameter 13, %WITHIN%: ESCS



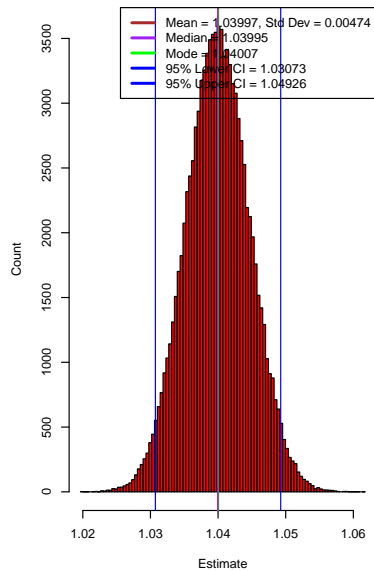
Distribution of: Parameter 14, %WITHIN%: FCFMLR'



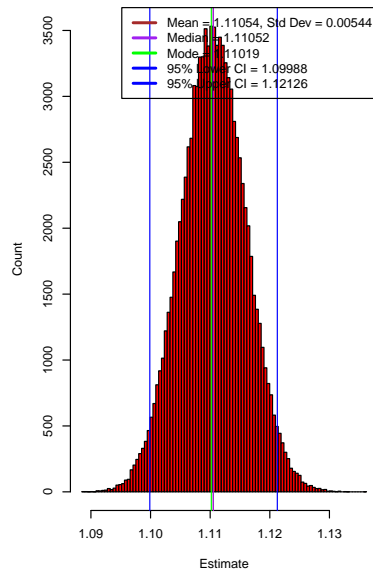
Distribution of: Parameter 15, %WITHIN%: FLCONF



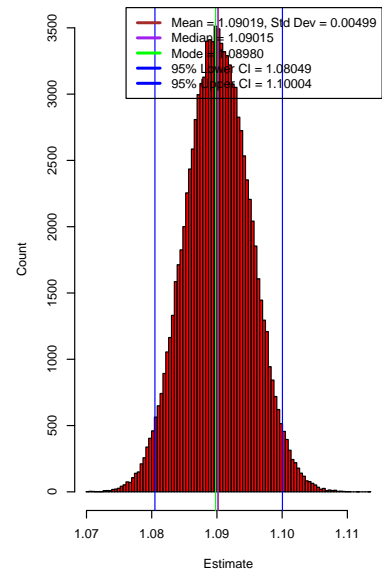
Distribution of: Parameter 16, %WITHIN%: FLSCHO



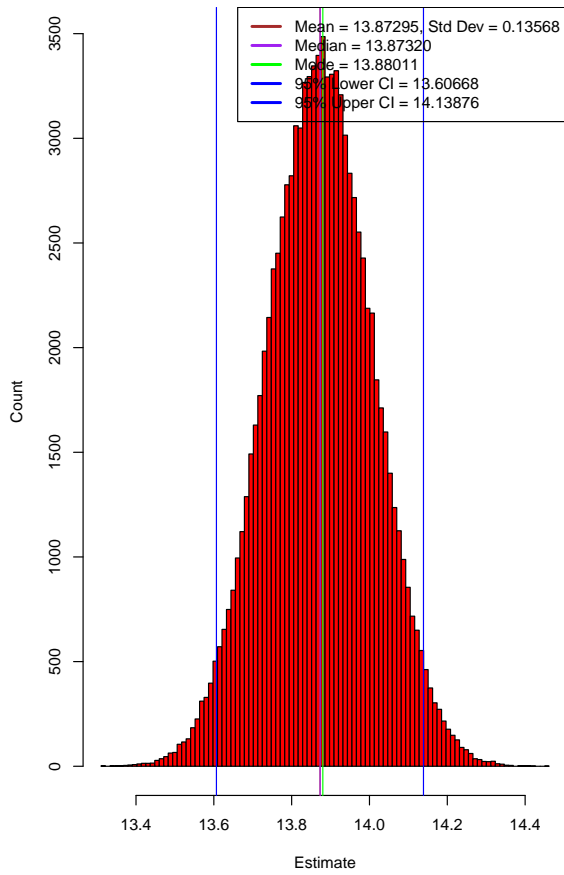
Distribution of: Parameter 17, %WITHIN%: NOBULL



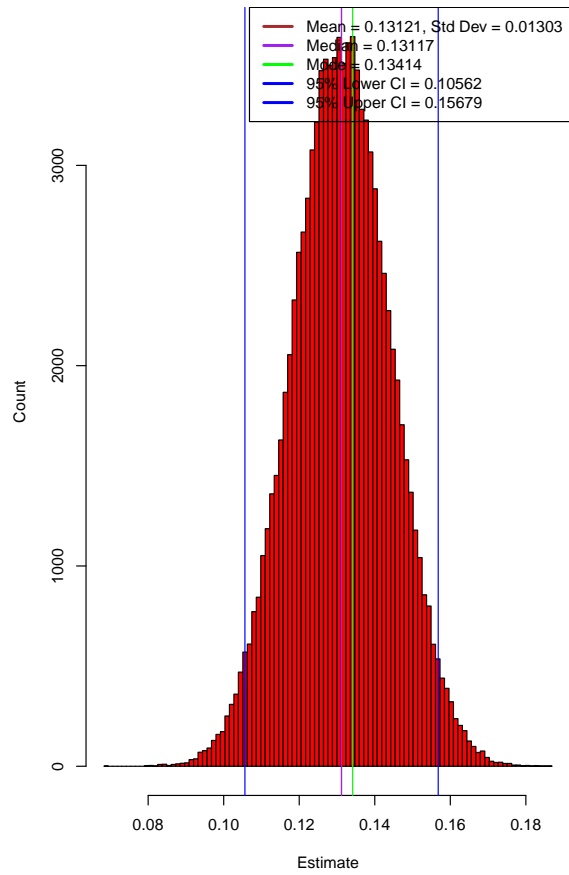
Distribution of: Parameter 18, %WITHIN%: FLFAMIL



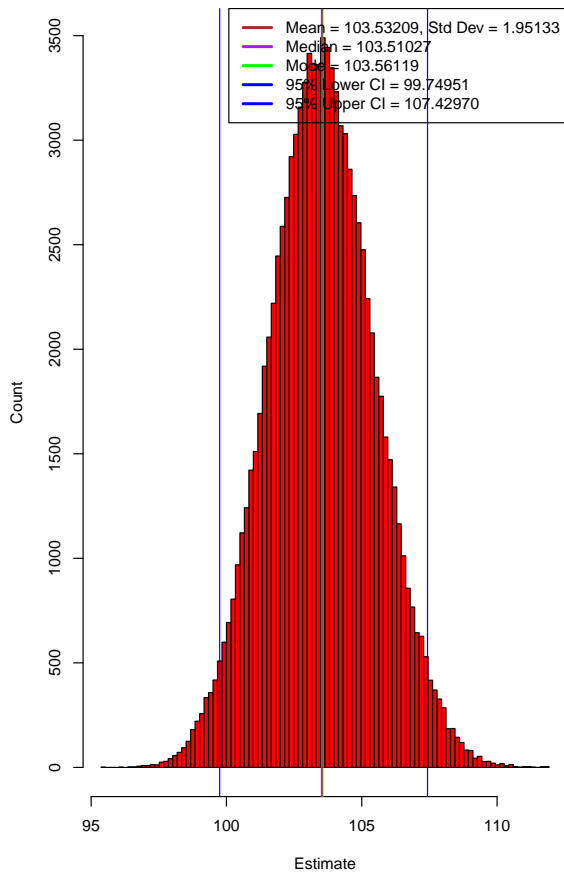
Distribution of: Parameter 19, %BETWEEN%: [ STRATIO ]



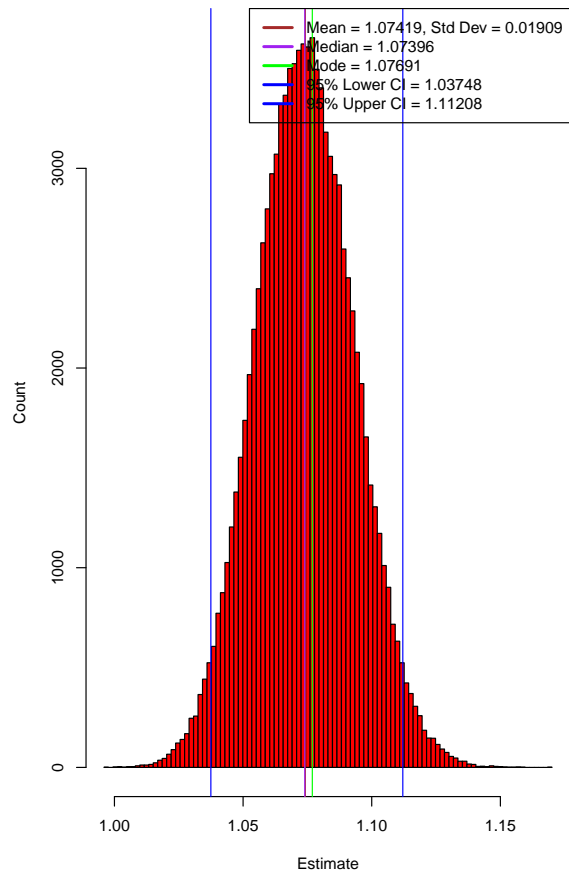
Distribution of: Parameter 20, %BETWEEN%: [ EDUSHORT ]



