Identifying School Climate Variables Associated with Students' Financial Literacy Outcomes

A Cross-Country Comparison Using PISA 2018 Data

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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

Contents

List of Tables

List of Figures

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 (**bucherkoenen:2016**) 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. Following statistical theory, PISA designers firstly recognise the hierarchical nature of education research data such that students are nested in schools, and schools are further nested in countries. In addition, 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. Lastly, PISA consulted and synthesised multiple schools of thoughts (OECD, 2019) 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, 2020) 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 three research questions:

RQ1. Having controlled for demographic characteristics such as socio-economic status, sex and immmigration history, to what extent can the variation in students' financial literacy outcomes be accounted for by each of the school climate variables mentioned above.

RQ2. How does the total effect each school climate variable carries decompose into cognitive and affect pathways.

RQ3. How do these effects differ across countries.

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, 2020) 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* (United Nations, 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.

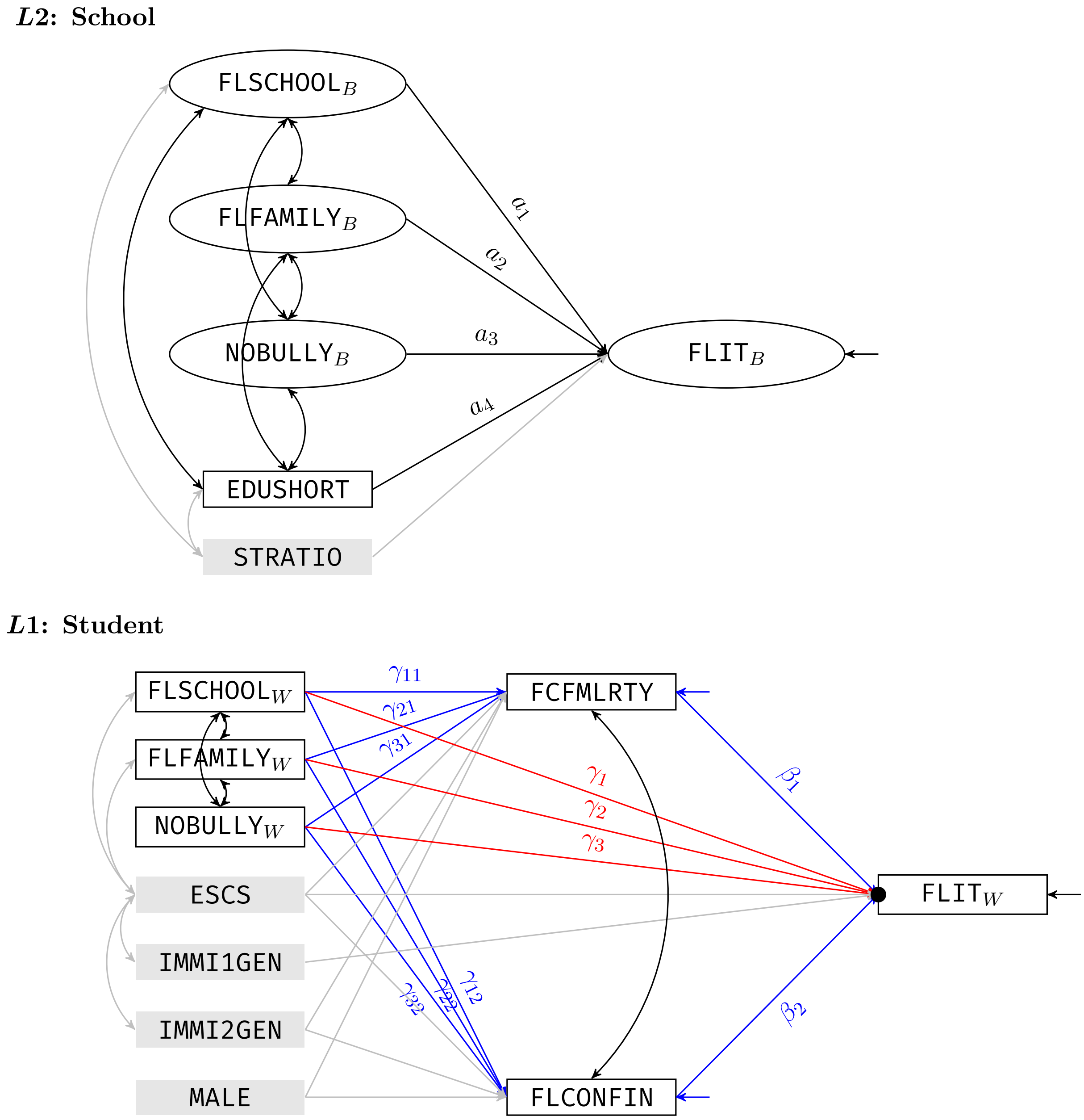
Table 2.1

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

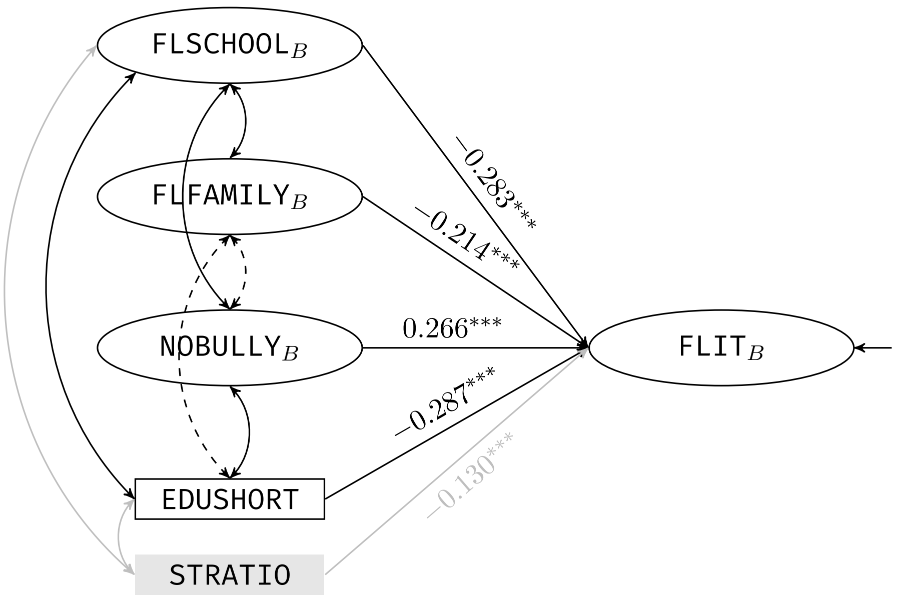


Note. [Insert notes here.]

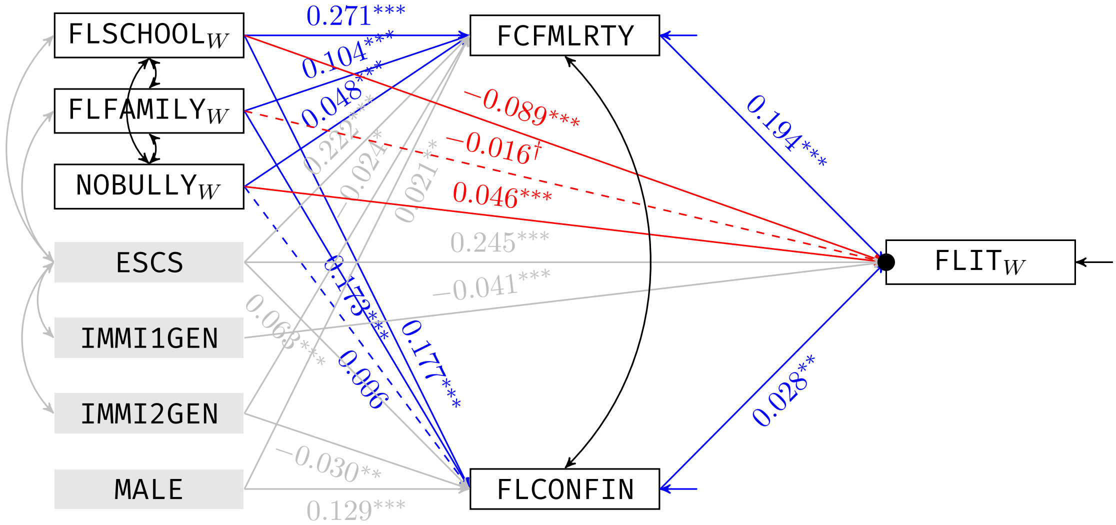
Figure 2.2

Path Diagram

***L*2: School**

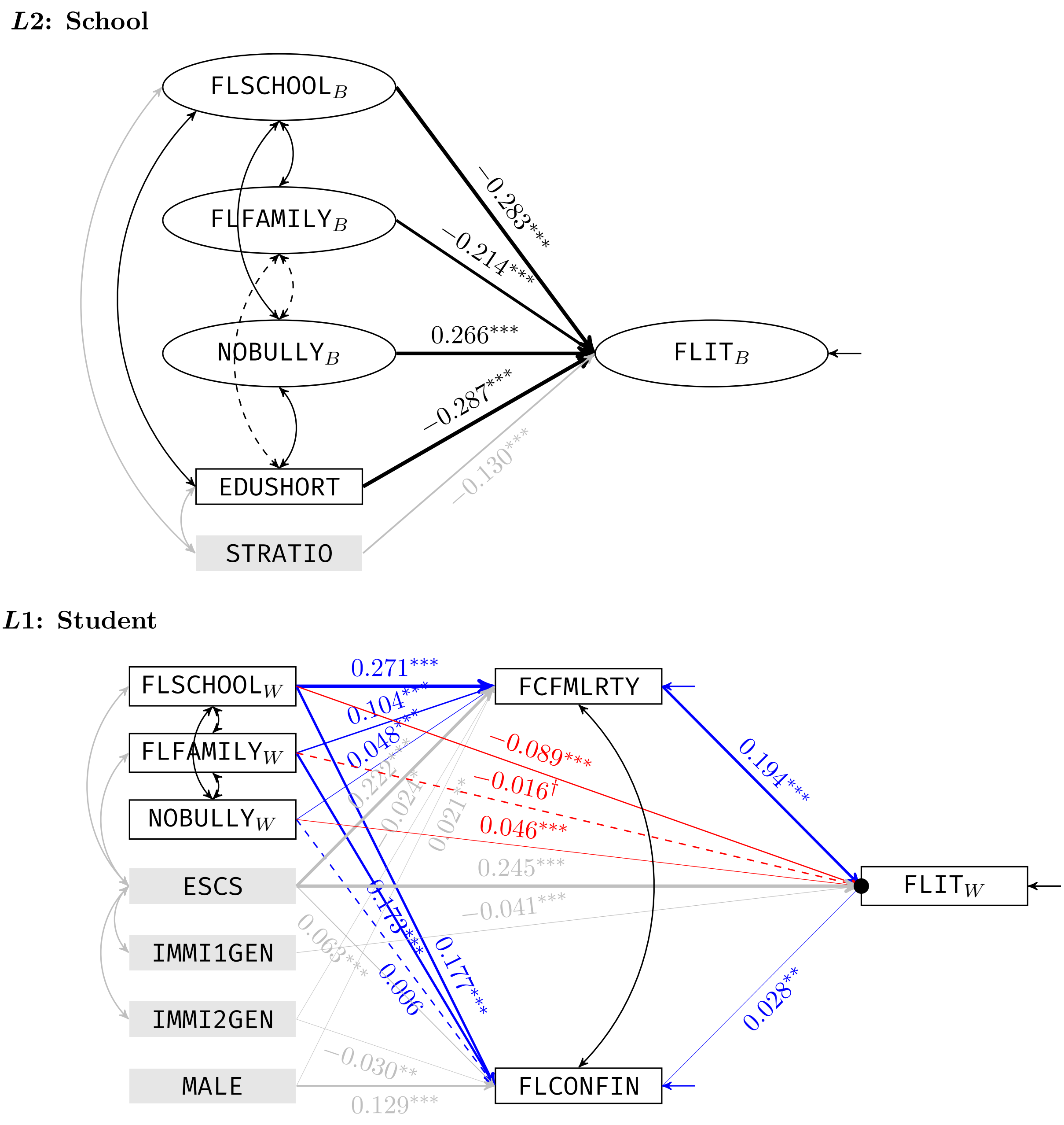


***L*1: Student**



Note. [Insert notes here.]

Figure 2.3
Path Diagram



Note. [Insert notes here.]

Chapter 3 Methods

3.1 Sample

This study drew its primary data soruce from PISA 2018 database (OECD, 2020) containing 107,174 observations spanning 20 countries, in which students were asked about their demographic background, family lives and school experiences. For the financial literacy section, in particular, students responded to qustions 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 fianncial literacy. Ten plausible values were subsequently generated by PISA organisers as measures of students' financial literacy outcomes and were used as the dependent variable (`FLIT`).

