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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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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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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.

Chapter 3 Methods

3.1 Sample

This study drew its primary data source from OECD's PISA 2018 database. Responses from both student (OECD, 2020a) and school questionnaires (OECD, 2020c) were captured and merged into a master data file using R's (Version 4.0.5, R Core Team, 2021) intsvy package (Version 2.5, Caro & Biecek, 2017) (see Section B.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, Spain, and the USA. 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). Under PISA 2018 sampling design, all student candidates were born in the year 2002 in international grades 7 or higher (Chapter 4 of *PISA 2018 Technical Report*, OECD (2020b), p. 29) and will be referred to as "15-year-old" in this study.

3.2 Measures

3.2.1 School Climate Variables

Following Wang and Degol's (2016) framework, this study selected variable `FLSCHOOL` "financial education in school lessons" as an indicator for the academic domain of school climate; `FLFAMILY` "parental involvement in matters of financial literacy" (i.e., "financial socialisation") for the community engagement dimension, `NOBULLY` (reverse coding of `BEINGBULLIED` such that larger numbers imply safer schools) as an indicator for school safety, and lastly `EDUSHORT` "shortage of educational material" as an indicator of the resource availability aspect of the institutional environment of schools. 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 (see Chapter 9 of *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: School climate (Input, X)	Exogenous variable: Demographic control	Endogenous variable: Financial literacy Affective (Mediator, M)	Endogenous variable: 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 within- and between-level components are marked with subscript $_W$ and $_B$ respectively.

3.2.2 Affective 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-scaled 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 reliabilities).

3.2.3 Financial Literacy Performance Measure

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).

3.2.4 Control Variables

In the 2018 PISA cycle, the OECD simplified its computation of the 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 was 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) into 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. The variable ST004D01T from the student questionnaire (OECD, 2020a) represented students' gender and was transformed into a binary variable with female being the reference group: 0 = female; 1 = male.

3.3 Multilevel Structural Equation Modelling (MSEM)

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 advancement 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 $L1$ school climate variables FLSCHOOL, FLFAMILY, NOBULLY as well as the cognitive outcome FLIT into their corresponding within- and between-level components (subscript $_W$ and $_B$ respectively). This doubly latent MSEM approach controls measurement error at both the student- and school-levels as well as sampling error due to the aggregation of $L1$ variables to form $L2$ constructs (Lüdtke et al., 2011; Lüdtke et al., 2009; Marsh et al., 2012). Subscript $_{ij}$ in the MSEM model below represents the within-group component of the MLC decomposition and subscript $_j$ stands for the between-group component:

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 ($L2$):

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

with the residual distribution assumptions

$$\begin{pmatrix} r_{ij}^{M_1} \\ r_{ij}^{M_2} \\ r_{ij}^{Y} \end{pmatrix} \sim \mathrm{MVN}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{M_1}^2 & 0 & 0 \\ 0 & \sigma_{M_2}^2 & 0 \\ 0 & 0 & \sigma_{Y_W}^2 \end{pmatrix}\right], \text{ and } \varepsilon_j^{Y} \sim \mathcal{N}\left(0,\ \sigma_{Y_B}^2\right), \tag{3.3}$$

where MVN$(\cdot)$ and $\mathcal{N}(\cdot)$ stand for multivariate normal and normal distribution respectively.

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:

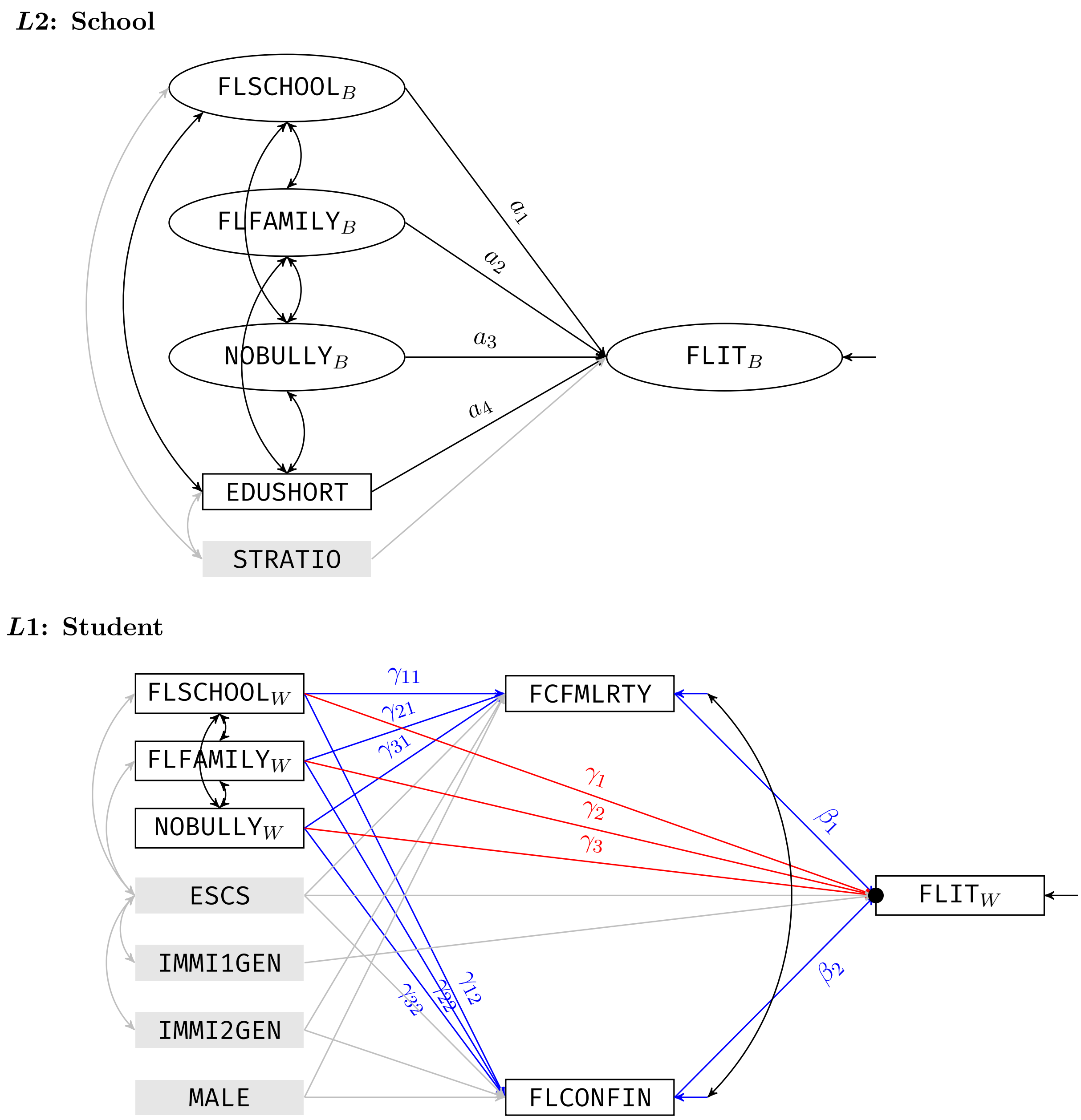
$$\begin{aligned}
\begin{bmatrix} \mathtt{FCFMLRTY}_{ij} \\ \mathtt{FLCONFIN}_{ij} \\ \mathtt{FLIT}_{ij} \end{bmatrix} &= \begin{pmatrix} \alpha_j^{M_1} \\ \alpha_j^{M_2} \\ \alpha_j^{Y_W} \end{pmatrix} + \begin{pmatrix} 0 & 0 & \beta_1 \\ 0 & 0 & \beta_2 \\ 0 & 0 & 0 \end{pmatrix}^{\mathsf{T}} \begin{bmatrix} \mathtt{FCFMLRTY}_{ij} \\ \mathtt{FLCONFIN}_{ij} \\ \mathtt{FLIT}_{ij} \end{bmatrix} \\
&\quad + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_1 \\ \gamma_{21} & \gamma_{22} & \gamma_2 \\ \gamma_{31} & \gamma_{32} & \gamma_3 \\ \gamma_{41} & \gamma_{42} & \gamma_4 \\ 0 & 0 & \gamma_5 \\ \gamma_{61} & \gamma_{62} & 0 \\ \gamma_{71} & \gamma_{72} & 0 \end{pmatrix}^{\mathsf{T}} \begin{bmatrix} \mathtt{FLSCHOOL}_{ij} \\ \mathtt{FLFAMILY}_{ij} \\ \mathtt{NOBULLY}_{ij} \\ \mathtt{ESCS}_{ij} \\ \mathtt{IMMI1GEN}_{ij} \\ \mathtt{IMMI2GEN}_{ij} \\ \mathtt{MALE}_{ij} \end{bmatrix} + \begin{pmatrix} r_{ij}^{M_1} \\ r_{ij}^{M_2} \\ r_{ij}^{Y_W} \end{pmatrix}, \\
\begin{pmatrix} \alpha_j^{M_1} \\ \alpha_j^{M_2} \\ \alpha_j^{Y_W} \end{pmatrix} &= \begin{pmatrix} \alpha_{00}^{M_1} \\ \alpha_{00}^{M_2} \\ \alpha_{00}^{Y} \end{pmatrix} + \begin{pmatrix} 0 & 0 & a_1 \\ 0 & 0 & a_2 \\ 0 & 0 & a_3 \\ 0 & 0 & a_4 \\ 0 & 0 & a_5 \end{pmatrix}^{\mathsf{T}} \begin{bmatrix} \mathtt{FLSCHOOL}_j \\ \mathtt{FLFAMILY}_j \\ \mathtt{NOBULLY}_j \\ \mathtt{EDUSHTG}_j \\ \mathtt{STRATIO}_j \end{bmatrix} + \begin{pmatrix} 0 \\ 0 \\ \varepsilon_j^{Y_B} \end{pmatrix}.
\end{aligned} \tag{3.4}$$

3.4 Missing Data Treatment

Missing data are the norm rather than the exception in empirical studies and they demand great care from the researchers to ensure analytical validity. While fulll information maximum likelihood has 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) when 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 multilevel MI under the assumption that data were missing at random (Little & Rubin, 2019). In addition, since PISA 2018 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 the 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). Finally, the first 50,000 burn-in iterations were discarded and any two draws were separated by 5,000 iterations to avoid autocorrelation

Figure 3.1

Path Diagram Illustrating the Two-level SEM Predicting Youth's Financial Literacy Outcomes



Note. School climate variables FLSCHOOL, FLFAMILY, and NOBULLY, as well as cognitive outcome FLIT are decomposed into the within- and between-components (subscript $_W$ and $_B$ respectively) using the multilevel latent covariate (MLC) approach. Direct pathways are coloured in red while indirect in blue. Control variables are shaded in gray.

(see Section B.2 for input file)—a safe setting even for moderate to high percentage missings (Grund et al., 2016). See Table B.3 for imputation results and diagnostic plots.

3.5 Sampling Weights

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. Under the advisory of Asparouhov (2006), $L1$ weights were 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).

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 standard 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 Evaluation

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. Supported by large sample size ($N = 107,162$) and low missing rate (maximum 22.08%), conventional cutoffs of RMSEA $\leq$ .06, SRMR $\leq$ .08, CFI $\geq$ .95 and TLI $\geq$ .95 are likely to be suitable for model comparison purposes.

Iterations whose model fit indices fell short of the abovementioned cutoff criteria were further investigated using modification indices and (fully standardised) expected parameter change (EPC). Modification indices (ModInd) suggest how much a model's χ^2 statistic would decrease by should a fixed parameter were freely estimated; a ModInd greater than 3.84 (cirtical value of χ^2_1 at $\alpha = .05$) warrants further consideration for theoretical plausibility (Whittaker, 2012). Expected parameter changes (EPC), in contrast, indicate the estimated value of a fixed parameter if it were added to a model and freely estimated, providing a more direct estimate of the size of the misspecification for the parameters under consideration. Kaplan (1989) compared ModInd and EPC's impact on empirical studies and concluded that the former had a tendency to suggest freeing implausible parameters while the latter were more likely to recommended reasonable candidates to the model. This study made use of the decision rule prescribed by Saris et al. (1987) to freely estimate a parameter when both ModInd and EPC are large. Model modification decisions were applied sequentially under the advisory of MacCallum et al. (1992) and with close consideration to theoretical ground to ensure underlying substantive assumptions were justified.

Two operational concerns were relavant to the curent study. Firstly, since **M*plus*** Version 8.5 only accepts one data set for the modification procedures, the file containing the first plausible value was selected for the model evaluation purposes. Secondly, three versions of the EPC were reported by **M*plus***: E.P.C. (Saris et al., 1987), Std E.P.C (Kaplan, 1989) and StdYX E.P.C. (Chou & Bentler, 1993). This study adopted the latter most version largely due to its invariance property resultant from both parameter and residual standardisations. Improper solutions with standardised estimates greater than 1.0 and/or with negative variances (i.e., Heywood cases) were ignored during decision-making process.

Chapter 4 Results

4.1 Descriptive Statistics and Correlations

Table 4.1 presents descriptive statistics of all measures included in the MSEM models. $L1$ variable `NOBULLY` and $L2$ variable `STRATIO` were highlighted as particularly non-normal due to sizeable disagreements between their means and medians in combination with significant skewness. The MLR estimator introduced in Section 3.6 explicitly takes non-normalality into account when computing robust standard errors, safeguard the validity of subsequent analyses. These asymmetric variables suggested that majority of 15-year-olds experienced safe schools and classrooms overcrowding was uncommon in PISA 2018.

Correlations in Table 4.2 further suggested that schools and families cared about youth's financial literacy in synchrony ($\overline{\rho} \approx .23$) and both efforts were associated with higher affective outcomes ($\overline{\rho}$ between .17 and .28). Additionally, students' ESCS were positively correlated with both familiarity with ($\overline{\rho} = .23$) and achievement in ($\overline{\rho} \approx .29$) financial literacy. Lastly, there was a positive correlation between familiarity and confidence ($\overline{\rho} \approx 0.23$) and a similar strength existed between confidence and performace ($\overline{\rho} = 0.23$).

Correlations at school-level exhibited interesting patterns. Schools with strong emphases on financial education also tended to have engaging parents ($\overline{\rho} \approx .24$), a relationship similar to its $L1$ counterpart in size and magnitude. Although the negative correlation between resource shortage and school safety ($\overline{\rho} \approx -.21$) was expected, it remained counterintuitive that schools that were less safe ($\overline{\rho} \approx -.47$) and were suffering from resource shortages ($\overline{\rho} \approx .31$) tended to be more active in delivering financial education programs. Finally, average performance tended to be higher in safer ($\overline{\rho} \approx .43$) and better equiped ($\overline{\rho} \approx -.44$) schools; while higher levels of school ($\overline{\rho} \approx -.53$) and family interventions ($\overline{\rho} \approx -.36$) have been observed from schools that under-performed in financial literacy.