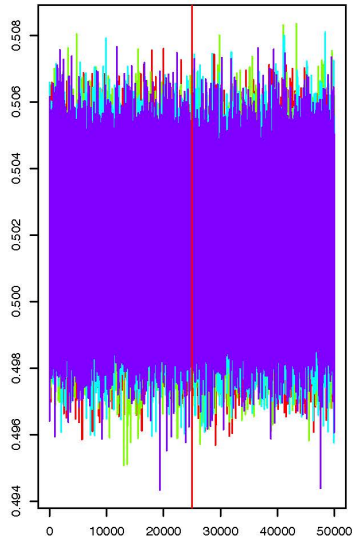
Distribution of: Parameter 21, %BETWEEN%: STRATIO



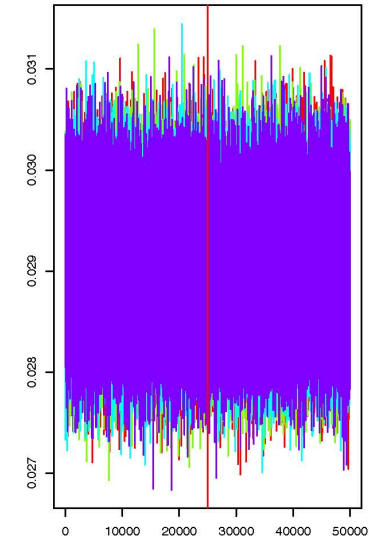
Distribution of: Parameter 22, %BETWEEN%: EDUSHORT



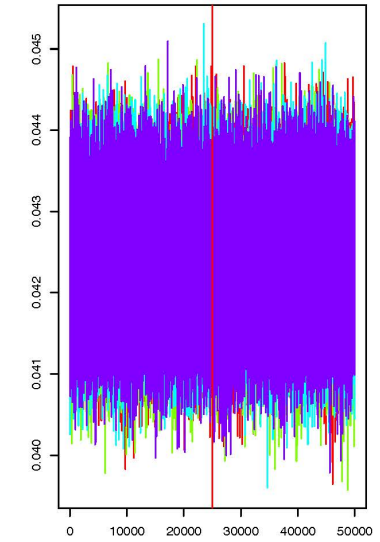
Trace plot of: Parameter 1, %WITHIN%: [ MALE ]



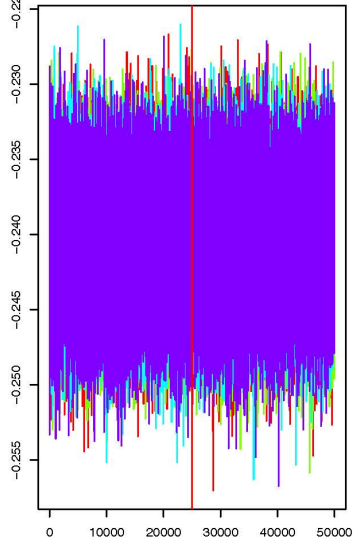
Trace plot of: Parameter 2, %WITHIN%: [ IMMI1GEN



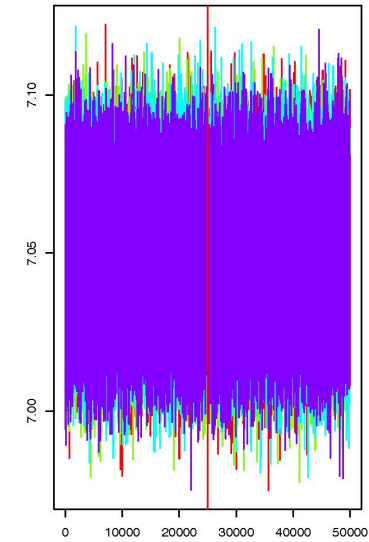
Trace plot of: Parameter 3, %WITHIN%: [ IMMI2GEN



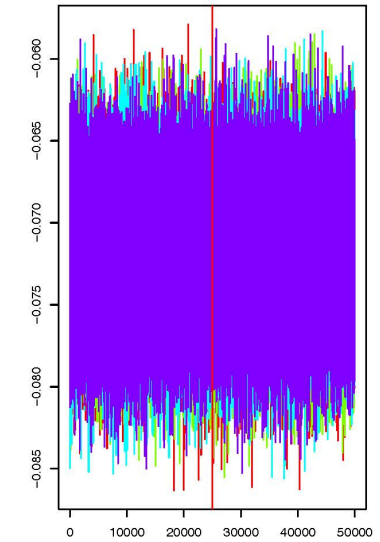
Trace plot of: Parameter 4, %WITHIN%: [ ESCS ]



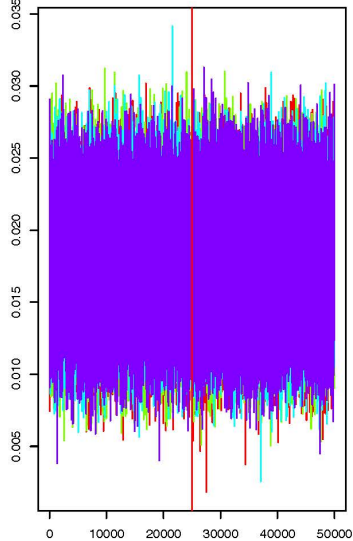
Trace plot of: Parameter 5, %WITHIN%: [ FCFMLRT'



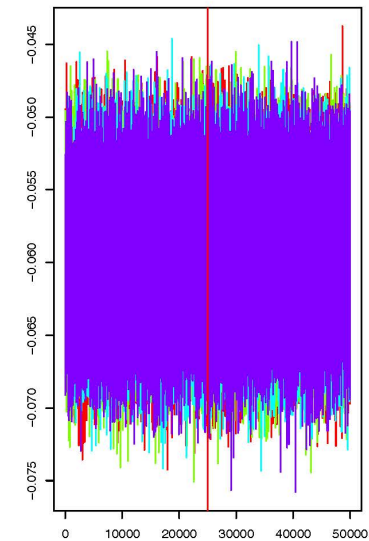
Trace plot of: Parameter 6, %WITHIN%: [ FLCONFIN



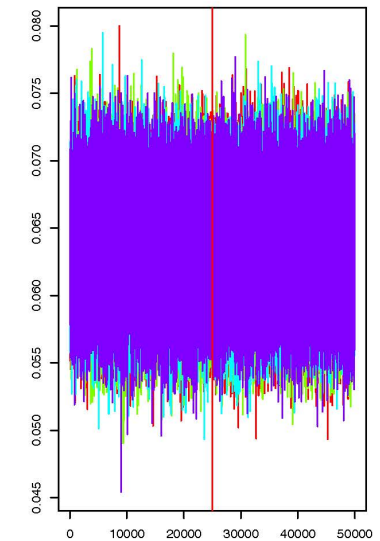
Trace plot of: Parameter 7, %WITHIN%: [ FLSCHOOL



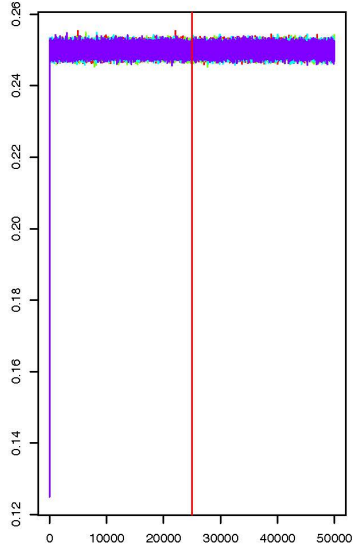
Trace plot of: Parameter 8, %WITHIN%: [ NOBULLY



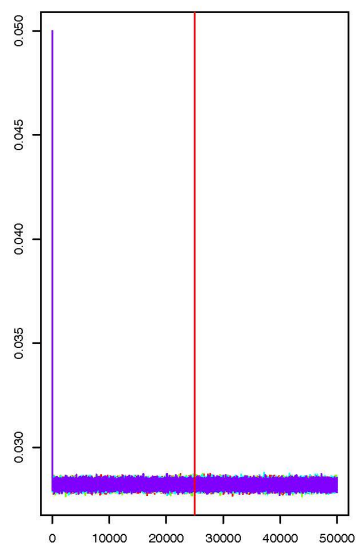
Trace plot of: Parameter 9, %WITHIN%: [ FLFAMILY



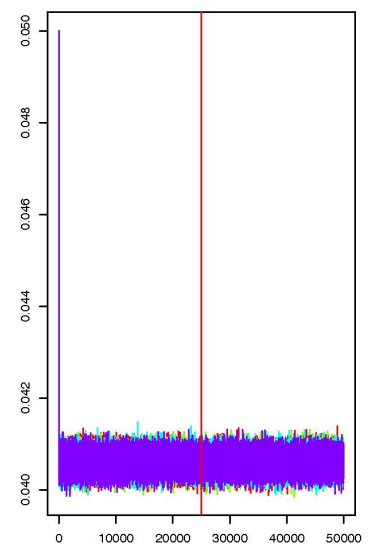
Trace plot of: Parameter 10, %WITHIN%: MALE



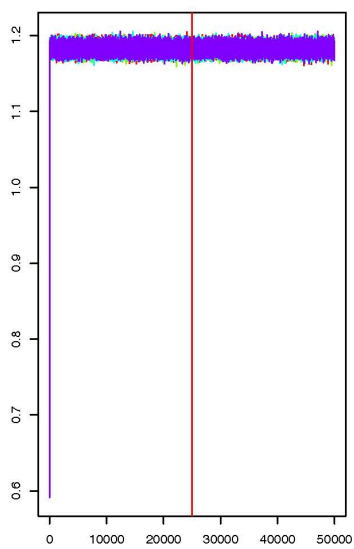
Trace plot of: Parameter 11, %WITHIN%: IMMI1GEI