Student-level independent variables are

School-level independent variables are

3.2 Measures

3.2.1 Cognitive Measure of Financial Literacy

3.2.2 Affective Aspects of Financial Literacy

3.2.3 Demographic Variables

3.2.4 Reliability of Level-two Averages

3.3 Model

Student-level (L_1):

$$\begin{aligned}
\texttt{FCFMLRTY}_{ij} &= \alpha_j^{M_1} + \gamma_{11}\texttt{FLSCHOOL}_{ij} + \gamma_{21}\texttt{FLFAMILY}_{ij} + \gamma_{31}\texttt{NOBULLY}_{ij} \\
&\quad + \gamma_{41}\texttt{ESCS}_{ij} + \gamma_{61}\texttt{IMMI2GEN}_{ij} + \gamma_{71}\texttt{MALE}_{ij} + r_{ij}^{M_1} \\
\texttt{FLCONFIN}_{ij} &= \alpha_j^{M_2} + \gamma_{12}\texttt{FLSCHOOL}_{ij} + \gamma_{22}\texttt{FLFAMILY}_{ij} + \gamma_{32}\texttt{NOBULLY}_{ij} \\
&\quad + \gamma_{42}\texttt{ESCS}_{ij} + \gamma_{62}\texttt{IMMI2GEN}_{ij} + \gamma_{72}\texttt{MALE}_{ij} + r_{ij}^{M_2} \\
\texttt{FLIT}_{ij} &= \alpha_j^{Y} + \beta_1\texttt{FCFMLRTY}_{ij} + \beta_2\texttt{FLCONFIN}_{ij} \\
&\quad + \gamma_{1}\texttt{FLSCHOOL}_{ij} + \gamma_{2}\texttt{FLFAMILY}_{ij} + \gamma_{3}\texttt{NOBULLY}_{ij} \\
&\quad + \gamma_{4}\texttt{ESCS}_{ij} + \gamma_{5}\texttt{IMMI1GEN}_{ij} + r_{ij}^{Y}
\end{aligned} \tag{3.1}$$

School-level (L_2):

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

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 (L_1)

and random intercept $\boldsymbol{\alpha}_j = \boldsymbol{\alpha}_{00} + \boldsymbol{A}\boldsymbol{w}_j + \boldsymbol{\varepsilon}_j$ for school-level (L_2):

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

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 in 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 (Lambert, 2018, p. 314). Additionally, the first 50000 MCMC iterations were discarded to ensure stablility and any two draws were separated with 5000 iterations to avoid autocorrelation (see Section A.1 for input file)—a safe setting even for moderate to high percentage missings (Grund et al., 2016). Diagnostic plots in Section A.3 presented visual evidence for convergence with imputation results summarised in Table A.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

4.2 Correlation matrices

4.2.1 Across countries

4.2.2 Across levels: Country | School | Students

4.3 Examination of measurement models

Table 4.1

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†	−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**

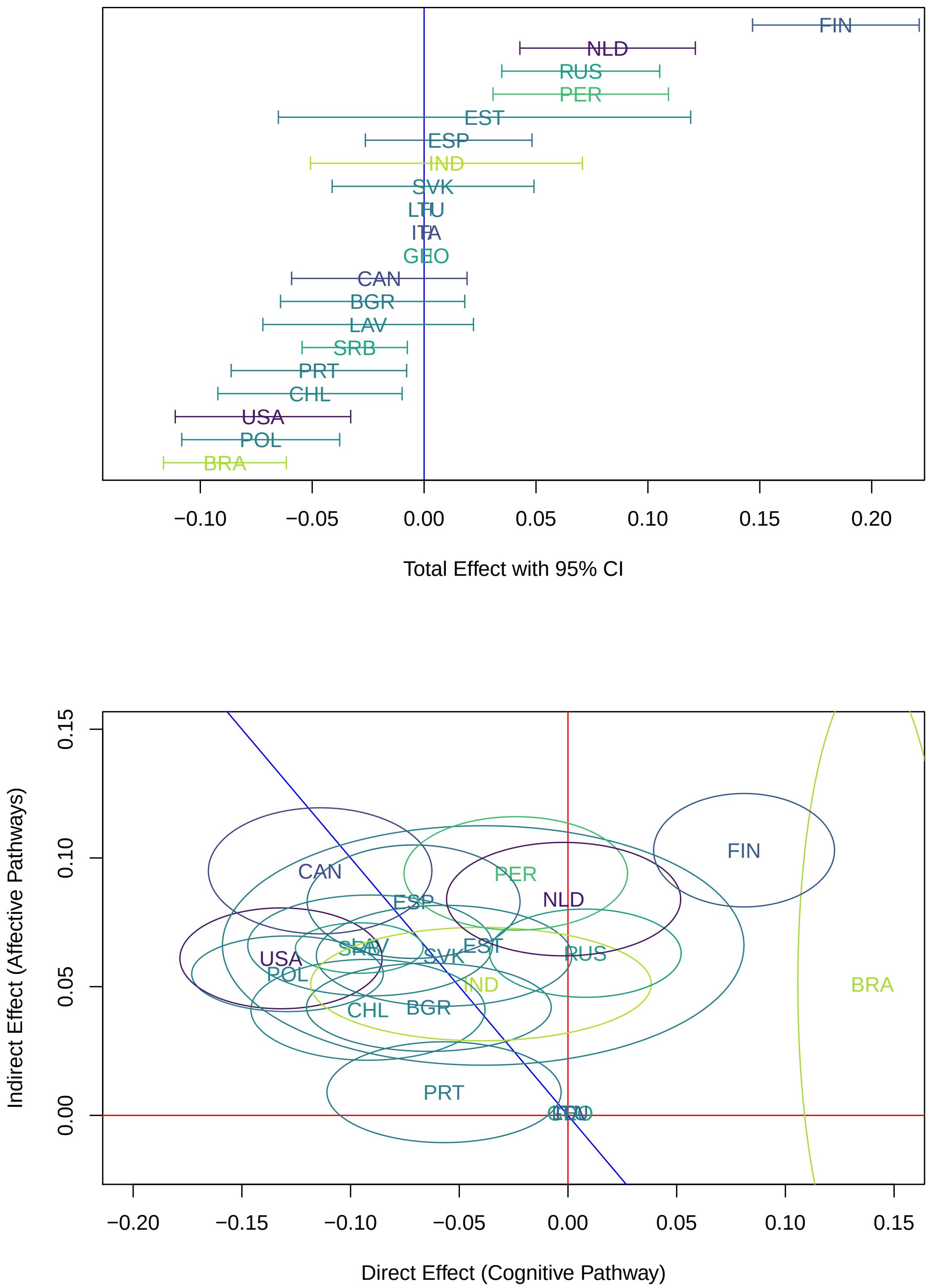
Continued

Variable	Model parameter	Null Model 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 *L*1		0.005	0.003	0.016	0.000	0.015	0.000	0.015	0.000
SRMR *L*2		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

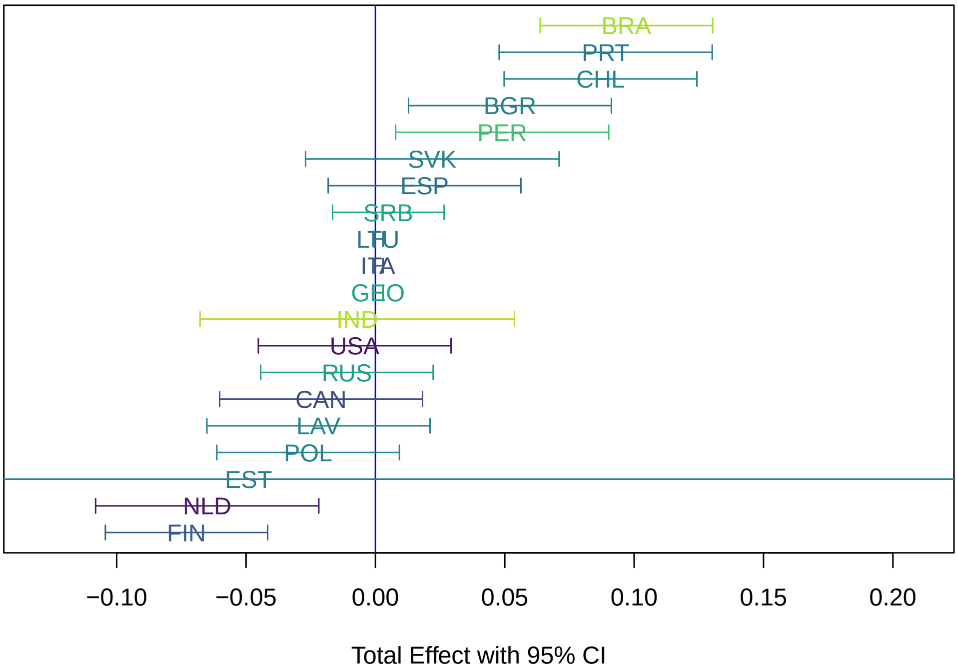
Figure 4.1
Total, Direct and Indirect Effects of School Intervention (`FLSCHOOL`)

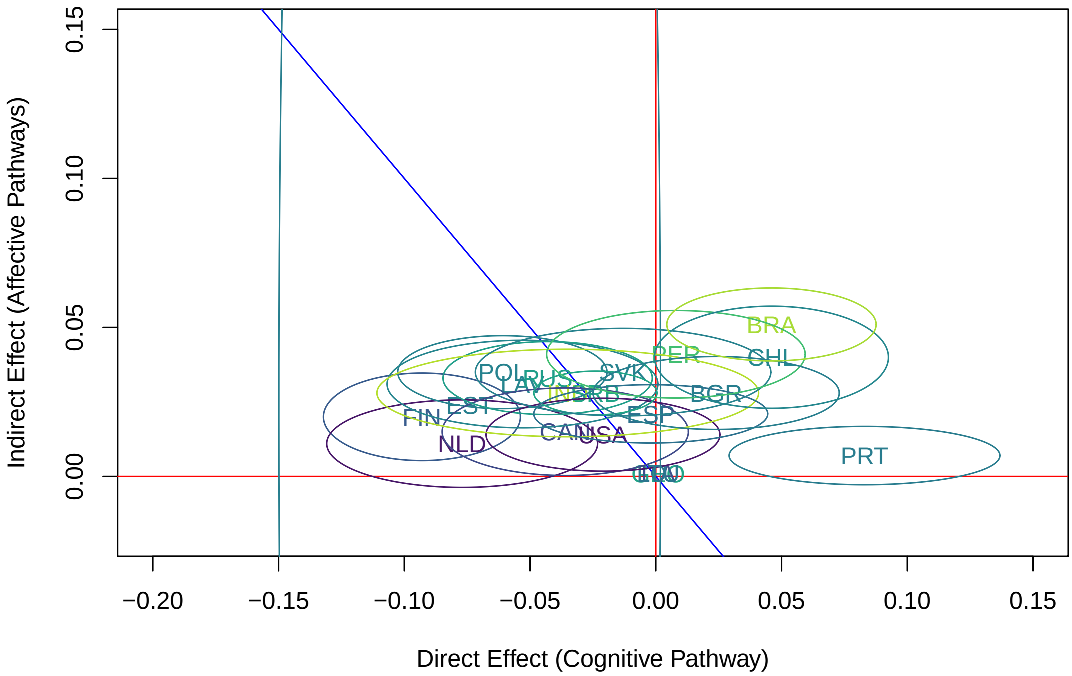


Note. Countries with high (low) financial knowlege indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the verticle blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the verticle, horizontal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

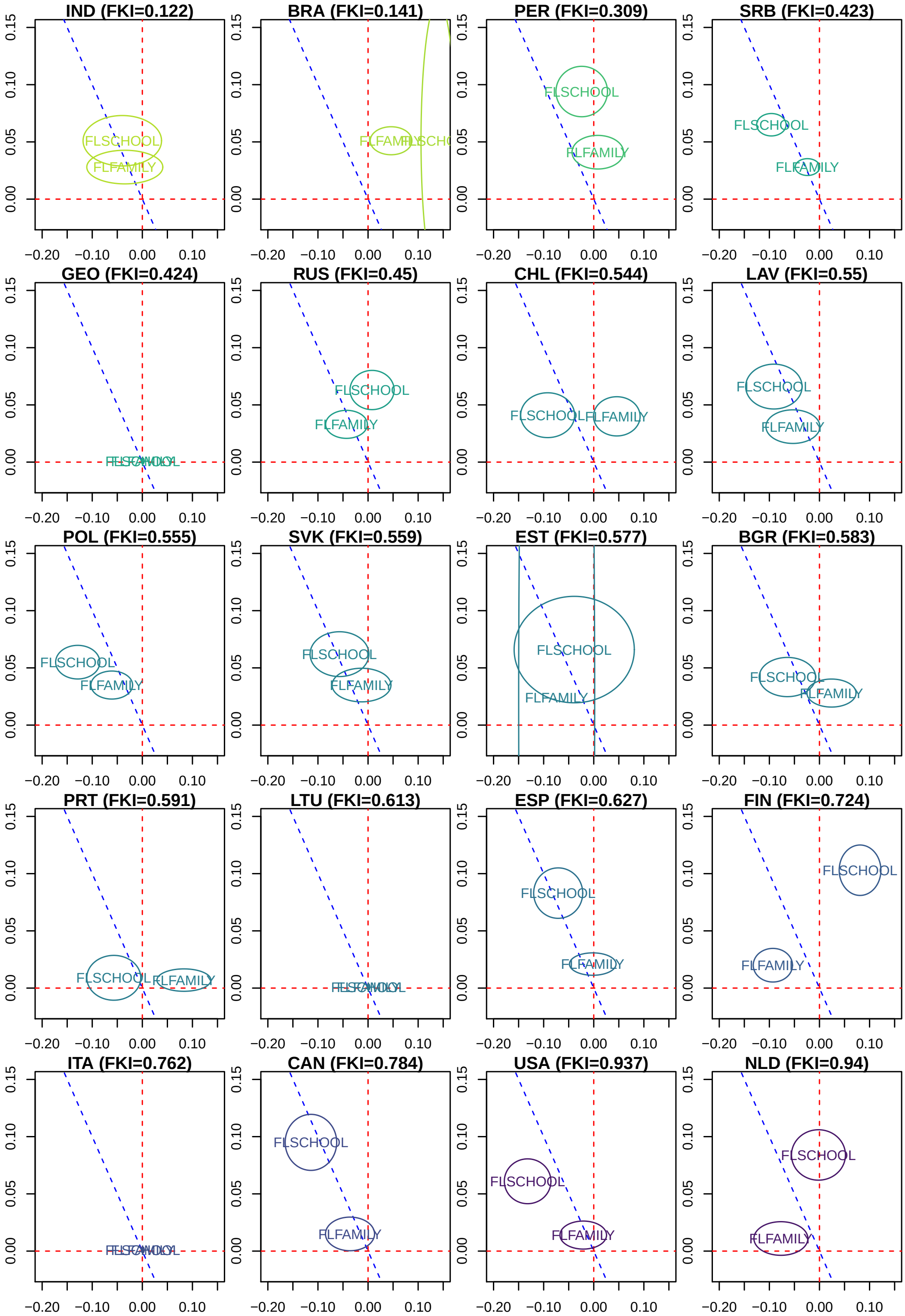




Note. Countries with high (low) financial knowlege indices are represented in darker (lighter) colours. Top panel: Estimates with 95% confidence intervals crossing the verticle blue line are not statistically significant. Lower panel: Estimates whose 95% confidence ellipses cross the verticle, horizontal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

A.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
```

A.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      *
```