4.2 Intra-class Correlation and Effective Sample Size

The intraclass correlation ρ_1 can be computed from the random effects ANOVA model ("Null model" in Table 4.3):

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 (within, $L1$)	`FLSCHOOL`	96435	10.01	0.126	0.018	1.020	1.040	0.189	−0.343	−1.564	2.317
	`FLFAMILY`	95133	11.23	0.011	0.064	1.044	1.090	0.121	0.030	−2.042	2.452
	`NOBULLY`	83499	22.08	0.782	−0.059	1.054	1.110	−1.078	0.664	−3.859	0.782
	`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
	`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
	`FLIT` [b]	107162	0.00	481.970	478.291	97.074	9,423.320	−0.089	−0.340	114.256	827.977
School (between, $L2$)	`EDUSHORT`	6346	4.30	0.100	0.131	1.036	1.073	0.341	−0.188	−1.421	2.959
	`STRATIO`	5626	15.16	11.886	13.873	10.171	103.449	4.021	25.425	1.000	100.000

Note. [a] Missing rates were computed based on $N_{L1} = 107,162$ students and $N_{L2} = 6,631$ schools. [b] For descriptive statistics purpose *only*, `FLIT` was obtained by averaging ten plausible values `PV1FLIT` to `PV10FLIT`.

Table 4.2

Correlations between Variables used in the MSEM Models

$L1$/within-level		1	2	3	4	5	6	7	8	9	10
1	$\texttt{FLSCHOOL}_W$										
2	$\texttt{FLFAMILY}_W$	$.227^{***}$									
3	$\texttt{NOBULLY}_W$	$-.032^{***}$	$-.044^{***}$								
4	ESCS	$.054^{***}$	$.093^{***}$	$-.003$							
5	IMMI1GEN	$-.002$	$-.001$	$.006$	$.038^{**}$						
6	IMMI2GEN	$-.009$	$.003$	$.019^{\dagger}$	$.040^{*}$	$-.046^{***}$					
7	MALE	$.049^{***}$	$-.039^{***}$	$-.071^{***}$	$.026^{*}$	$-.003$	$-.006$				
8	FCFMLRTY	$.280^{***}$	$.174^{***}$	$.023^{*}$	$.230^{***}$	$-.009$	$-.017$	$.029^{**}$			
9	FLCONFIN	$.201^{***}$	$.190^{***}$	$-.020^{*}$	$.070^{***}$	$.002$	$-.029^{**}$	$.116^{***}$	$.228^{***}$		
10	$\texttt{FLIT}_W$	$-.021^{\dagger}$	$.021^{*}$	$.053^{***}$	$.288^{***}$	$-.029^{*}$	$.025^{\dagger}$	$.020^{\dagger}$	$.230^{***}$	$.068^{***}$	

$L2$/between-level		11	12	13	14	15	16
11	$\texttt{FLSCHOOL}_B$						
12	$\texttt{FLFAMILY}_B$	$.239^{**}$					
13	$\texttt{NOBULLY}_B$	$-.468^{***}$	$-.065$				
14	EDUSHORT	$.313^{***}$	$.053$	$-.207^{**}$			
15	STRATIO	$-.082^{*}$	$.131^{*}$	$.026$	$-.043$		
16	$\texttt{FLIT}_B$	$-.529^{***}$	$-.356^{***}$	$.426^{***}$	$-.438^{***}$	$-.101^{**}$	

Note. The MLC procedure decomposes school climate variables FLSCHOOL, FLFAMILY and NOBULLY as well as financial literacy outcomes FLIT into their within- and between-components (subscript $_W$ and $_B$ respectively). Correlations at each level refer to the maximum-likelihood estimated within- and between-covariance matrices respectively. All statistics are average results over ten imputed data sets, denoted as $\overline{\rho}$ in the text.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

$$\rho_1 = \frac{\text{School-level residual variance}}{\text{Total residual variance}} = \frac{\text{var}\left(\varepsilon_j^{Y_B}\right)}{\text{var}\left(r_{ij}^{Y_W}\right) + \text{var}\left(\varepsilon_j^{Y_B}\right)} = \frac{5240}{6122 + 5240} = 0.461. \quad (4.1)$$

This result suggested that 46.1% of the variation in financial literacy performance was due to the clustering in schools.

For sample size adjustment, Snijders and Bosker (2012) advised to first of all calculate the design effect of one's multilevel model:

$$\text{design effect} = 1 + (\text{average group size} - 1)\rho_1 = 1 + \left(\frac{107,162}{6,631} - 1\right) \times 0.461 = 7.989, \quad (4.2)$$

then compute the effective sample size:

$$N_{\text{effective}} = \frac{N_{\text{original}}}{\text{design effect}} = \frac{107,162}{7.989} = 13,414. \quad (4.3)$$

This result signaled that students from the same school were so similar in their financial literacy outcomes that the sample size of 107,162 used by this study was only equivalent to a simple random sample using 13,414 students. This result not only provided assurance of a sufficiently large sample size required by asymptotic theories but also highlighted the strong effect of schools for understanding youth's financial literacy development.

4.3 Intermediate Models

In order to separate the incremental effect attributable to school-level variables, a student-level only model was first established as a reference ("Single-level model" in Table 4.3). Even with $L1$-only variables, model fit indices CFI = .97, TLI = .927 and SRMR = .016 jointly suggested that the proposed input (school climate)–mediator (affect)–output (financial literacy cognitive outcome) model was a meaningful one. Next, school-level variables were allowed to covary between one other on top of the $L1$ structure, forming a two-level saturated model. This procedure had an effect of decomposing the total residual variances into student- and school-levels. As a result, $L1$ residual variance reduced by more than a quater from 7,866 to 5,764, indicating the necessity of the $L2$ structure.

4.4 Full Model

Relationships amongst school-level variables were further introduced at $L2$, transforming the saturated model into the final MSEM model as illustrated in Figure 3.1.

4.4.1 Model Fit

Model fit indices CFI $=$ .968, SRMR_{L1} $=$ .015 and SRMR_{L2} $=$ .030 all satisfied the cut-off criteria suggested by Hu and Bentler (1999) while TLI $=$ .903 fell slightly short of being good but still acceptable—a penalty on the growing number of variables introduced. On balance, there was sufficient evidence suggesting good fit between the proposed MSEM model and financial literacy data.

4.4.2 Student-level Relationships

School Climate Variables

All three $L1$ school climate variables shared statistically significant relationships with financial literacy performance (`FLIT`). A safe school environment (`NOBULLY`) was positively correlated with financial literacy via both the direct pathway and through mediation with familiarity (`FCFMLRTY`).

Efforts by schools (`FLSCHOOL`) and families (`FLFAMILY`), on the other hand, had more nuanced reltionships with the cognitive outcome. Both variables had strong positive associations with `FLIT` via affective mediation pathways, but statistically significant *negative* relationships via direct pathways. Such positive-negative pair happened to cancel each other for `FLFAMILY`, leading to a non-significant result should finaical socialisation and financial literacy were correlated superficially. The negative cognitive path overshadowed the positive affective pathways for `FLSCHOOL`, leading to a, seemingly paradoxical, negative overall relationship between classroom efforts and financial literacy outcomes.

Demographic Attributes

The strongest covariation identified by this study was between students' ESCS and their financial literacy outcomes. Substantial positive associations have been observed along both the direct and indirect pathways. Having controlled ESCS as a confounder is therefore essential for the study of school climate effects.

The relationship between one's immigration history and their financial literacy performance also delivered important insight. Children who relocated to the host country between births and reaching 15-year-old (`IMMI1GEN` $= 1$) seemed to possess *less knowledge* in financial matters whereas the offspring of migrants did not show deficiency in knowledge, but in affects.

Meanwhile, school curricula addressing students' affinity towards finance-related topics would likely to benefit not only second-generation migrants but also young girls. This conjecture was made based on the observed "male premium" in financial literacy performance—everything

Table 4.3

Model Parameters and Fit Indices of Multilevel Regressions for the Total Sample

Variable — path	Model parameter	Null model Coef	Null model *SE*	Single-level model Coef	Single-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	*SE*	Single-level model Coef	*SE*	Two-level saturated Coef	*SE*	Two-level structured Coef	*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	$\text{var}\left(r_{ij}^{Y_W}\right)$	6121.904	131.192	7866.408	114.555	5763.677	130.133	5763.690	130.133
School-level	$\text{var}\left(\varepsilon_j^{Y_B}\right)$	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	.000	.970	.002	.970	.002	.968	.002
TLI		1.000	.000	.927	.004	.899	.007	.903	.007
SRMR *L*1		.005	.003	.016	.000	.015	.000	.015	.000
SRMR *L*2		.011	.005			.014	.002	.030	.006

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

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

else held equal, 15-year-old boys on average demonstrated higher financial capability, an effect fully mediated by affective variables especially through higher confidence.

4.4.3 School-level Relationships

Shortages in either capital or labour resources were associated with lower average financial literacy outcomes at the school-level. The MSEM showed a negative relationship between the fourth element of school climate variable, educational resource shortage `EDUSHORT`, and average `FLIT`. In fact, the association between schools' physical capital and their educational output remained one of the strongest statistical relationships reported by this study, over twice the size of that between labour arrangement (student-teacher ratio `STRATIO`) and financial literacy achievement.

4.4.4 Contextual Effects

One particular strength of an MSEM is its ability to model contextual effects. In a school research context, there exists a *contextual effect* when school-level characteristics contribute to individual learners' outcomes beyond what can be explained by student-level characteristics. Following Marsh et al. (2009)'s procedure, this study obtained the point estimate of the unstandardised contextual effect for `FLSCHOOL`:

$$\text{Unstandardised contextual effect} = \widehat{a}_1 - \widehat{\gamma}_1 = -49.339 - (-7.078) = -42.261, \tag{4.4}$$

and its standardised solution:

$$\begin{aligned}
&\text{Standardised contextual effect} \\
&= \frac{\text{Unstandardised contextual effect} \times \sqrt{\widehat{\text{var}}\,(\texttt{FLSCHOOL}_B)}}{\sqrt{\widehat{a}_1^2 \cdot \widehat{\text{var}}\,(\texttt{FLSCHOOL}_B) + \widehat{\text{var}}\,(\texttt{FLIT}_B) + \widehat{\gamma}_1^2 \cdot \widehat{\text{var}}\,(\texttt{FLSCHOOL}_W) + \widehat{\text{var}}\,(\texttt{FLIT}_W)}} \\
&= \frac{(-42.261) \times \sqrt{0.114}}{\sqrt{(-49.339)^2 \times 0.114 + 3226.753 + (-7.078)^2 \times 1.009 + 6576.975}} \\
&= -\,0.163,\ (-0.142 \text{ if calculated manually due to cummulative rounding errors})
\end{aligned} \tag{4.5}$$

while the associated standard error can be obtained using the delta method (Raykov & Marcoulides, 2004). Table 4.4 summarised the contextual effect estimates for `FLSCHOOL`, `FLFAMILY`, and `NOBULLY`. These results suggested that students' financial literacy performance was not only affected by individual characteristics and endavour but also heavily influenced by the larger school environment surounding the learners. Lastly, the effect size (ES) statistics in Table 4.4 further suggested that the significant contextual effect findings were unlikely to be a mere statistical artifect out of large sample sizes, evidenced by their large sizes ($|\text{ES}| \approx .38$ and $.33$) and robustness against various of calculation methods (conventional ES1 by Tymms (2004) and recent innovation ES2 and ES3 by Marsh et al. (2009)).

Table 4.4

Contextural Effects and Effect Sizes

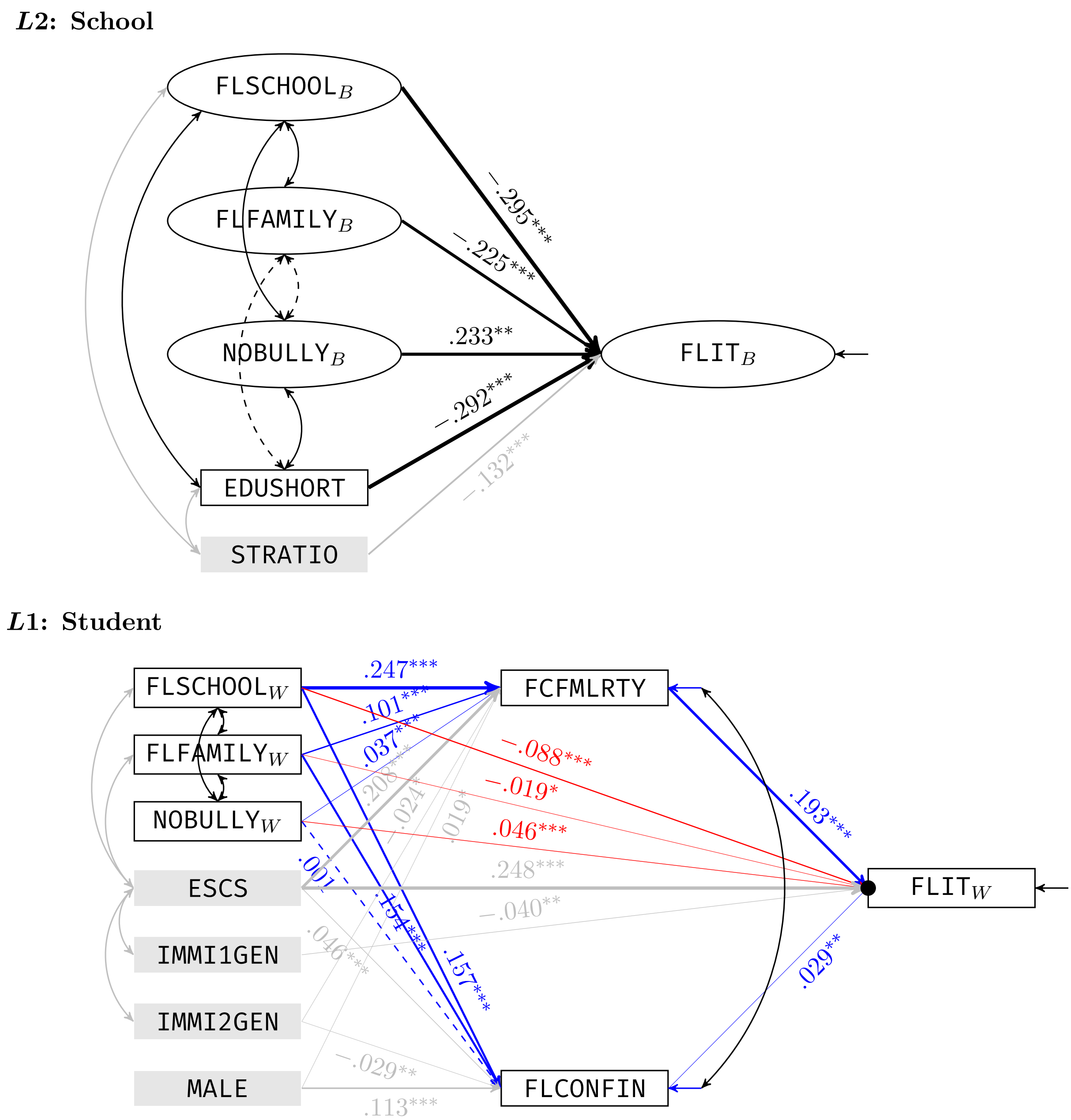
Contextual relationship	Contextual effect Est	Contextual effect *SE*	**Standardised contextual effect** Est	**Standardised contextual effect** *SE*
FLSCHOOL	−42.261	10.720***	−0.163	0.041***
FLFAMILY	−75.808	20.353***	−0.144	0.037***
NOBULLY	60.071	19.673**	0.144	0.046**

Contextual relationship	Effect size 1 Est	Effect size 1 *SE*	**Effect size 2** Est	**Effect size 2** *SE*	Effect size 3 Est	Effect size 3 *SE*
FLSCHOOL	−0.380	0.099***	−0.378	0.098***	−0.369	0.092***
FLFAMILY	−0.332	0.084***	−0.332	0.084***	−0.328	0.081***
NOBULLY	0.331	0.107**	0.331	0.107**	0.326	0.102**

Note. Contextual effect computations and standardisations were based on the procedure documented in Marsh et al.'s (2009) supplemental Model 8. Marked in bold, standardised contextual effect and effect size 2 were recommended for decision-making. Effect sizes 1 (Tymms, 2004) was provided as reference due to its compatibility with Cohen's d (Cohen, 1992). More recently, Marsh et al. (2009) advocated for an effect size procedure involving total variances from *both* levels (ES3) over that from only $L1$ (ES2) (see Marsh et al., 2009, p. 792). Since consensus so far appears to be with ES2, ES3 was provided for future reference.