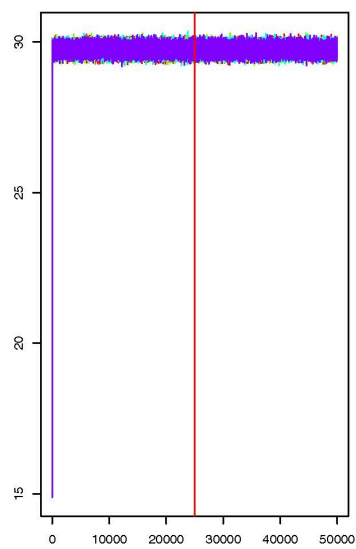
Trace plot of: Parameter 12, %WITHIN%: IMMI2GEI



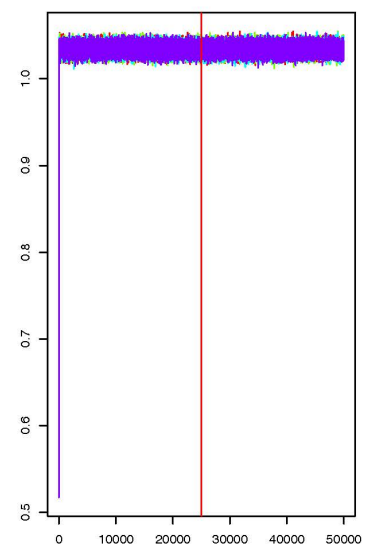
Trace plot of: Parameter 13, %WITHIN%: ESCS



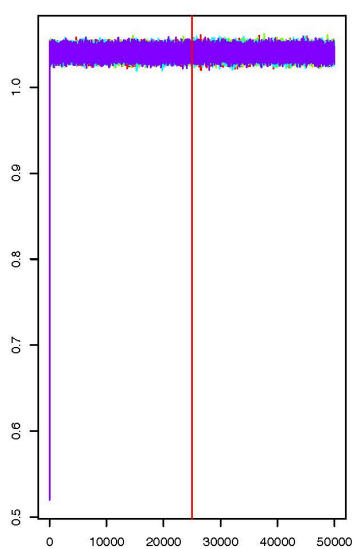
Trace plot of: Parameter 14, %WITHIN%: FCFMLRT



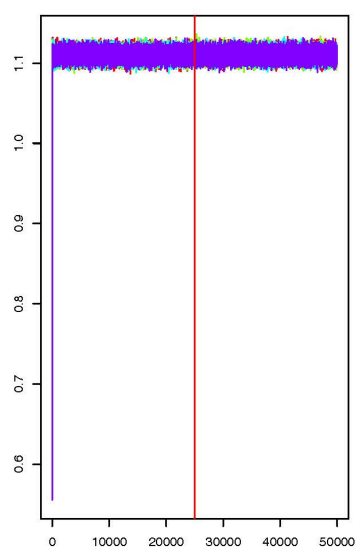
Trace plot of: Parameter 15, %WITHIN%: FLCONFII



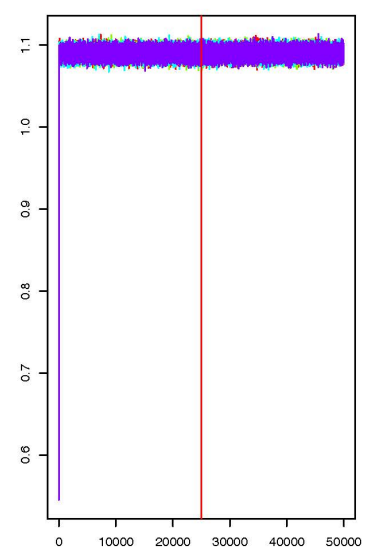
Trace plot of: Parameter 16, %WITHIN%: FLSCHOO



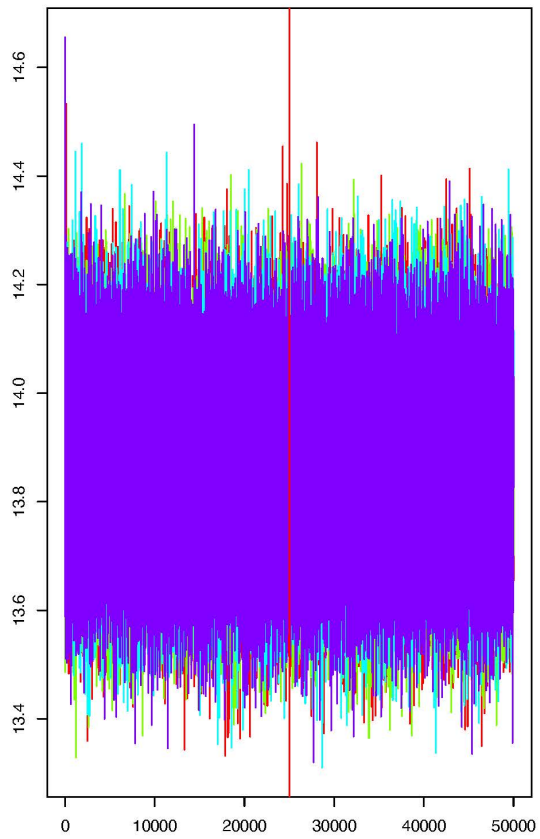
Trace plot of: Parameter 17, %WITHIN%: NOBULL\



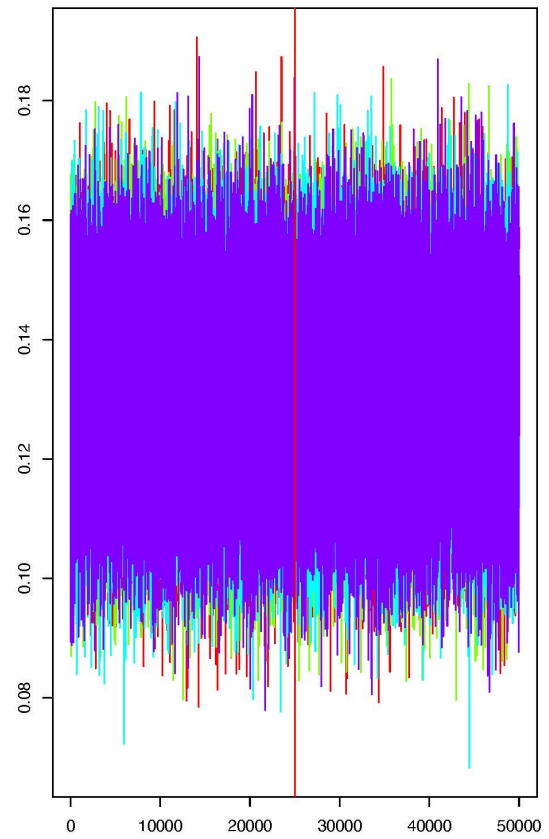
Trace plot of: Parameter 18, %WITHIN%: FLFAMIL\



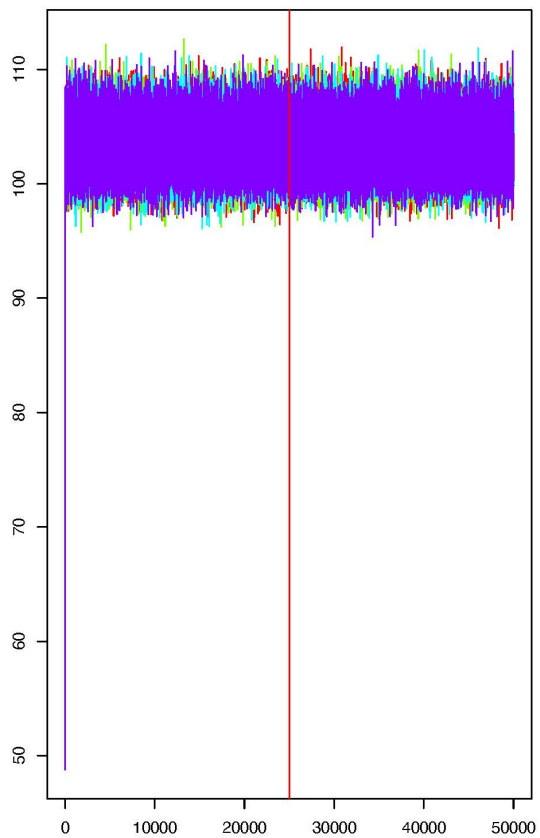
Trace plot of: Parameter 19, %BETWEEN%: [ STRATIO ]



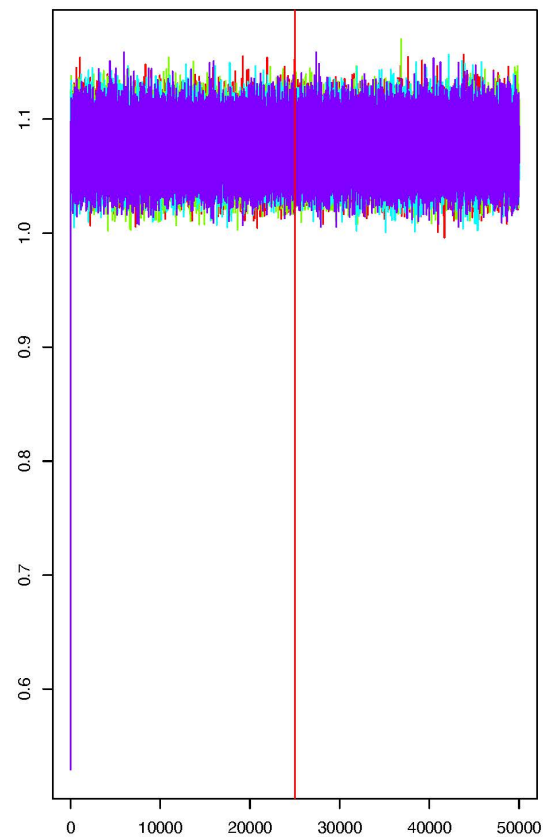
Trace plot of: Parameter 20, %BETWEEN%: [ EDUSHORT ]