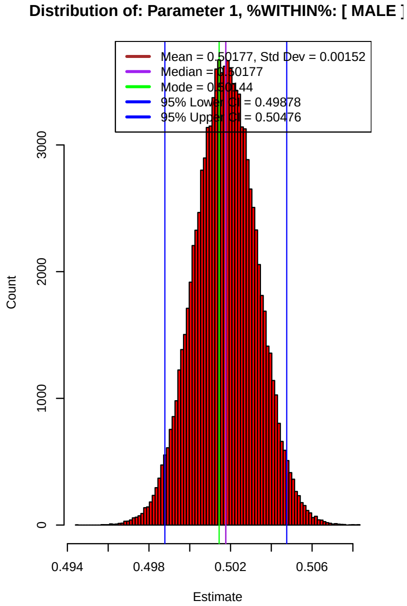
A.3 Diagnostic Plots

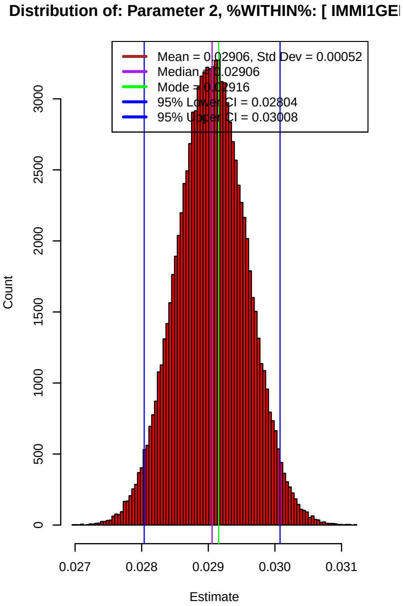
Table A.1

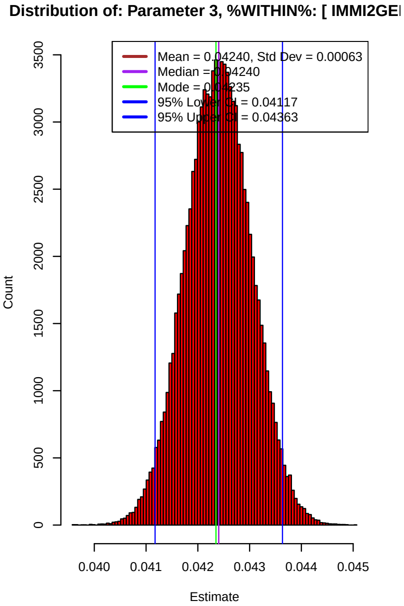
Summary of Diagnostic Plots of Multilevel Multiple Imputation

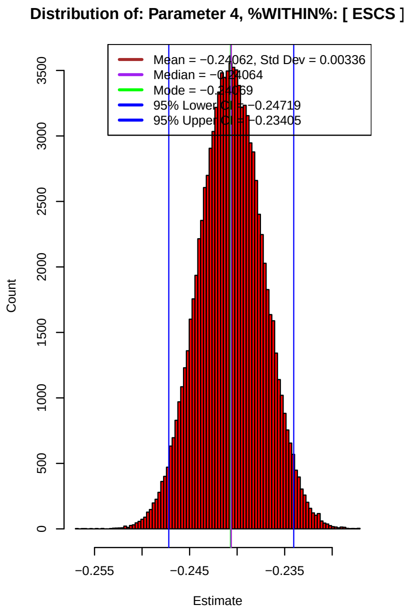
Parameter number	Parameter label	Modelling level	Brief description	Posterior mean	Posterior variance	95% CI of distribution	Chain converged	AR-free chains
1	MALE	Within	Whether participant is male	0.502		(0.499, 0.505)	Yes	4
2	IMMI1GEN	Within	Whether participant migrated to this country	0.029		(0.028,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

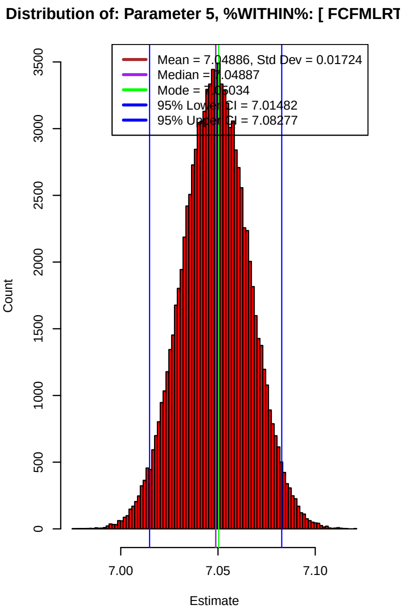
Note. Notes go here.

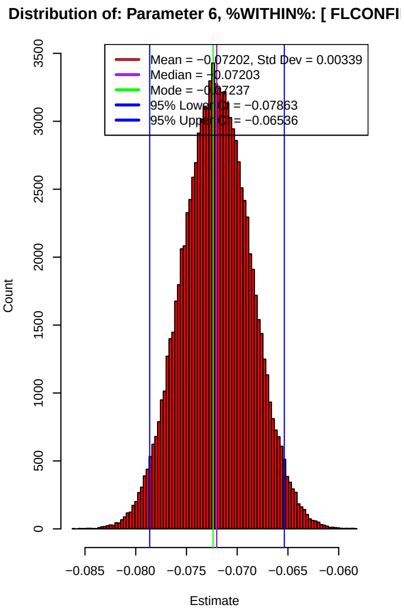

Distribution of: Parameter 1, %WITHIN%: [MALE]
Mean = 0.50177, Std Dev = 0.00152
Median = 0.50177
Mode = 0.50144
95% Lower CI = 0.49878
95% Upper CI = 0.50476
Count
Estimate

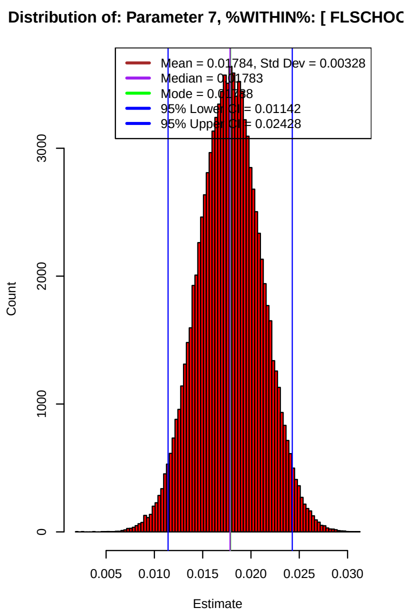

Distribution of: Parameter 2, %WITHIN%: [IMMI1GE
Mean = 0.02906, Std Dev = 0.00052
Median = 0.02906
Mode = 0.02916
95% Lower CI = 0.02804
95% Upper CI = 0.03008
Count
Estimate

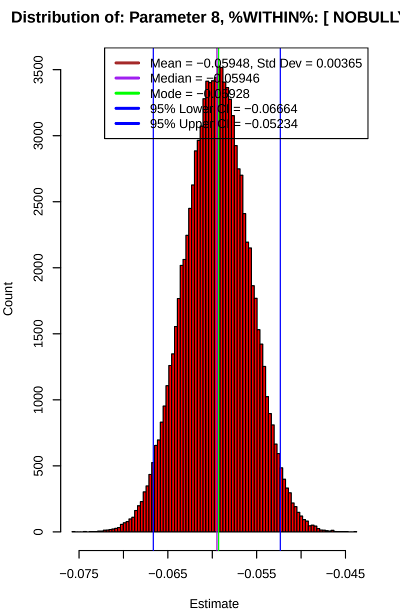

Distribution of: Parameter 3, %WITHIN%: [IMMI2GE
Mean = 0.04240, Std Dev = 0.00063
Median = 0.04240
Mode = 0.04235
95% Lower CI = 0.04117
95% Upper CI = 0.04363
Count
Estimate

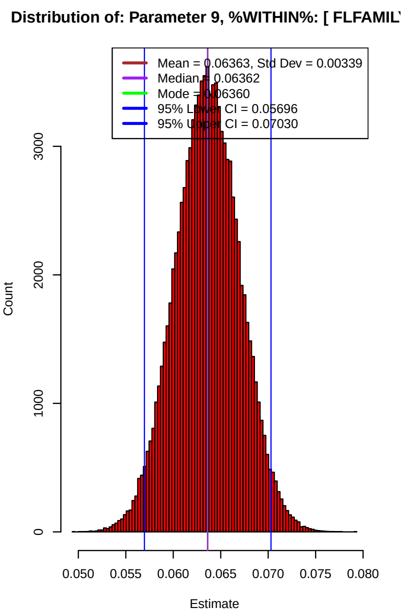

Distribution of: Parameter 4, %WITHIN%: [ESCS]
Mean = −0.24062, Std Dev = 0.00336
Median = −0.24064
Mode = −0.24059
95% Lower CI = −0.24719
95% Upper CI = −0.23405
Count
Estimate

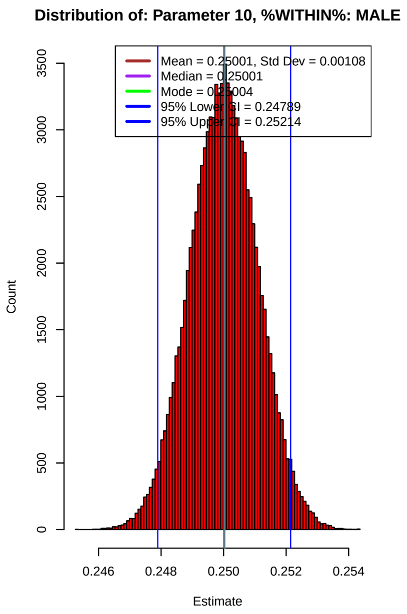

Distribution of: Parameter 5, %WITHIN%: [FCFMLRT
Mean = 7.04886, Std Dev = 0.01724
Median = 7.04887
Mode = 7.05034
95% Lower CI = 7.01482
95% Upper CI = 7.08277
Count
Estimate

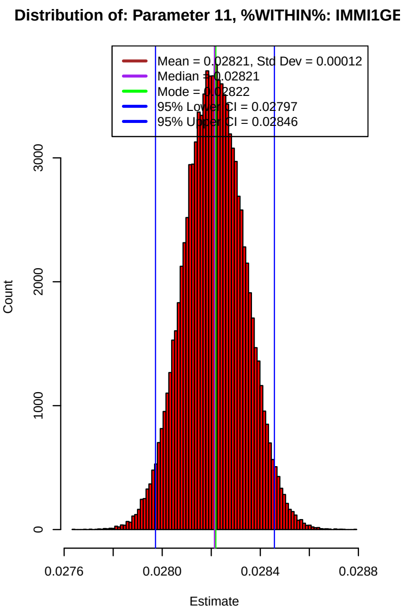

Distribution of: Parameter 6, %WITHIN%: [FLCONFI
Mean = −0.07202, Std Dev = 0.00339
Median = −0.07203
Mode = −0.07237
95% Lower CI = −0.07863
95% Upper CI = −0.06536
Count
Estimate

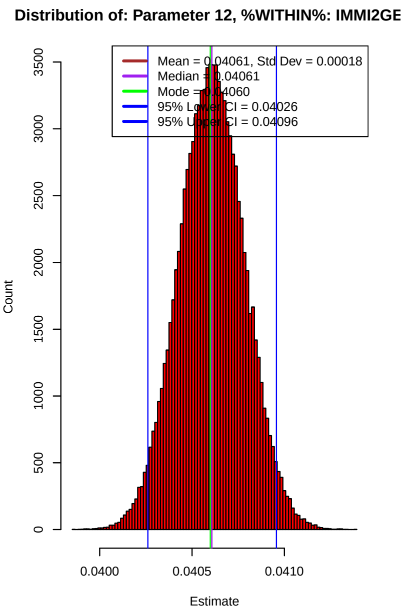

Distribution of: Parameter 7, %WITHIN%: [FLSCHOC
Mean = 0.01784, Std Dev = 0.00328
Median = 0.01783
Mode = 0.01788
95% Lower CI = 0.01142
95% Upper CI = 0.02428
Count
Estimate

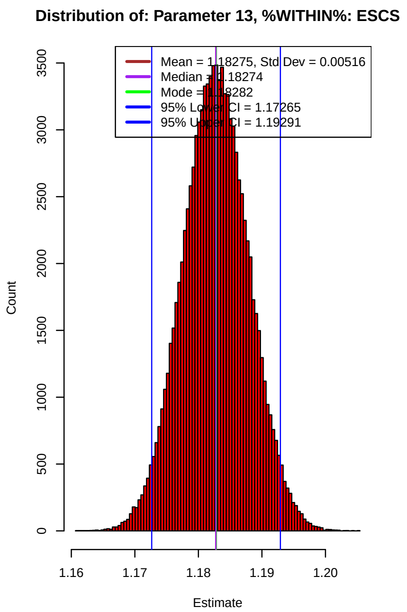

Distribution of: Parameter 8, %WITHIN%: [NOBULLY
Mean = −0.05948, Std Dev = 0.00365
Median = −0.05946
Mode = −0.05928
95% Lower CI = −0.06664
95% Upper CI = −0.05234
Count
Estimate

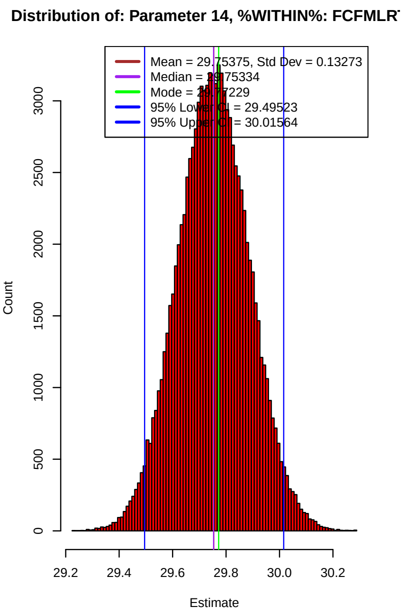

Distribution of: Parameter 9, %WITHIN%: [FLFAMILY
Mean = 0.06363, Std Dev = 0.00339
Median = 0.06362
Mode = 0.06360
95% Lower CI = 0.05696
95% Upper CI = 0.07030
Count
Estimate

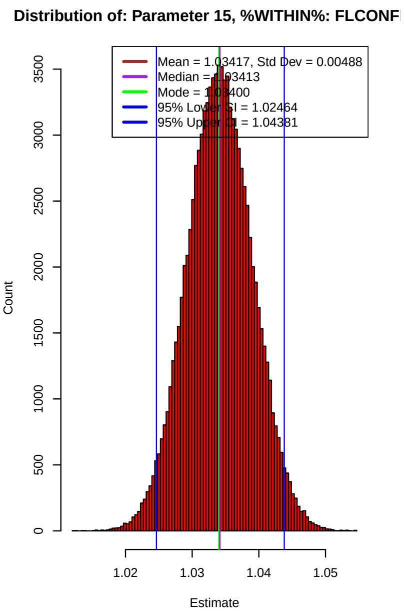

Distribution of: Parameter 10, %WITHIN%: MALE
Mean = 0.25001, Std Dev = 0.00108
Median = 0.25001
Mode = 0.25004
95% Lower CI = 0.24789
95% Upper CI = 0.25214
Count
Estimate

