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

A Multilevel Structural Equation Modelling Approach

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

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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

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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 envrionment 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 genuently 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' congnitive 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, respetively. Macroeconomic data needed for these computations can be sourced from the World Bank (World Bank, 2020) and the United Nations' *Human Development Reports* (UN, 2020).

Combining individual and institutional data cources 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

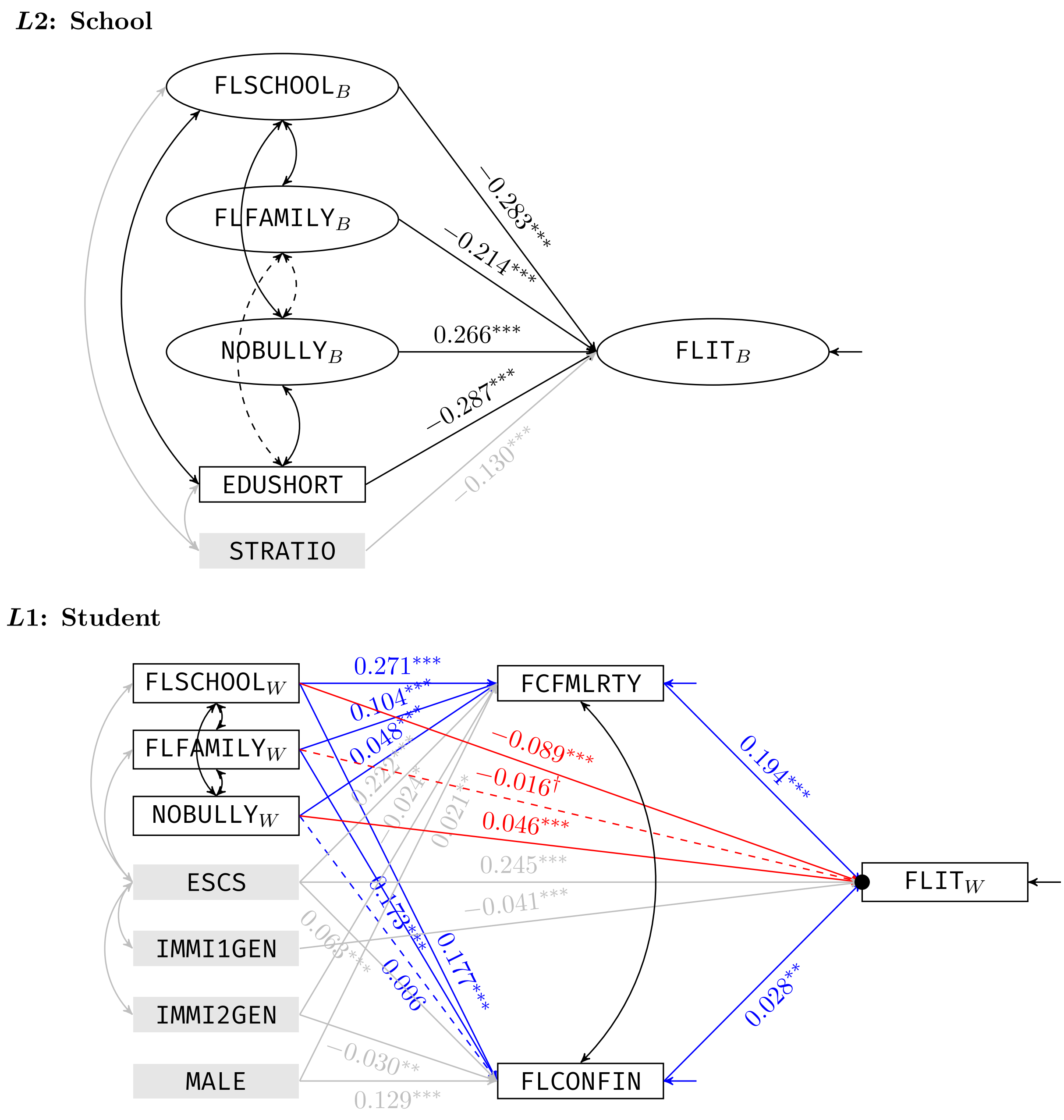
Percentages of Missing Values

CNT	MALE	IMMI1GEN	IMMI2GEN	ESCS	FCFMLRTY	FLCONFIN	PERFEED	TEACHINT	FLSCHOOL	DISCRIM†	BELONG	BULLY	FLFAMILY	CURSUPP†	PASCHPOL†	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†	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. † marks the country and variables that are excluded from subsequent analyses.

Figure 2.1

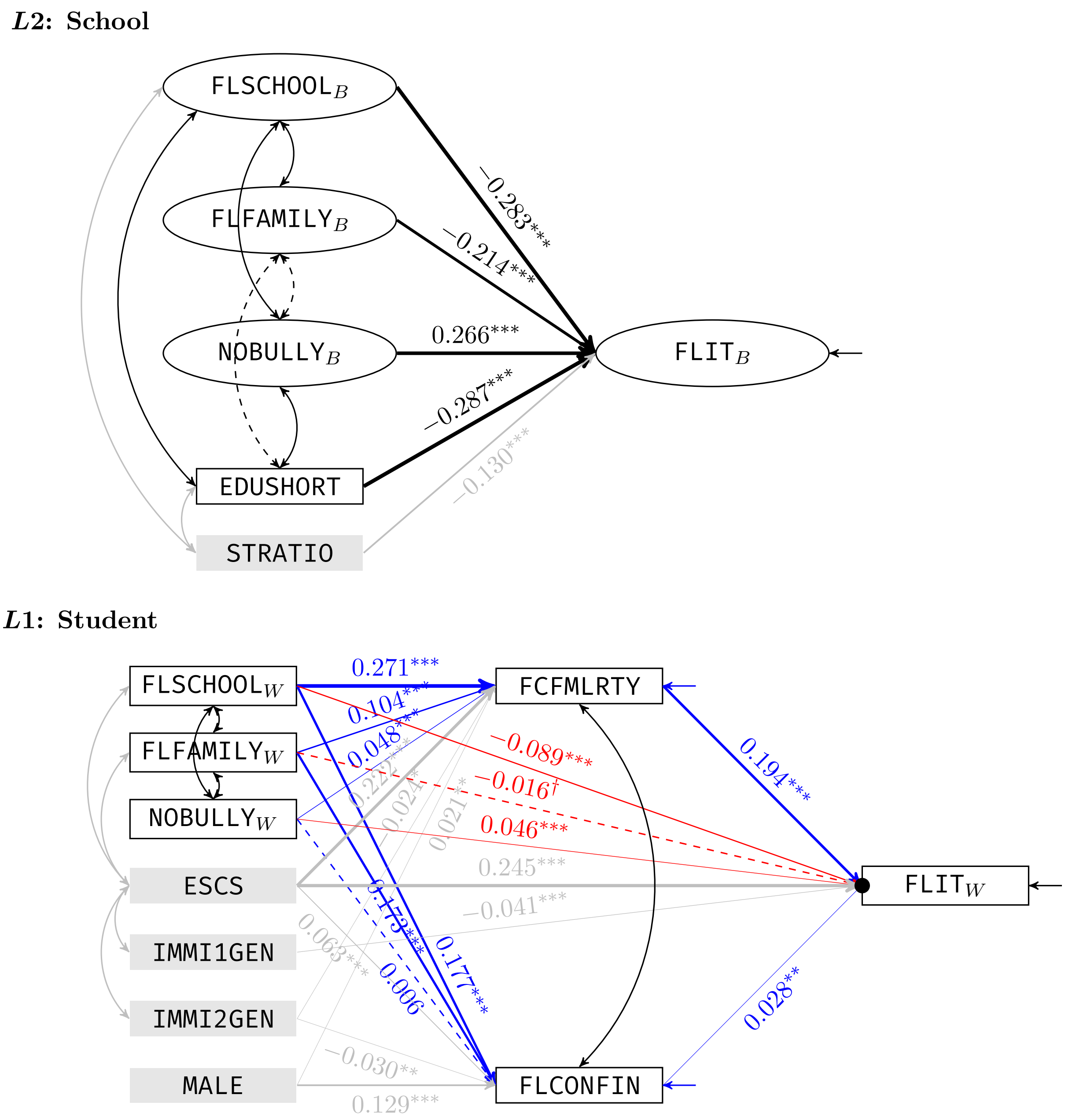
Path Diagram



Note. [Insert notes here.]

Figure 2.2

Path Diagram



Note. [Insert notes here.]

Chapter 3 Methods

3.1 Sample

This study drew its primary data soruce 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) including the following 20 participating countries[1]: Brazil, Bulgaria, Canada, Chile, Estonia, Finland, Georgia, Indonesia, Italy, Latvia, Lithuania, the Netherlands, Peru, Poland, Portugal, Russian Federation[2], Serbia, Slovak Republic, Span, and the USA. Due to clerical error concerns, twelve observations without school weights were dropped, leading to a sample size of 107,162 students nested in 6,631 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 envrironment has been operationised 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 imply 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 OECD 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 (refer to Chapter 9 of *PISA 2018 Technical Report* (OECD, 2020b, pp. 14–15) for analytical details).

[1] 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.

[2] 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 (Input, X)	Demographic control	Financial literacy Affective (Mediator, M)	Financial literacy Cognitive (Outcome, Y)
School-level ($L2$)	$\texttt{FLSCHOOL}_B$ $\texttt{FLFAMILY}_B$ $\texttt{NOBULLY}_B$ EDUSHORT	STRAIO		$\texttt{FLIT}_B$
Student-level ($L1$)	$\texttt{FLSCHOOL}_W$ $\texttt{FLFAMILY}_W$ $\texttt{NOBULLY}_W$	ESCS IMMI1GEN IMMI2GEN MALE	FCFMLRTY FLCONFIN	$\texttt{FLIT}_W$

Note. The multilevel latent covariate (MLC) approach has been applied to the student-level school climate variables FLSCHOOL, FLFAMILY, and NOBULLY, as well as to the outcome variable FLIT. The within- and between-level components are then marked with subscript $_W$ and $_B$ respectively.

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

Conventional multilevel modelling approaches assume the observed group means to be prefectly reliable when individual-level characteristics are aggregated to the group-level—a particularly questionable assumption in current study. Thanks to recent advancedment in both theoretical derivations (Lüdtke et al., 2008; Marsh et al., 2009) and computation power (Muthén & Muthén, 1998–2017), the multilevel latent covariate (MLC) approach has enabled the current project to decompose student-level school climate variables FLSCHOOL, FLFAMILY, NOBULLY as well as the cognitive outcome FLIT into their corresponding within- and between-level components (with subscript $_W$ and $_B$ respectively), substantially enhancing analyses credibility.

3.2.4 Control Variables

In the 2018 PISA cycle, the OECD simplified its computation for 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 the *Technical Report* (OECD, 2020b) visualised this procedure while Avvisati (2020) further exmined the validity and reliability of the ESCS construct.

Students' immigration status were determined by synthesising 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 information enabled the derivation of two binary variables IMMI1GEN and IMMI2GEN to mark first- and second-generation migrants respectively, with natives being the reference group receiving zero entries for both categories.

Lastly, variable ST004D01T from the student questionnaire (OECD, 2020a) was transformed into a binary variable with female being the reference group: 0 = female; 1 = male.

3.3 Model Equations

In the interest of maximum compatibility with multilevel modelling conventions (Snijders & Bosker, 2012), this paper continued to use subscript $_{ij}$ and $_j$ for student- and school-level variables respectively in its model equations. Since the MLC approach (see Section 3.2.3) had been applied to the within-between decomposition, subscript $_j$ now stands for the between-group component, rather than a (manifect) averages from its individual-level constituents.

Student-level ($L1$):

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

School-level ($L2$):

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

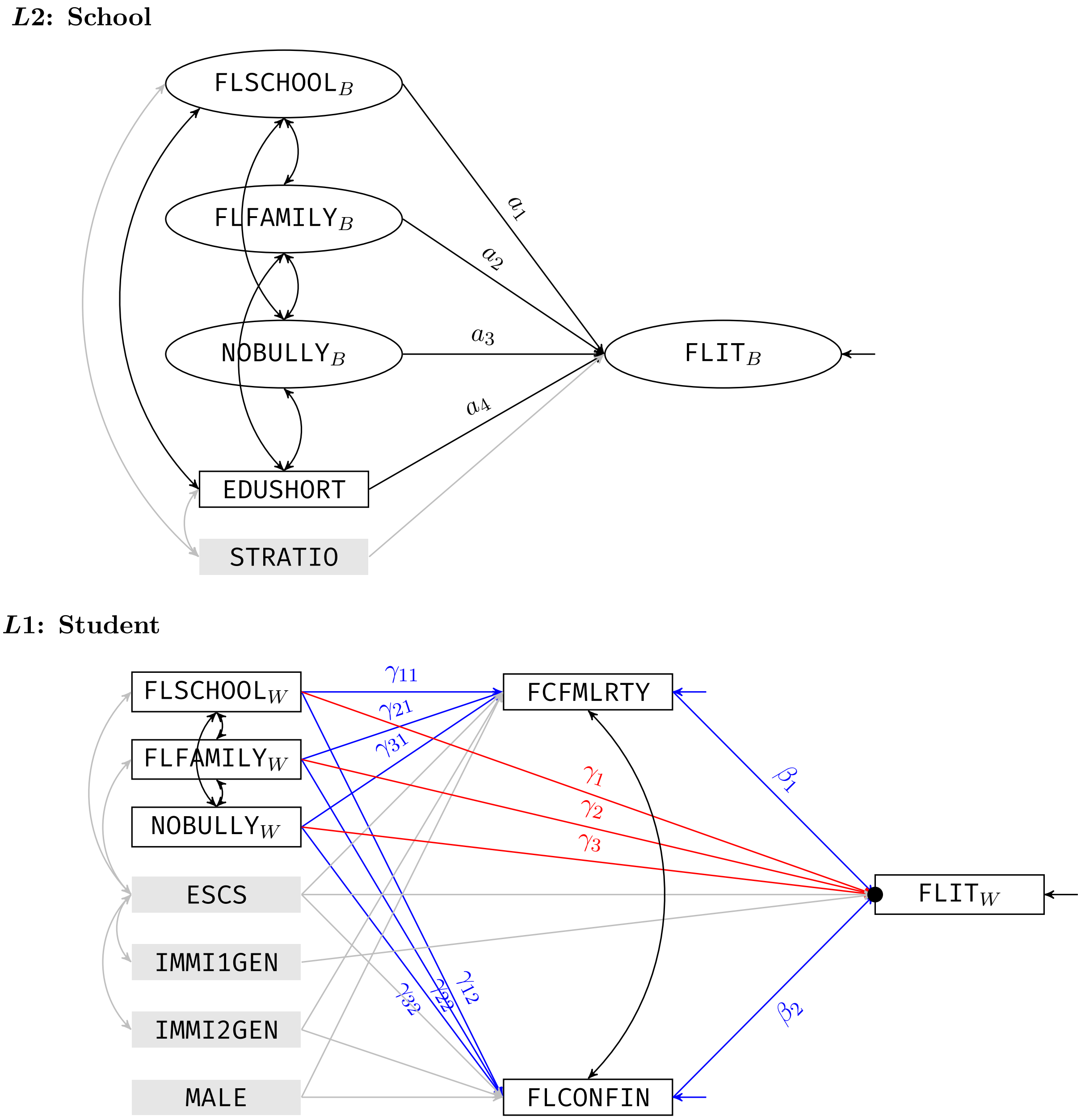
Using Kaplan's (2009) notation $\boldsymbol{y}_{ij} = \boldsymbol{\alpha}_j + \mathbf{B}_j\boldsymbol{y}_{ij} + \boldsymbol{\Gamma}_j\boldsymbol{x}_{ij} + \boldsymbol{r}_{ij}$ for student-level ($L1$) and random intercept $\boldsymbol{\alpha}_j = \boldsymbol{\alpha}_{00} + \boldsymbol{A}\boldsymbol{w}_j + \boldsymbol{\varepsilon}_j$ for school-level ($L2$), the model equations can be further condensed into a matrix form, with the corresponding path diagram in Figure 3.1:

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

3.4 Missing Data Treatment

Missing data are the norm rather than the exception in empirical research and they demand great care from the researchers to ensure analytical validity. While fulll information maximum likelihood enjoys the benefit of being well understood and readily availabe in software, the multiple imputation (MI) approach outperforms (a) when the data set contains mixtures of incomplete categorical and continuous variables, (b) when dealing with questionnaire data where items usually come in parcels, (c) fwhen auxiliary variables are required and lastly, (d) when the missing completely at random assumption cannot be reasonably assumed (Enders & Mansolf, 2018). These considerations conclusively directed the current study towards the multilevel MI route under the assumption that data were missing at random (Little & Rubin, 2019). In addition, since 2018 PISA financial literacy source files 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 **M***plus*'s (Version 8.5, Muthén and Muthén (1998–2017)) unrestricted variance-covariance model ("JM-AM H1", Asparouhov & Muthén, 2010b) using Bayes estimator, 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). Finaly, the first 50000 MCMC iterations were discarded to ensure stablility and any two draws

Figure 3.1
Path Diagram



Note. [Insert notes here.]