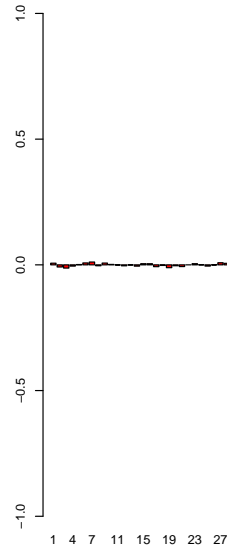
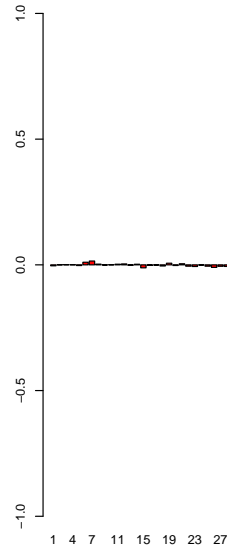
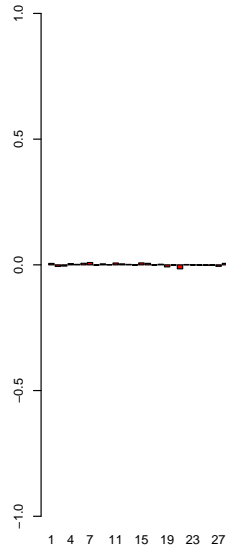
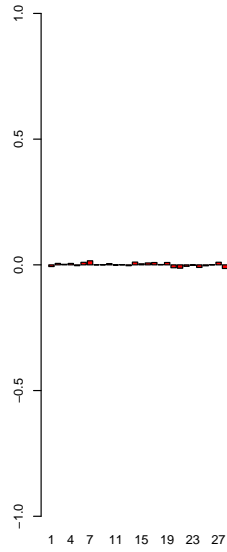
Trace plot of: Parameter 21, %BETWEEN%: STRATIO



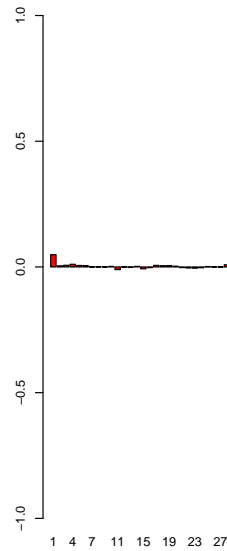
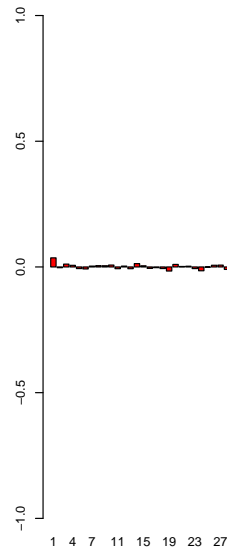
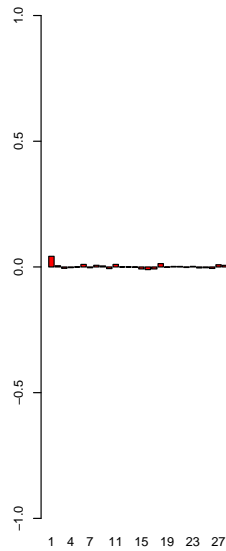
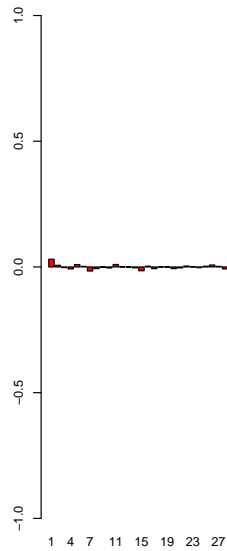
Trace plot of: Parameter 22, %BETWEEN%: EDUSHORT



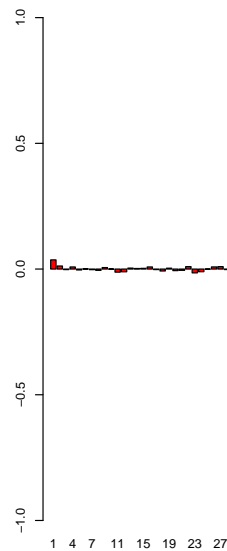
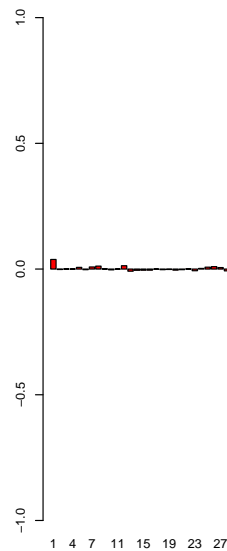
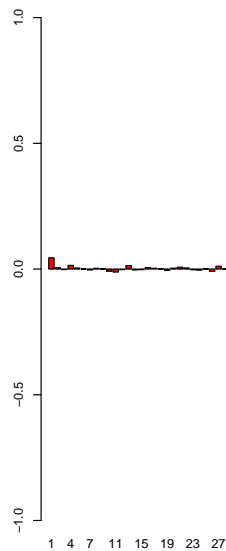
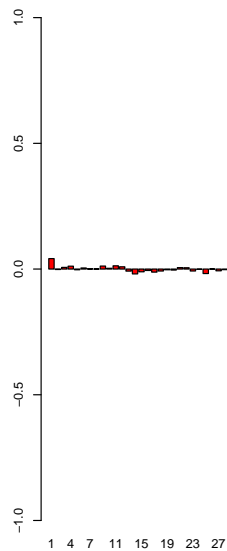
1): Parameter 1, %WITHIN%: [ MALE ] 2): Parameter 1, %WITHIN%: [ MALE ] 3): Parameter 1, %WITHIN%: [ MALE ] 4): Parameter 1, %WITHIN%: [ MALE ]



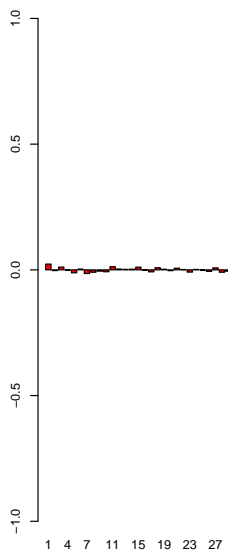
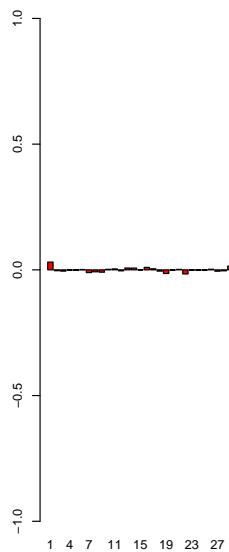
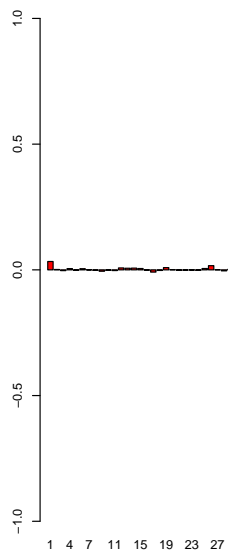
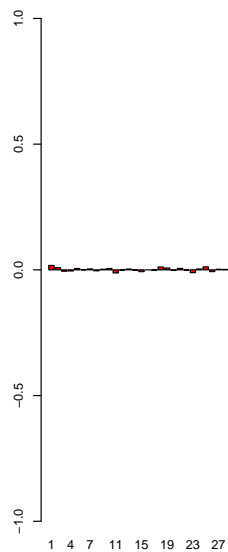
): Parameter 2, %WITHIN%: [IMMI1GEI ): Parameter 2, %WITHIN%: [IMMI1GEI ): Parameter 2, %WITHIN%: [IMMI1GEI ): Parameter 2, %WITHIN%: [IMMI1GEI



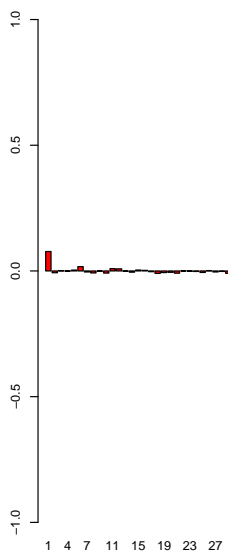
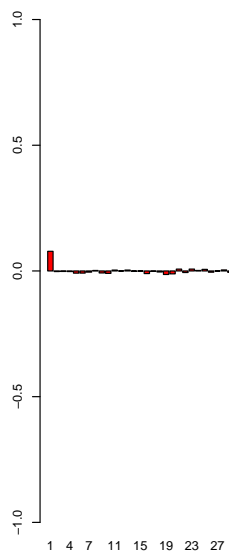
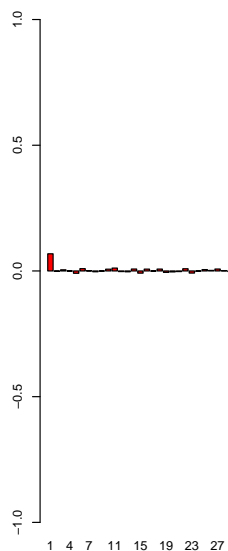
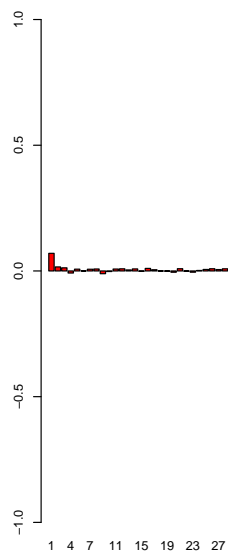
): Parameter 3, %WITHIN%: [IMMI2GEI): Parameter 3, %WITHIN%: [IMMI2GEI): Parameter 3, %WITHIN%: [IMMI2GEI): Parameter 3, %WITHIN%: [IMMI2GEI