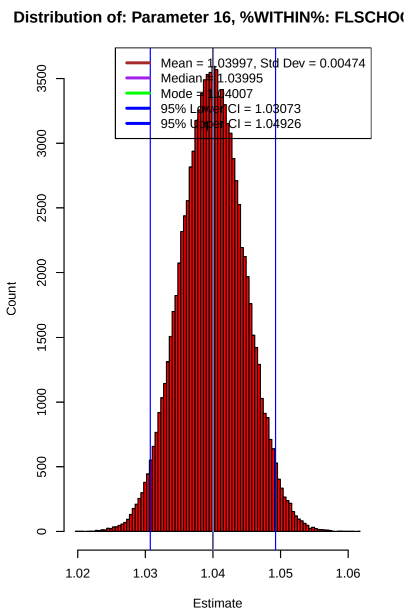

Distribution of: Parameter 11, %WITHIN%: IMMI1GE
Mean = 0.02821, Std Dev = 0.00012
Median = 0.02821
Mode = 0.02822
95% Lower CI = 0.02797
95% Upper CI = 0.02846
Count
Estimate

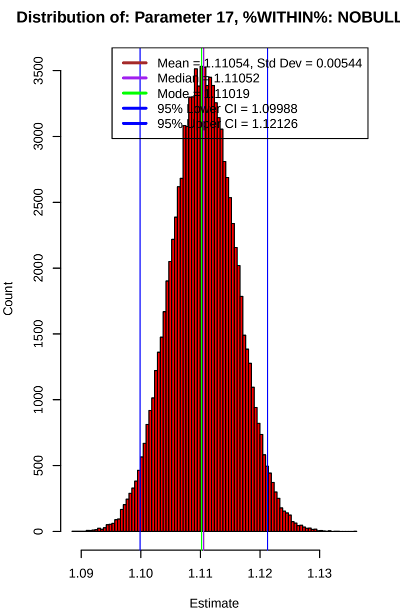

Distribution of: Parameter 12, %WITHIN%: IMMI2GE
Mean = 0.04061, Std Dev = 0.00018
Median = 0.04061
Mode = 0.04060
95% Lower CI = 0.04026
95% Upper CI = 0.04096
Count
Estimate

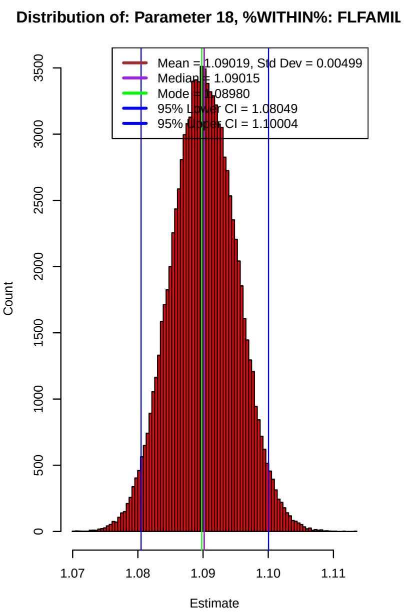

Distribution of: Parameter 13, %WITHIN%: ESCS
Mean = 1.18275, Std Dev = 0.00516
Median = 1.18274
Mode = 1.18282
95% Lower CI = 1.17265
95% Upper CI = 1.19291
Count
Estimate

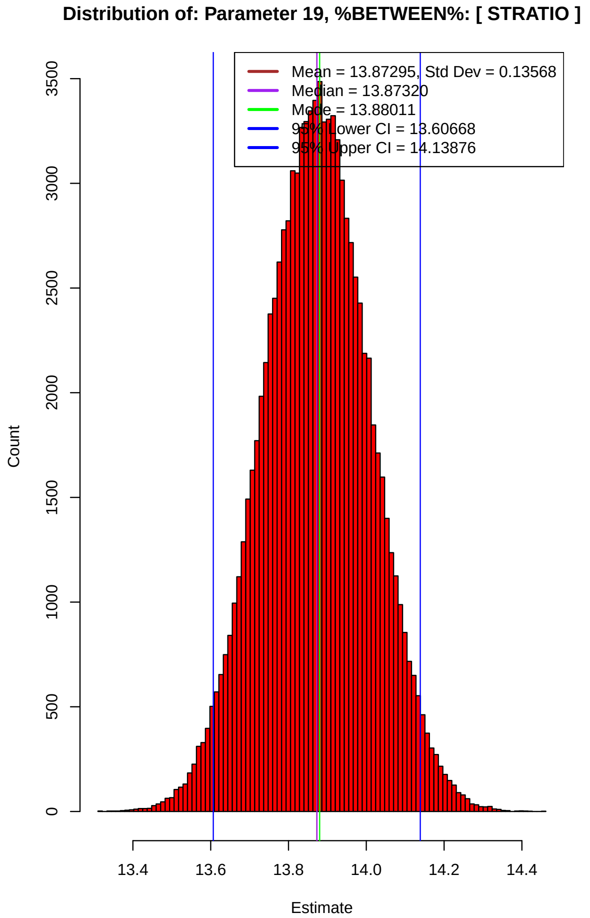

Distribution of: Parameter 14, %WITHIN%: FCFMLR
Mean = 29.75375, Std Dev = 0.13273
Median = 29.75334
Mode = 29.77229
95% Lower CI = 29.49523
95% Upper CI = 30.01564
Count
Estimate

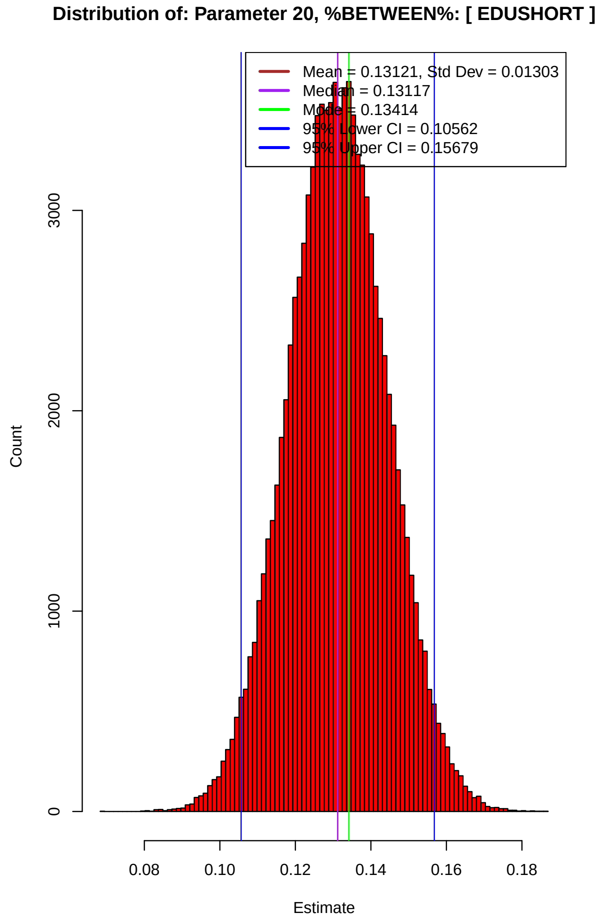

Distribution of: Parameter 15, %WITHIN%: FLCONF
Mean = 1.03417, Std Dev = 0.00488
Median = 1.03413
Mode = 1.03400
95% Lower CI = 1.02464
95% Upper CI = 1.04381
Count
Estimate

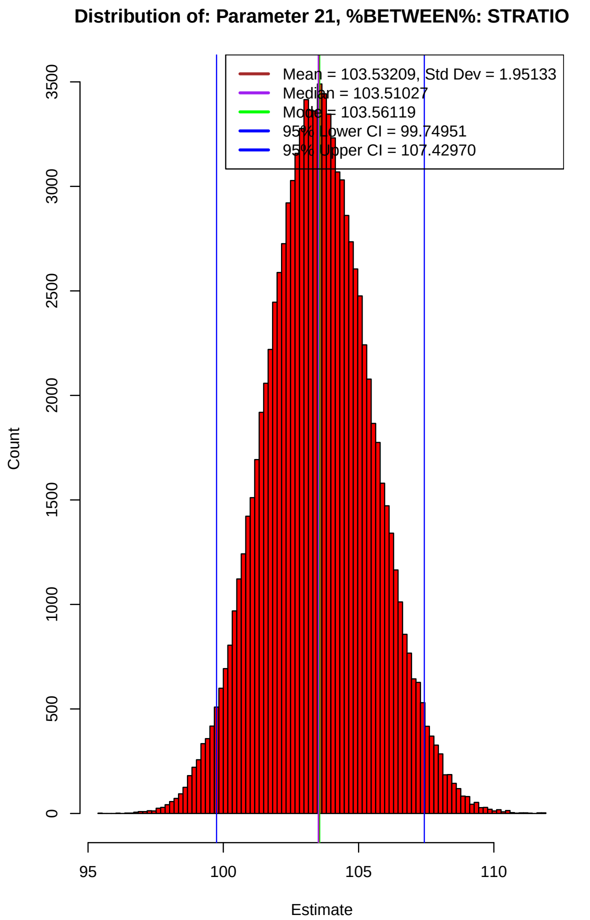

Distribution of: Parameter 16, %WITHIN%: FLSCHO
Mean = 1.03997, Std Dev = 0.00474
Median = 1.03995
Mode = 1.04007
95% Lower CI = 1.03073
95% Upper CI = 1.04926
Count
Estimate

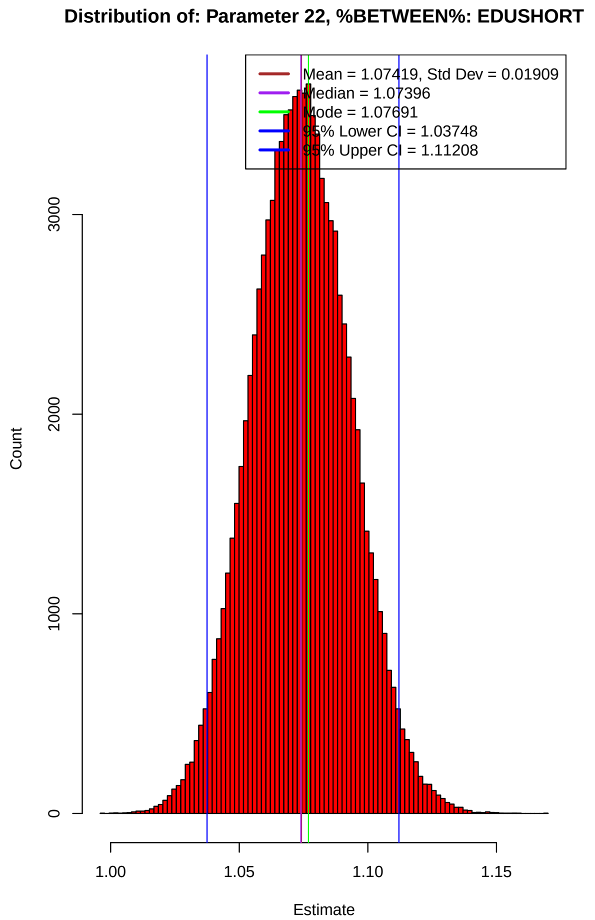

Distribution of: Parameter 17, %WITHIN%: NOBULL
Mean = 1.11054, Std Dev = 0.00544
Median = 1.11052
Mode = 1.11019
95% Lower CI = 1.09988
95% Upper CI = 1.12126
Count
Estimate

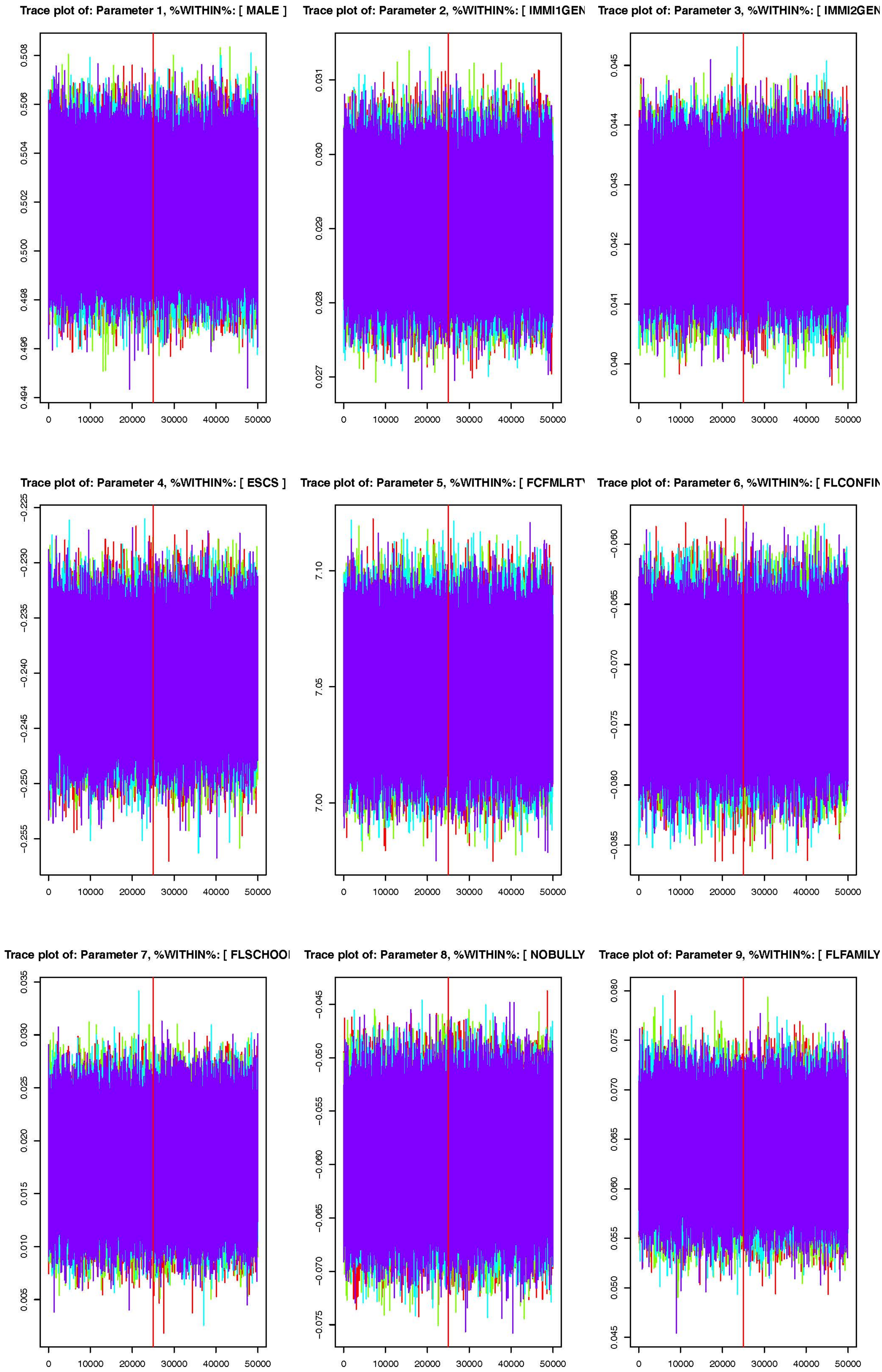

Distribution of: Parameter 18, %WITHIN%: FLFAMIL
Mean = 1.09019, Std Dev = 0.00499
Median = 1.09015
Mode = 1.08980
95% Lower CI = 1.08049
95% Upper CI = 1.10004
Count
Estimate