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). Table C.1 summarised the imputation results, followed by the diagnostic plots demonstrating convergence.

3.5 Weights and Scaling Considerations

Due to PISA's two-stage sampling design, schools and students were selected with *unequal* probabilities (Chapter 3, OECD (2009), pp. 47–56). A proper incorporation of sampling weights is therefore crucial for establishing unbiased estimations. This study has made use of both student and school weights. More specifically, $L1$ weights have been scaled such that they sum to the sample size in each cluster while $L2$ weights were adjusted so that the product of the between- and within-weights sums to the total sample size (Muthén & Muthén, 2017, pp. 622–624) under the advisory of Asparouhov (2006).

3.6 Estimator

This study accepted **M*plus***'s default setting of pseudo maximum likelihood (MLR) estimator for the hierachical modelling (Chapter 16, Muthén & Muthén, 2017, pp. 666 & 668). MLR's robust standare errors are in general Huber-White sandwich estimators (Huber, 1967; White, 1982) with asymptotic standard error corrections using observed residual variances. Literature has long recognised MLR's robust χ^2 tests and standard errors as being more accurate than the asymptotic tests when data are non-normal and when models are mis-specified (Chou et al., 1991; Curran et al., 1996). In the multilevel modelling context, robust χ^2 and standard errors may also provide protection against unmodelled heterogeneity resanltant from mis-specification at the group-level or from omitting a level (Hox et al., 2010).

3.7 Model Comparison

Multiple imputation substantially complicates model fit interpretations. It is important to reflect that Rubin's (1987) rules apply only to *model parameters* under the assumption that over repeated samples, estimates eventually form normal curves peaked at some population values. The distributions of fit indices, on the other hand, are almost always unknown or non-normal, imposing high standards of proof onto any proposed aggregation procedures. Early work such as Meng and Rubin (1992) on pooled likelihood ratio statistic, the precursor to many model fit indices, has been substantiated by simulation studies more recently with encouraging results that it is feasible to construct pooled information criteria (Claeskens & Consentino, 2008) as well as pooled model fit indices (Asparouhov & Muthén, 2010a) under MI. Enders and Mansolf (2018) further suggested that with large samples ($N > 100$) and low missing rates ($< 30\%$–40%), common cutoff criteria such as Hu and Bentler (1999) remain valid. This study took advantage of **M*plus***'s capability of automatically pooling model fit information in the presence of MI. Thanks to its sample size ($N = 107,162$) and low missing rate (maximum 22.08%), conventional cutoffs of RMSEA ≤ 0.06, SRMR $\leq .08$, CFI $\geq .95$ and TLI ≥ 0.95 were used for model comparison purposes.

Chapter 4 Results

4.1 Descriptive statistics

Table 4.1

Descriptive Statistics

Analysis level	Variable label	Non-missing sample size	Missing rate (%)[a]	Median	M	SD	Variance	Skewness	Excess kurtosis	Minimum	Maximum
Student	FLSCHOOL	96435	10.01	0.126	0.018	1.020	1.040	0.189	−0.343	−1.564	2.317
(within, $L1$)	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	EDUSHORT	6346	4.30	0.100	0.131	1.036	1.073	0.341	−0.188	−1.421	2.959
(between, $L2$)	STRATIO	5626	15.16	11.886	13.873	10.171	103.449	4.021	25.425	1.000	100.000

Note. [a] 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*
FIXED EFFECTS									
Intercept		454.154	2.690^{***}	451.451	1.449^{***}	445.812	2.578^{***}	486.820	4.500^{***}
Student-level Predictors									
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	γ_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	γ_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	γ_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	γ_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)	γ_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	$0.002^{\dagger}$	−0.006	0.002^{**}	−0.006	0.002^{**}
— via FCFMLRTY	$\gamma_{61}\beta_1$			−0.003	$0.002^{\dagger}$	−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^{**}

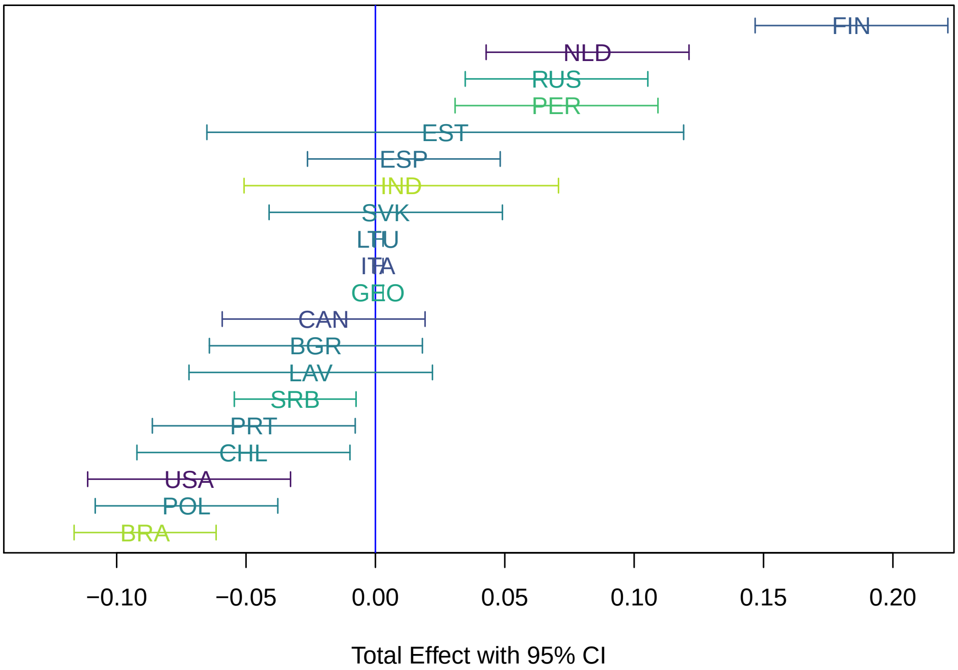
Continued

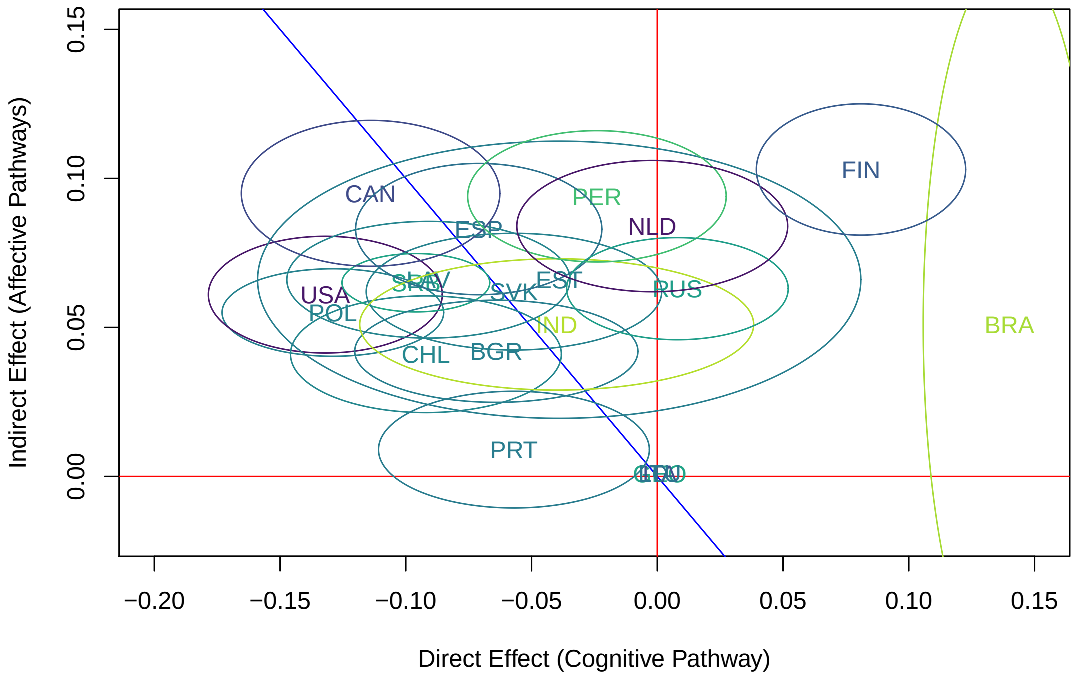
Variable	Model parameter	Null Model Coef	Null Model *SE*	One-level Model Coef	One-level Model *SE*	Two-level Saturated Coef	Two-level Saturated *SE*	Two-level Structured Coef	Two-level Structured *SE*
School-level Predictors									
`FLSCHOOL`	a_1							-0.295	0.066^{***}
`FLFAMILY`	a_2							-0.225	0.057^{***}
`NOBULLY`	a_3							0.233	0.069^{***}
`EDUSHORT`	a_4							-0.292	0.038^{***}
`STRADIO`	a_5							-0.132	0.026^{***}
RANDOM EFFECTS (residual variances of FLIT)									
Student-level	$\text{var}\left(r_{ij}^{Y}\right)$	6121.904	131.192	7866.408	114.555	5763.677	130.133	5763.690	130.133
School-level	$\text{var}\left(\varepsilon_{j}^{Y}\right)$	5240.477	202.004			3264.618	193.892	1705.616	135.044
MODEL FIT INDICES		Est	*SD*	Est	*SD*	Est	*SD*	Est	*SD*
AIC		1253984	1093	3429058	1534	3468075	1661	3468108	1650
BIC		1254013	1093	3429566	1534	3468727	1661	3468740	1650
χ^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 $L1$		0.005	0.003	0.016	0.000	0.015	0.000	0.015	0.000
SRMR $L2$		0.011	0.005			0.014	0.002	0.030	0.006

Note. All p values in this table are two-tailed.
$^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.4 Address the research question

Figure 4.1
Total, Direct and Indirect Effects of School Intervention (`FLSCHOOL`)

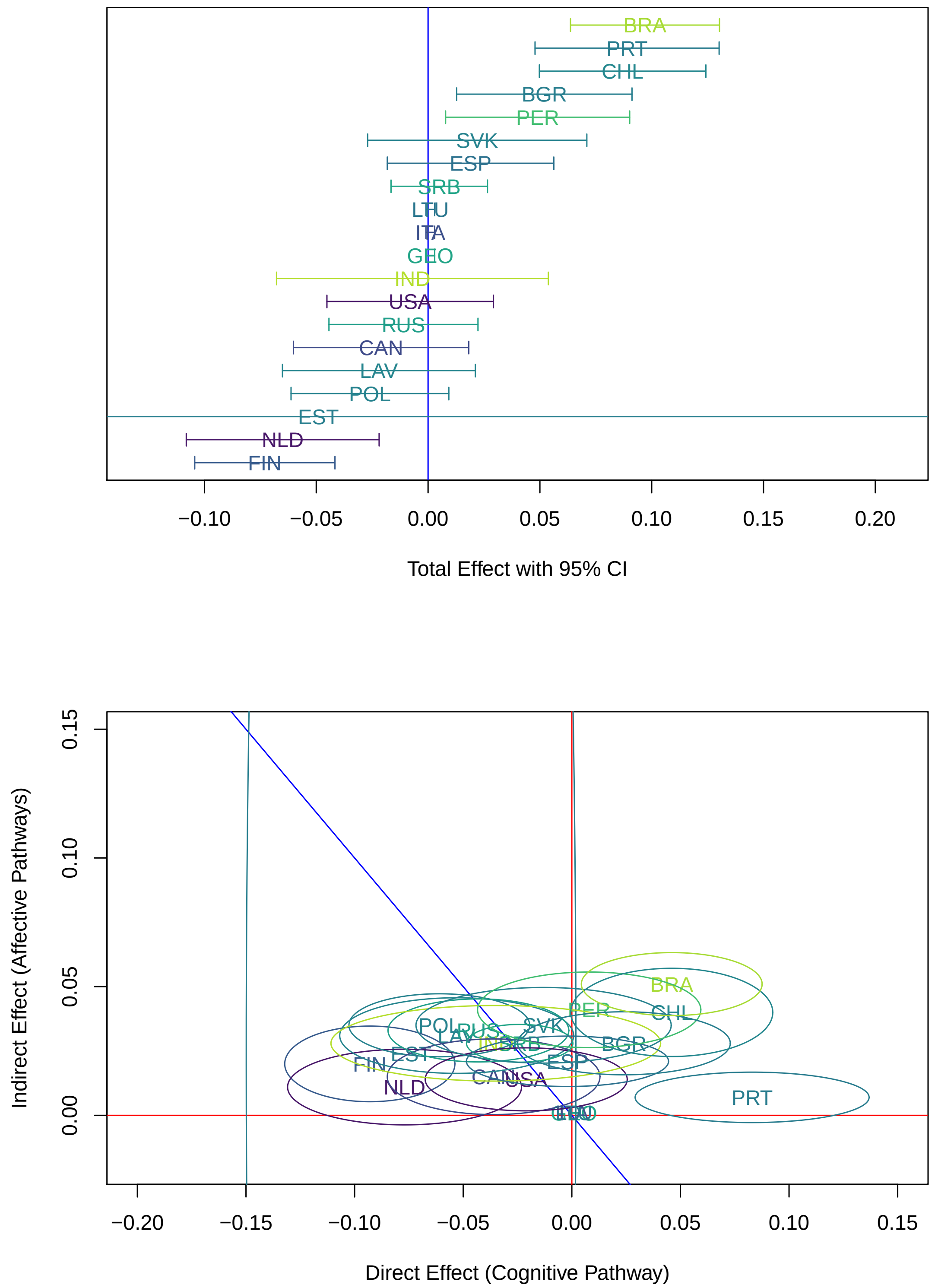




Note. Countries with high (low) financial knowlege indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the verticle blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the verticle, horizontal and −45° lines are not significant for direct, indirect and total effect, respectively.