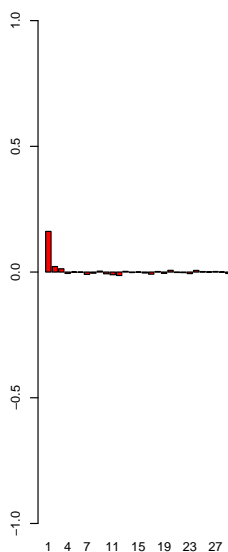
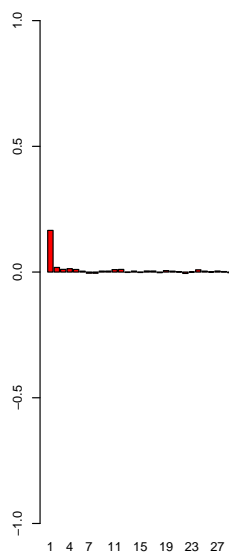
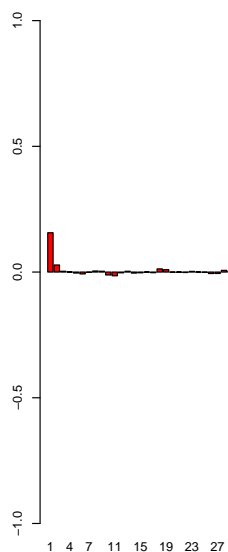
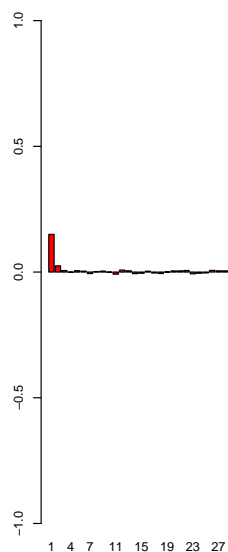
1 ): Parameter 4, %WITHIN%: [ ESCS ] 2 ): Parameter 4, %WITHIN%: [ ESCS ] 3 ): Parameter 4, %WITHIN%: [ ESCS ] 4 ): Parameter 4, %WITHIN%: [ ESCS ]



): Parameter 5, %WITHIN%: [ FCFMLRT): Parameter 5, %WITHIN%: [ FCFMLRT): Parameter 5, %WITHIN%: [ FCFMLRT): Parameter 5, %WITHIN%: [ FCFMLRT

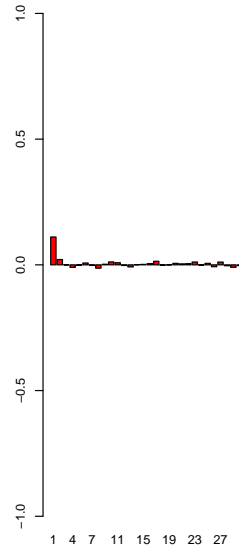
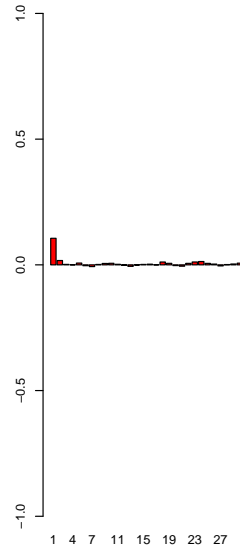
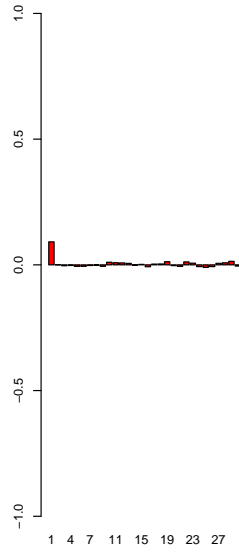
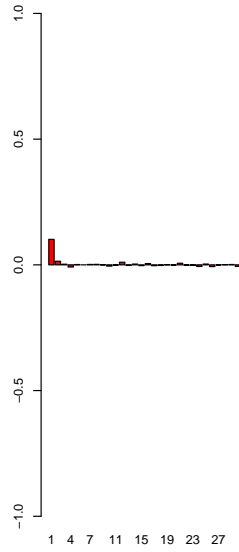


): Parameter 6, %WITHIN%: [ FLCONFII ): Parameter 6, %WITHIN%: [ FLCONFII ): Parameter 6, %WITHIN%: [ FLCONFII ): Parameter 6, %WITHIN%: [ FLCONFII

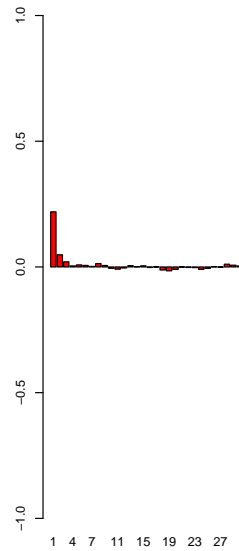
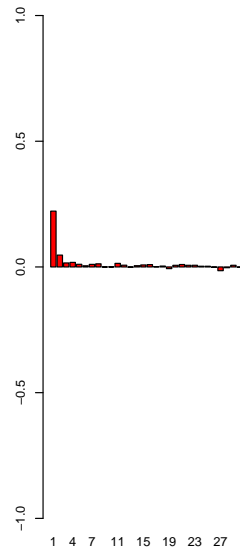
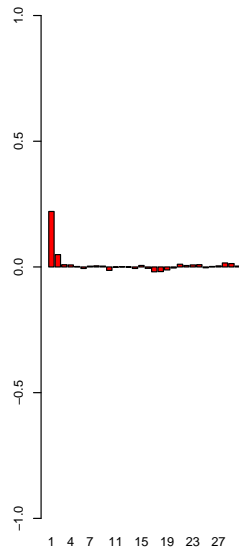
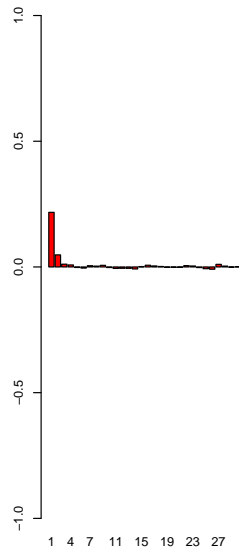




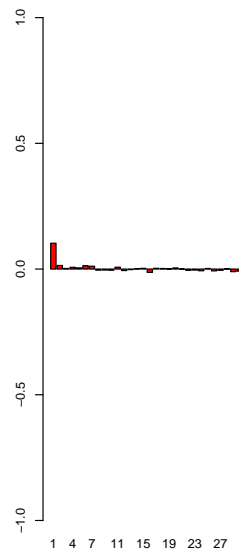
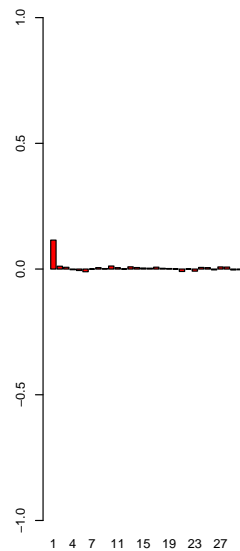
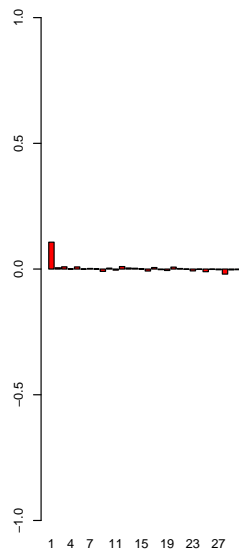
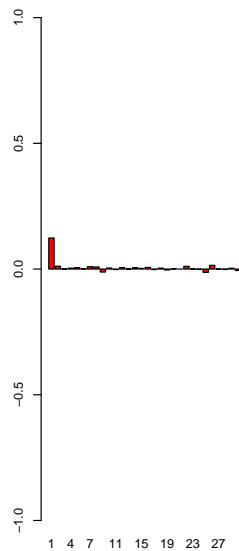
): Parameter 7, %WITHIN%: [ FLSCHOO): Parameter 7, %WITHIN%: [ FLSCHOO): Parameter 7, %WITHIN%: [ FLSCHOO): Parameter 7, %WITHIN%: [ FLSCHOO