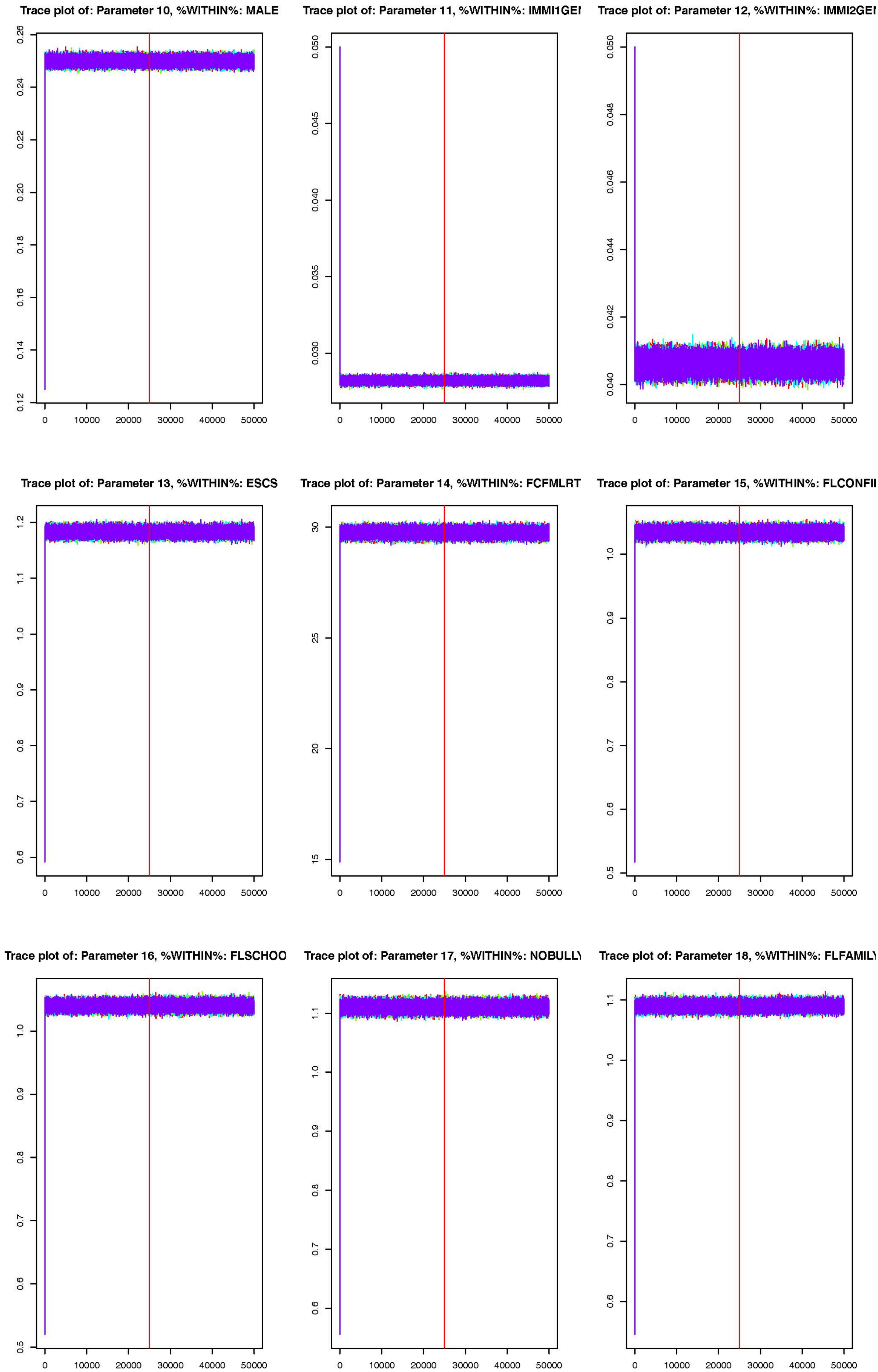

Distribution of: Parameter 19, %BETWEEN%: [STRATIO]
Mean = 13.87295, Std Dev = 0.13568
Median = 13.87320
Mode = 13.88011
95% Lower CI = 13.60668
95% Upper CI = 14.13876
Count
Estimate


Distribution of: Parameter 20, %BETWEEN%: [EDUSHORT]
Mean = 0.13121, Std Dev = 0.01303
Median = 0.13117
Mode = 0.13414
95% Lower CI = 0.10562
95% Upper CI = 0.15679
Count
Estimate

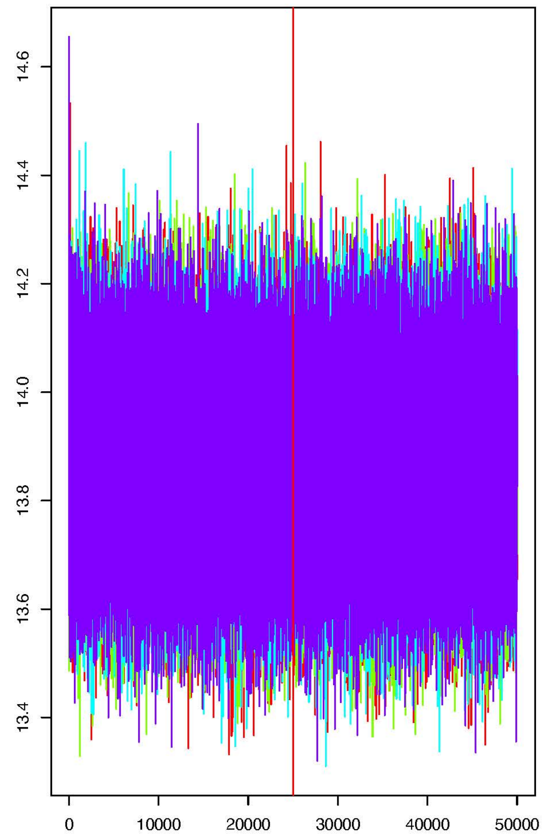

Distribution of: Parameter 21, %BETWEEN%: STRATIO
Mean = 103.53209, Std Dev = 1.95133
Median = 103.51027
Mode = 103.56119
95% Lower CI = 99.74951
95% Upper CI = 107.42970
Count
Estimate


Distribution of: Parameter 22, %BETWEEN%: EDUSHORT
Mean = 1.07419, Std Dev = 0.01909
Median = 1.07396
Mode = 1.07691
95% Lower CI = 1.03748
95% Upper CI = 1.11208
Count
Estimate

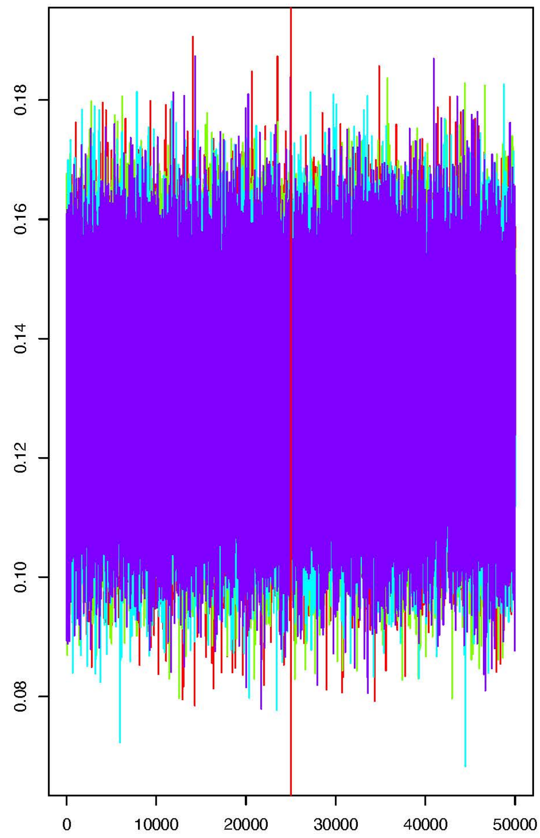

Trace plot of: Parameter 1, %WITHIN%: [MALE]
0.494
0.496
0.498
0.500
0.502
0.504
0.506
0.508
Trace plot of: Parameter 2, %WITHIN%: [IMMI1GEN
0.027
0.028
0.029
0.030
0.031
Trace plot of: Parameter 3, %WITHIN%: [IMMI2GEN
0.040
0.041
0.042
0.043
0.044
0.045
Trace plot of: Parameter 4, %WITHIN%: [ESCS]
−0.255
−0.250
−0.245
−0.240
−0.235
−0.230
−0.225
Trace plot of: Parameter 5, %WITHIN%: [FCFMLRTY
7.00
7.05
7.10
Trace plot of: Parameter 6, %WITHIN%: [FLCONFIN
−0.085
−0.080
−0.075
−0.070
−0.065
−0.060
Trace plot of: Parameter 7, %WITHIN%: [FLSCHOOL
0.005
0.010
0.015
0.020
0.025
0.030
0.035
Trace plot of: Parameter 8, %WITHIN%: [NOBULLY
−0.075
−0.070
−0.065
−0.060
−0.055
−0.050
−0.045
Trace plot of: Parameter 9, %WITHIN%: [FLFAMILY
0.045
0.050
0.055
0.060
0.065
0.070
0.075
0.080
0
10000
20000
30000
40000
50000


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

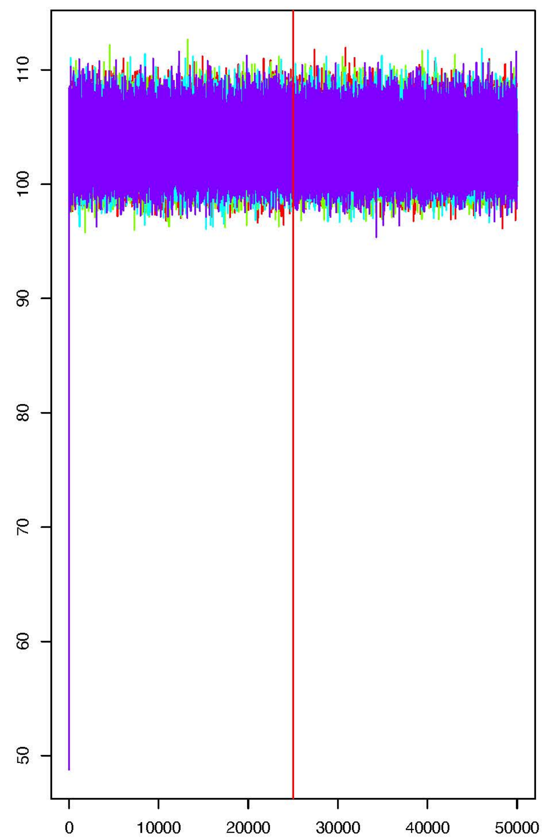
Trace plot of: Parameter 19, %BETWEEN%: [STRATIO]



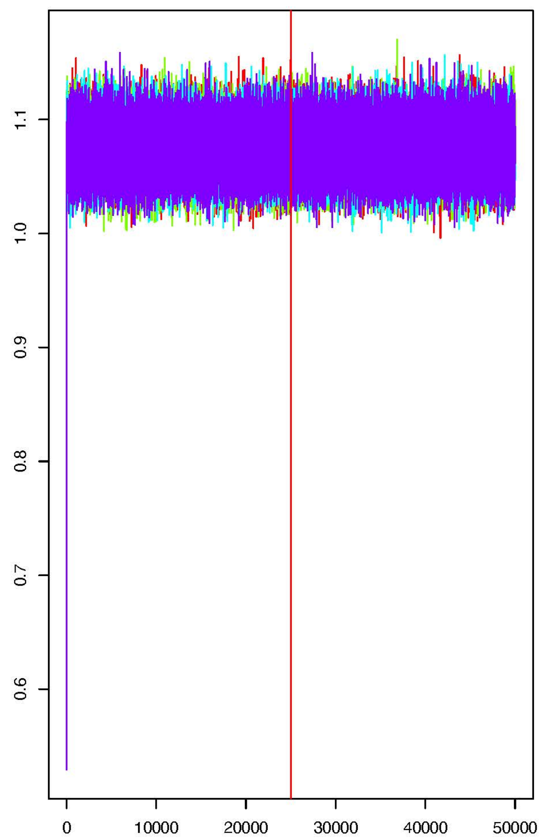
Trace plot of: Parameter 20, %BETWEEN%: [EDUSHORT]



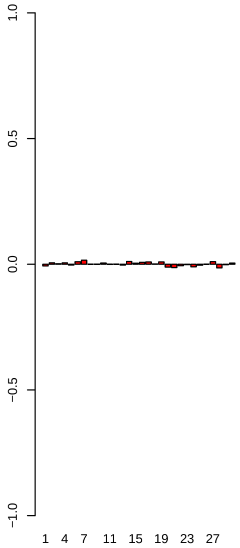
Trace plot of: Parameter 21, %BETWEEN%: STRATIO



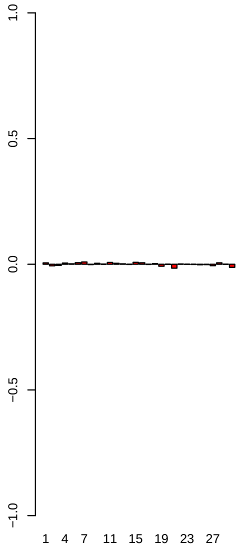
Trace plot of: Parameter 22, %BETWEEN%: EDUSHORT