Figure 4.1

Two-level Structural Equation Model Predicting Youth's Financial Literacy Outcomes



Note. This multilevel structural equation model predicts youth's financial literacy outcomes using PISA 2018 data, with mediating effects of familiarity with, and confidence in, financial matters at student-level. Statistics are standardised regression coefficients. Dashed lines represent nonsignificant relations at $\alpha = .05$ level. Student-level school climate variables and cognitive outcome are decomposed into the within- and between-components (subscript $_W$ and $_B$ respectively) using the MLC approach. Direct pathways are coloured in red and indirect in blue. Control variables are shaded in gray.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Chapter 5 Discussion

5.1 Overview

"It takes a village to raise a child." This study hence looked into the dual mechanisms of how 15-year-old students acquired financial literacy and how the school environment enveloping them facilitated such process. By accounting for the hierarchical data structure, sampling weights, missing data imputation, as well as measurement errors and sampling errors, this study was able to ascertain the marginal effects of the four school climate variables: academic, community, safety and resources. More specifically, student-level models revealed key roles affective variables played in mediating youth's financial literacy formation. Individual charactersitics such as socio-economic status, immigration history and sex differences all carried significant explanatory power in explaining variations in financial literacy performance. At the school-level, strong capital and labour endowments were both found to be markers for high average performance along with school's efforts into enhancing learners' safety.

The study results also revealed key insight that was initially less intuitive. At both individual- and school-levels, the associations between explicit finance-related teaching activities and contemporaneous were found to be *negative*. In addition, the relationships between financial socialisation, i.e., parental invovlment in cultivating youth's financial understanding, and performance outcomes were shown to be positive along the affective pathways (the "heart pathways") but negative along the cognitive pathway (the "mind pathway"). Interestingly, these two effects happened to be similar in size but opposite in sign, leading to an apparent nil resul should one superficially correlate parental effort with outcome measure. At the school-level, both classroom activities and parental care, on average, tended to flow preferentially towards students who were yet to master their financial capabilities. Sizeable contextual effects further confirmed these negative associations even after the subtraction of individual learner components, therefore suggesting schools rather than learners as the source of the observed negative correlations.

5.2 $L1$ Relationships: Financial Literacy Acquisition

5.3 $L2$ Relationships: Impact of School Factors

This observation is important for policy design—while a knowledge-based remedial program would address the urgent needs of some learners with migration background, an inclusive pedagogical intervention needs to be complemented with strategies promoting financial affects.

5.4 Limitation on Causal Inferences

5.5 Future Research Direction

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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

NSD – Norsk senter for forskningsdata AS Harald Hårfagres gate 29 Tel: +47-55 58 21 17 nsd@nsd.no Org.nr. 985 321 884
NSD – Norwegian Centre for Research Data NO-5007 Bergen, NORWAY Faks: +47-55 58 96 50 www.nsd.no

Appendix B Analysis Code, Additional Tables and Figures

B.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)

# 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. 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 scale reliabilities [a]		OECD countries	16.89	16.89	16.58	16.63	16.89
		Partner countries	16.90	16.90	16.59	16.64	16.90
Reference for item parameters [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).

B.2 Multilevel Multiple Imputation

```
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
```

```
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
```

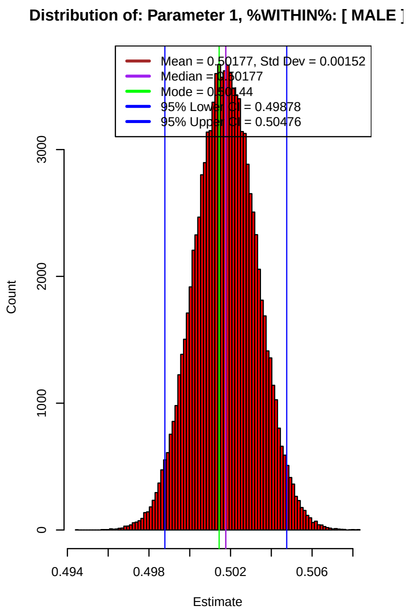
```
Means
    STRATIO           13.873       0.136      0.000      13.608      14.140      *
    EDUSHORT           0.131       0.013      0.000       0.106       0.157      *

Variances
    STRATIO          103.514       1.948      0.000      99.805     107.425      *
    EDUSHORT           1.074       0.019      0.000       1.038       1.112      *
```

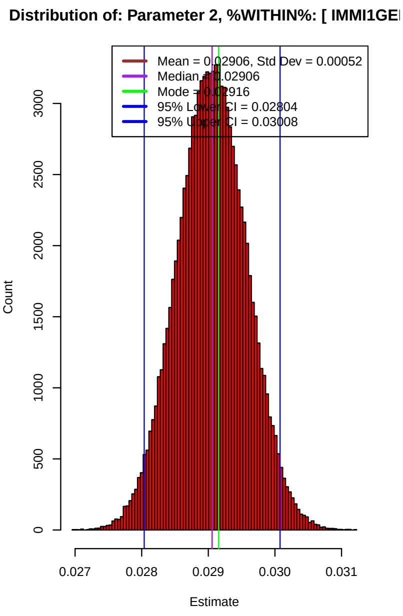
Table B.3

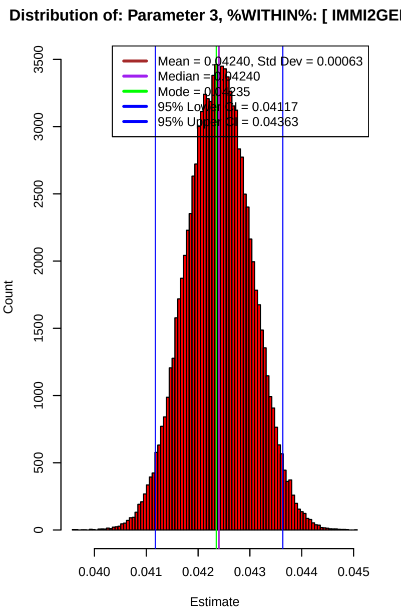
Summary of Diagnostic Plots of Multilevel Multiple Imputation

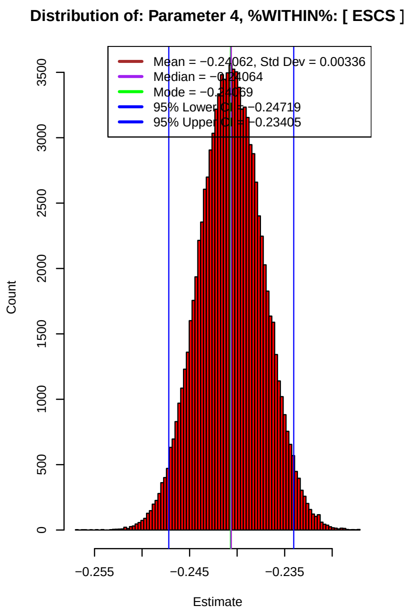
Parameter number	Parameter label	Modelling level	Brief description	Posterior mean	Posterior variance	95% credibility interval	Chain converged	AR-free chains
1	MALE	Within	Whether participant is male	0.502		(0.499, 0.505)	Yes	4
2	IMMI1GEN	Within	Whether participant migrated to this country	0.029		(0.028,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

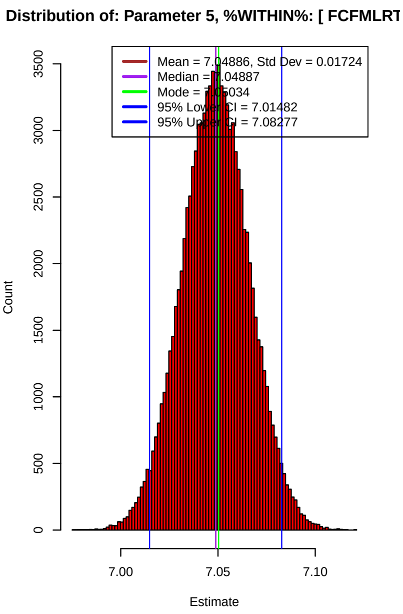
Note. Notes go here.

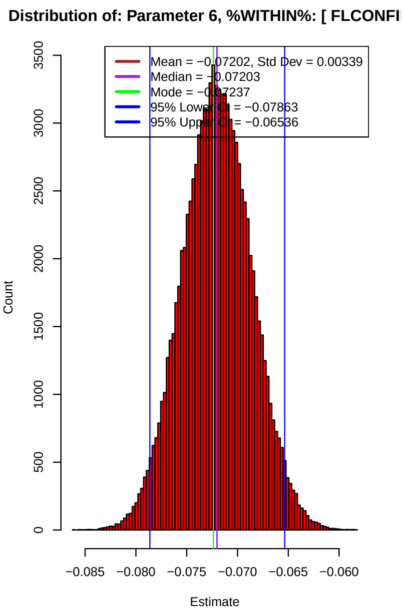

Distribution of: Parameter 1, %WITHIN%: [MALE]
Mean = 0.50177, Std Dev = 0.00152
Median = 0.50177
Mode = 0.50144
95% Lower CI = 0.49878
95% Upper CI = 0.50476
Count
Estimate

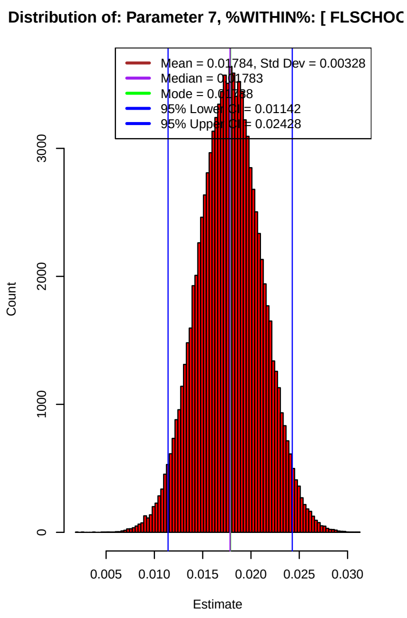

Distribution of: Parameter 2, %WITHIN%: [IMMI1GE
Mean = 0.02906, Std Dev = 0.00052
Median = 0.02906
Mode = 0.02916
95% Lower CI = 0.02804
95% Upper CI = 0.03008
Count
Estimate

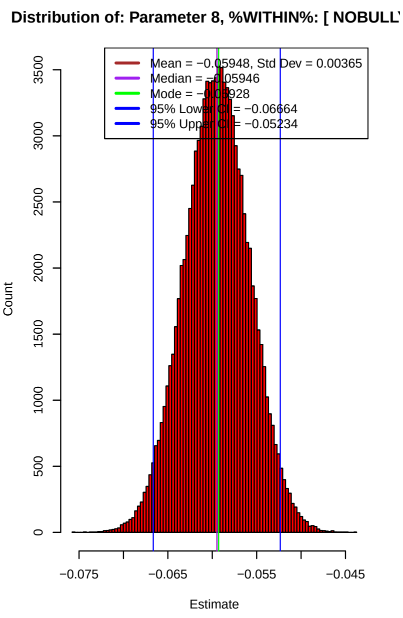

Distribution of: Parameter 3, %WITHIN%: [IMMI2GE
Mean = 0.04240, Std Dev = 0.00063
Median = 0.04240
Mode = 0.04235
95% Lower CI = 0.04117
95% Upper CI = 0.04363
Count
Estimate

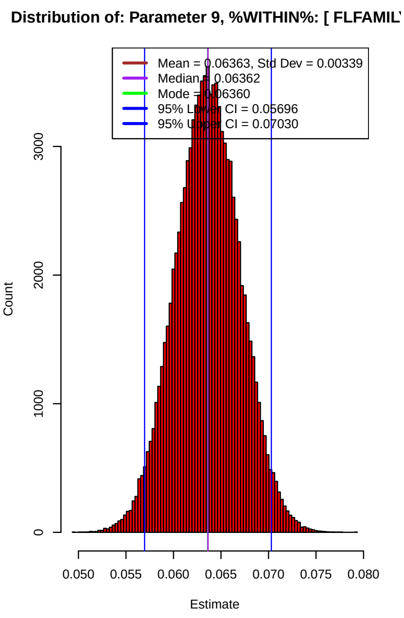

Distribution of: Parameter 4, %WITHIN%: [ESCS]
Mean = −0.24062, Std Dev = 0.00336
Median = −0.24064
Mode = −0.24059
95% Lower CI = −0.24719
95% Upper CI = −0.23405
Count
Estimate