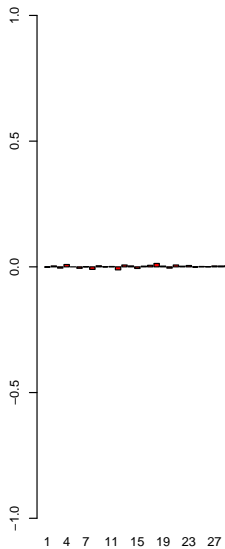
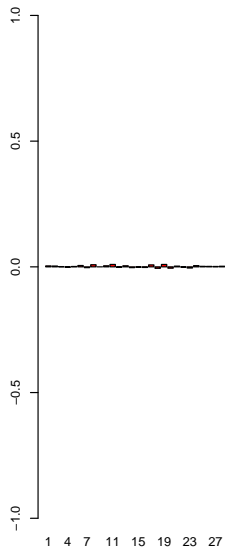
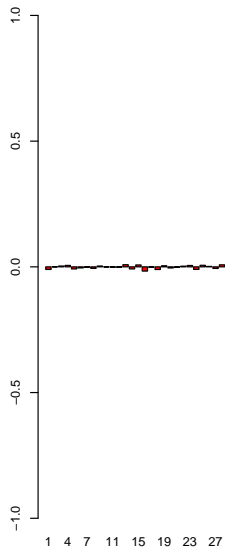
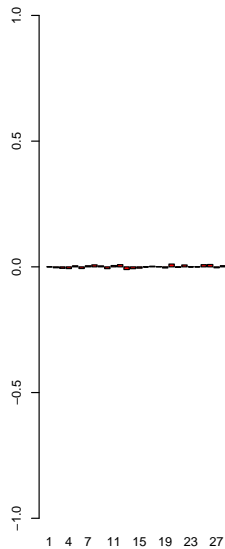
): Parameter 8, %WITHIN%: [ NOBULLY ): Parameter 8, %WITHIN%: [ NOBULLY ): Parameter 8, %WITHIN%: [ NOBULLY ): Parameter 8, %WITHIN%: [ NOBULLY



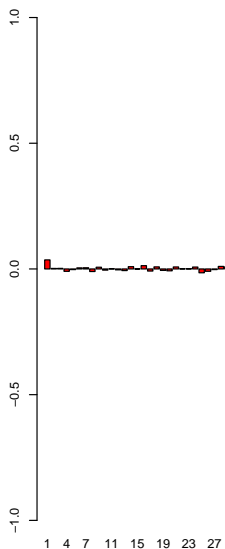
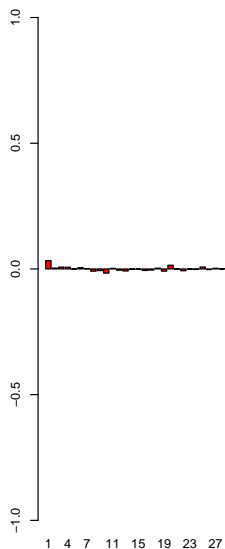
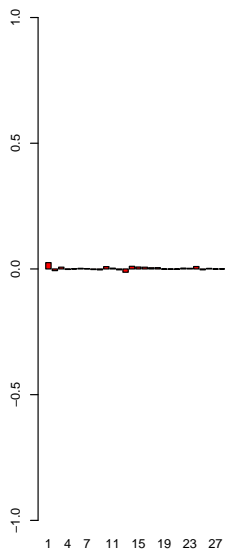
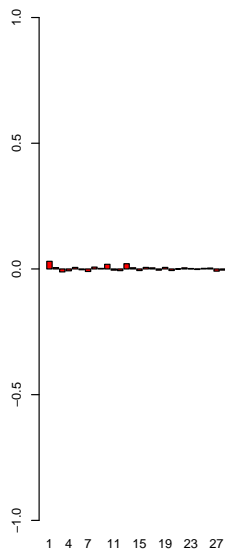
): Parameter 9, %WITHIN%: [ FLFAMILY ): Parameter 9, %WITHIN%: [ FLFAMILY ): Parameter 9, %WITHIN%: [ FLFAMILY ): Parameter 9, %WITHIN%: [ FLFAMILY )



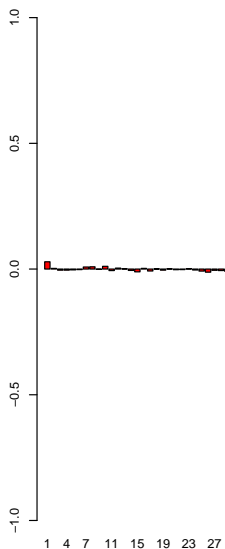
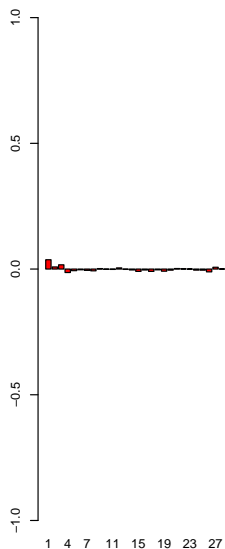
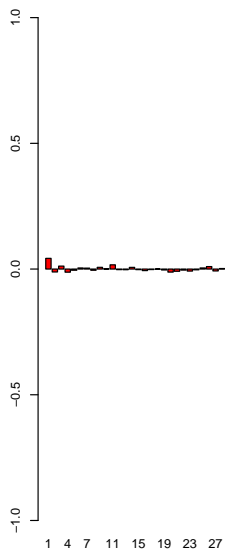
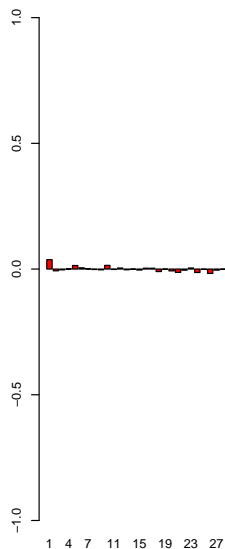
1 ): Parameter 10, %WITHIN%: MALE    2 ): Parameter 10, %WITHIN%: MALE    3 ): Parameter 10, %WITHIN%: MALE    4 ): Parameter 10, %WITHIN%: MALE



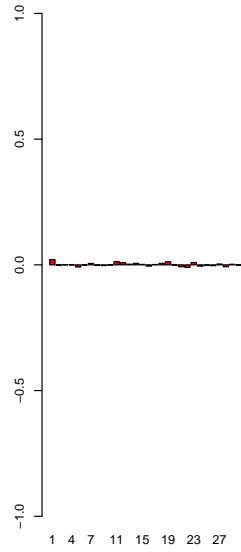
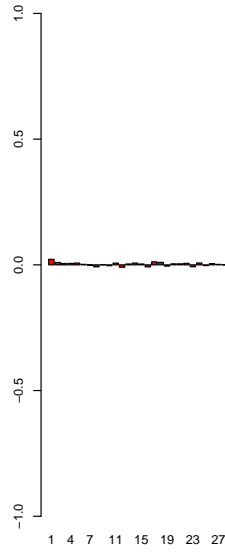
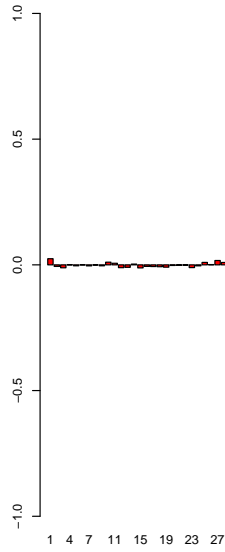
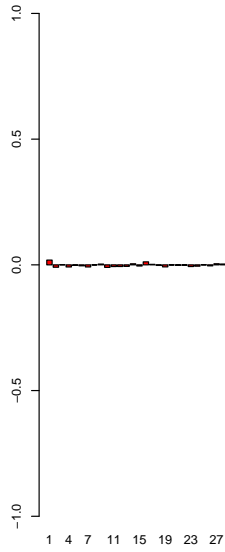
5 ): Parameter 11, %WITHIN%: IMMI1GEN    6 ): Parameter 11, %WITHIN%: IMMI1GEN    7 ): Parameter 11, %WITHIN%: IMMI1GEN    8 ): Parameter 11, %WITHIN%: IMMI1GEN



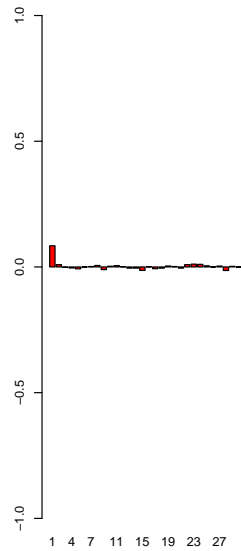
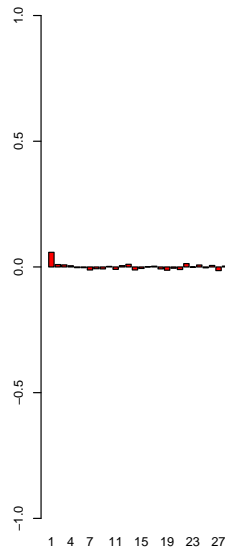
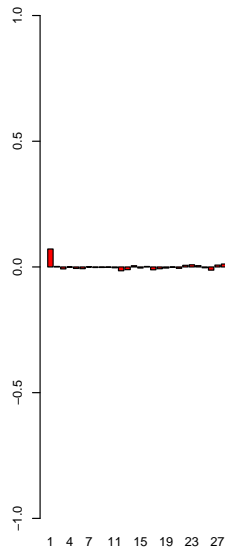
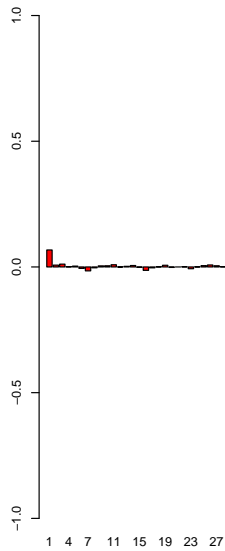
9 ): Parameter 12, %WITHIN%: IMMI2GEN    10 ): Parameter 12, %WITHIN%: IMMI2GEN    11 ): Parameter 12, %WITHIN%: IMMI2GEN    12 ): Parameter 12, %WITHIN%: IMMI2GEN