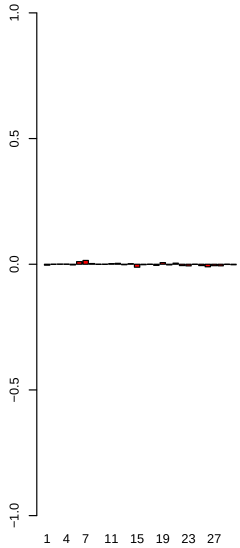
1): Parameter 1, %WITHIN%: [MALE]



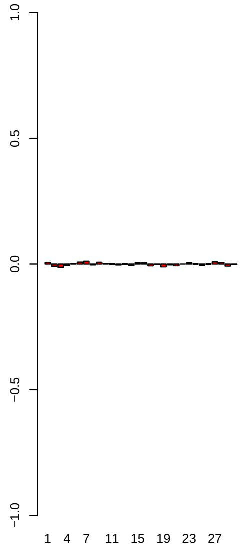
2): Parameter 1, %WITHIN%: [MALE]



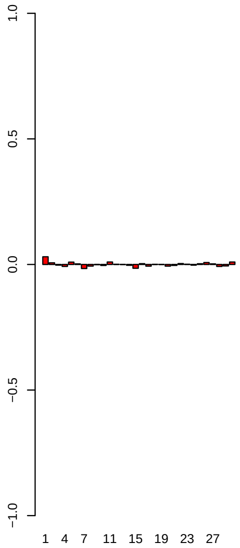
3): Parameter 1, %WITHIN%: [MALE]



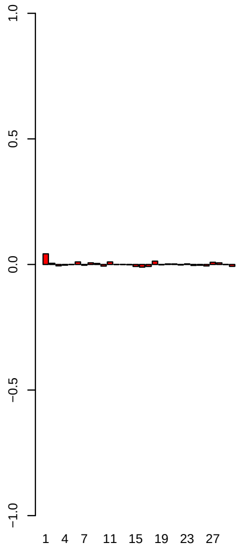
4): Parameter 1, %WITHIN%: [MALE]



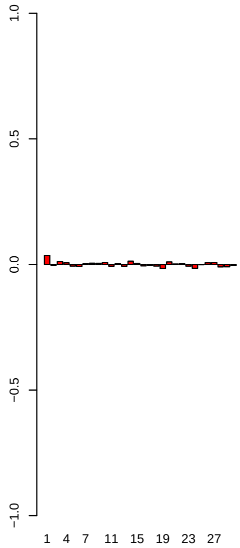
): Parameter 2, %WITHIN%: [IMMI1GE



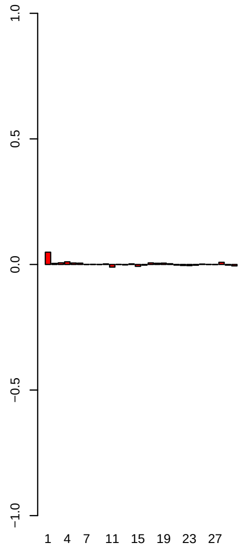
): Parameter 2, %WITHIN%: [IMMI1GE



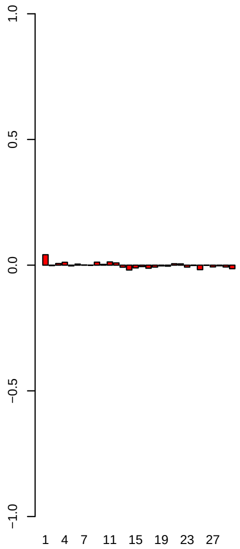
): Parameter 2, %WITHIN%: [IMMI1GE



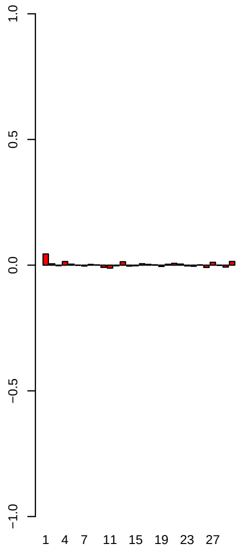
): Parameter 2, %WITHIN%: [IMMI1GE



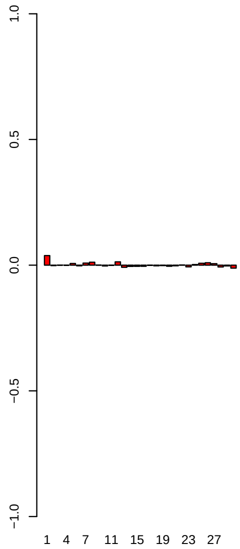
): Parameter 3, %WITHIN%: [IMMI2GE



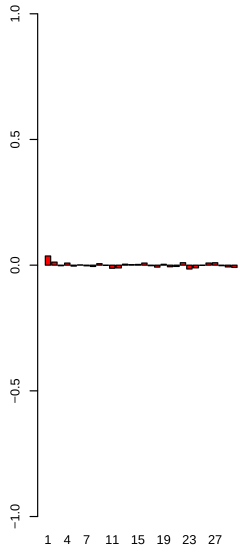
): Parameter 3, %WITHIN%: [IMMI2GE

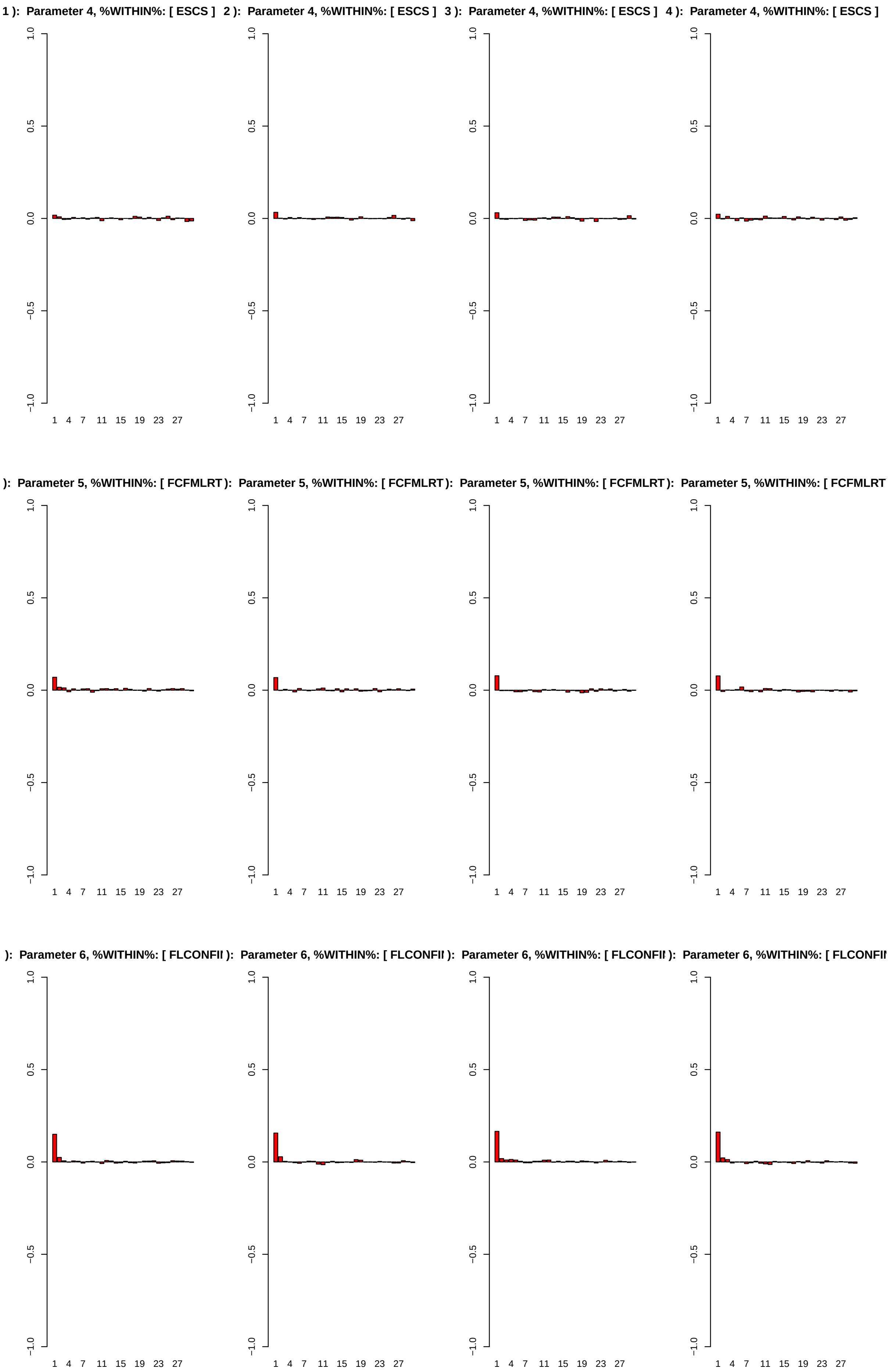


): Parameter 3, %WITHIN%: [IMMI2GE



): Parameter 3, %WITHIN%: [IMMI2GE




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
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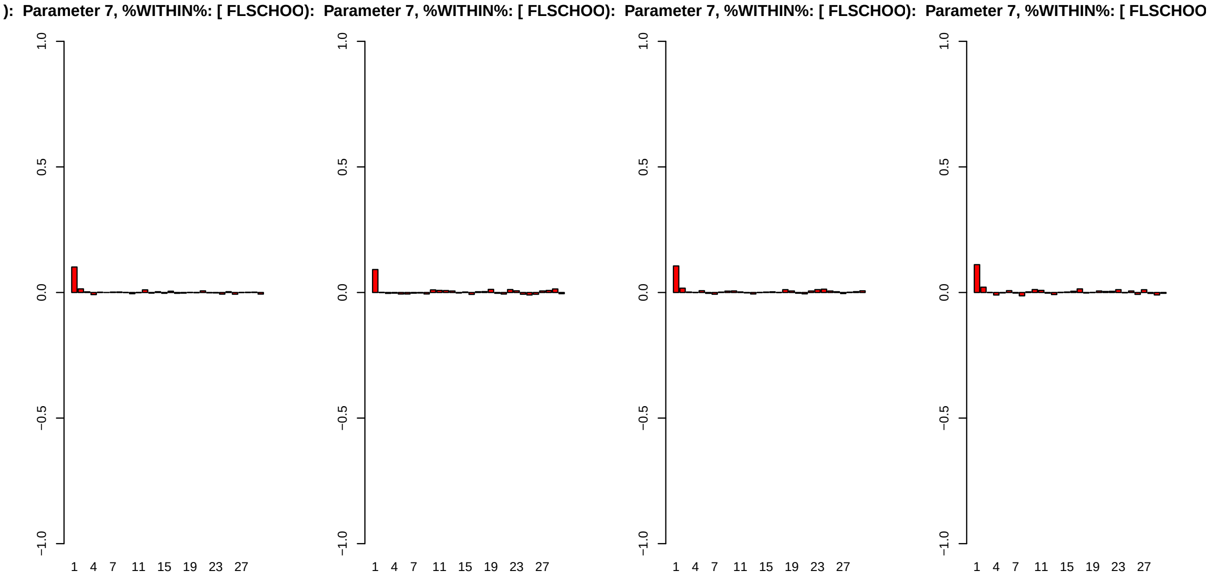
−0.5
−1.0
1 4 7 11 15 19 23 27


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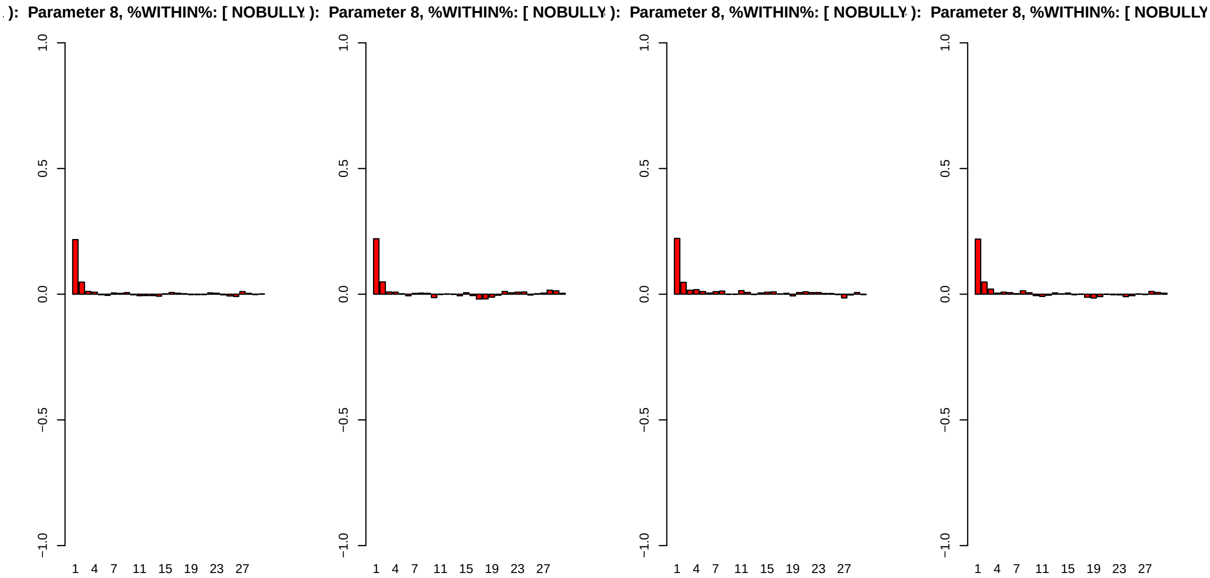
): Parameter 7, %WITHIN%: [FLSCHOO