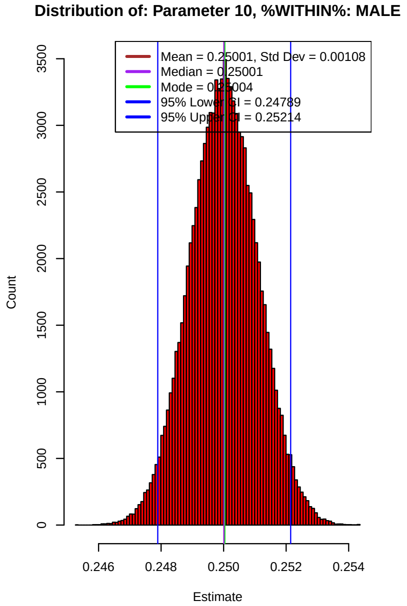

Distribution of: Parameter 5, %WITHIN%: [FCFMLRT
Mean = 7.04886, Std Dev = 0.01724
Median = 7.04887
Mode = 7.05034
95% Lower CI = 7.01482
95% Upper CI = 7.08277
Count
Estimate

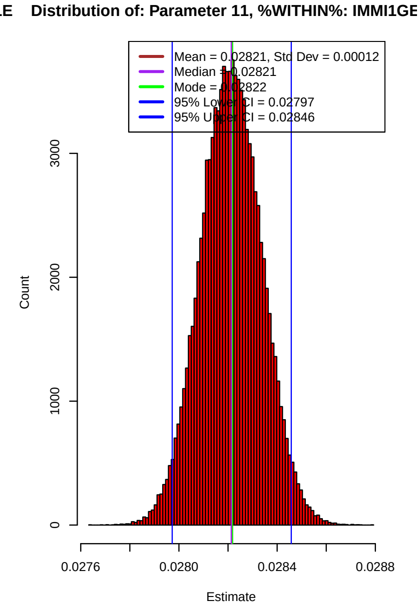

Distribution of: Parameter 6, %WITHIN%: [FLCONFI
Mean = −0.07202, Std Dev = 0.00339
Median = −0.07203
Mode = −0.07237
95% Lower CI = −0.07863
95% Upper CI = −0.06536
Count
Estimate

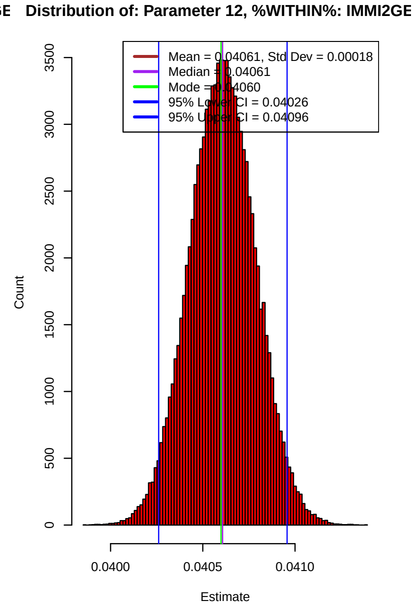

Distribution of: Parameter 7, %WITHIN%: [FLSCHOO
Mean = 0.01784, Std Dev = 0.00328
Median = 0.01783
Mode = 0.01788
95% Lower CI = 0.01142
95% Upper CI = 0.02428
Count
Estimate

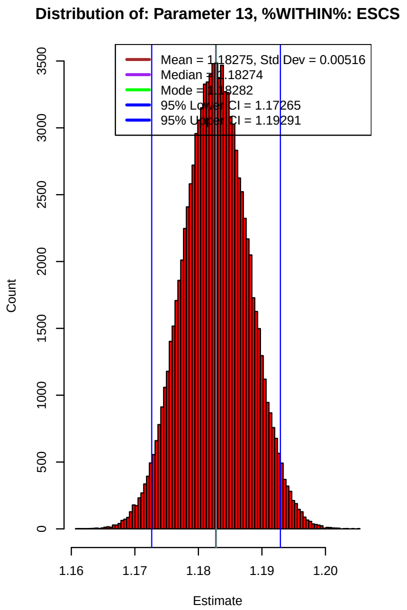

Distribution of: Parameter 8, %WITHIN%: [NOBULLY
Mean = −0.05948, Std Dev = 0.00365
Median = −0.05946
Mode = −0.05928
95% Lower CI = −0.06664
95% Upper CI = −0.05234
Count
Estimate

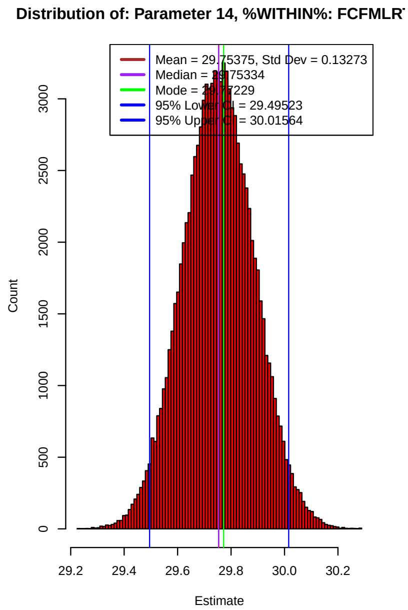

Distribution of: Parameter 9, %WITHIN%: [FLFAMILY
Mean = 0.06363, Std Dev = 0.00339
Median = 0.06362
Mode = 0.06360
95% Lower CI = 0.05696
95% Upper CI = 0.07030
Count
Estimate

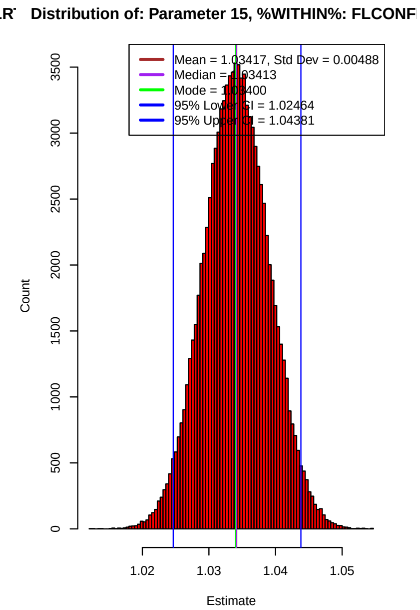

Distribution of: Parameter 10, %WITHIN%: MALE
Mean = 0.25001, Std Dev = 0.00108
Median = 0.25001
Mode = 0.25004
95% Lower CI = 0.24789
95% Upper CI = 0.25214
Count
Estimate

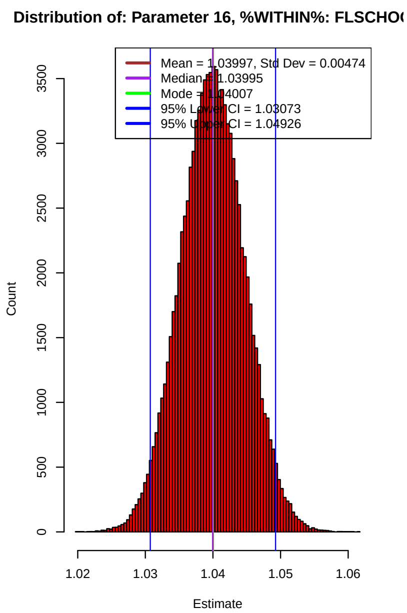

Distribution of: Parameter 11, %WITHIN%: IMMI1GE
Mean = 0.02821, Std Dev = 0.00012
Median = 0.02821
Mode = 0.02822
95% Lower CI = 0.02797
95% Upper CI = 0.02846
Count
Estimate

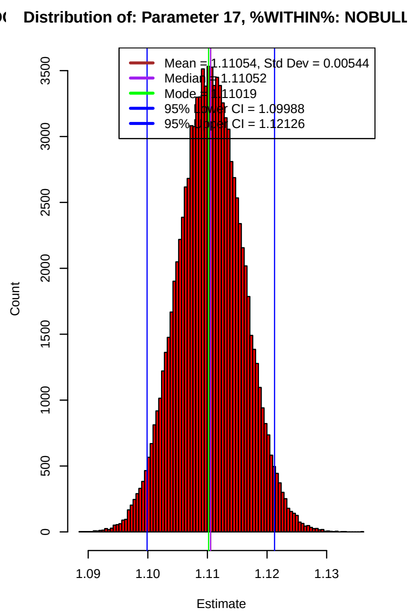

Distribution of: Parameter 12, %WITHIN%: IMMI2GE
Mean = 0.04061, Std Dev = 0.00018
Median = 0.04061
Mode = 0.04060
95% Lower CI = 0.04026
95% Upper CI = 0.04096
Count
Estimate

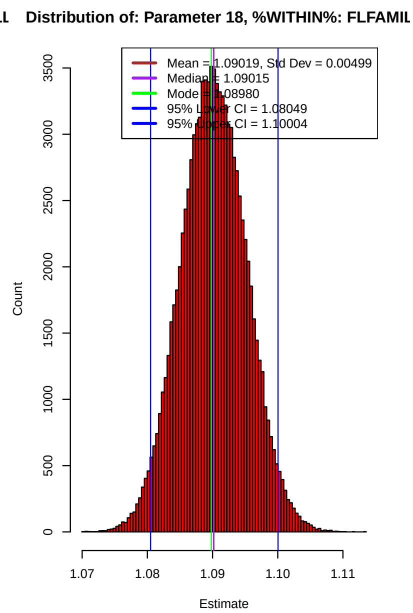

Distribution of: Parameter 13, %WITHIN%: ESCS
Mean = 1.18275, Std Dev = 0.00516
Median = 1.18274
Mode = 1.18282
95% Lower CI = 1.17265
95% Upper CI = 1.19291
Count
Estimate

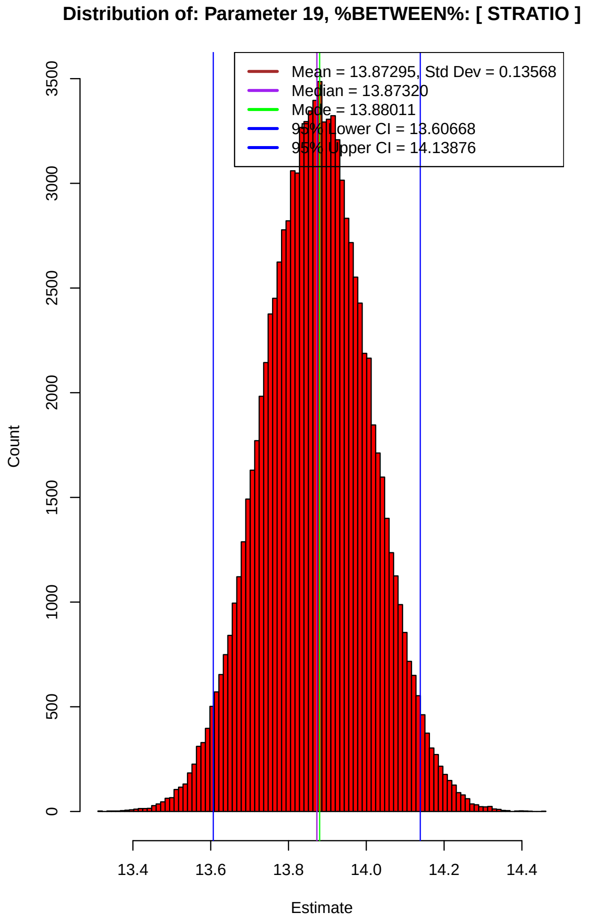

Distribution of: Parameter 14, %WITHIN%: FCFMLRT
Mean = 29.75375, Std Dev = 0.13273
Median = 29.75334
Mode = 29.77229
95% Lower CI = 29.49523
95% Upper CI = 30.01564
Count
Estimate

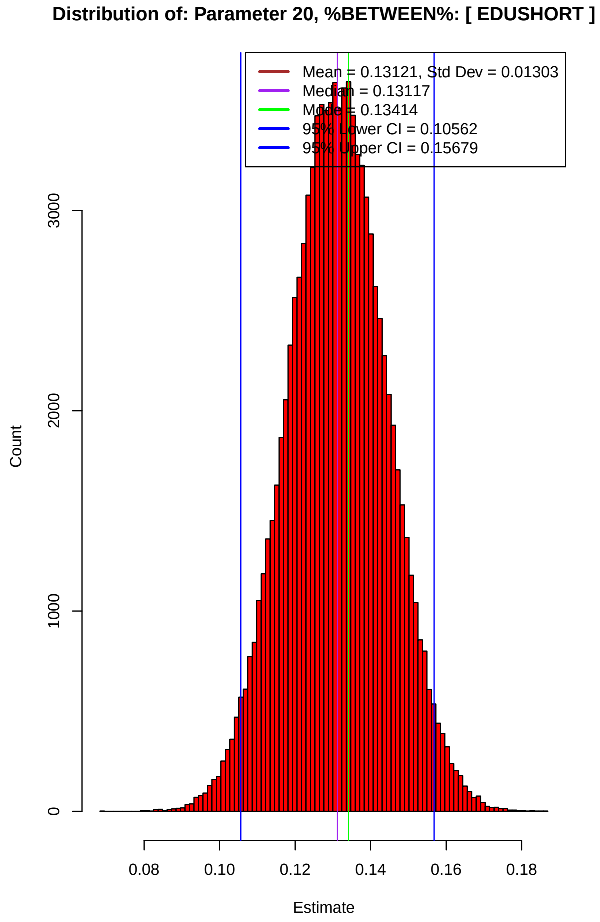

Distribution of: Parameter 15, %WITHIN%: FLCONF
Mean = 1.03417, Std Dev = 0.00488
Median = 1.03413
Mode = 1.03400
95% Lower CI = 1.02464
95% Upper CI = 1.04381
Count
Estimate

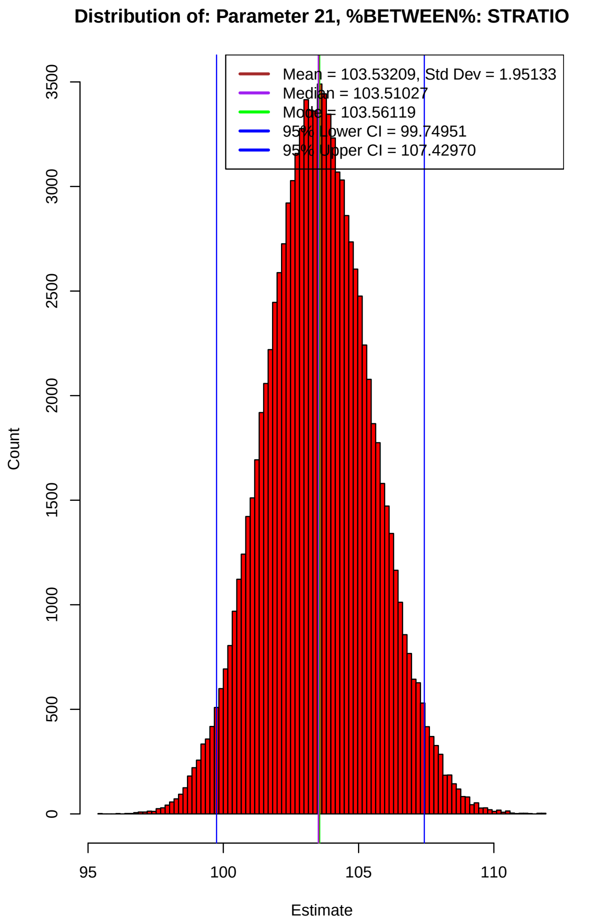

Distribution of: Parameter 16, %WITHIN%: FLSCHO
Mean = 1.03997, Std Dev = 0.00474
Median = 1.03995
Mode = 1.04007
95% Lower CI = 1.03073
95% Upper CI = 1.04926
Count
Estimate