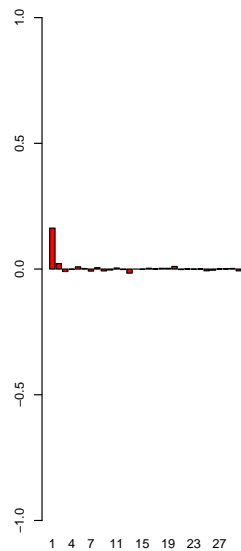
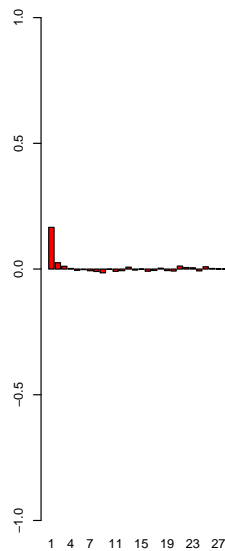
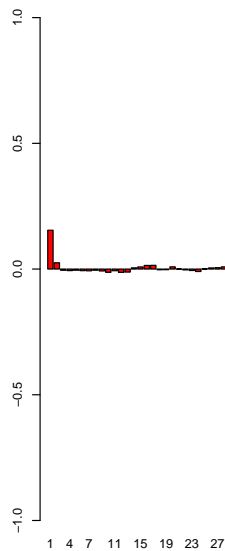
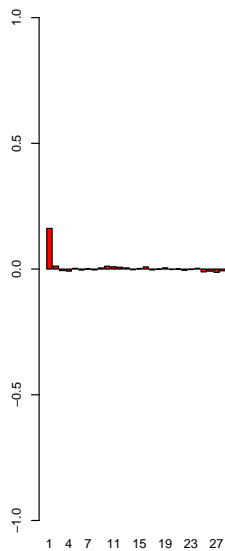
1): Parameter 13, %WITHIN%: ESCS    2): Parameter 13, %WITHIN%: ESCS    3): Parameter 13, %WITHIN%: ESCS    4): Parameter 13, %WITHIN%: ESCS



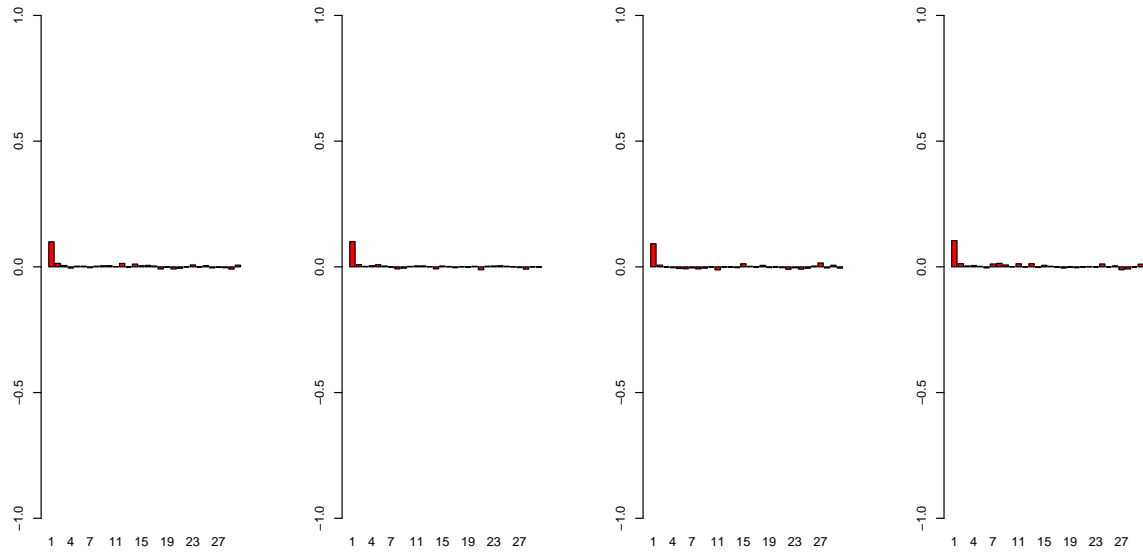
5): Parameter 14, %WITHIN%: FCFMLRT)    6): Parameter 14, %WITHIN%: FCFMLRT)    7): Parameter 14, %WITHIN%: FCFMLRT)    8): Parameter 14, %WITHIN%: FCFMLRT)



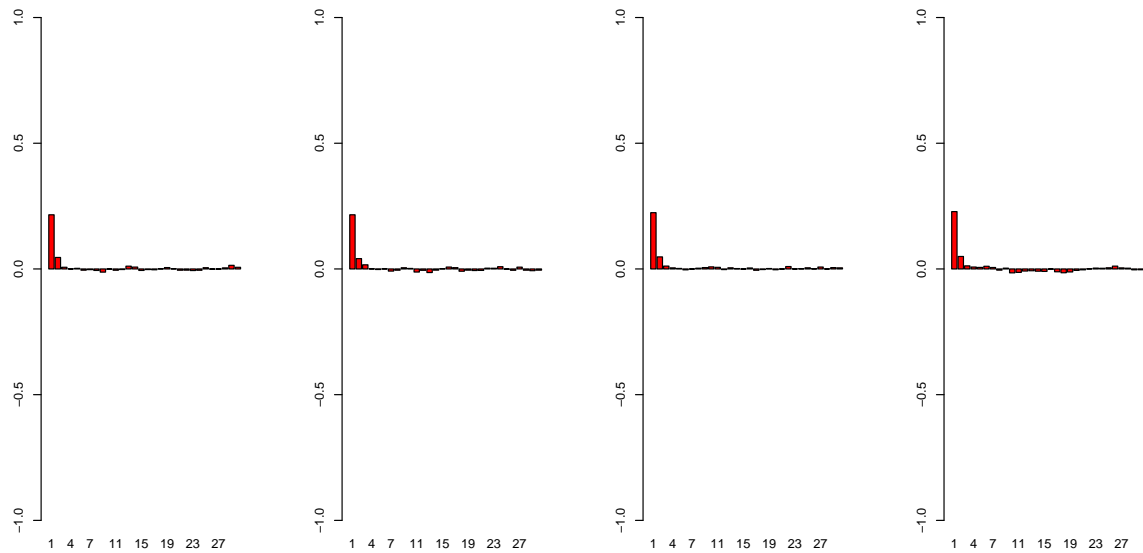
9): Parameter 15, %WITHIN%: FLCONFID)    10): Parameter 15, %WITHIN%: FLCONFID)    11): Parameter 15, %WITHIN%: FLCONFID)    12): Parameter 15, %WITHIN%: FLCONFID)



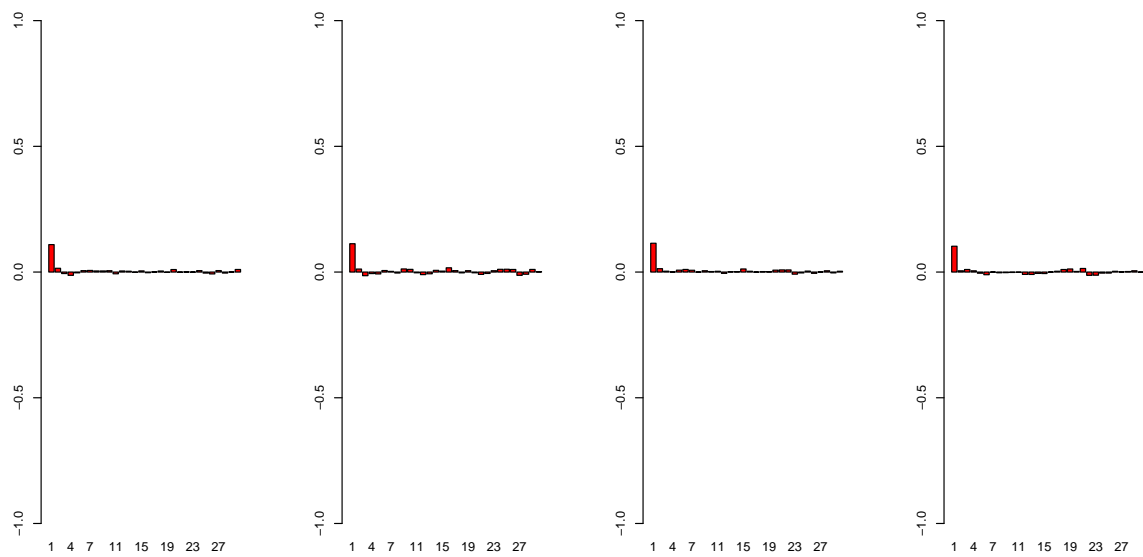
) : Parameter 16, %WITHIN%: FLSCHOO): Parameter 16, %WITHIN%: FLSCHOO): Parameter 16, %WITHIN%: FLSCHOO): Parameter 16, %WITHIN%: FLSCHOO