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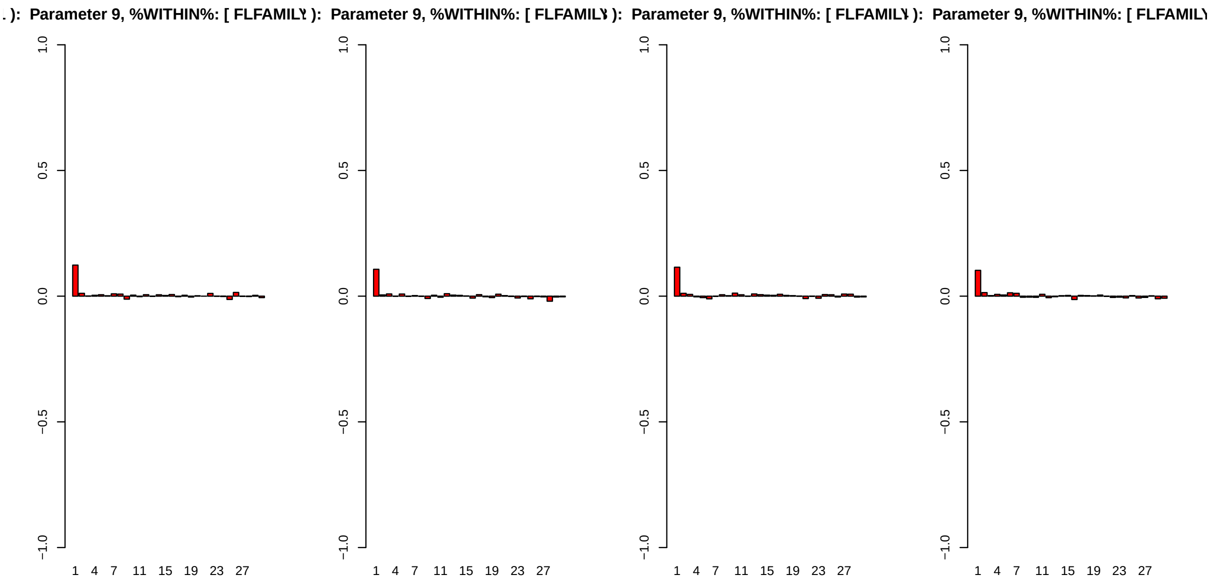
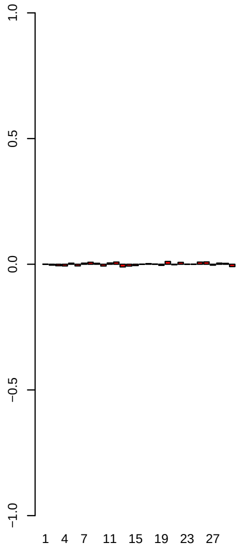
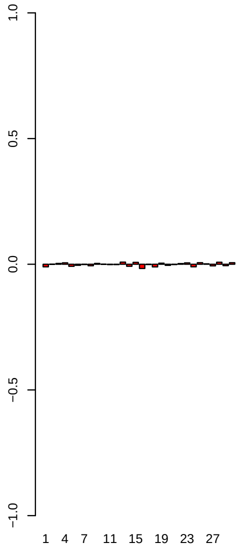

): Parameter 9, %WITHIN%: [FLFAMIL
): Parameter 9, %WITHIN%: [FLFAMIL
): Parameter 9, %WITHIN%: [FLFAMIL
): Parameter 9, %WITHIN%: [FLFAMIL

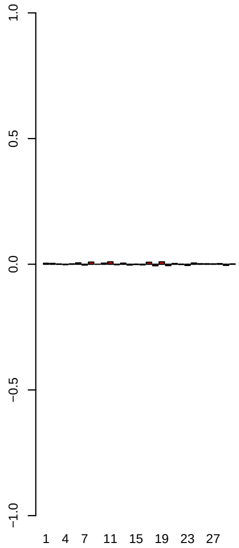
1): Parameter 10, %WITHIN%: MALE



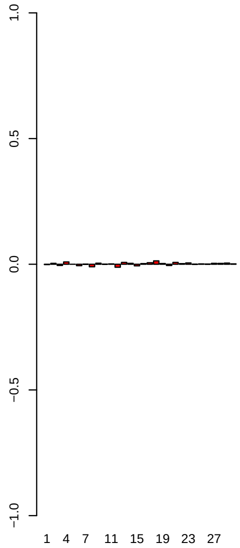
2): Parameter 10, %WITHIN%: MALE



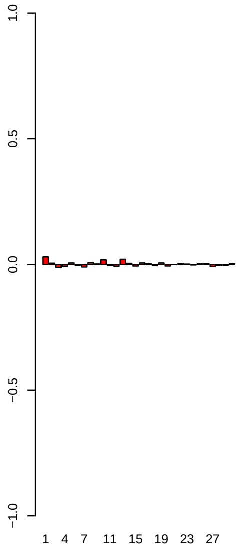
3): Parameter 10, %WITHIN%: MALE



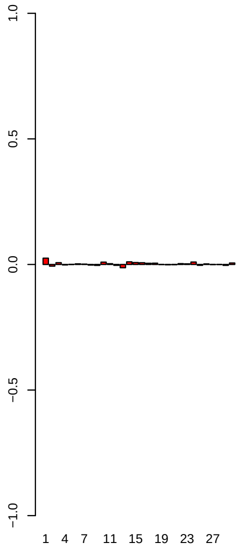
4): Parameter 10, %WITHIN%: MALE



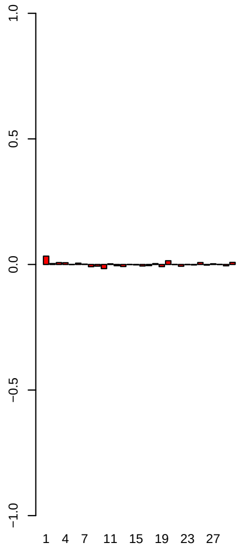
): Parameter 11, %WITHIN%: IMMI1GEN



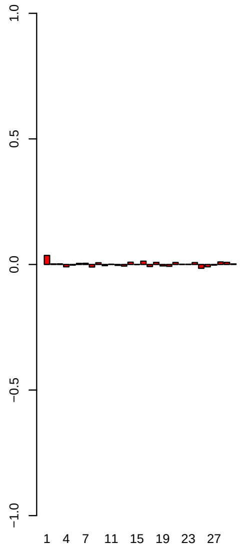
): Parameter 11, %WITHIN%: IMMI1GEN



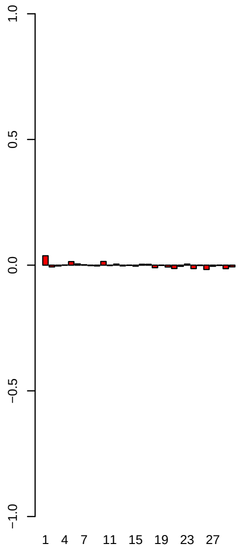
): Parameter 11, %WITHIN%: IMMI1GEN



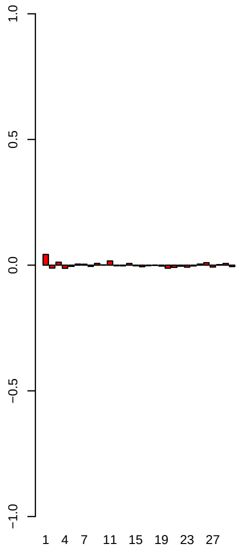
): Parameter 11, %WITHIN%: IMMI1GEN



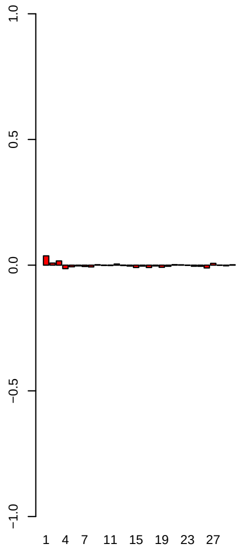
): Parameter 12, %WITHIN%: IMMI2GEN



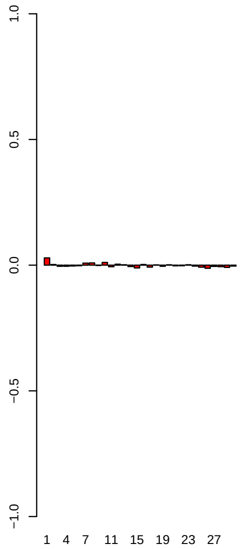
): Parameter 12, %WITHIN%: IMMI2GEN



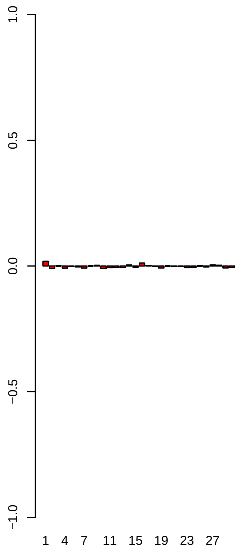
): Parameter 12, %WITHIN%: IMMI2GEN



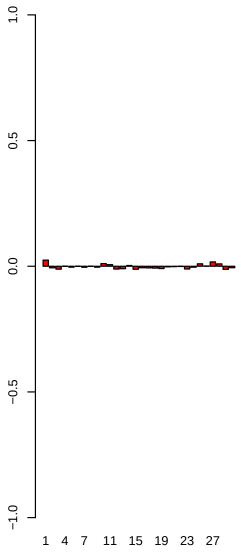
): Parameter 12, %WITHIN%: IMMI2GEN



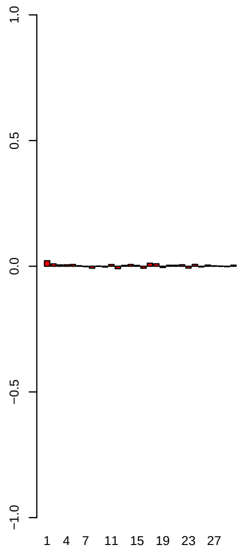
1): Parameter 13, %WITHIN%: ESCS



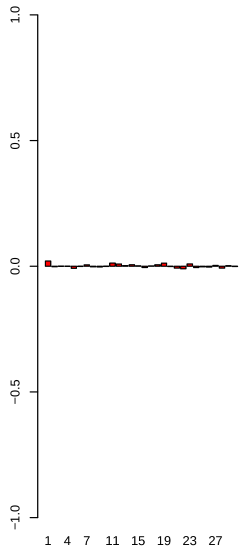
2): Parameter 13, %WITHIN%: ESCS



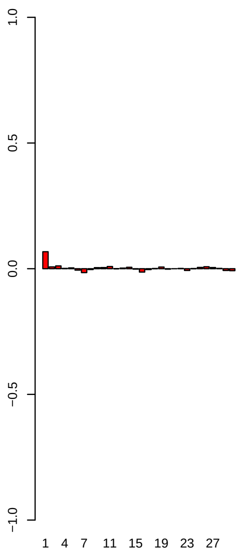
3): Parameter 13, %WITHIN%: ESCS



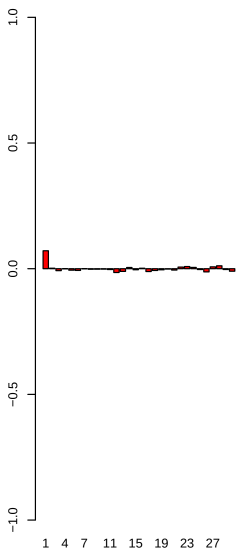
4): Parameter 13, %WITHIN%: ESCS



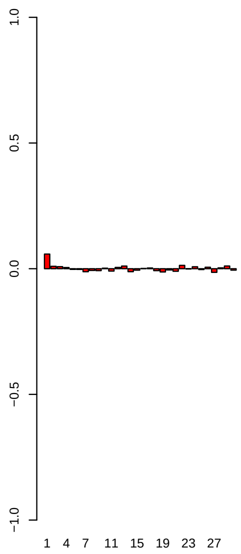
): Parameter 14, %WITHIN%: FCFMLRT'



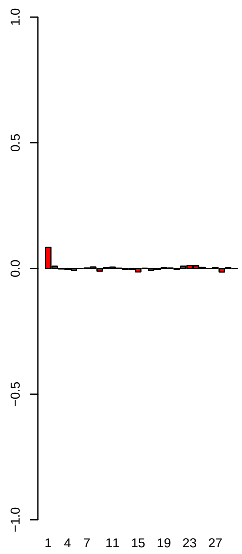
): Parameter 14, %WITHIN%: FCFMLRT'



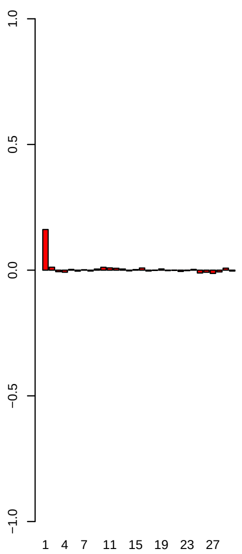
): Parameter 14, %WITHIN%: FCFMLRT'



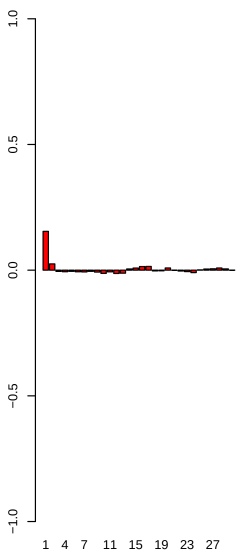
): Parameter 14, %WITHIN%: FCFMLRT'



): Parameter 15, %WITHIN%: FLCONFIN



): Parameter 15, %WITHIN%: FLCONFIN



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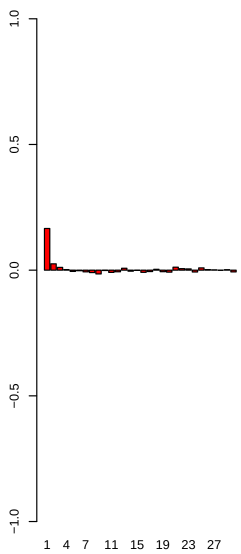

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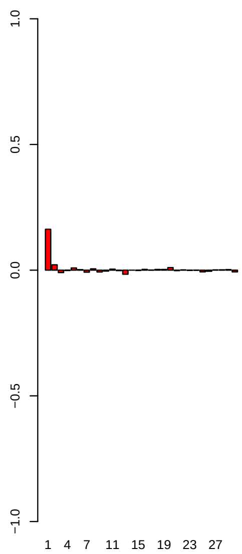