Figure 4.2

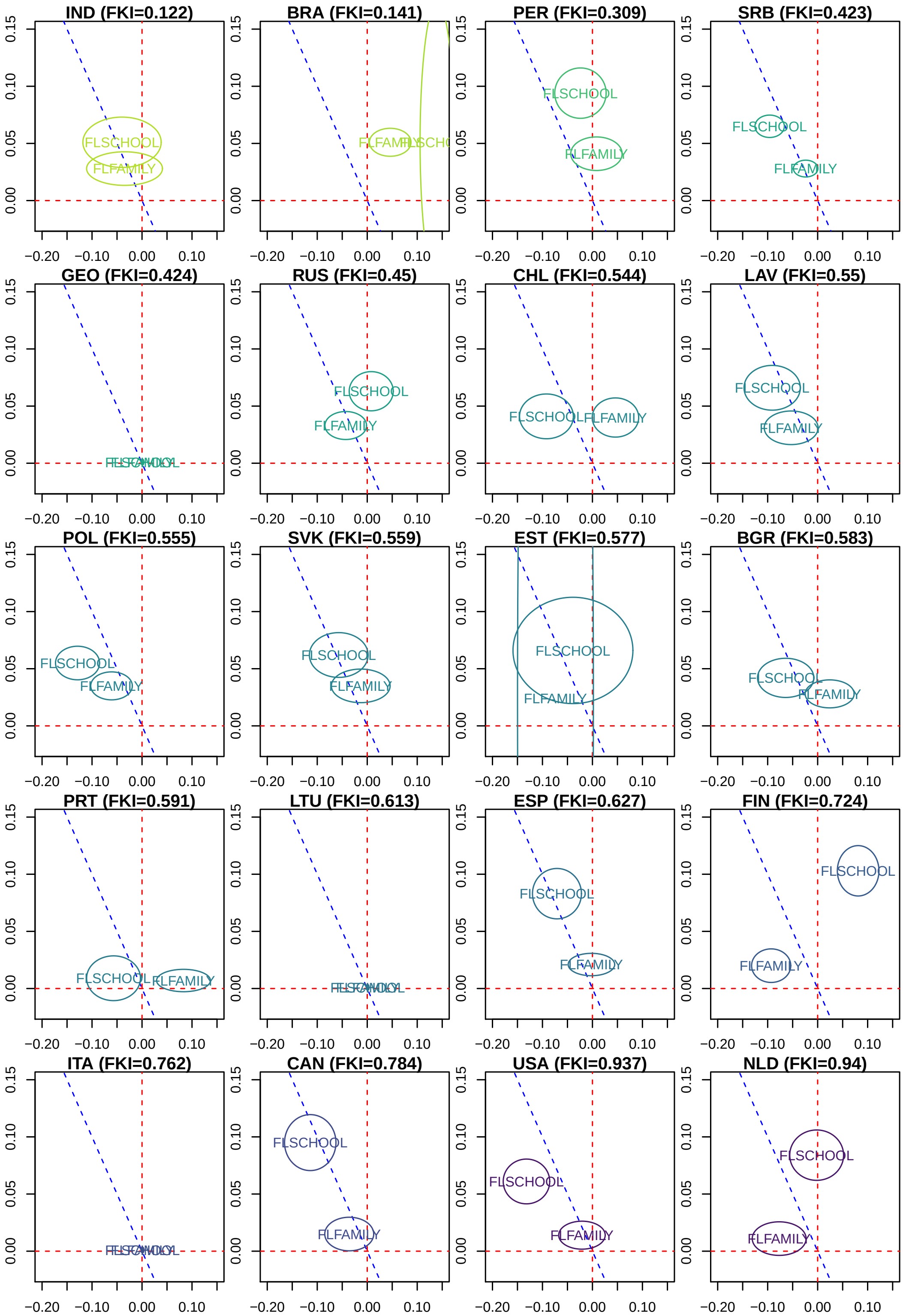
Total, Direct and Indirect Effects of Financial Socialisation (`FLFAMILY`)



Note. Countries with high (low) financial knowlege indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the verticle blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the verticle, horizontal and $-45°$ 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 hozitonal 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

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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)
Norwegian (/personvernombud/meld_prosjekt/meldeplikttest.html)

NSD (/) > Personverntjenester (/personvernombud/) > Data Protection Services (/personvernombud/en/) > Notify project (/personvernombud/en/notify/) > Notification Test

Denne siden på norsk (/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).

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).

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)

Notifying changes (/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/)

Research methods (/personvernombud/en/help/research_methods/)

Information and consent (/personvernombud/en/help/information_consent/)

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

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Appendix B Analysis Code, Additional Tables and Figures

B.1 Chapter 1 Introduction

Chapter 1 does not contain any analysis code.

B.2 Chapter 2 Conceptual Framework

Chapter 2 does not contain any analysis code.

B.3 Chapter 3 Method

B.3.1 Data Merging

```r
# Import SPSS file into R
library(intsvy)
finlit ← pisa.select.merge(
    student.file = "CY07_MSU_FLT_QQQ.SAV", # file ext in capital
    school.file = "CY07_MSU_SCH_QQQ.sav", # file ext in lower case
    student = c(
    # Control variables
        "ST004D01T", # Student (Standardized) Gender
        "IMMIG", # Index Immigration status
        "ESCS", # Index of economic, social and cultural status
    # Mediators
        "FCFMLRTY", # Familiarity with concepts of finance (Sum)
        "FLCONFIN", # Confidence about financial matters (WLE)
    # Academic
        "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)
    ),
    school = c(
        "STRATIO", # Student-teacher ratio
        "EDUSHORT" # Shortage of educational material (WLE)
    ),
    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
        "SRB", "SVK", "ESP", "USA"
    )
)

names(finlit)
# 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
library(car)
```

```r
# Re-code Russian territories to RUS
finlit$CNT <- recode(finlit$CNT, "
    'QMR' = 'RUS';
    'QRT' = 'RUS'
")

finlit$CNTRYID <- recode(finlit$CNTRYID, "
    982 = 643;
    983 = 643
")

# Input country-level FKI
FKI <- recode(finlit$CNT, "
    'NLD' = 0.940;
    'USA' = 0.937;
    'CAN' = 0.784;
    'ITA' = 0.762;
    'FIN' = 0.724;
    'ESP' = 0.627;
    'LTU' = 0.613;
    'PRT' = 0.591;
    'BGR' = 0.583;
    'EST' = 0.577;
    'SVK' = 0.559;
    'POL' = 0.555;
    'LVA' = 0.550;
    'CHL' = 0.544;
    'RUS' = 0.450;
    'GEO' = 0.424;
    'SRB' = 0.423;
    'PER' = 0.309;
    'BRA' = 0.141;
    'IDN' = 0.122
")

# Recode ST004D01T from Sex to Male
MALE <- finlit$ST004D01T - 1

# Revert coding direction: bigger number => safer school
NOBULLY <- finlit$BEINGBULLIED * (-1)

# Recode IMMIG to 1st and 2nd generation
IMMI1GEN <- recode(finlit$IMMIG, "
    1 = 0;
    2 = 0;
    3 = 1
")

IMMI2GEN <- recode(finlit$IMMIG, "
    1 = 0;
    2 = 1;
    3 = 0
")

# Stitch spreadsheet together
names(finlit)
finlit <- cbind(
    FKI, finlit[, c(2:35)], MALE, IMMI1GEN, IMMI2GEN,
    finlit[, c(38:41)], NOBULLY, finlit[, c(43:46)]
)
head(finlit)
names(finlit)

# 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
rm(obs0, obs1)
```

Table B.1

Summary of Participating Countries

Country ID	Country code	Country name	School n	School %	Student n	Student %	Male n	Male %
76	BRA	Brazil	595	8.97	8,310	7.75	4,045	48.68
100	BGR	Bulgaria	197	2.97	4,110	3.84	2,147	52.24
124	CAN	Canada	492	7.42	7,762	7.24	3,858	49.70
152	CHL	Chile	251	3.79	4,482	4.18	2,254	50.29
233	EST	Estonia	229	3.45	4,166	3.89	2,080	49.93
246	FIN	Finland	204	3.08	4,328	4.04	2,199	50.81
268	GEO	Georgia	319	4.81	4,320	4.03	2,239	51.83
360	IND	Indonesia	395	5.96	7,132	6.66	3,454	48.43
380	ITA	Italy	539	8.13	9,182	8.57	4,706	51.25
428	LVA	Latvia	307	4.63	3,151	2.94	1,587	50.36
440	LTU	Lithuania	349	5.26	4,075	3.80	2,060	50.55
528	NLD	The Netherlands	151	2.28	3,042	2.84	1,549	50.92
604	PER	Peru	337	5.08	4,732	4.42	2,390	50.51
616	POL	Poland	235	3.54	4,294	4.01	2,080	48.44
620	PRT	Portugal	276	4.16	4,568	4.26	2,320	50.79
643	RUS	Russian Federation	558	8.42	9,124	8.51	4,601	50.43
688	SRB	Serbia	186	2.81	3,874	3.62	1,951	50.36
703	SVK	Slovak Republic	357	5.38	3,411	3.18	1,683	49.34
724	ESP	Spain	491	7.40	9,361	8.74	4,695	50.15
840	USA	The USA	163	2.46	3,738	3.49	1,871	50.05
		Total	6,631	100	107,162	100	53,769	50.18

χ^2 goodness-of-fit test	School χ^2_{19}	School p	Student χ^2_{19}	Student p	Male χ^2_{19}	Male p
	1,105.8	$< .001$	16,984	$< .001$	20.9	.34

Note. Twelve observations with missing school weights were removed due to clerical error concerns. χ^2 goodness-of-fit tests revealed that the data set was balanced in sex, but not all countries contributed equally to school and student counts.

Table B.2

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

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

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

Appendix C Multilevel Multiple Imputation

C.1 Mplus Input Code

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


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


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
        ;

    cluster = CNTSCHID;

    missing = all (-99);


ANALYSIS:
```

```
    processors = 64;                         ! Use all cores of HPC

    type = twolevel;
    estimator = Bayes;

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


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

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

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

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

C.2 Selected Mplus Output

```
MODEL FIT INFORMATION

Number of Free Parameters                              22

Bayesian Posterior Predictive Checking using Chi-Square

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

                            28408.938         28906.315

          Posterior Predictive P-Value                0.000

Information Criteria

          Deviance (DIC)                      2100842.641
          Estimated Number of Parameters (pD)      22.054



MODEL RESULTS

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

Within Level

 Means
    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      *
    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
    MALE               0.250       0.001      0.000       0.248       0.252      *
```

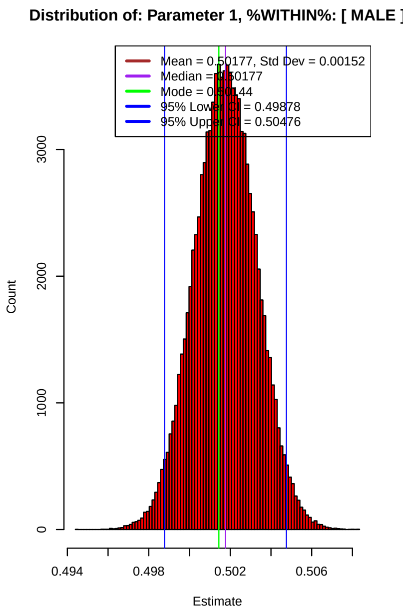
```
    IMMI1GEN          0.028      0.000      0.000      0.028      0.028      *
    IMMI2GEN          0.041      0.000      0.000      0.040      0.041      *
    ESCS              1.183      0.005      0.000      1.173      1.193      *
    FCFMLRTY         29.753      0.134      0.000     29.494     30.016      *
    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      *

Between Level

 Means
    STRATIO          13.873      0.136      0.000     13.608     14.140      *
    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      *
```

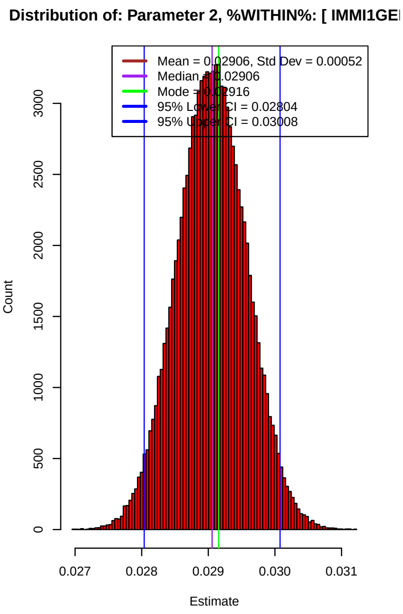
Table C.1

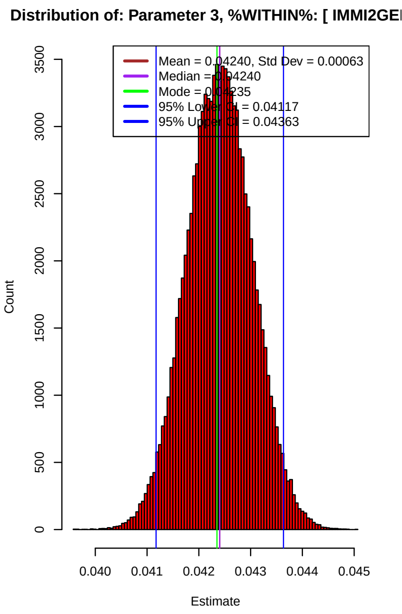
Summary of Diagnostic Plots of Multilevel Multiple Imputation

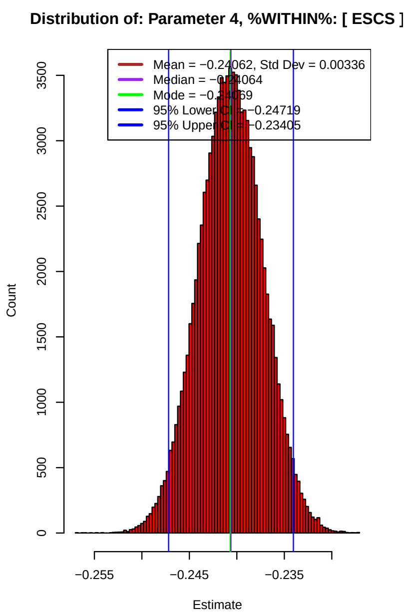
Parameter number	Parameter label	Modelling level	Brief description	Posterior mean	Posterior variance	95% credibility interval	Chain converged	AR-free chains
1	MALE	Within	Whether participant is male	0.502		(0.499, 0.505)	Yes	4
2	IMMI1GEN	Within	Whether participant migrated to this country	0.029		(0.028, 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

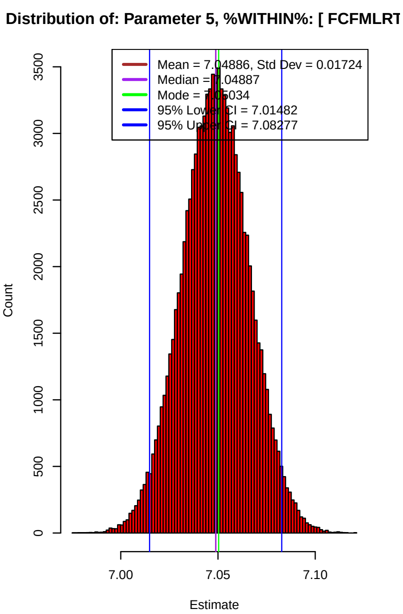
Note. Notes go here.