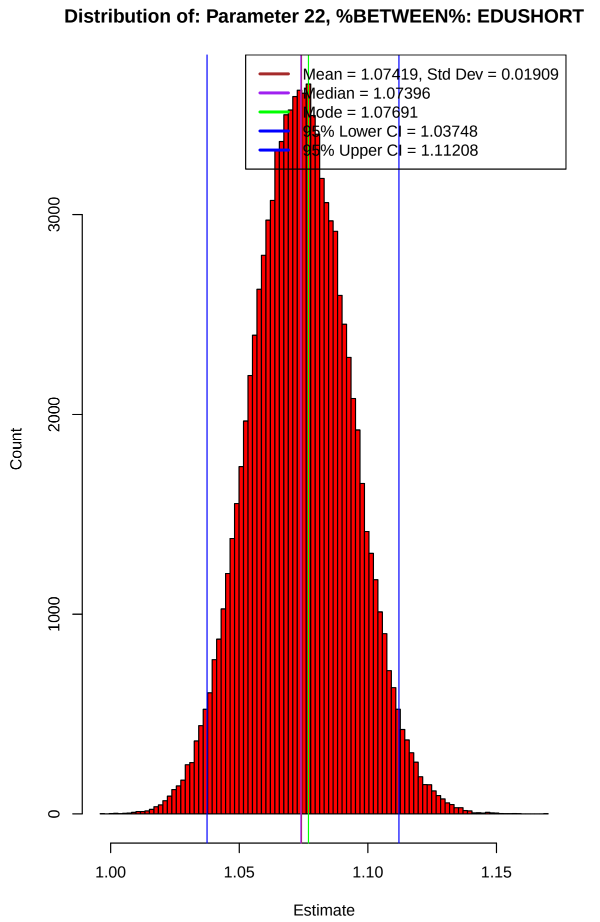

Distribution of: Parameter 17, %WITHIN%: NOBULL
Mean = 1.11054, Std Dev = 0.00544
Median = 1.11052
Mode = 1.11019
95% Lower CI = 1.09988
95% Upper CI = 1.12126
Count
Estimate

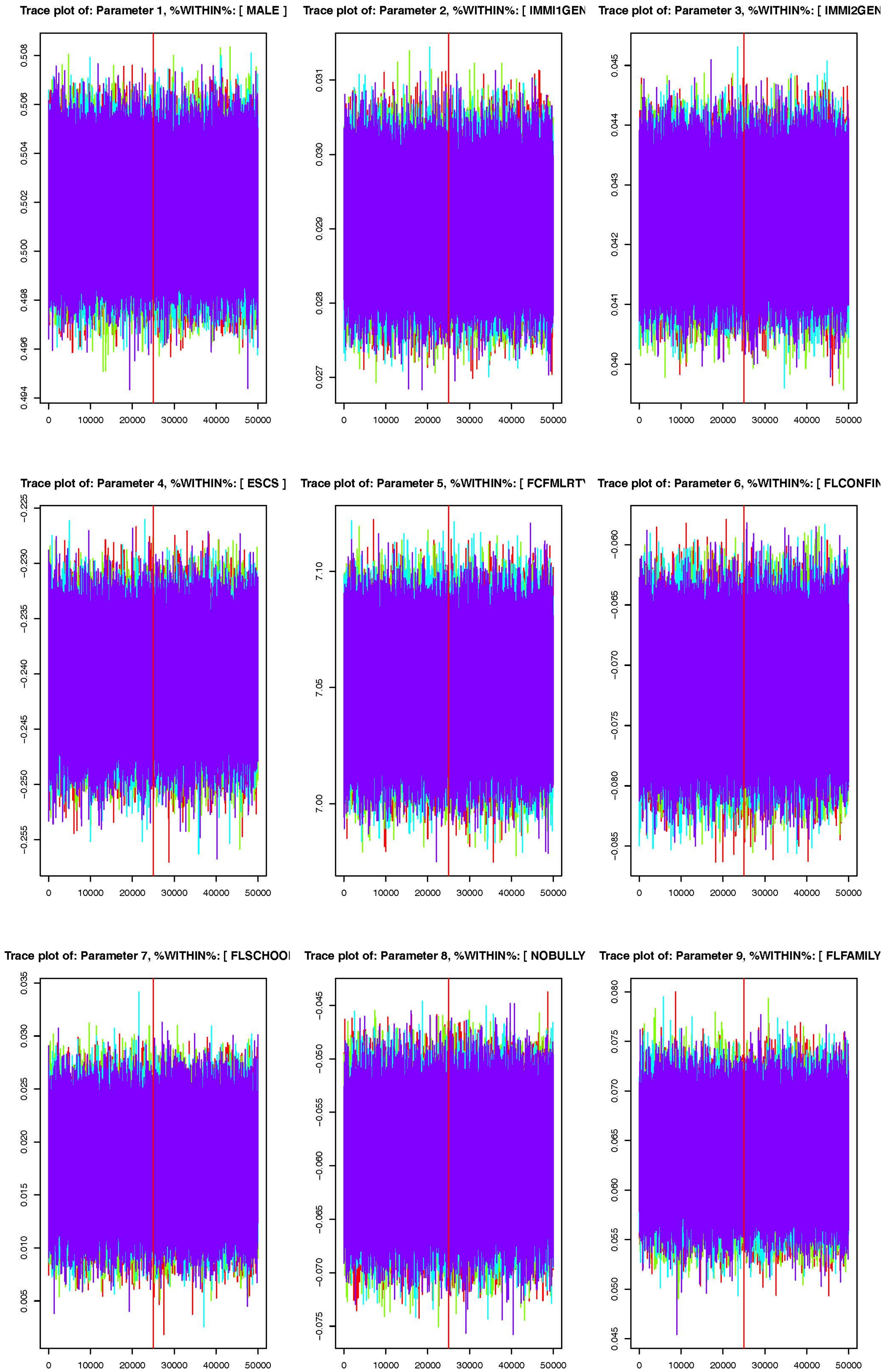

Distribution of: Parameter 18, %WITHIN%: FLFAMIL
Mean = 1.09019, Std Dev = 0.00499
Median = 1.09015
Mode = 1.08980
95% Lower CI = 1.08049
95% Upper CI = 1.10004
Count
Estimate


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
0
500
1000
1500
2000
2500
3000
3500
13.4
13.6
13.8
14.0
14.2
14.4

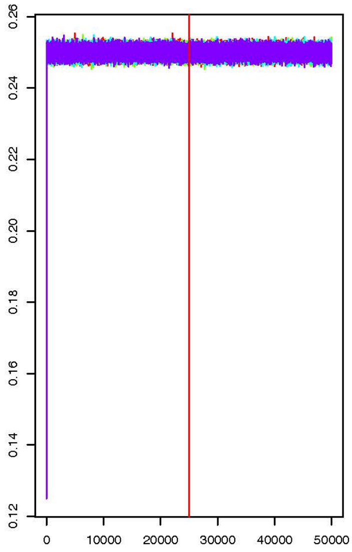

Distribution of: Parameter 20, %BETWEEN%: [EDUSHORT]
Mean = 0.13121, Std Dev = 0.01303
Median = 0.13117
Mode = 0.13414
95% Lower CI = 0.10562
95% Upper CI = 0.15679
Count
Estimate
0
1000
2000
3000
0.08
0.10
0.12
0.14
0.16
0.18


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
0
500
1000
1500
2000
2500
3000
3500
95
100
105
110

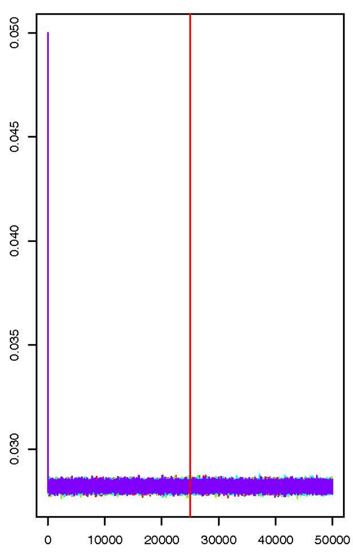

Distribution of: Parameter 22, %BETWEEN%: EDUSHORT
Mean = 1.07419, Std Dev = 0.01909
Median = 1.07396
Mode = 1.07691
95% Lower CI = 1.03748
95% Upper CI = 1.11208
Count
Estimate
0
1000
2000
3000
1.00
1.05
1.10
1.15


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

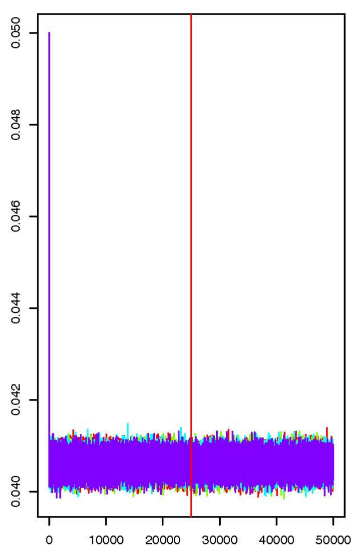
Trace plot of: Parameter 10, %WITHIN%: MALE



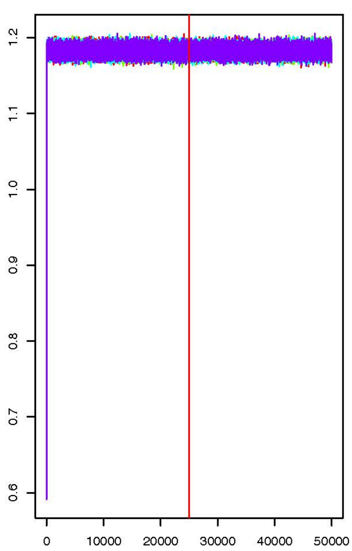
Trace plot of: Parameter 11, %WITHIN%: IMMI1GEI



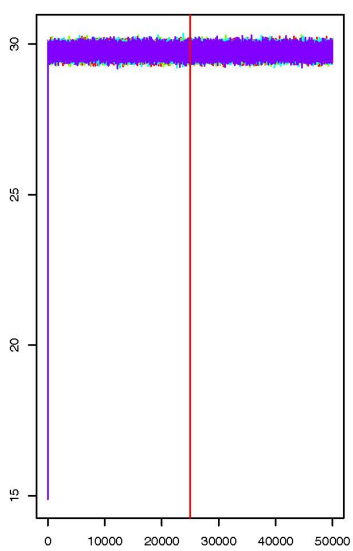
Trace plot of: Parameter 12, %WITHIN%: IMMI2GEI



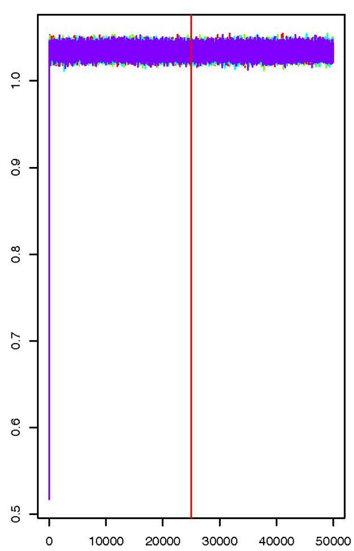
Trace plot of: Parameter 13, %WITHIN%: ESCS



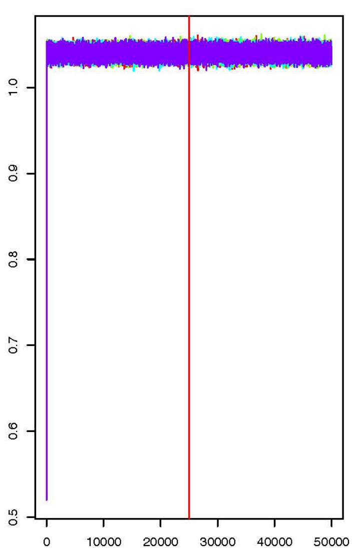
Trace plot of: Parameter 14, %WITHIN%: FCFMLRT



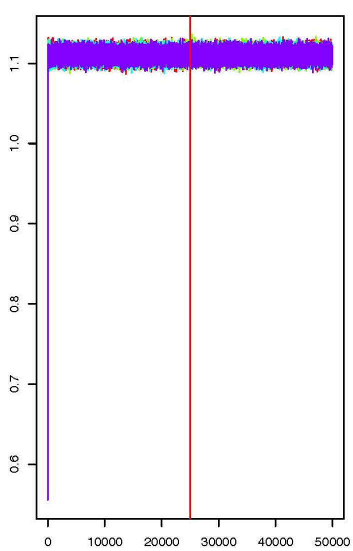
Trace plot of: Parameter 15, %WITHIN%: FLCONFII



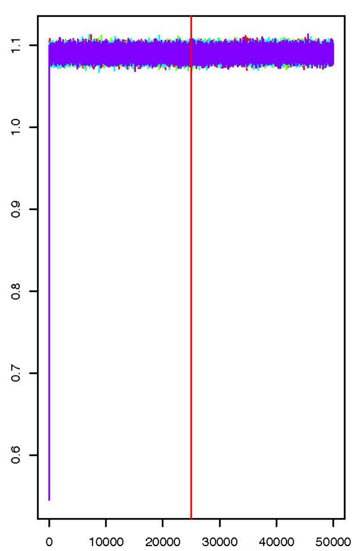
Trace plot of: Parameter 16, %WITHIN%: FLSCHOO



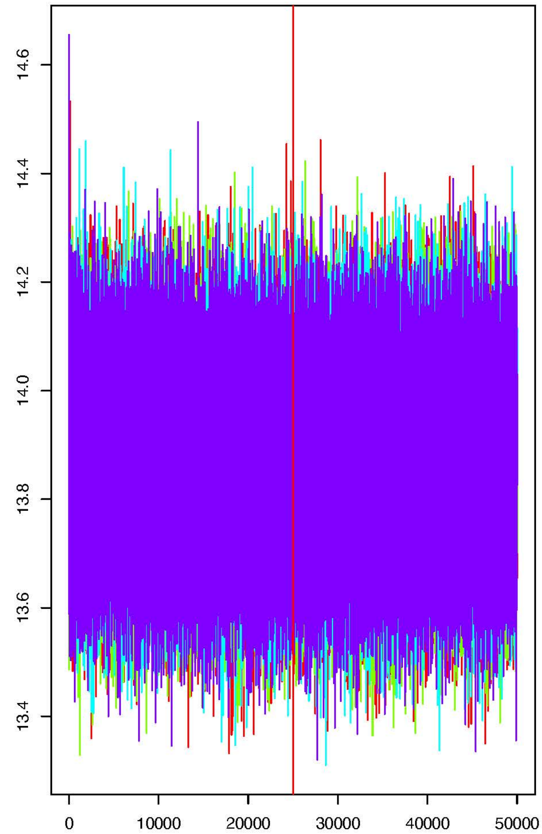
Trace plot of: Parameter 17, %WITHIN%: NOBULLY