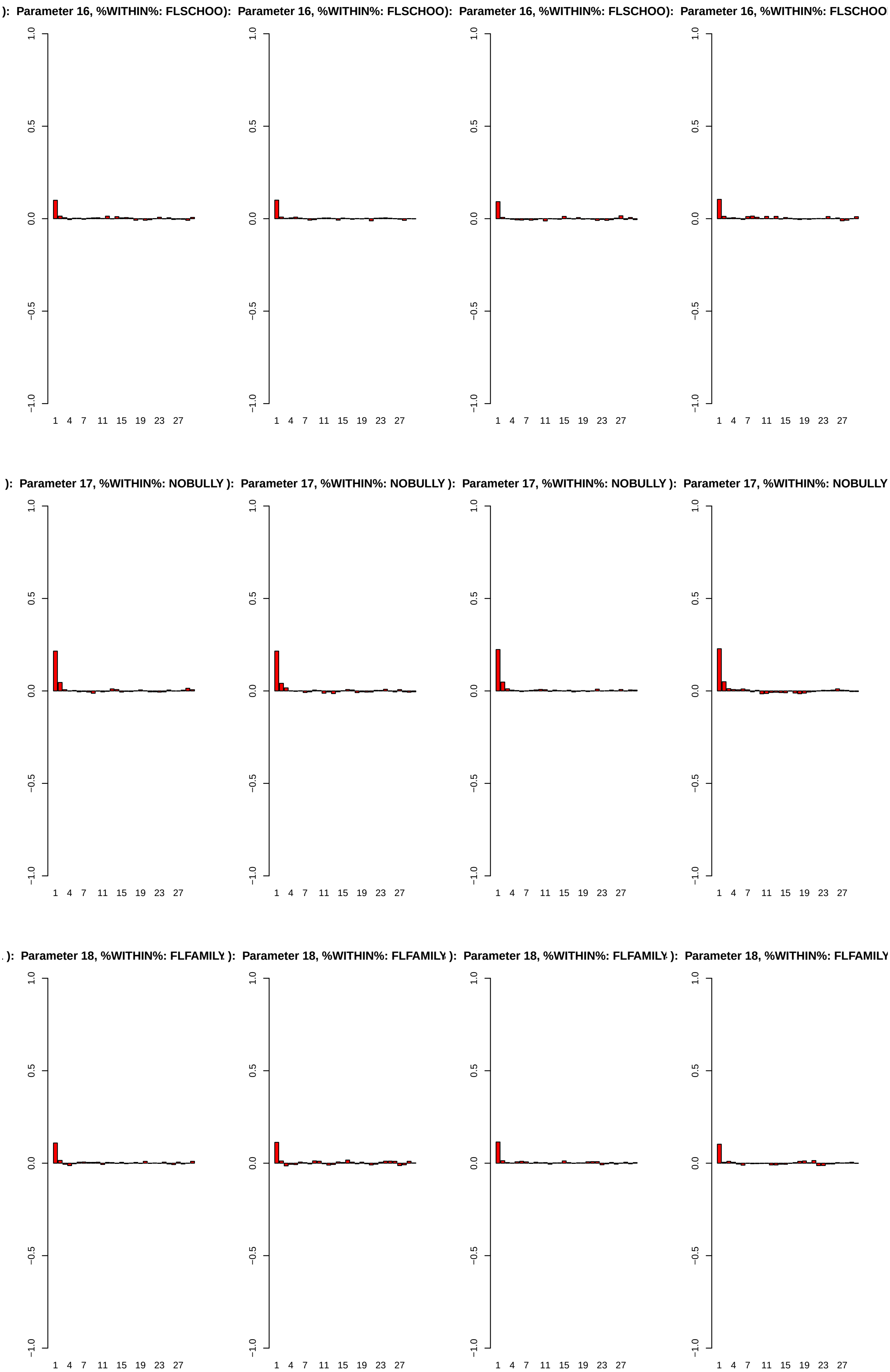
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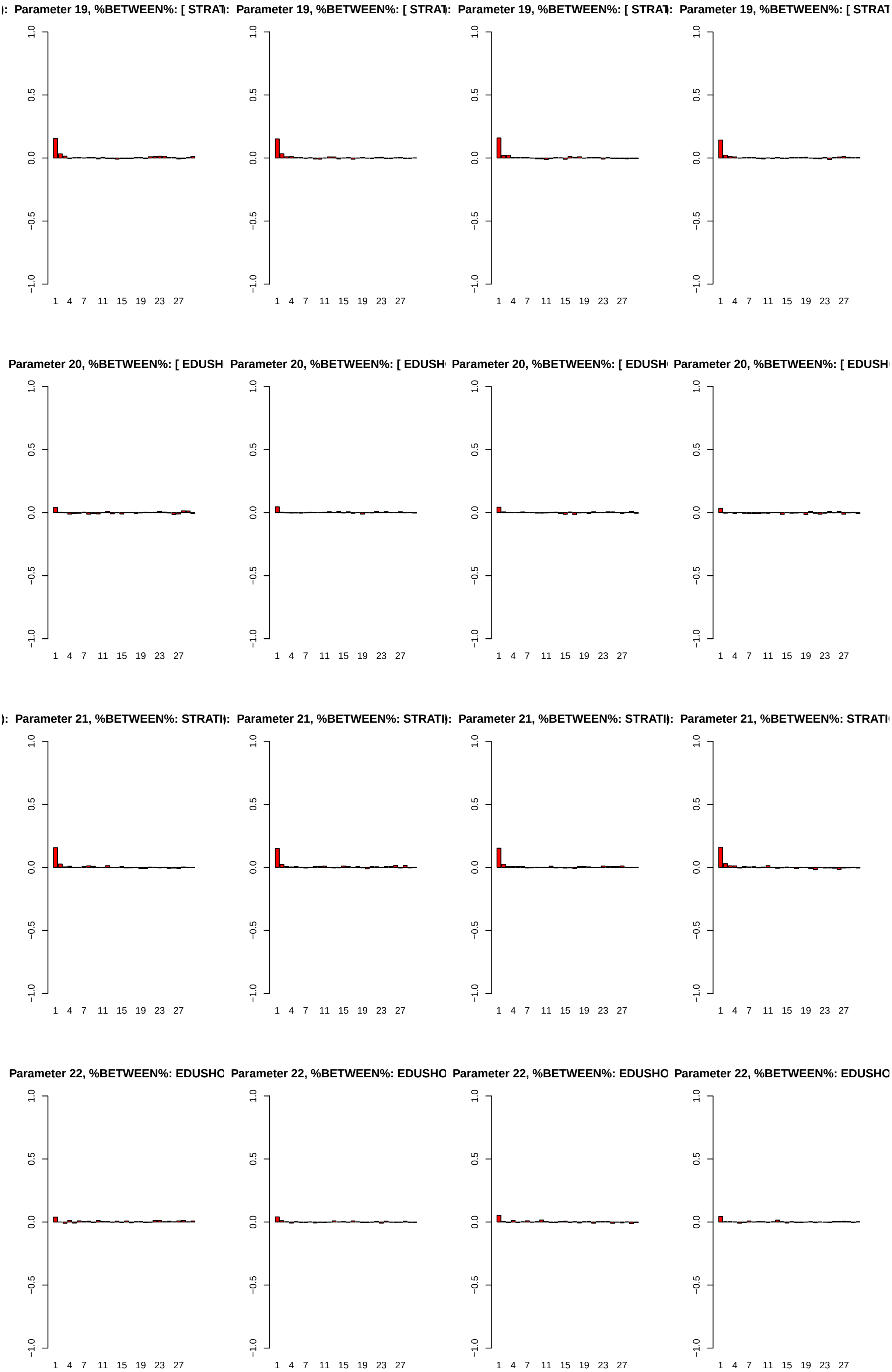
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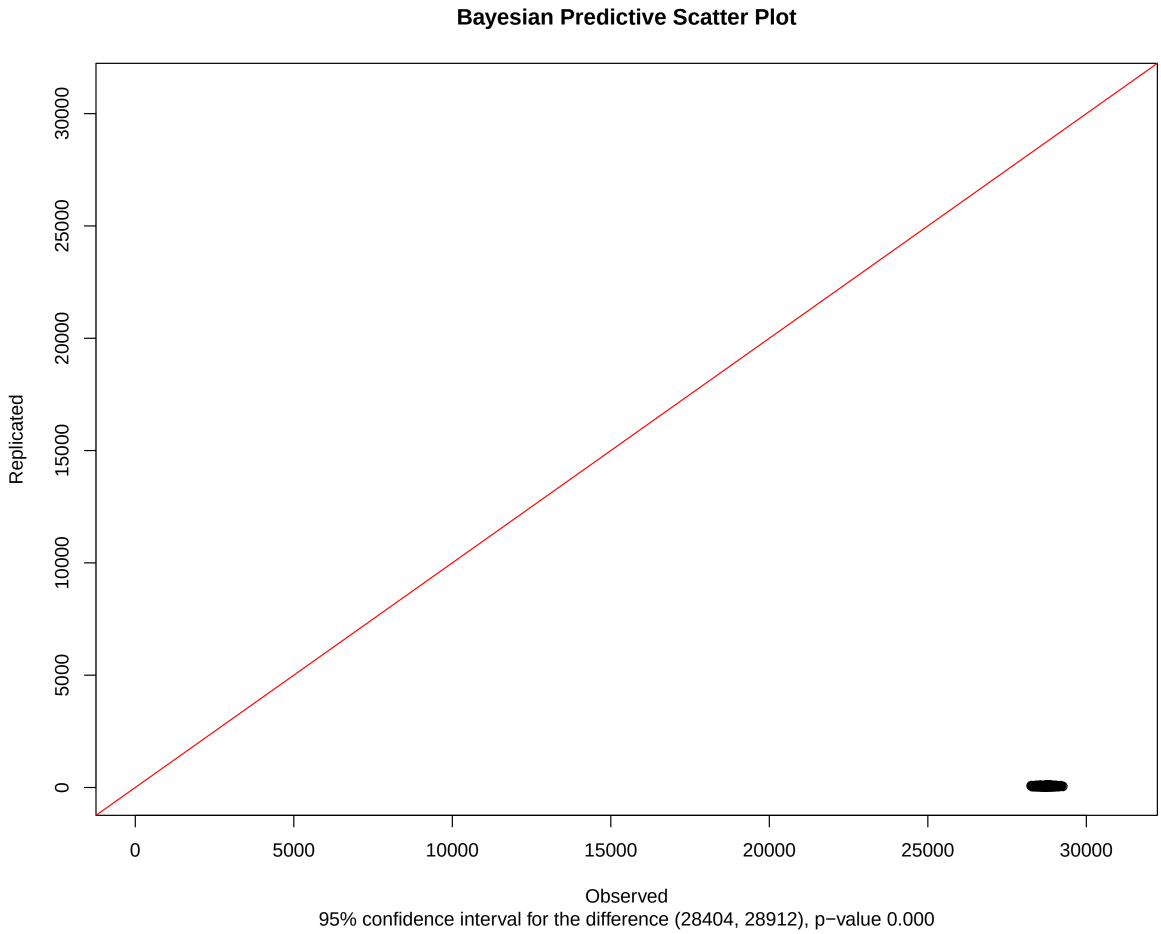
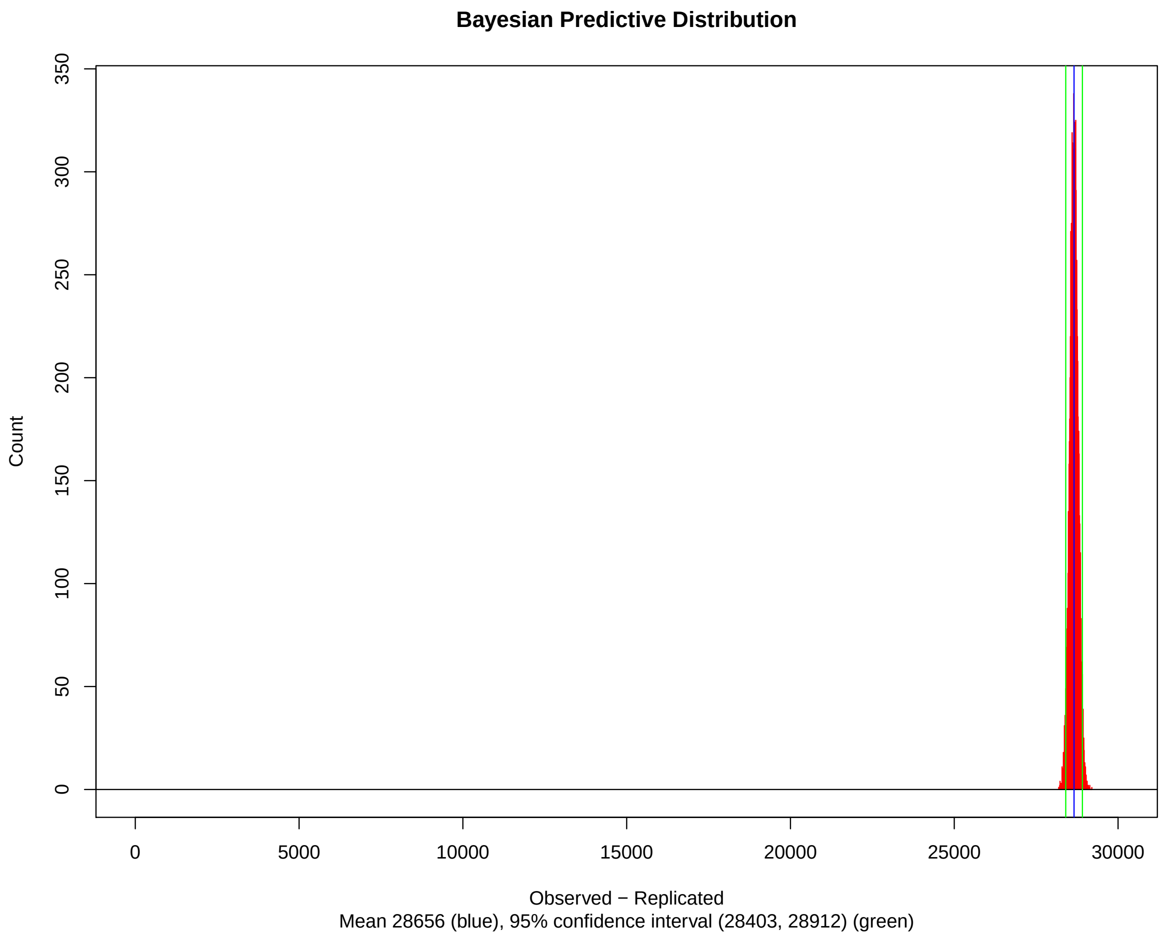

Bayesian Predictive Scatter Plot
Replicated
Observed
95% confidence interval for the difference (28404, 28912), p−value 0.000


Bayesian Predictive Distribution
Count
Observed − Replicated
Mean 28656 (blue), 95% confidence interval (28403, 28912) (green)