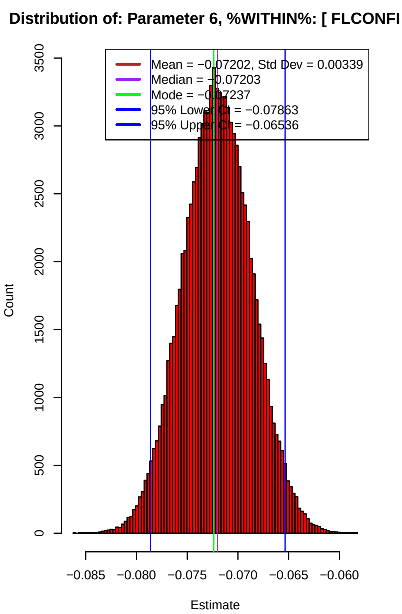

Distribution of: Parameter 1, %WITHIN%: [MALE]
Mean = 0.50177, Std Dev = 0.00152
Median = 0.50177
Mode = 0.50144
95% Lower CI = 0.49878
95% Upper CI = 0.50476
Count
Estimate

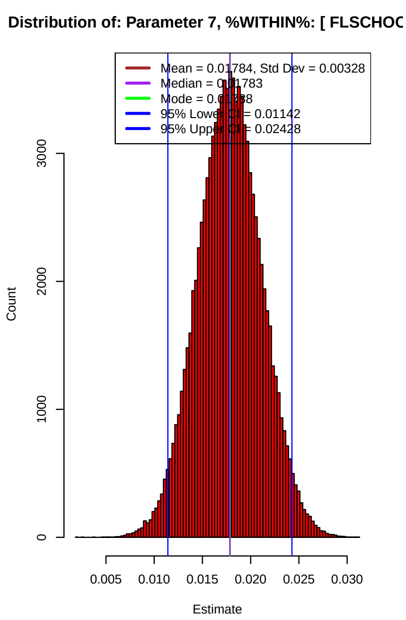

Distribution of: Parameter 2, %WITHIN%: [IMMI1GE
Mean = 0.02906, Std Dev = 0.00052
Median = 0.02906
Mode = 0.02916
95% Lower CI = 0.02804
95% Upper CI = 0.03008
Count
Estimate

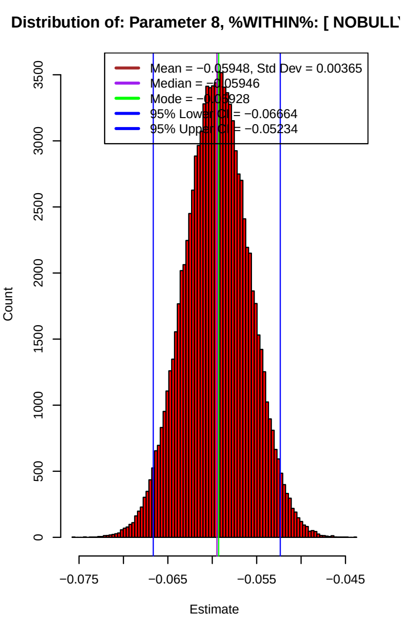

Distribution of: Parameter 3, %WITHIN%: [IMMI2GE
Mean = 0.04240, Std Dev = 0.00063
Median = 0.04240
Mode = 0.04235
95% Lower CI = 0.04117
95% Upper CI = 0.04363
Count
Estimate

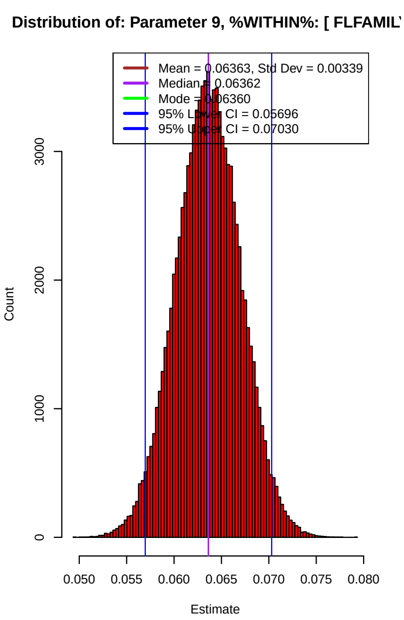

Distribution of: Parameter 4, %WITHIN%: [ESCS]
Mean = −0.24062, Std Dev = 0.00336
Median = −0.24064
Mode = −0.24069
95% Lower CI = −0.24719
95% Upper CI = −0.23405
Count
Estimate

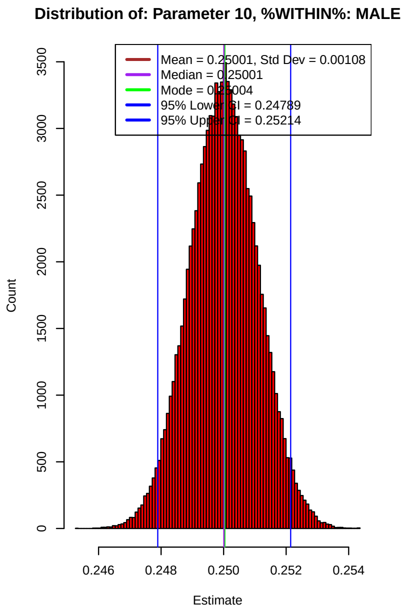

Distribution of: Parameter 5, %WITHIN%: [FCFMLRT
Mean = 7.04886, Std Dev = 0.01724
Median = 7.04887
Mode = 7.05034
95% Lower CI = 7.01482
95% Upper CI = 7.08277
Count
Estimate

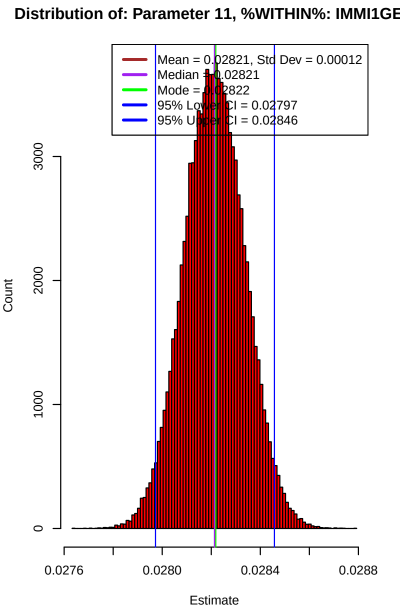

Distribution of: Parameter 6, %WITHIN%: [FLCONFI
Mean = −0.07202, Std Dev = 0.00339
Median = −0.07203
Mode = −0.07237
95% Lower CI = −0.07863
95% Upper CI = −0.06536
Count
Estimate

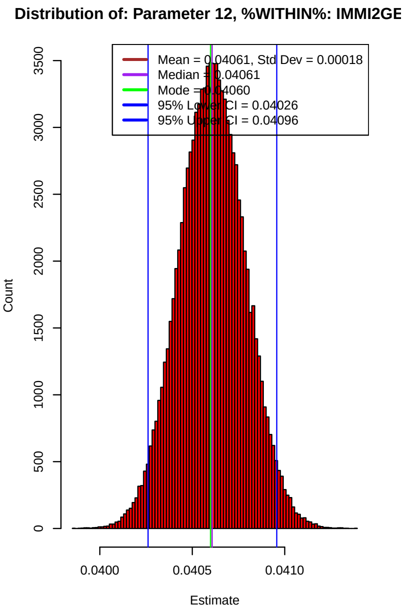

Distribution of: Parameter 7, %WITHIN%: [FLSCHOC
Mean = 0.01784, Std Dev = 0.00328
Median = 0.01783
Mode = 0.01838
95% Lower CI = 0.01142
95% Upper CI = 0.02428
Count
Estimate

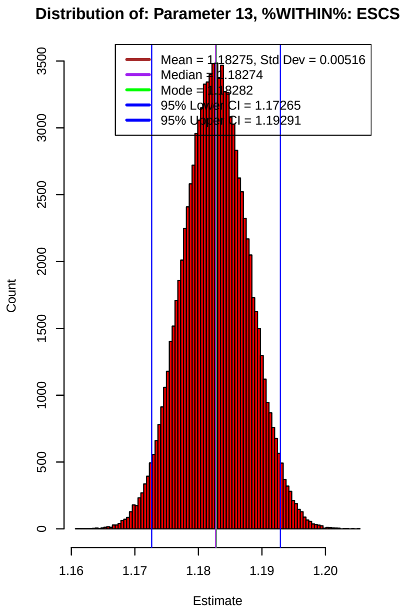

Distribution of: Parameter 8, %WITHIN%: [NOBULLY
Mean = −0.05948, Std Dev = 0.00365
Median = −0.05946
Mode = −0.05928
95% Lower CI = −0.06664
95% Upper CI = −0.05234
Count
Estimate

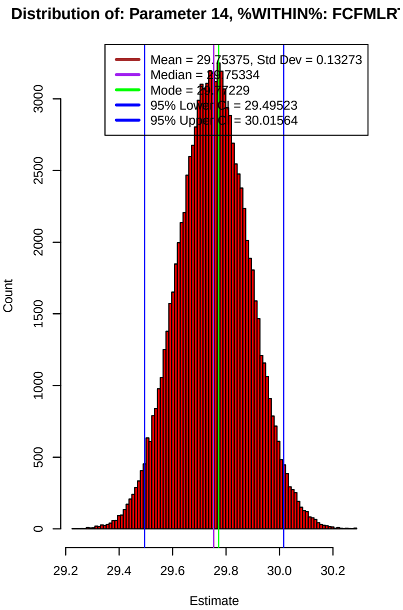

Distribution of: Parameter 9, %WITHIN%: [FLFAMILY
Mean = 0.06363, Std Dev = 0.00339
Median = 0.06362
Mode = 0.06360
95% Lower CI = 0.05696
95% Upper CI = 0.07030
Count
Estimate

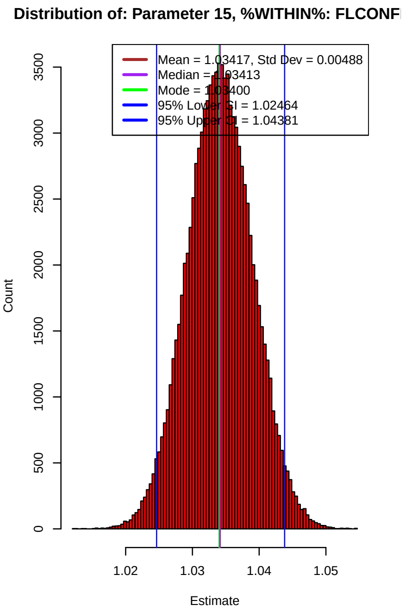

Distribution of: Parameter 10, %WITHIN%: MALE
Mean = 0.25001, Std Dev = 0.00108
Median = 0.25001
Mode = 0.25004
95% Lower CI = 0.24789
95% Upper CI = 0.25214
Count
Estimate

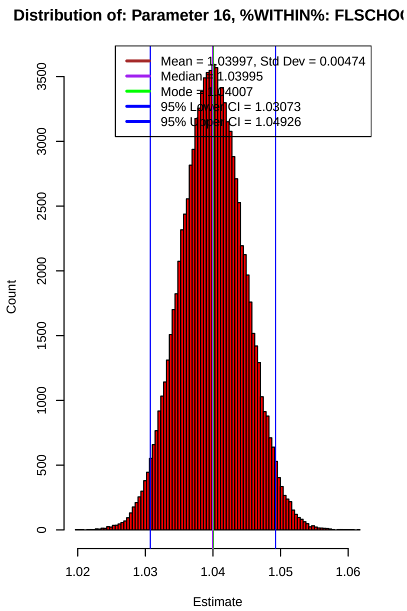

Distribution of: Parameter 11, %WITHIN%: IMMI1GE
Mean = 0.02821, Std Dev = 0.00012
Median = 0.02821
Mode = 0.02822
95% Lower CI = 0.02797
95% Upper CI = 0.02846
Count
Estimate

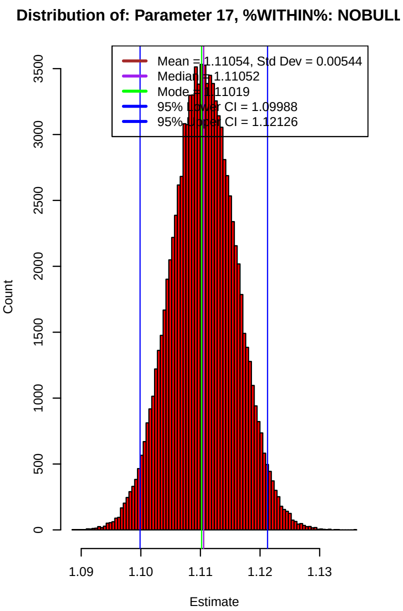

Distribution of: Parameter 12, %WITHIN%: IMMI2GE
Mean = 0.04061, Std Dev = 0.00018
Median = 0.04061
Mode = 0.04060
95% Lower CI = 0.04026
95% Upper CI = 0.04096
Count
Estimate

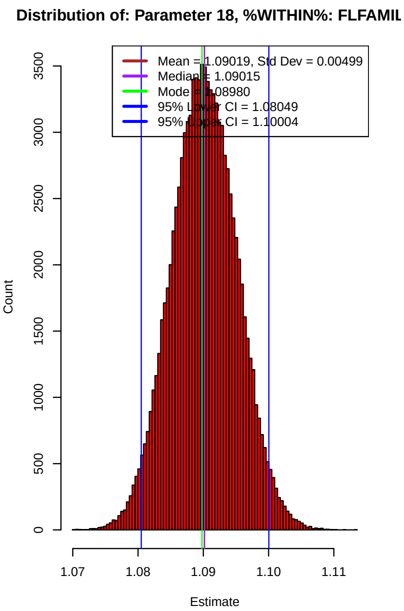

Distribution of: Parameter 13, %WITHIN%: ESCS
Mean = 1.18275, Std Dev = 0.00516
Median = 1.18274
Mode = 1.18282
95% Lower CI = 1.17265
95% Upper CI = 1.19291
Count
Estimate


Distribution of: Parameter 14, %WITHIN%: FCFMLR
Mean = 29.75375, Std Dev = 0.13273
Median = 29.75334
Mode = 29.77229
95% Lower CI = 29.49523
95% Upper CI = 30.01564
Count
Estimate

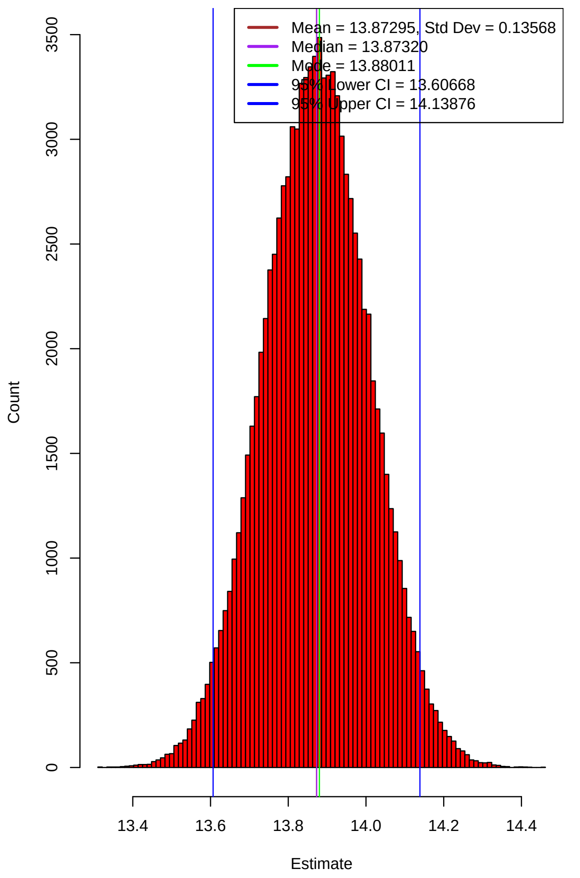

Distribution of: Parameter 15, %WITHIN%: FLCONF
Mean = 1.03417, Std Dev = 0.00488
Median = 1.03413
Mode = 1.03400
95% Lower CI = 1.02464
95% Upper CI = 1.04381
Count
Estimate


Distribution of: Parameter 16, %WITHIN%: FLSCHO
Mean = 1.03997, Std Dev = 0.00474
Median = 1.03995
Mode = 1.04007
95% Lower CI = 1.03073
95% Upper CI = 1.04926
Count
Estimate