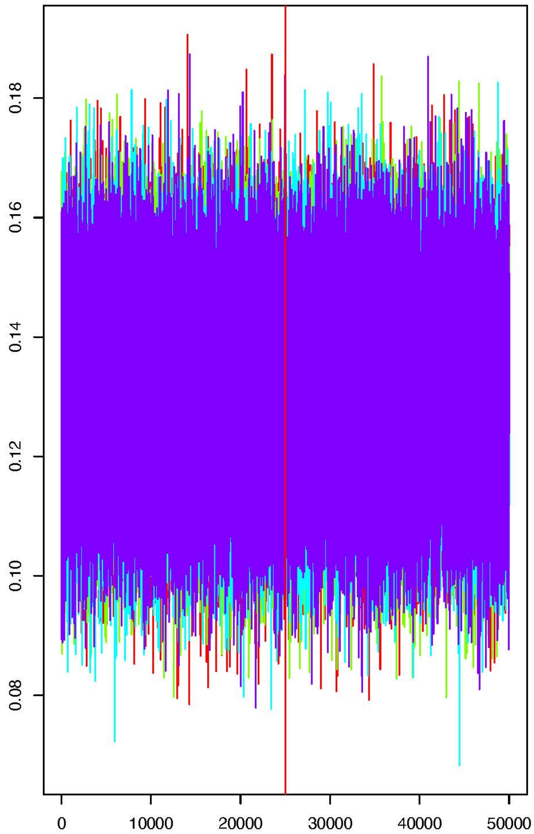
Trace plot of: Parameter 18, %WITHIN%: FLFAMILY



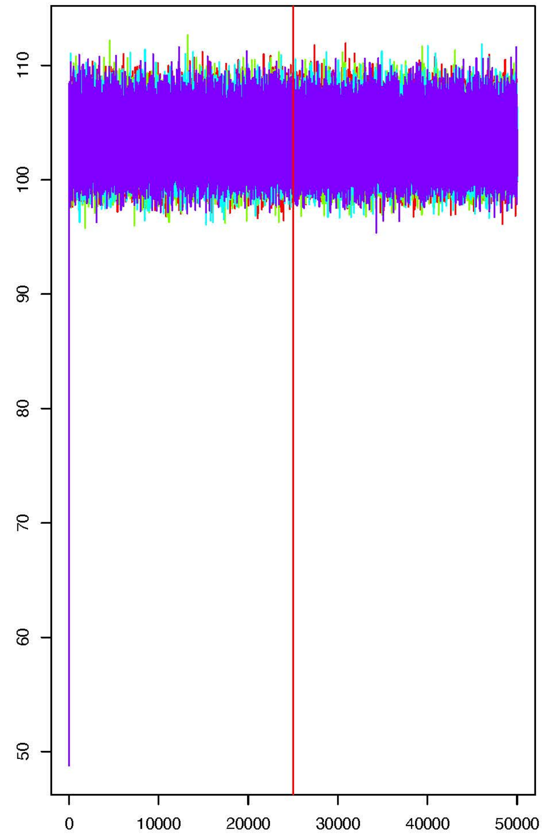
Trace plot of: Parameter 19, %BETWEEN%: [STRATIO]



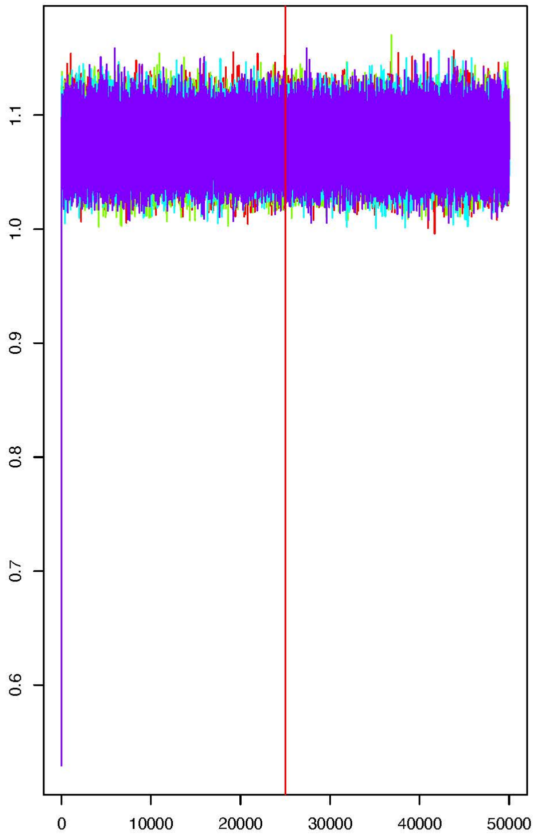
Trace plot of: Parameter 20, %BETWEEN%: [EDUSHORT]

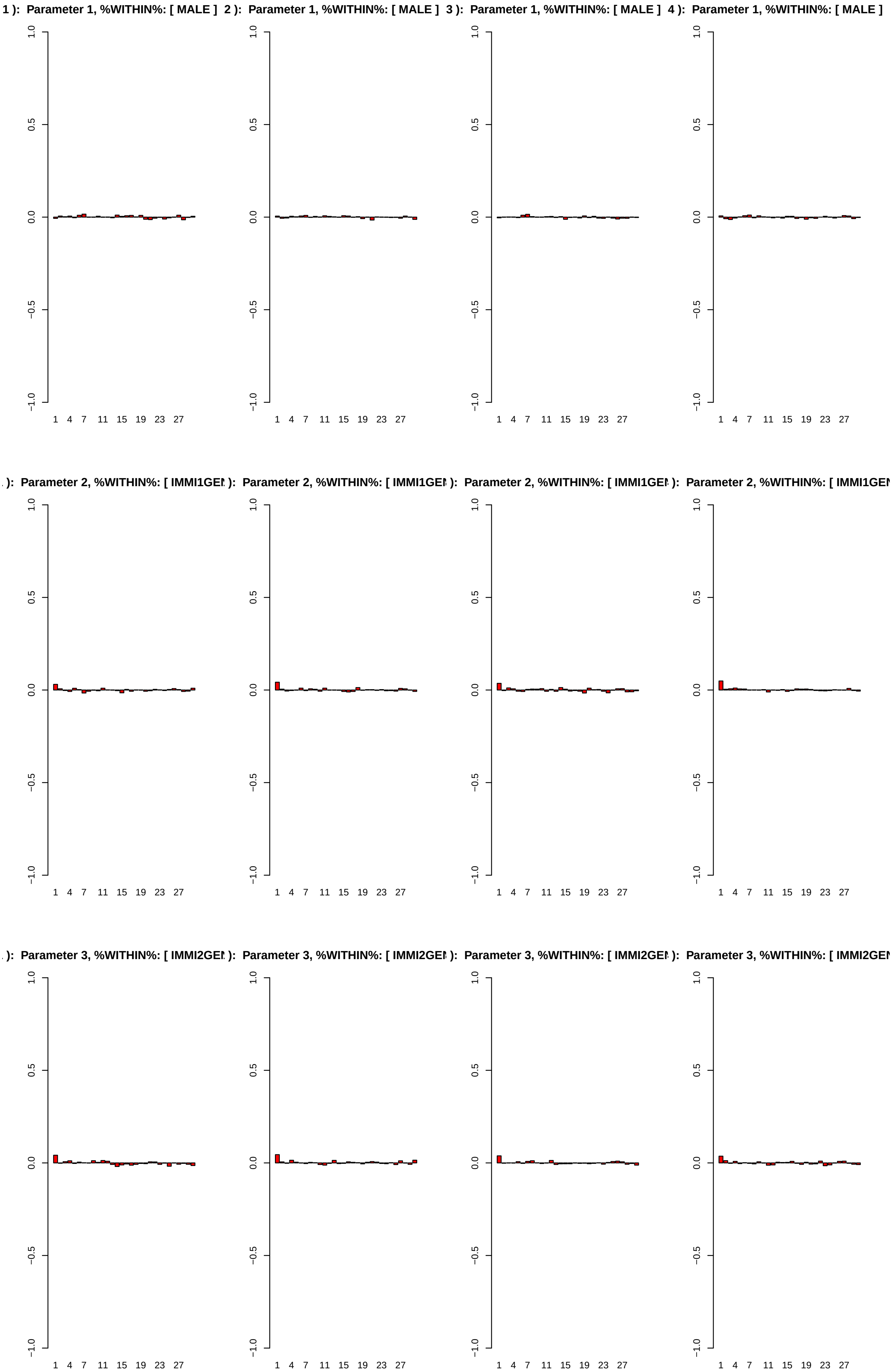


Trace plot of: Parameter 21, %BETWEEN%: STRATIO



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

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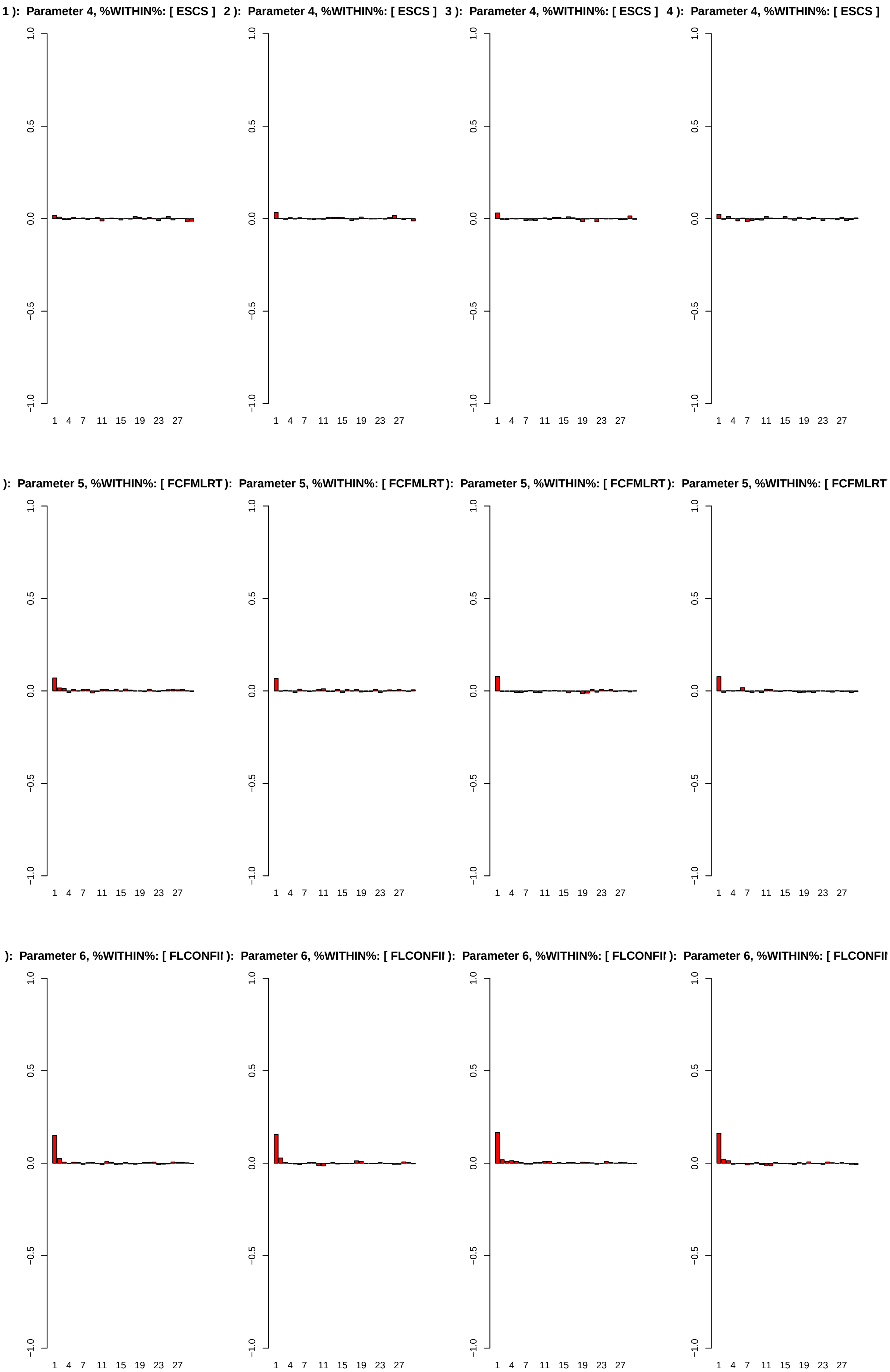
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): Parameter 5, %WITHIN%: [FCFMLRT
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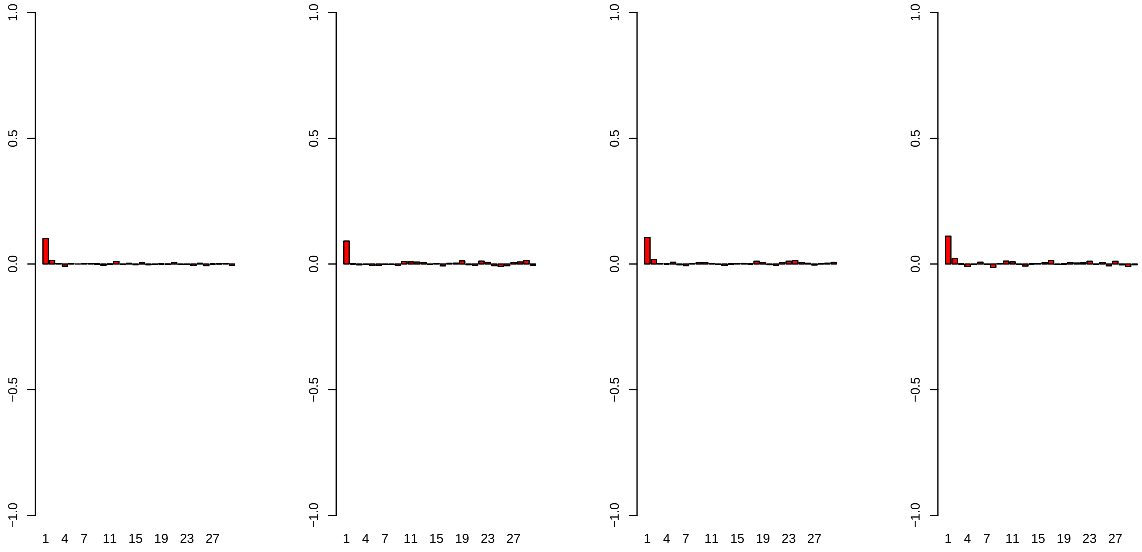