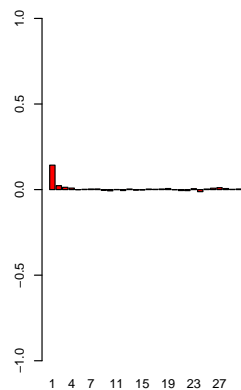
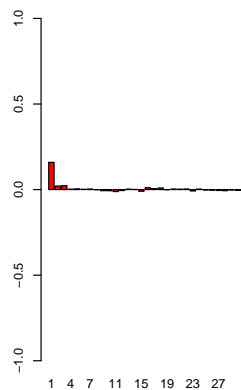
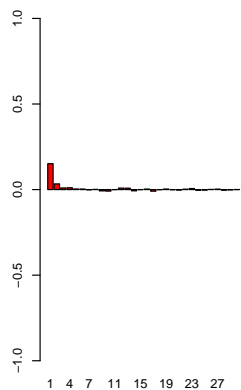
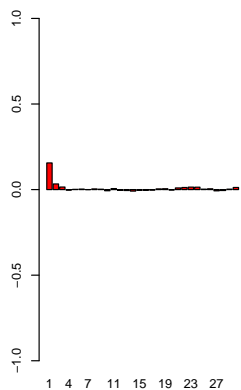
) : Parameter 17, %WITHIN%: NOBULLY ): Parameter 17, %WITHIN%: NOBULLY ): Parameter 17, %WITHIN%: NOBULLY ): Parameter 17, %WITHIN%: NOBULLY



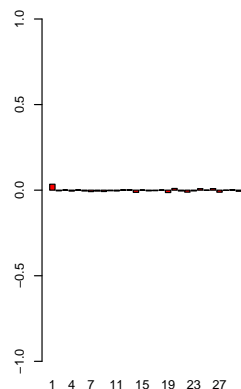
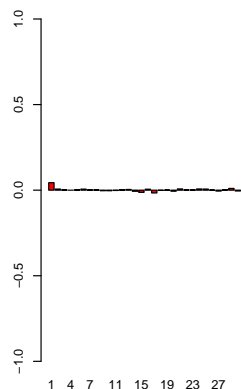
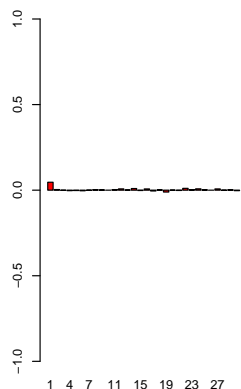
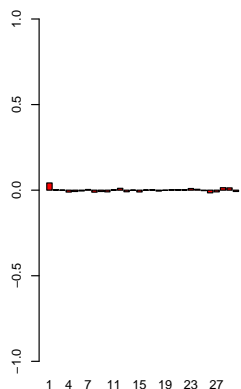
) : Parameter 18, %WITHIN%: FLFAMILY ): Parameter 18, %WITHIN%: FLFAMILY ): Parameter 18, %WITHIN%: FLFAMILY ): Parameter 18, %WITHIN%: FLFAMILY



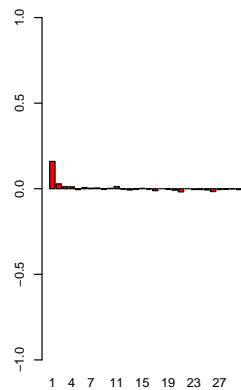
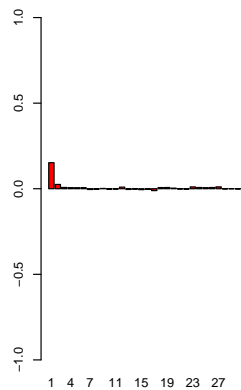
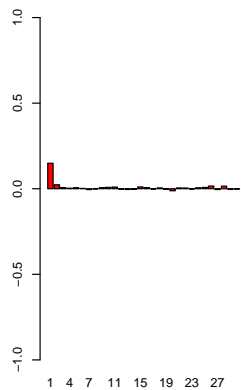
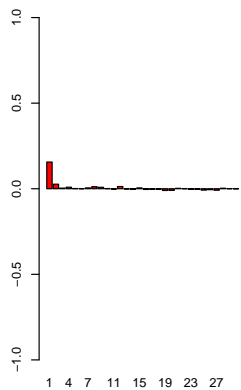
|: Parameter 19, %BETWEEN%: [ STRA]: Parameter 19, %BETWEEN%: [ STRA]: Parameter 19, %BETWEEN%: [ STRA]: Parameter 19, %BETWEEN%: [ STRA]



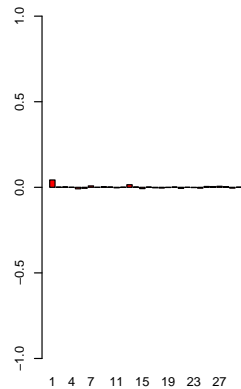
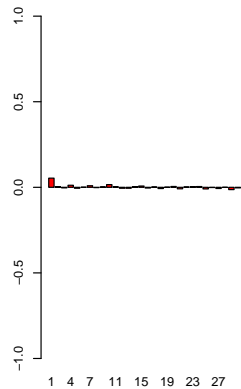
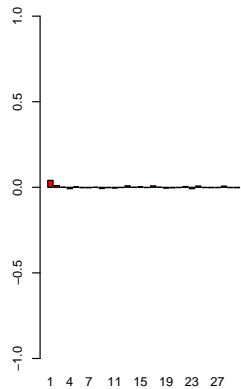
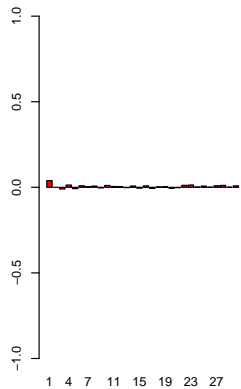
Parameter 20, %BETWEEN%: [ EDUSH| Parameter 20, %BETWEEN%: [ EDUSH| Parameter 20, %BETWEEN%: [ EDUSH| Parameter 20, %BETWEEN%: [ EDUSH|



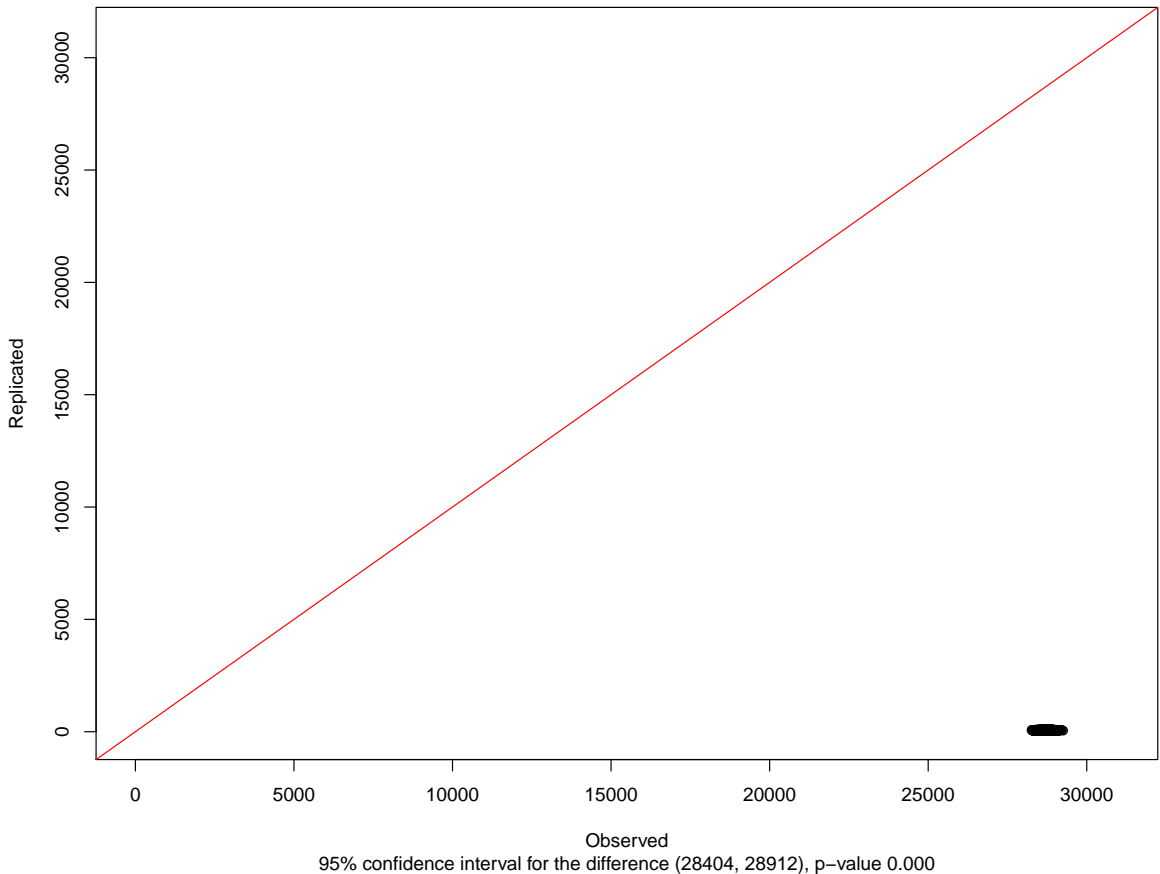
); Parameter 21, %BETWEEN%: STRATI); Parameter 21, %BETWEEN%: STRATI); Parameter 21, %BETWEEN%: STRATI); Parameter 21, %BETWEEN%: STRATI);



Parameter 22, %BETWEEN%: EDUSHO Parameter 22, %BETWEEN%: EDUSHO Parameter 22, %BETWEEN%: EDUSHO Parameter 22, %BETWEEN%: EDUSHO



Bayesian Predictive Scatter Plot



Bayesian Predictive Distribution