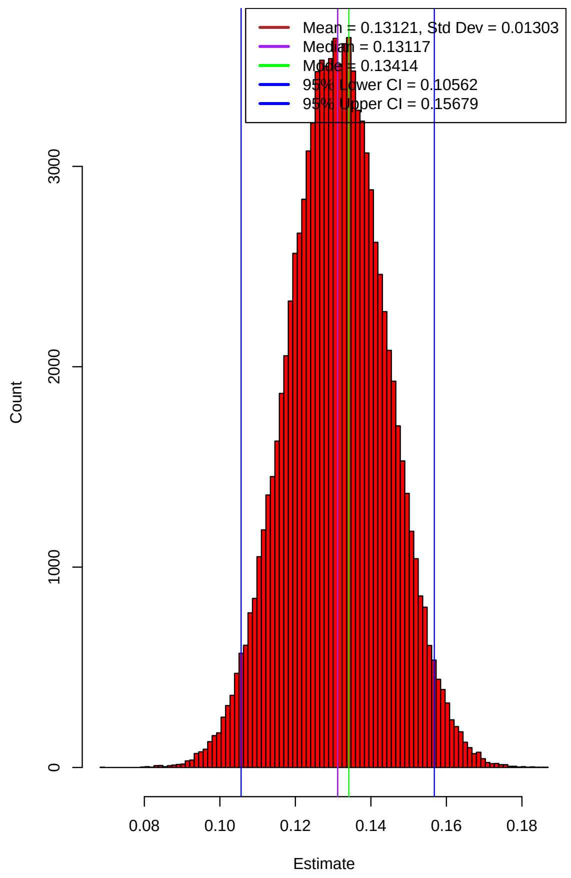

Distribution of: Parameter 17, %WITHIN%: NOBULL
Mean = 1.11054, Std Dev = 0.00544
Median = 1.11052
Mode = 1.11019
95% Lower CI = 1.09988
95% Upper CI = 1.12126
Count
Estimate


Distribution of: Parameter 18, %WITHIN%: FLFAMIL
Mean = 1.09019, Std Dev = 0.00499
Median = 1.09015
Mode = 1.08980
95% Lower CI = 1.08049
95% Upper CI = 1.10004
Count
Estimate

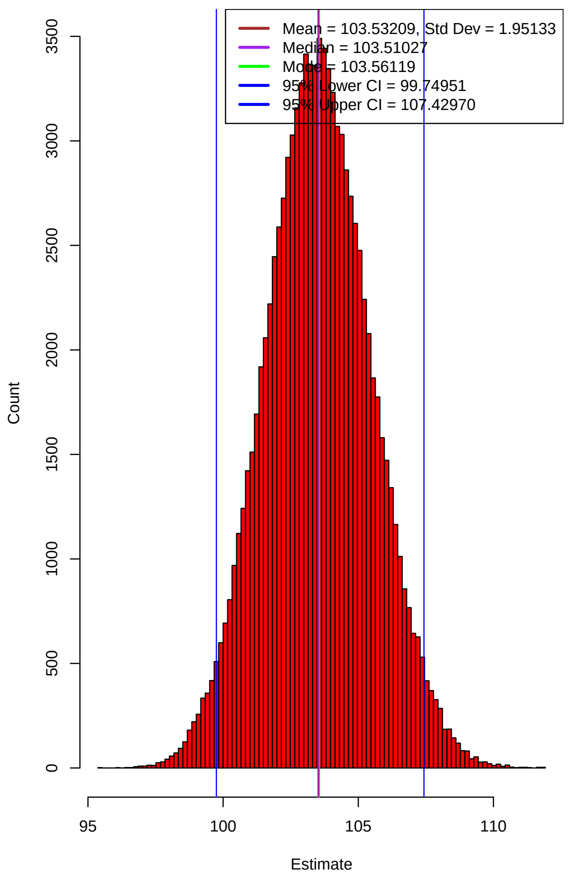
Distribution of: Parameter 19, %BETWEEN%: [STRATIO]



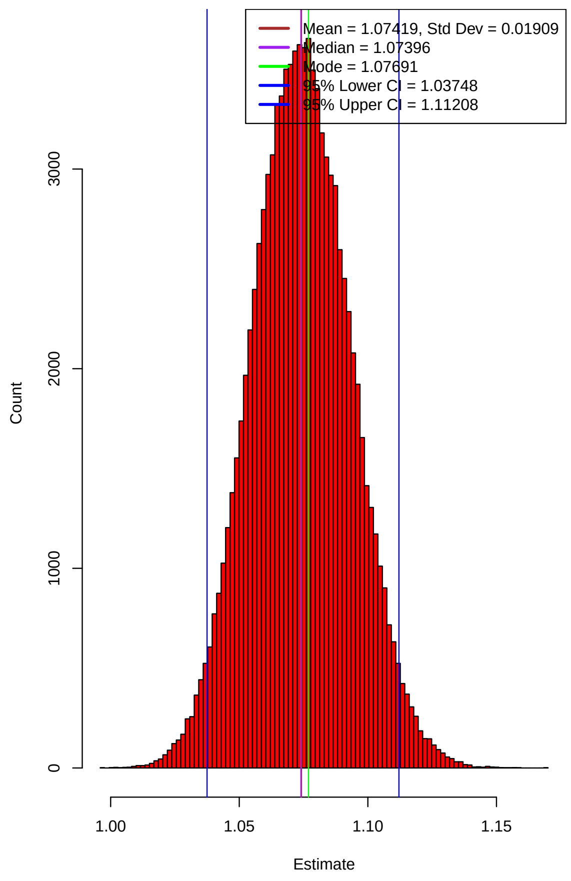
Distribution of: Parameter 20, %BETWEEN%: [EDUSHORT]



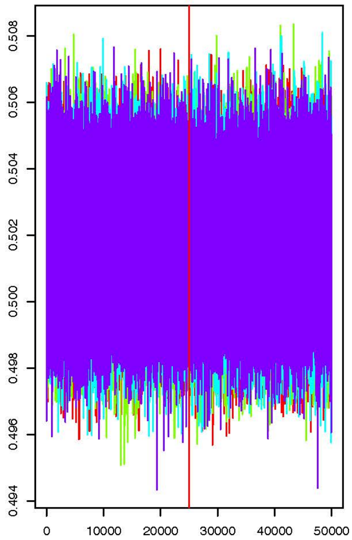
Distribution of: Parameter 21, %BETWEEN%: STRATIO



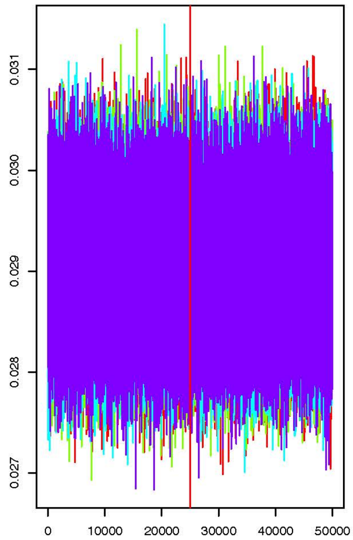
Distribution of: Parameter 22, %BETWEEN%: EDUSHORT



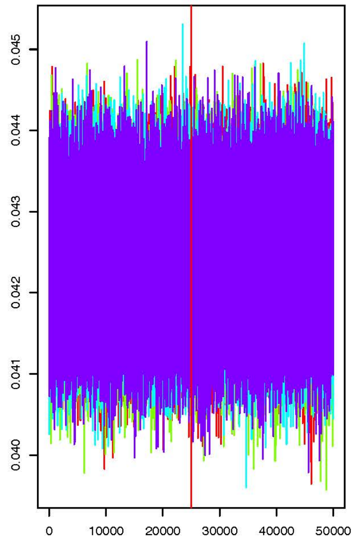
Trace plot of: Parameter 1, %WITHIN%: [MALE]



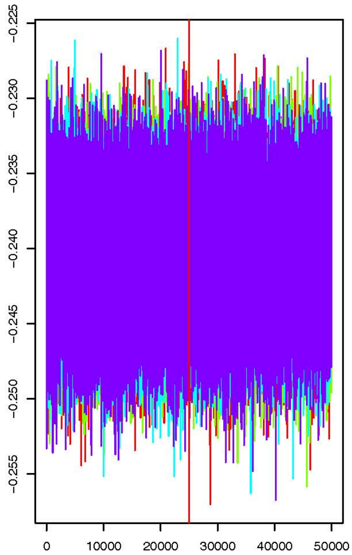
Trace plot of: Parameter 2, %WITHIN%: [IMMI1GEN



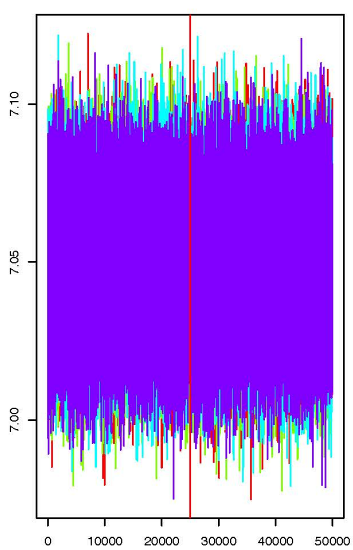
Trace plot of: Parameter 3, %WITHIN%: [IMMI2GEN



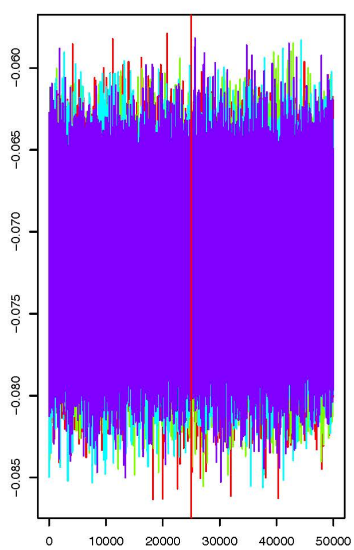
Trace plot of: Parameter 4, %WITHIN%: [ESCS]



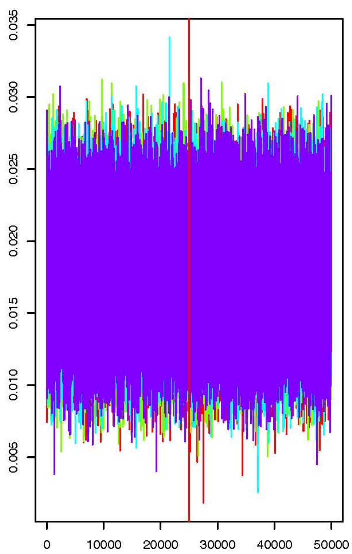
Trace plot of: Parameter 5, %WITHIN%: [FCFMLRTY



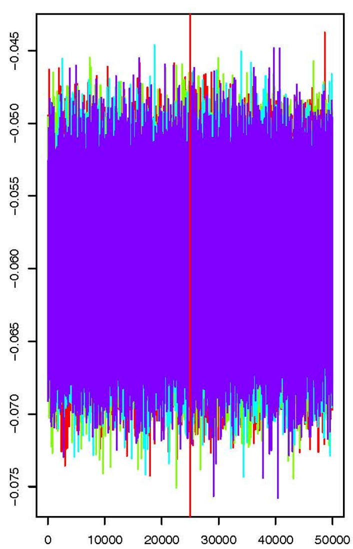
Trace plot of: Parameter 6, %WITHIN%: [FLCONFIN



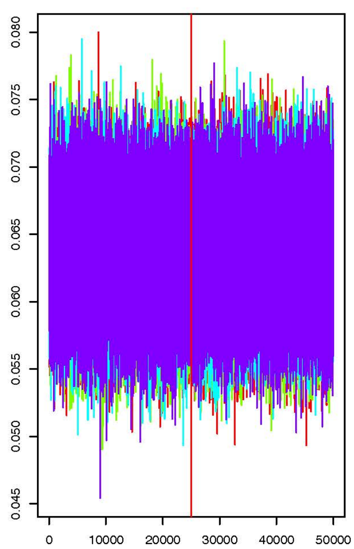
Trace plot of: Parameter 7, %WITHIN%: [FLSCHOOl

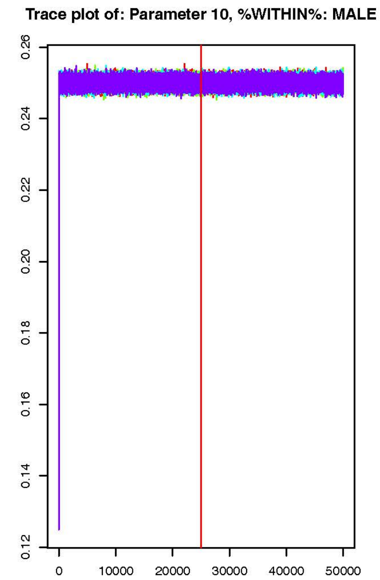


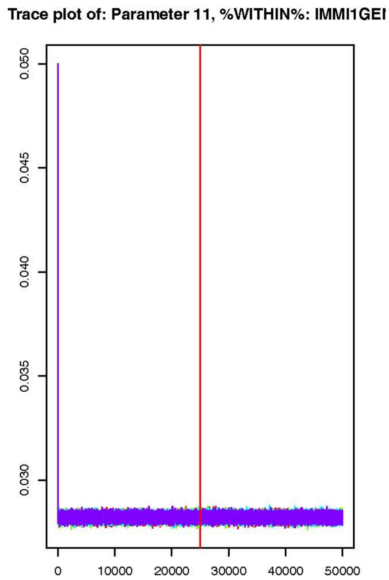
Trace plot of: Parameter 8, %WITHIN%: [NOBULLY

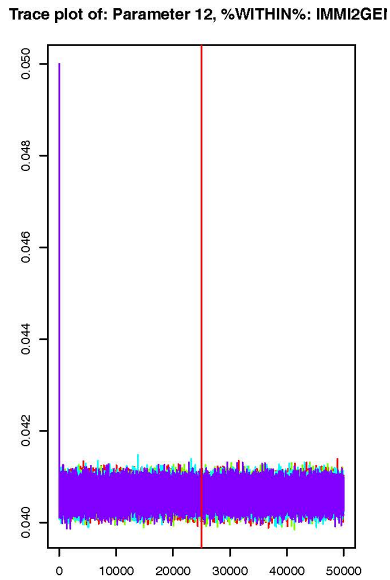


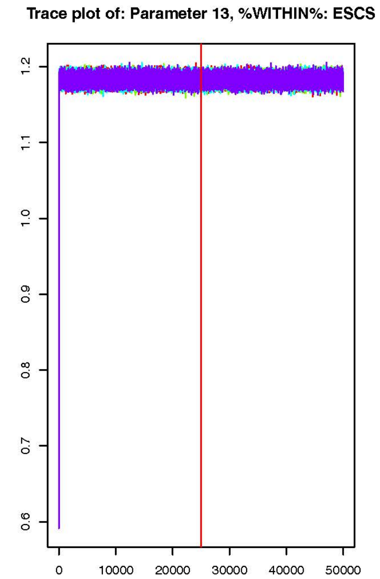
Trace plot of: Parameter 9, %WITHIN%: [FLFAMILY