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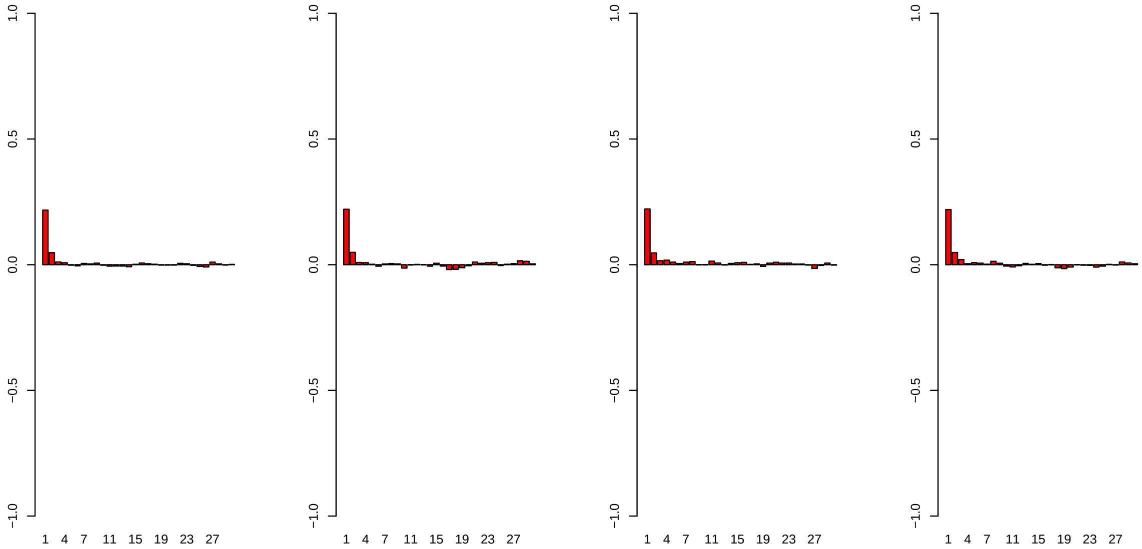

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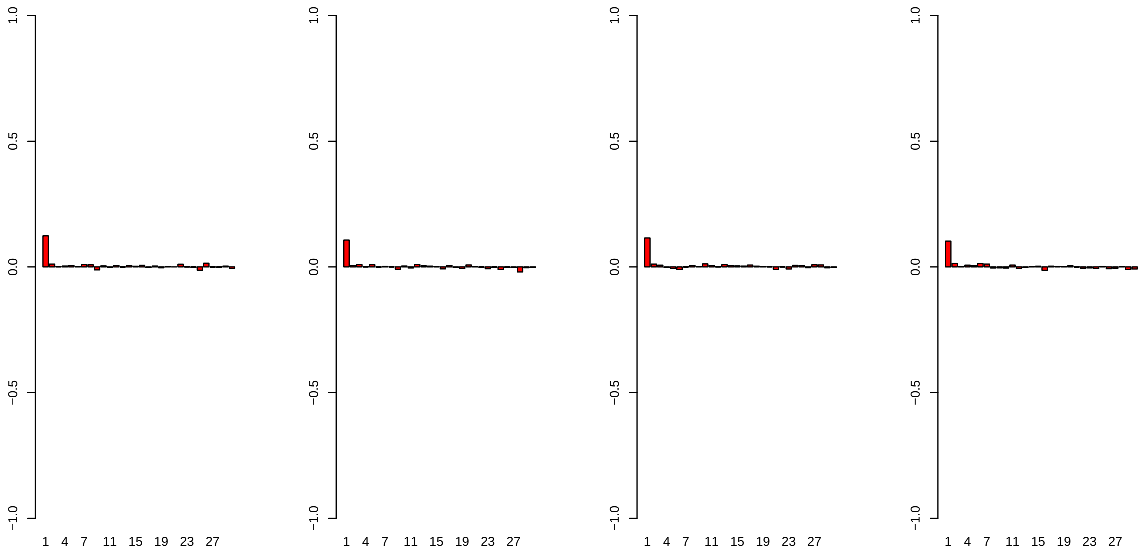

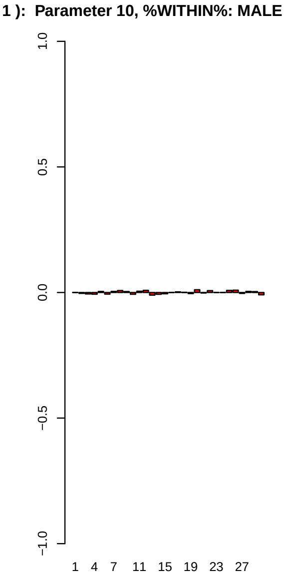
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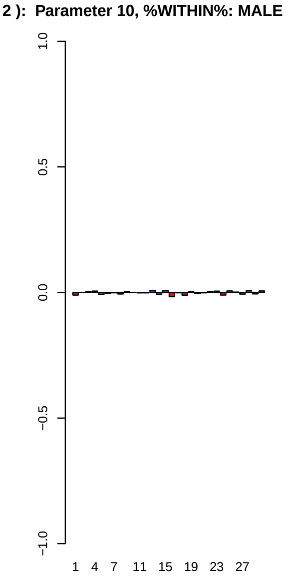
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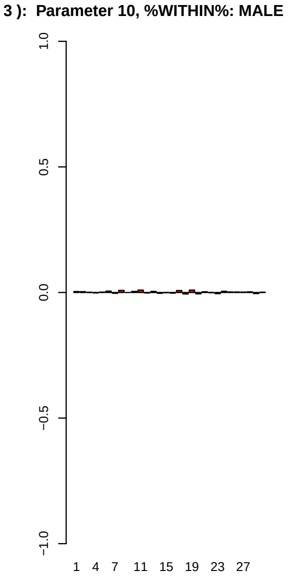
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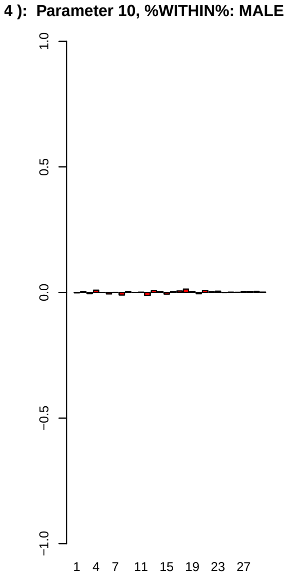
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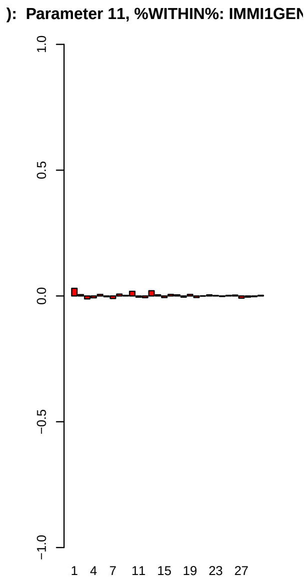
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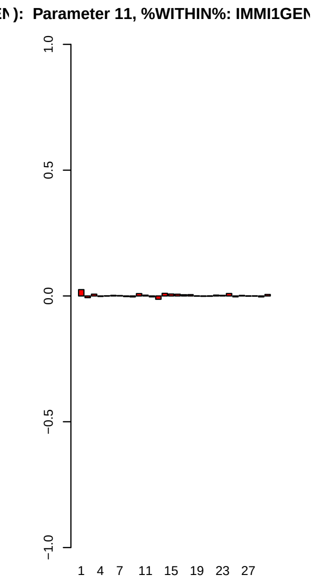
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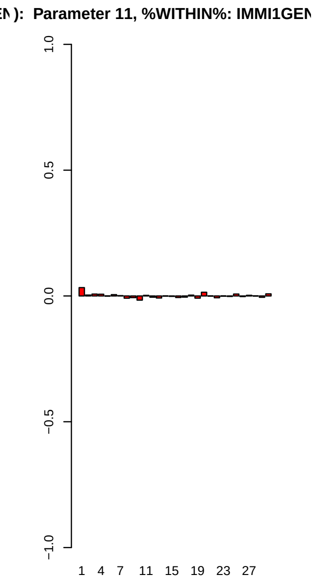
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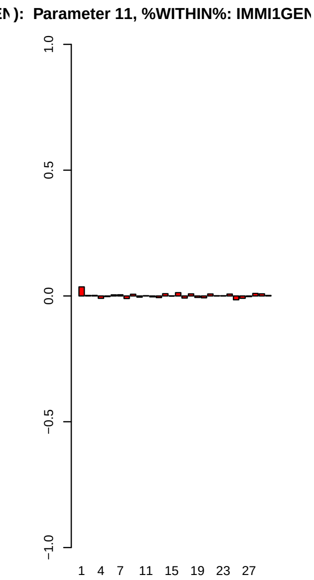
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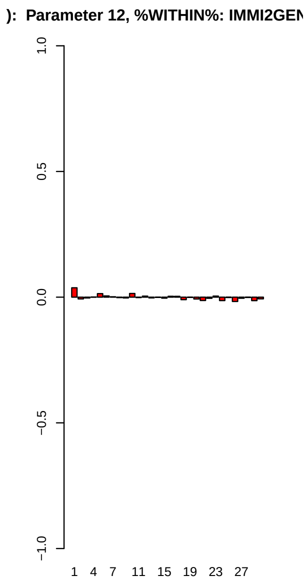
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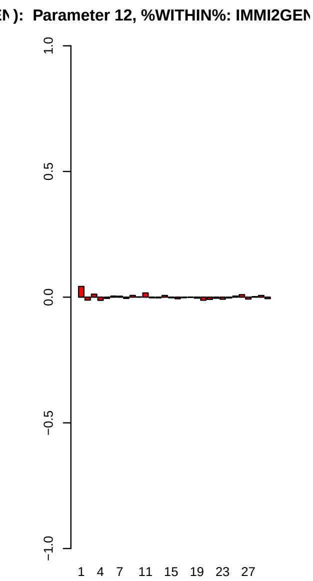
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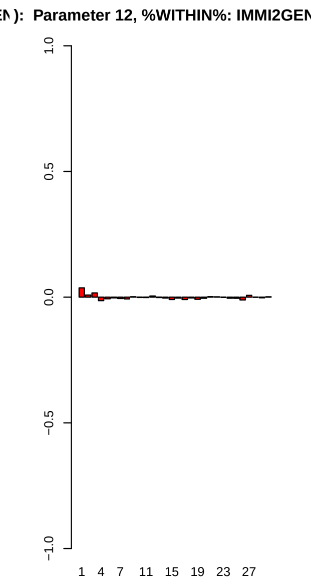
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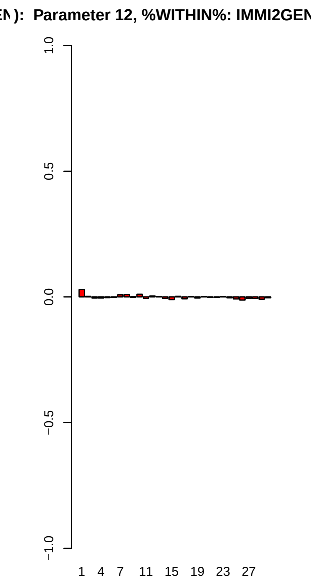
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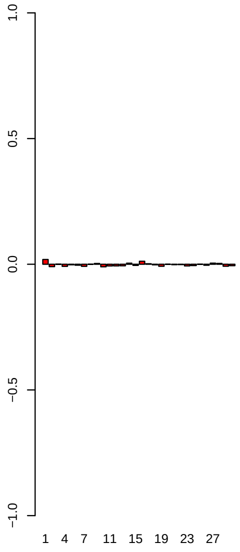

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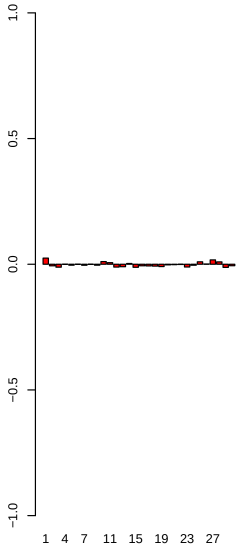

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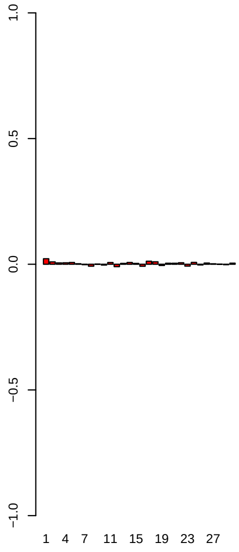

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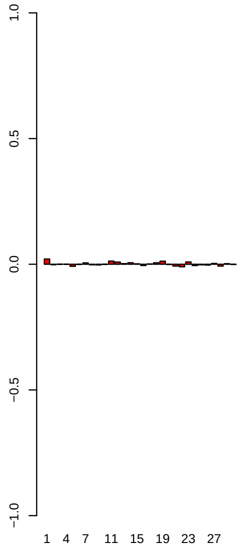

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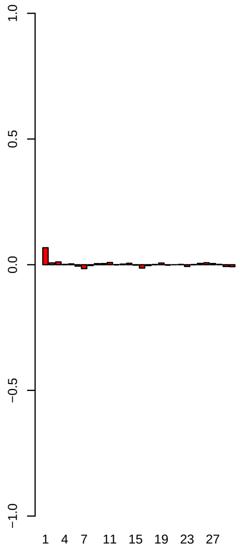

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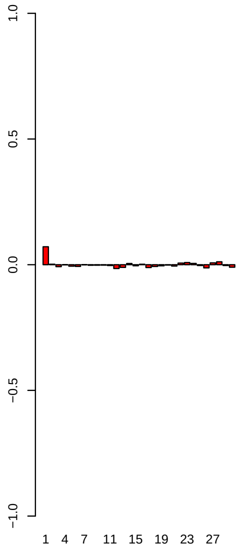

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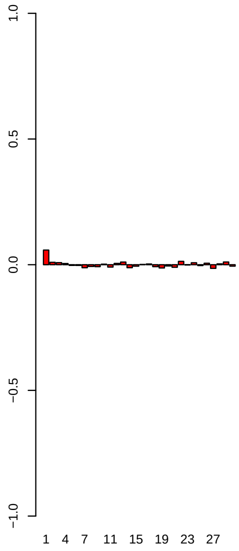