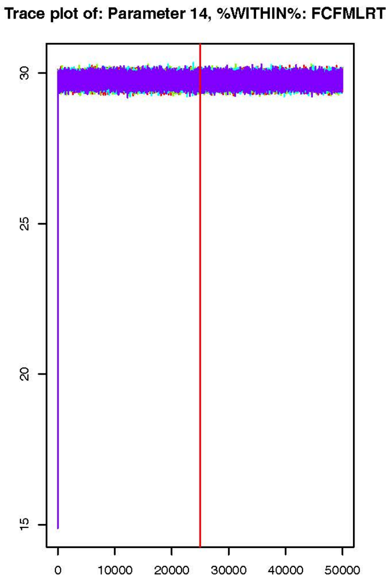


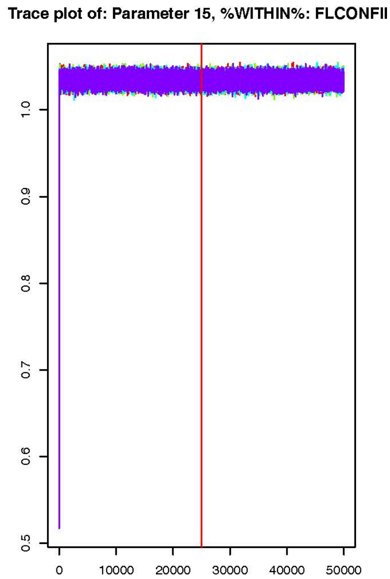

Trace plot of: Parameter 10, %WITHIN%: MALE

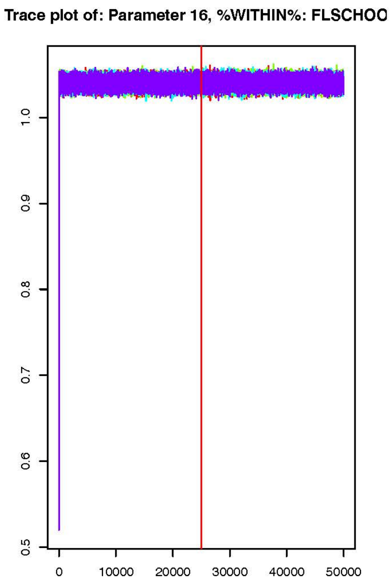

Trace plot of: Parameter 11, %WITHIN%: IMMI1GEI

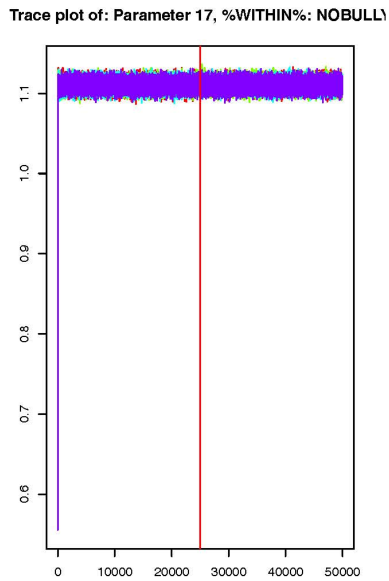

Trace plot of: Parameter 12, %WITHIN%: IMMI2GEI

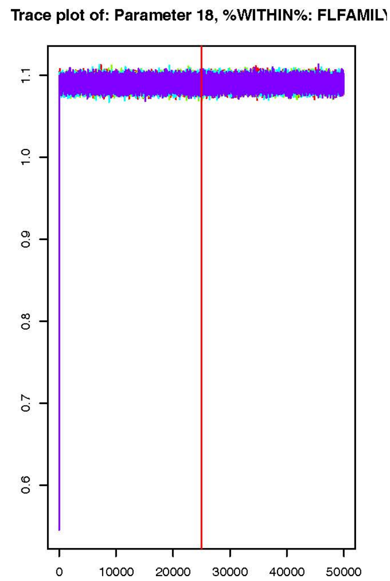

Trace plot of: Parameter 13, %WITHIN%: ESCS


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

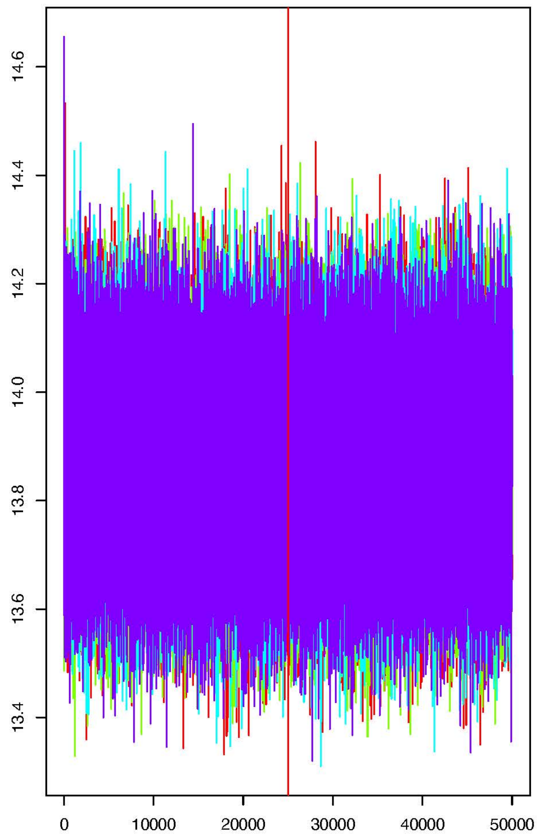

Trace plot of: Parameter 15, %WITHIN%: FLCONFII


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

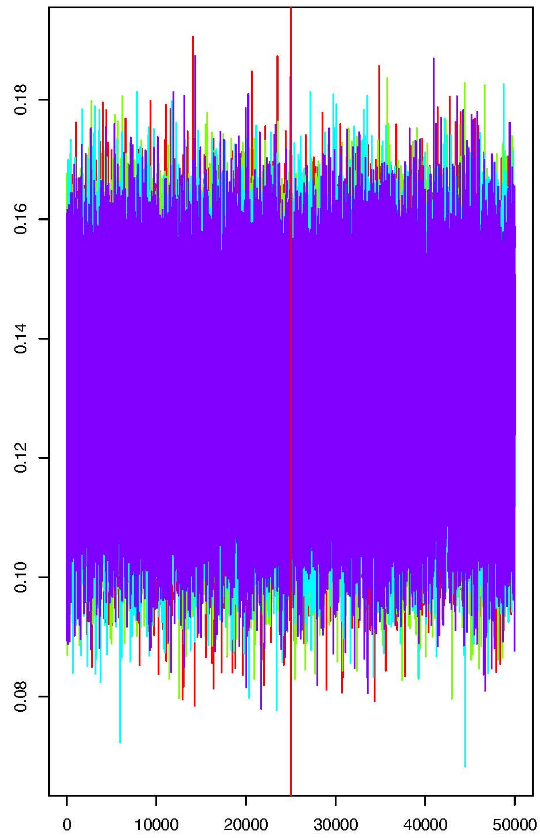

Trace plot of: Parameter 17, %WITHIN%: NOBULLY


Trace plot of: Parameter 18, %WITHIN%: FLFAMILY

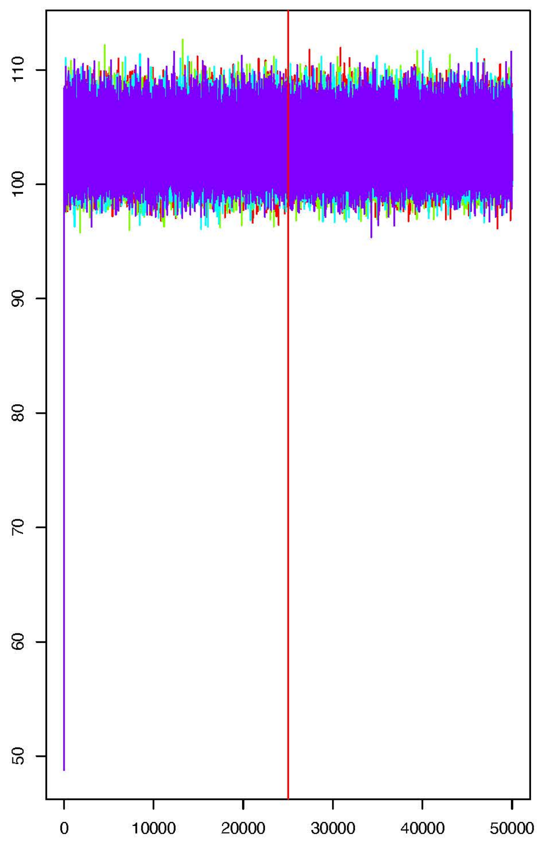
Trace plot of: Parameter 19, %BETWEEN%: [STRATIO]



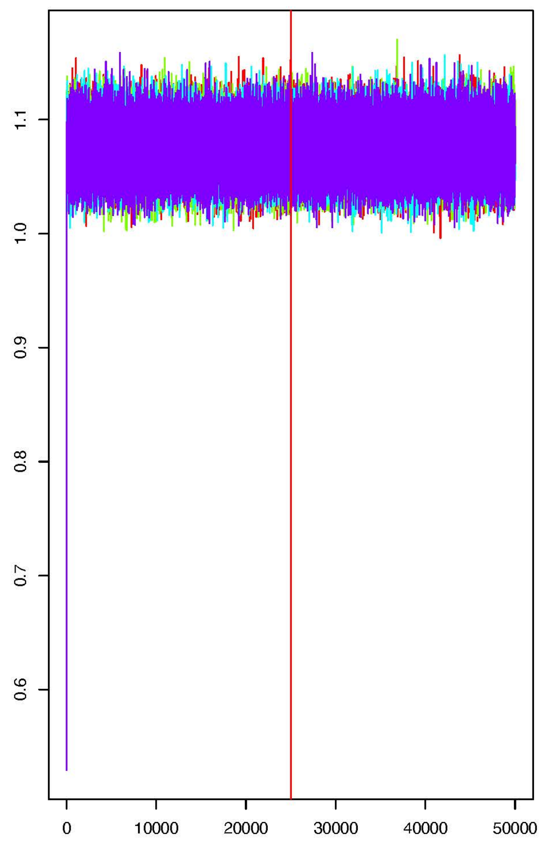
Trace plot of: Parameter 20, %BETWEEN%: [EDUSHORT]

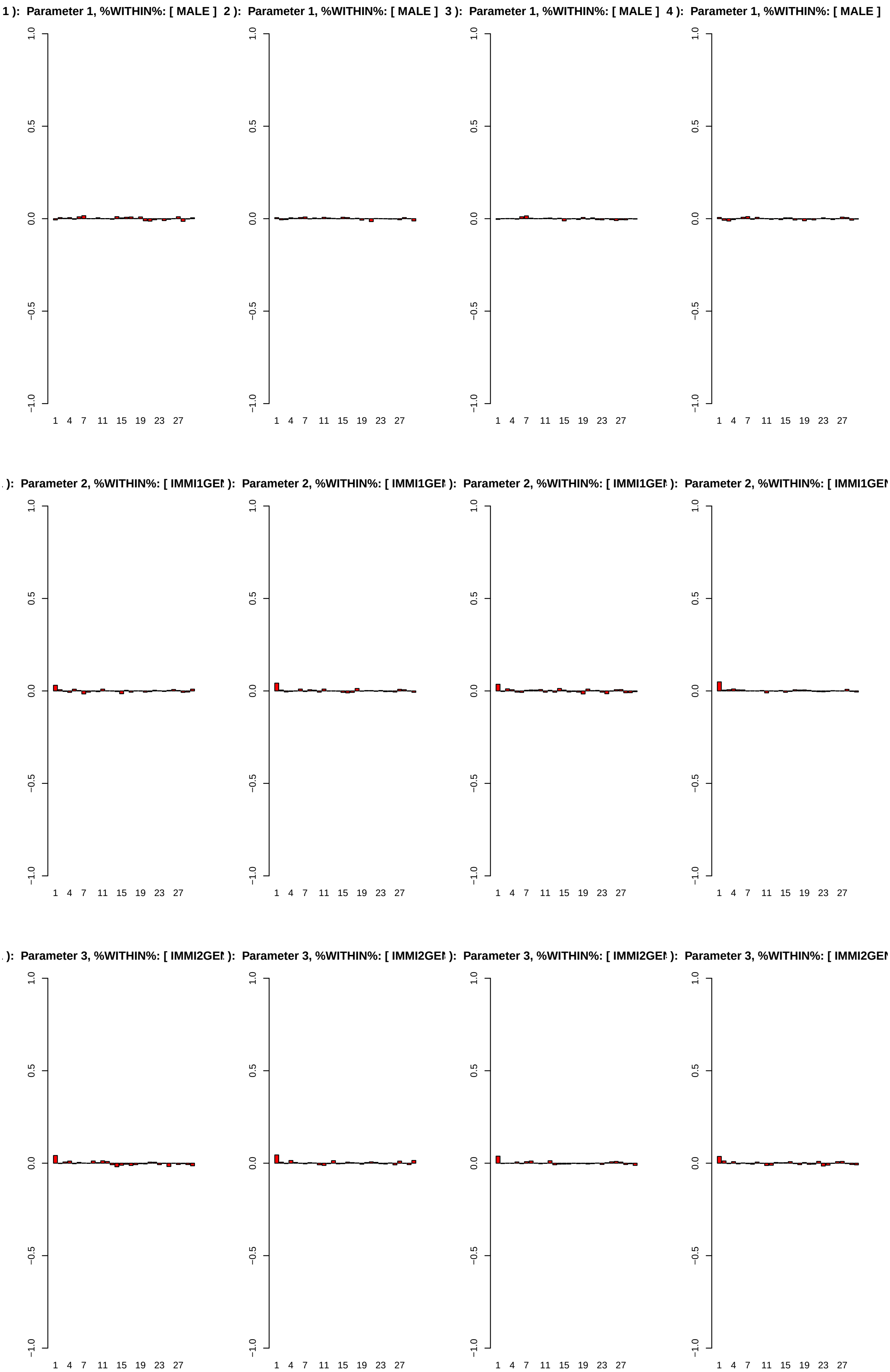


Trace plot of: Parameter 21, %BETWEEN%: STRATIO



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%: [IMMI1GEN
): Parameter 3, %WITHIN%: [IMMI2GEI
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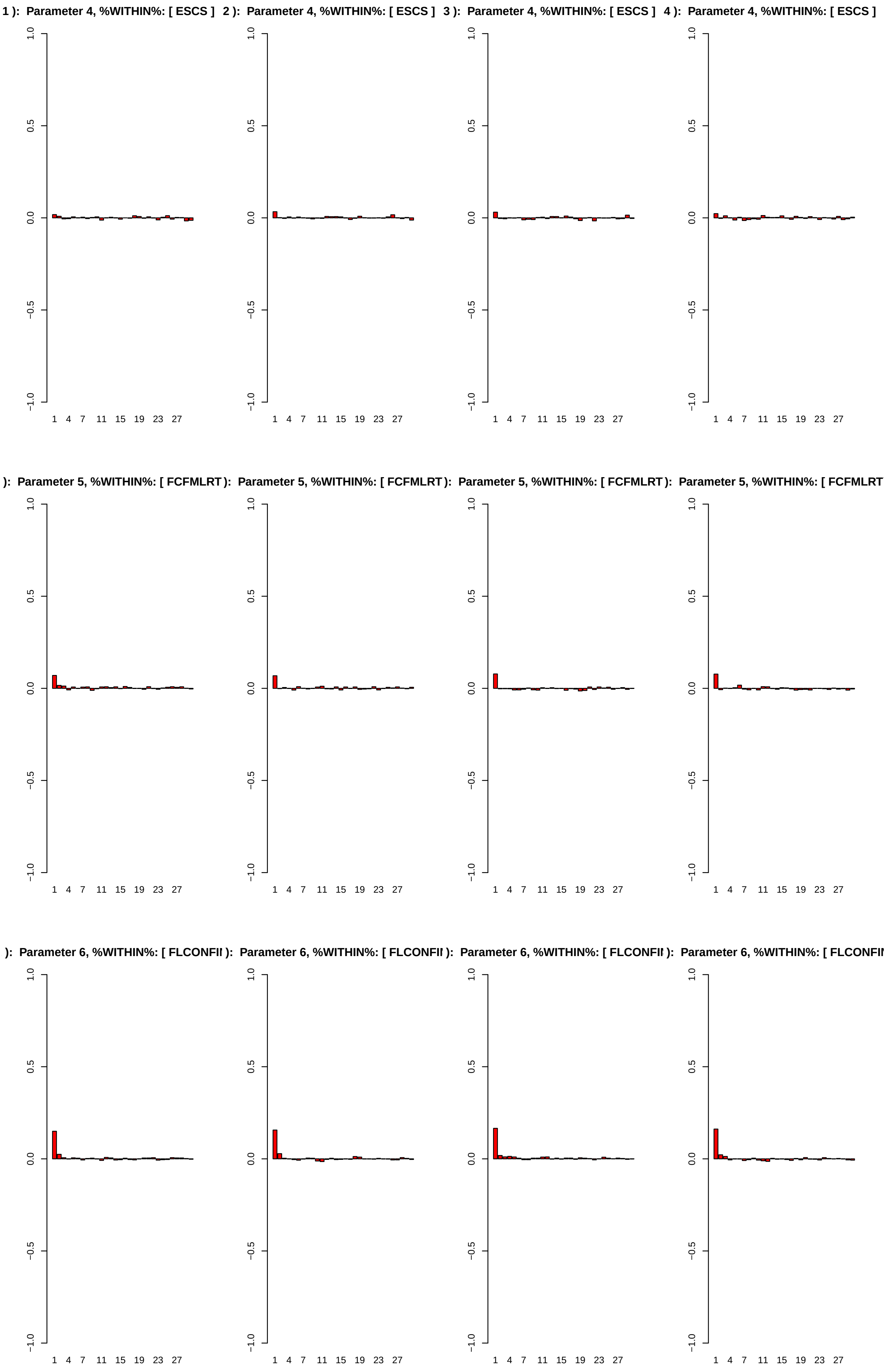
): Parameter 3, %WITHIN%: [IMMI2GEI
): Parameter 3, %WITHIN%: [IMMI2GEN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2): Parameter 4, %WITHIN%: [ESCS]
3): Parameter 4, %WITHIN%: [ESCS]
4): Parameter 4, %WITHIN%: [ESCS]
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1.0
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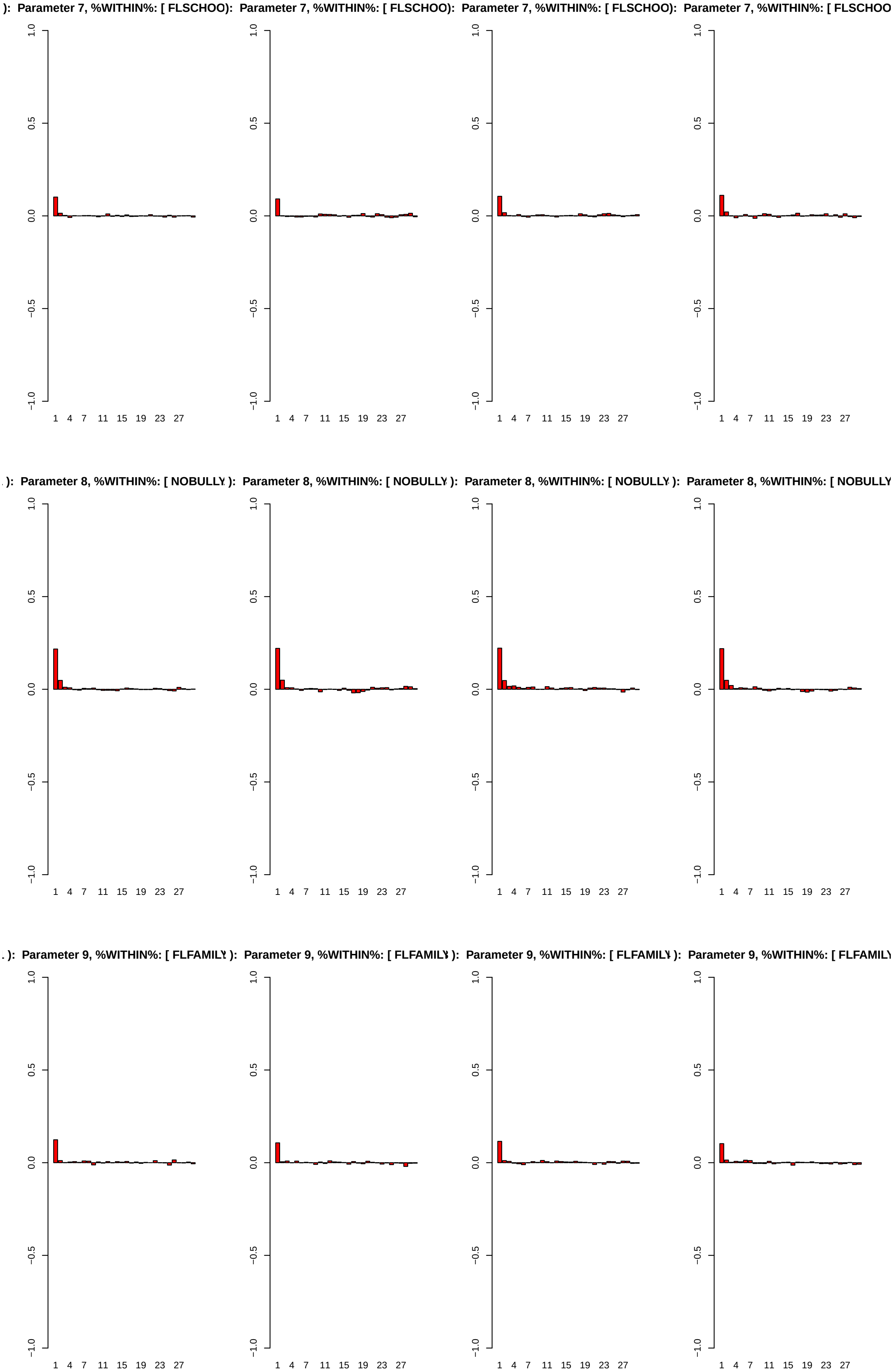
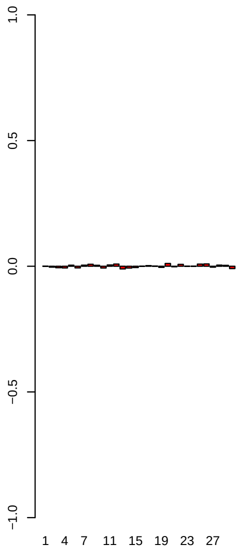
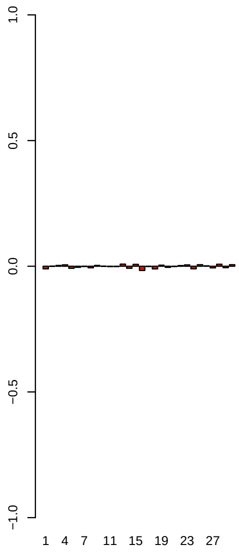
−0.5
−1.0
1 4 7 11 15 19 23 27


): 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
1.0
0.5
0.0
−0.5
−1.0
1 4 7 11 15 19 23 27

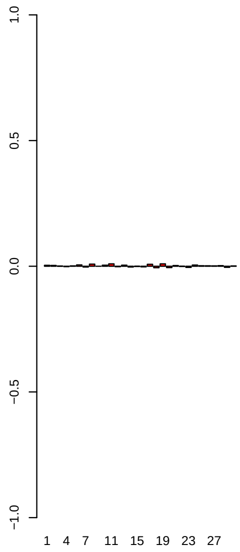
1): Parameter 10, %WITHIN%: MALE



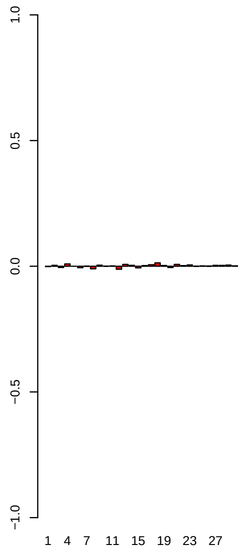
2): Parameter 10, %WITHIN%: MALE



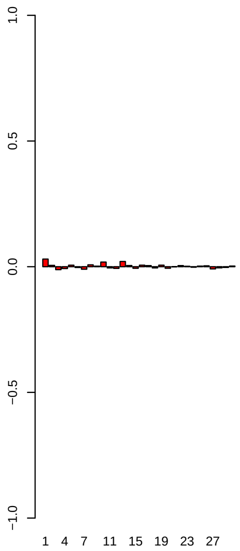
3): Parameter 10, %WITHIN%: MALE



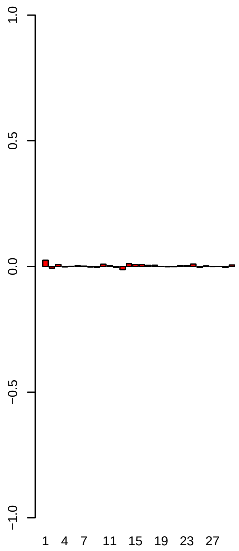
4): Parameter 10, %WITHIN%: MALE



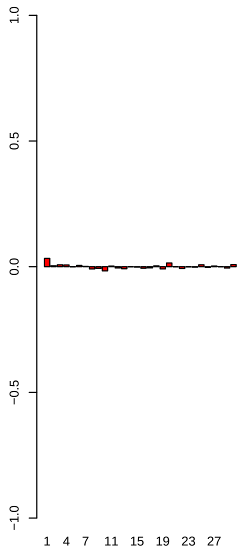
): Parameter 11, %WITHIN%: IMMI1GEN



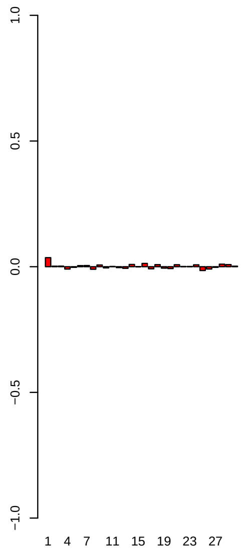
): Parameter 11, %WITHIN%: IMMI1GEN



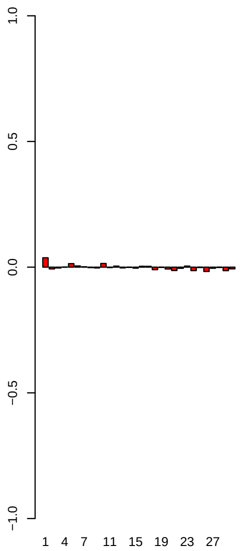
): Parameter 11, %WITHIN%: IMMI1GEN



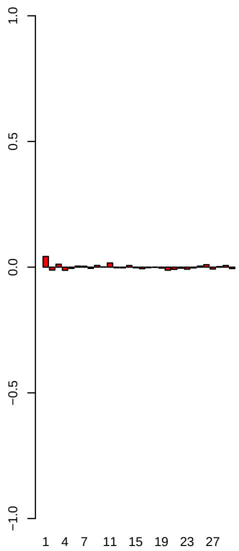
): Parameter 11, %WITHIN%: IMMI1GEN



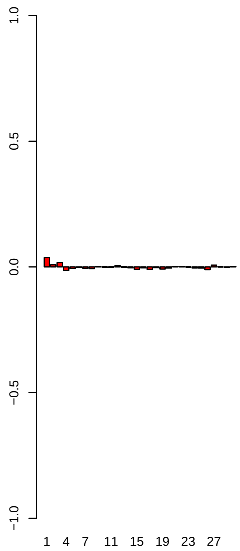
): Parameter 12, %WITHIN%: IMMI2GEN



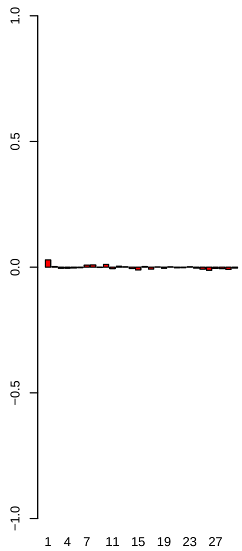
): Parameter 12, %WITHIN%: IMMI2GEN



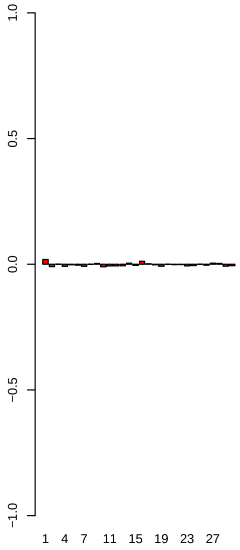
): Parameter 12, %WITHIN%: IMMI2GEN



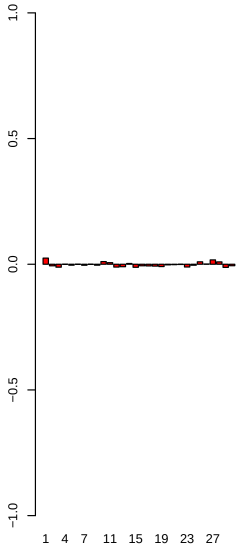
): Parameter 12, %WITHIN%: IMMI2GEN



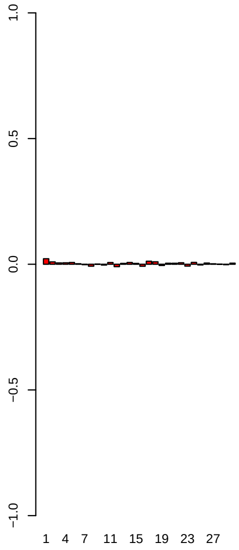
1): Parameter 13, %WITHIN%: ESCS



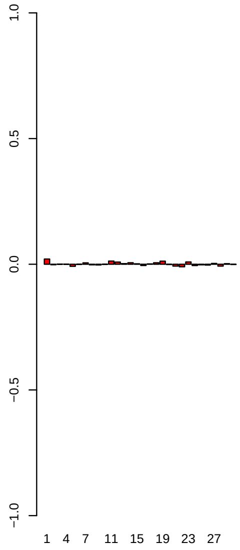
2): Parameter 13, %WITHIN%: ESCS



3): Parameter 13, %WITHIN%: ESCS



4): Parameter 13, %WITHIN%: ESCS



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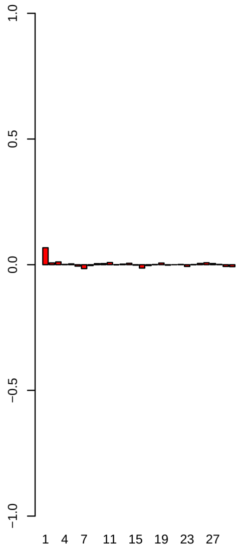

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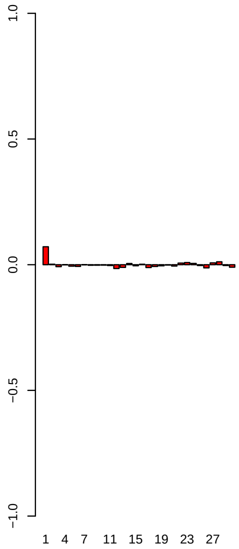

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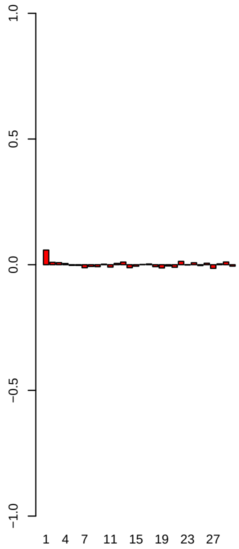

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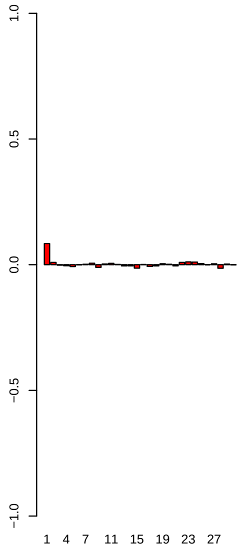

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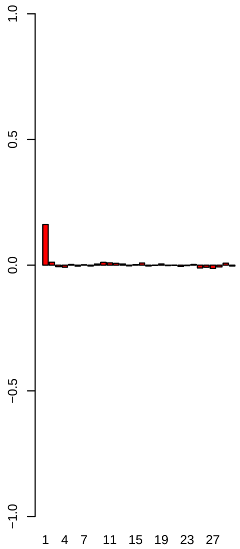

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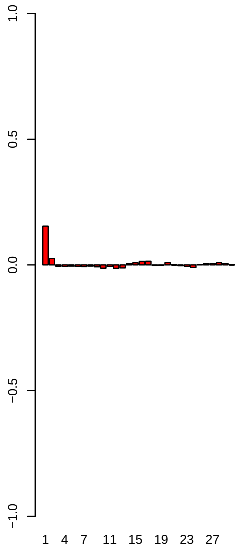

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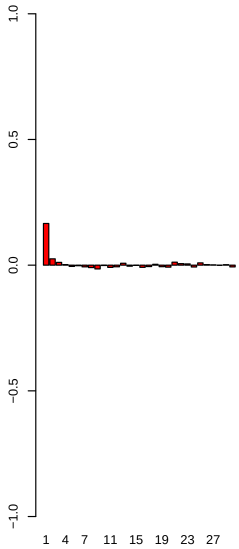

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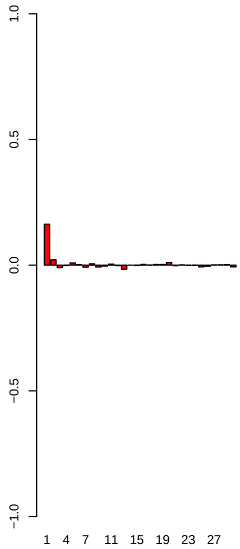

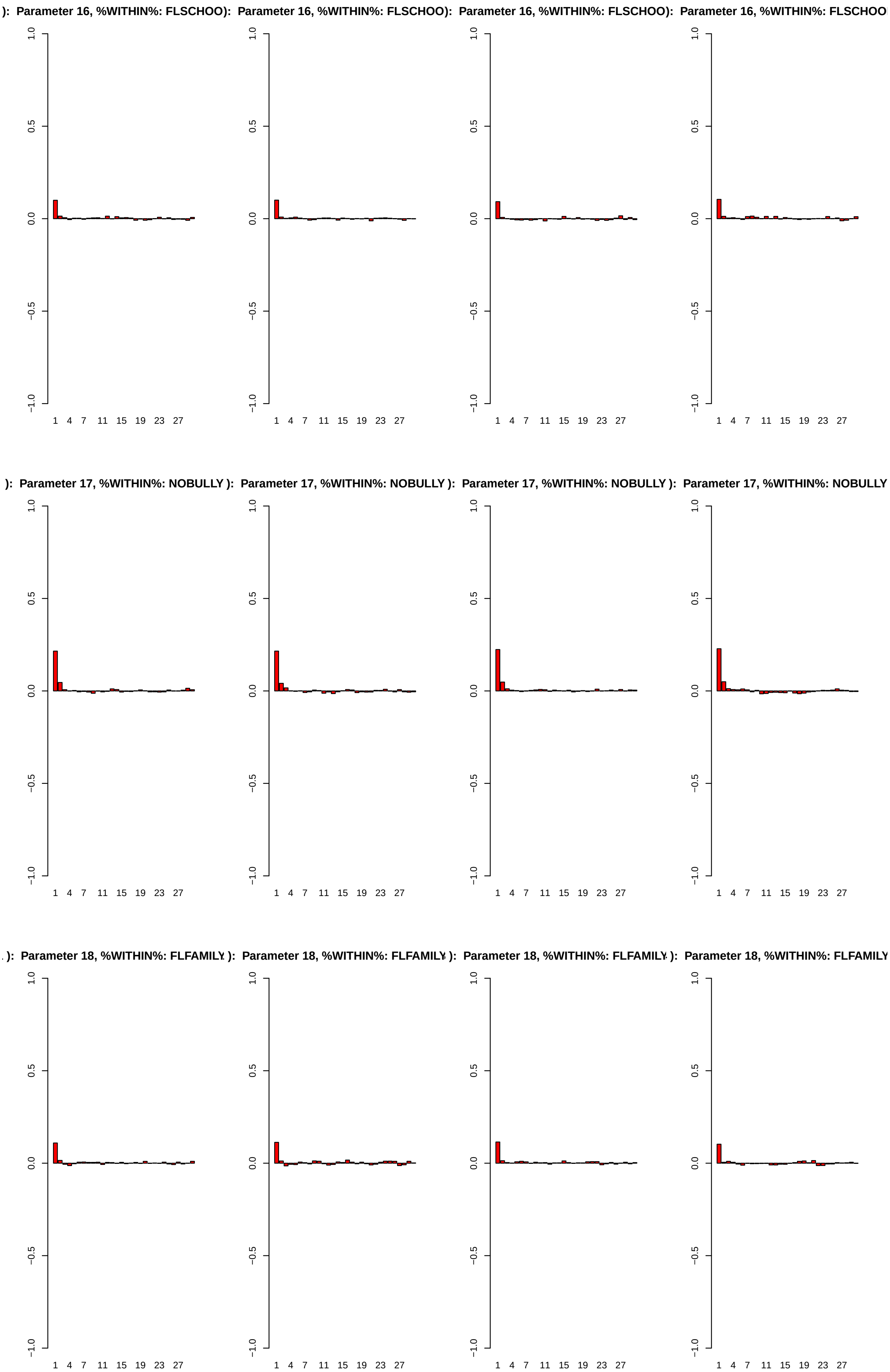
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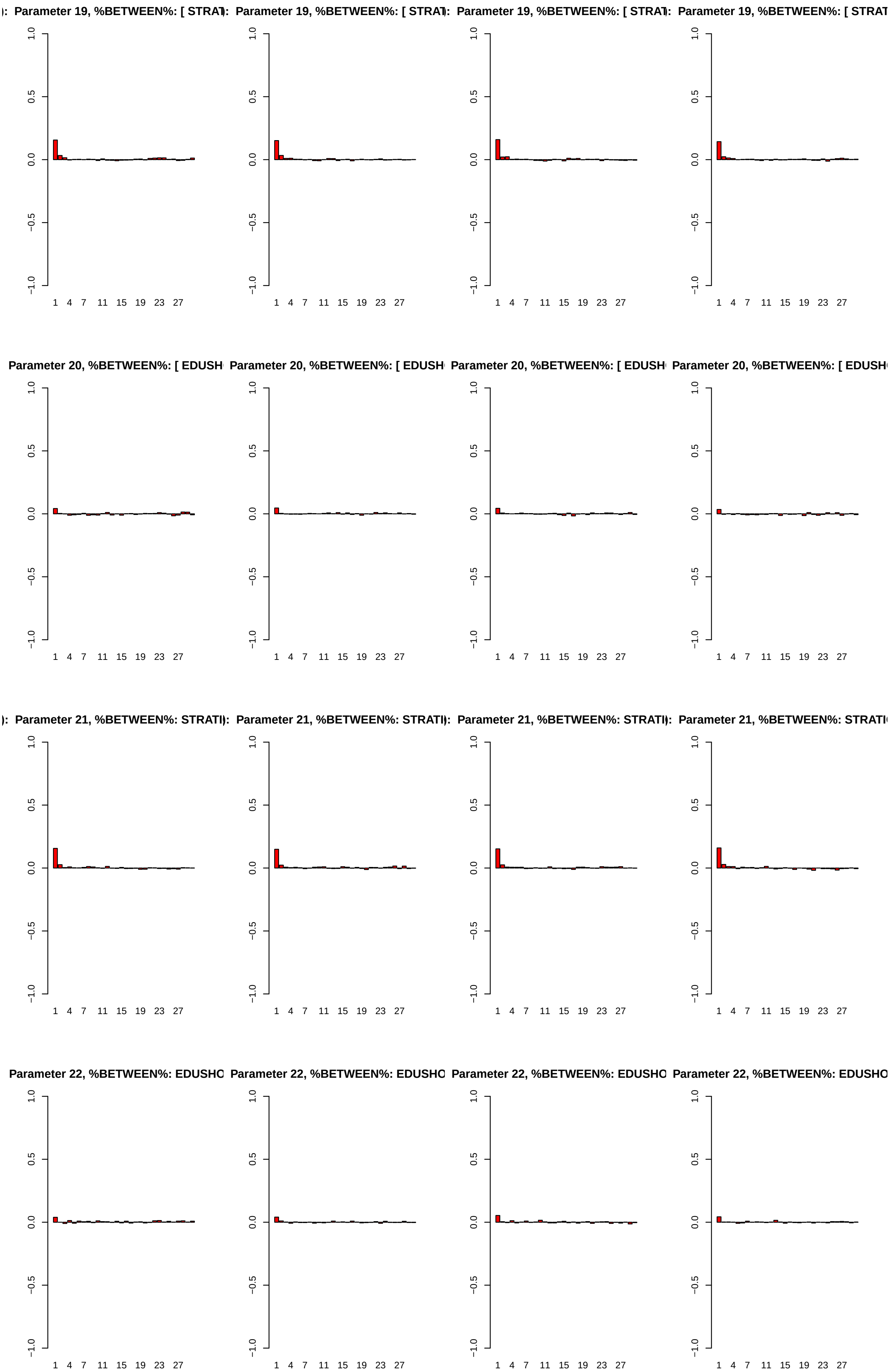
−1.0
1 4 7 11 15 19 23 27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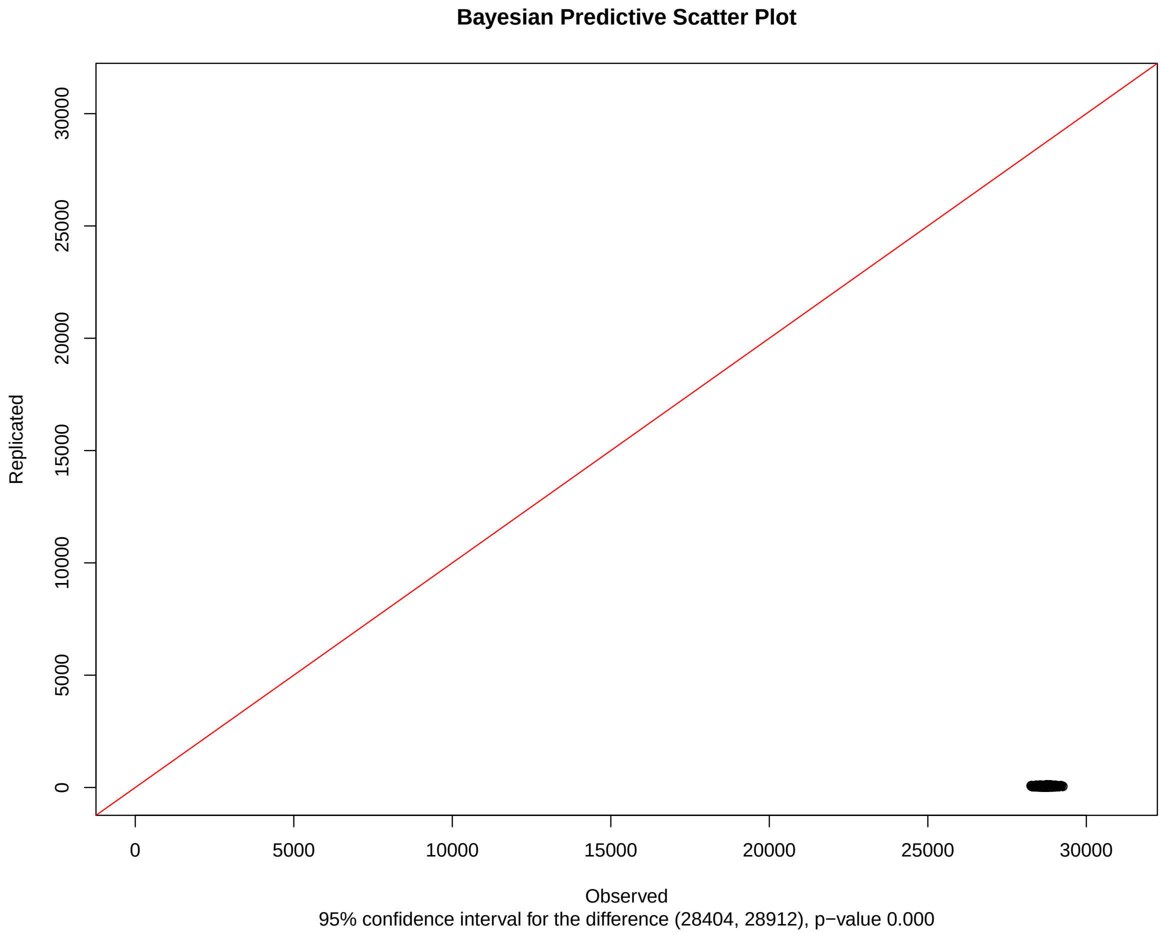
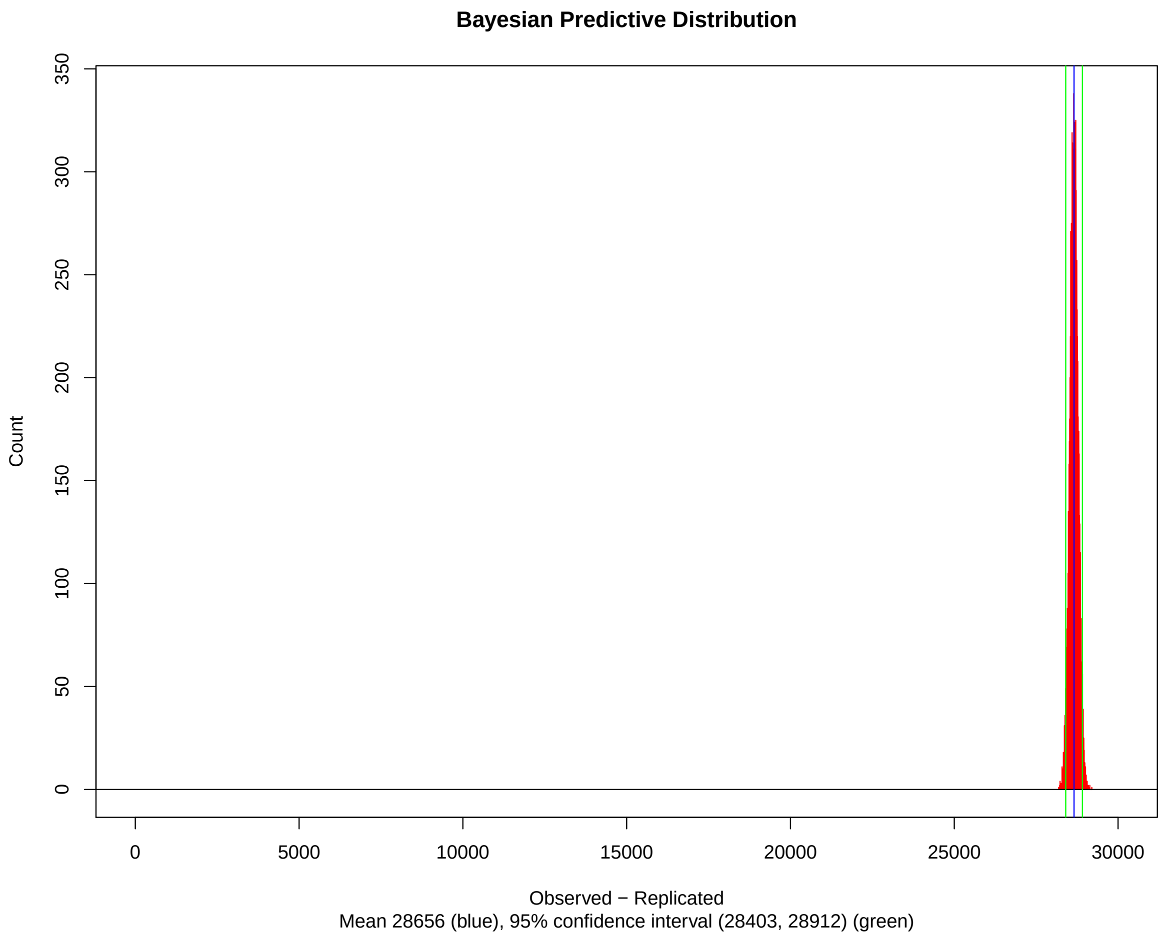

Bayesian Predictive Scatter Plot
Replicated
0
5000
10000
15000
20000
25000
30000
0
5000
10000
15000
20000
25000
30000
Observed
95% confidence interval for the difference (28404, 28912), p−value 0.000


Bayesian Predictive Distribution
Count
0
50
100
150
200
250
300
350
0
5000
10000
15000
20000
25000
30000
Observed − Replicated
Mean 28656 (blue), 95% confidence interval (28403, 28912) (green)