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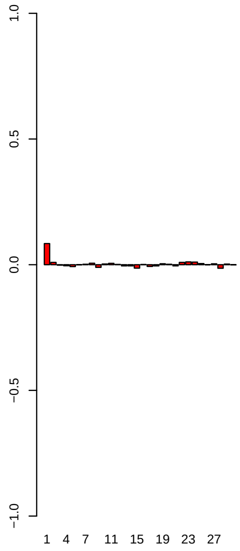

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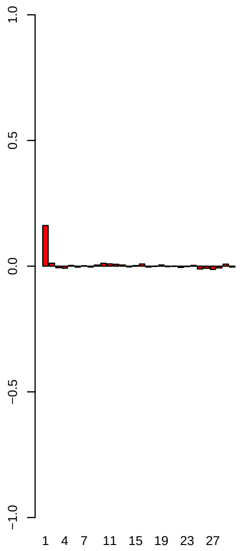

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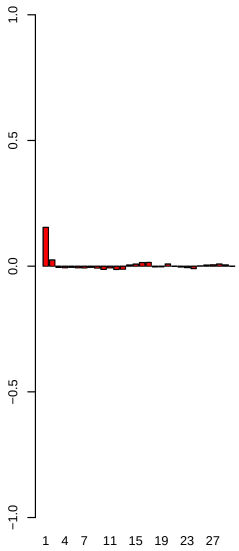

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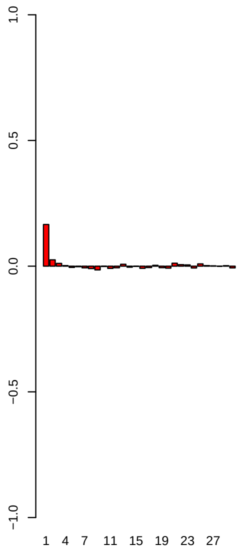

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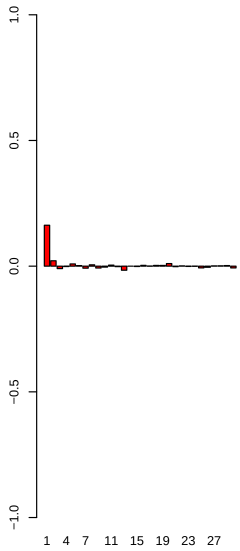

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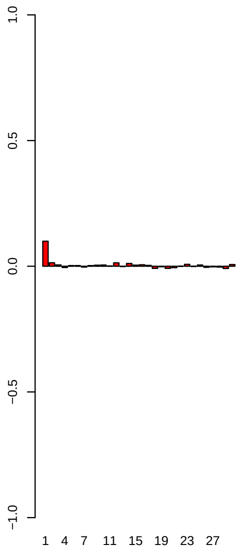

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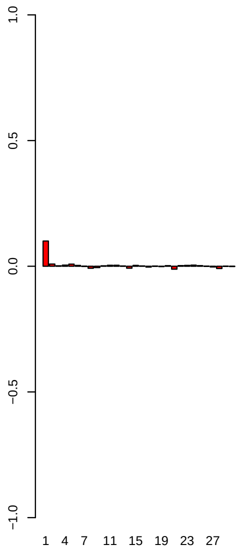

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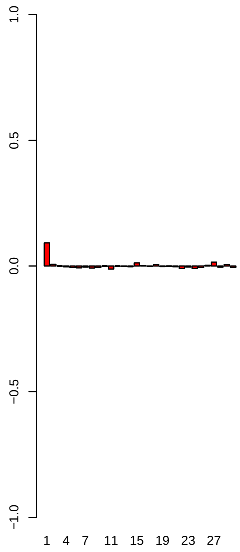

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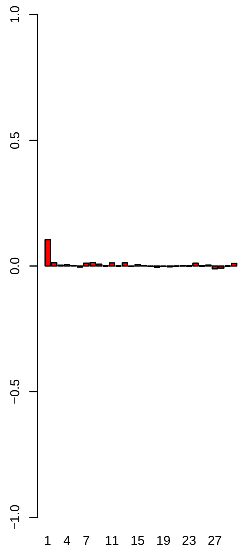

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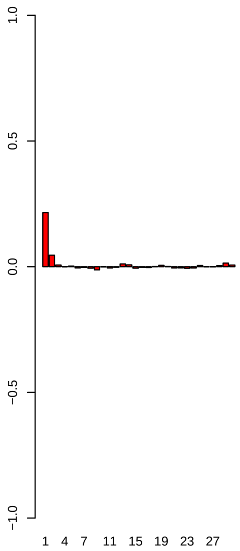

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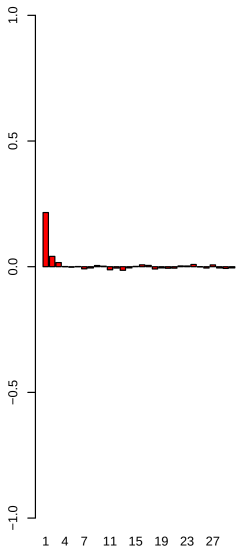

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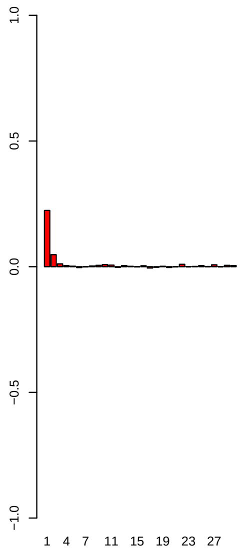

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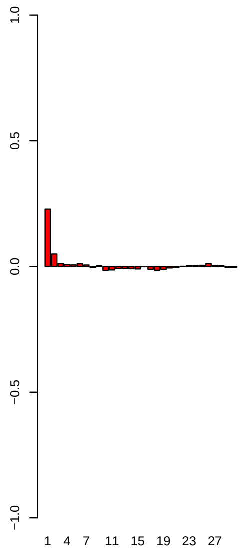

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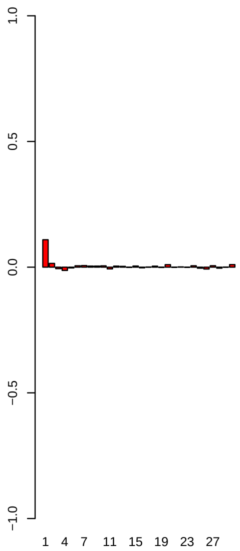

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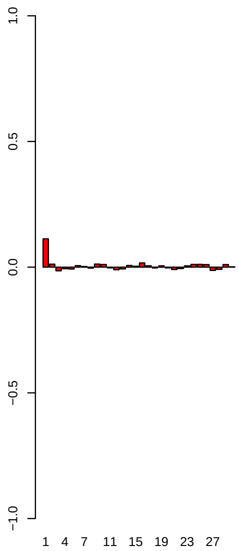

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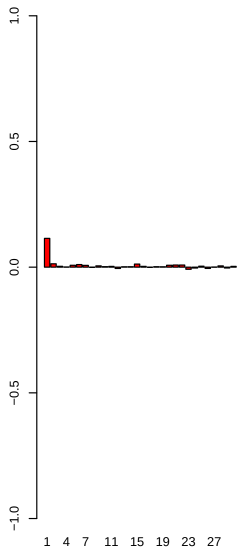

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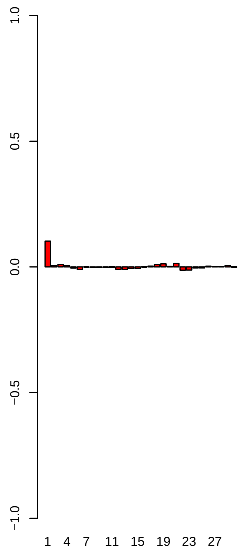

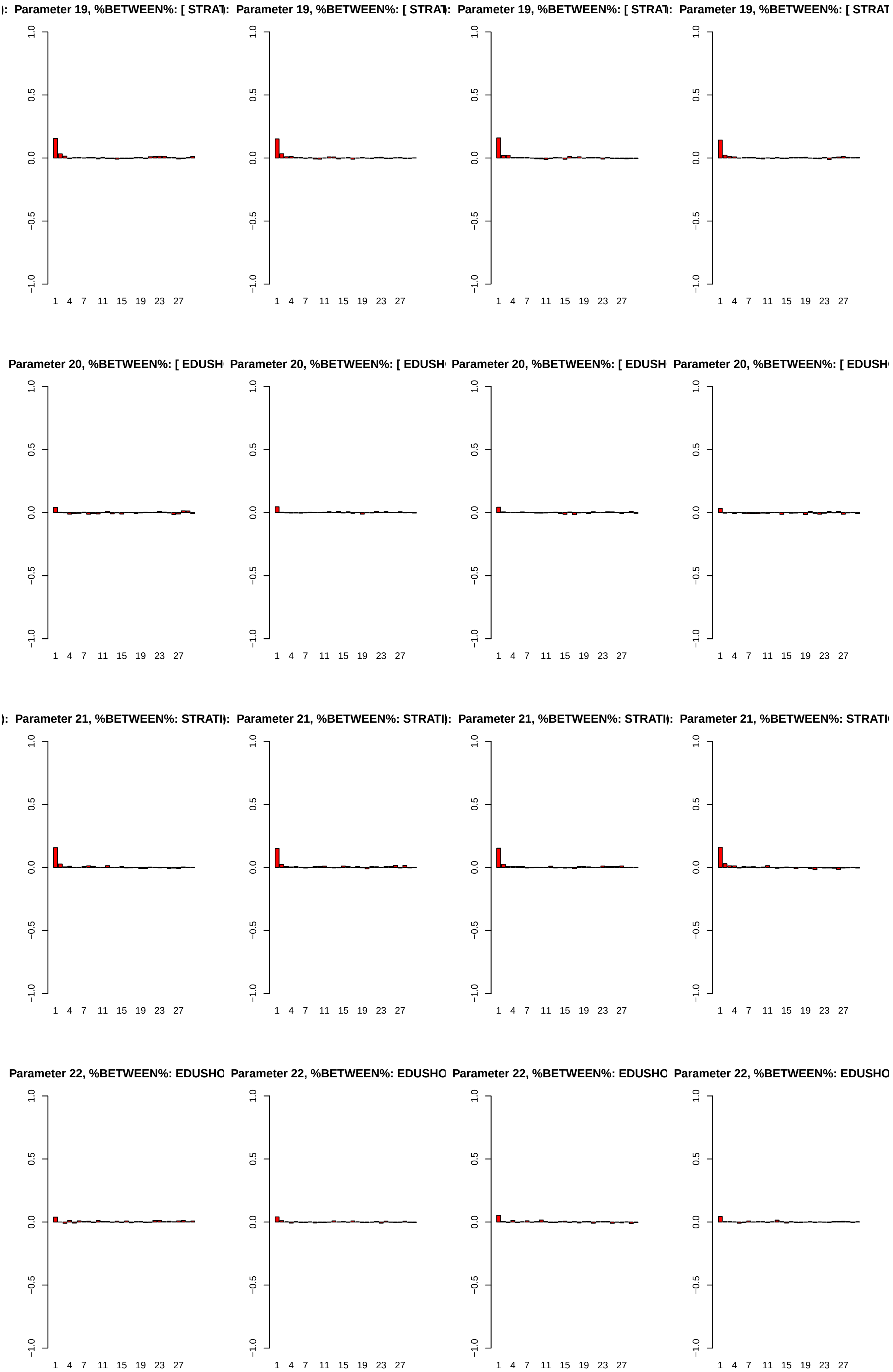
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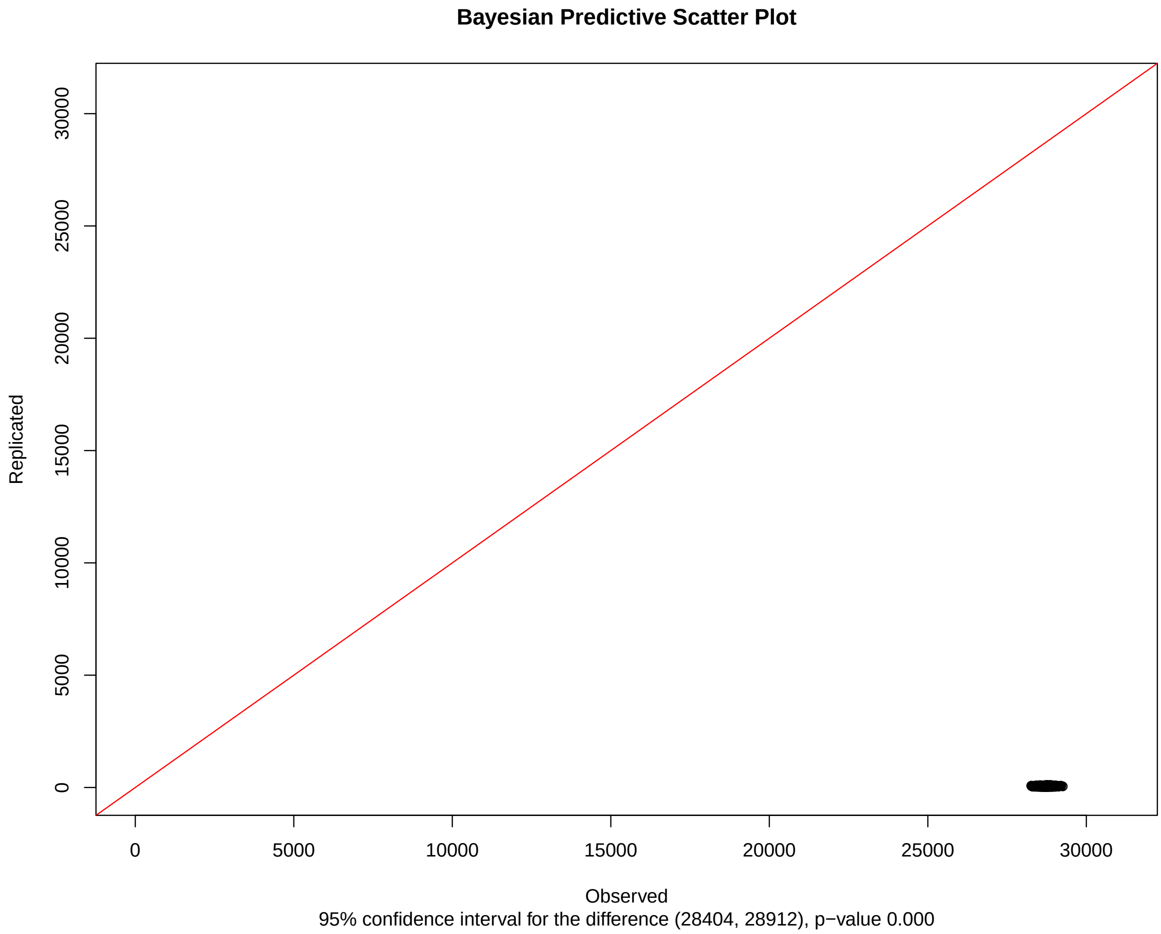
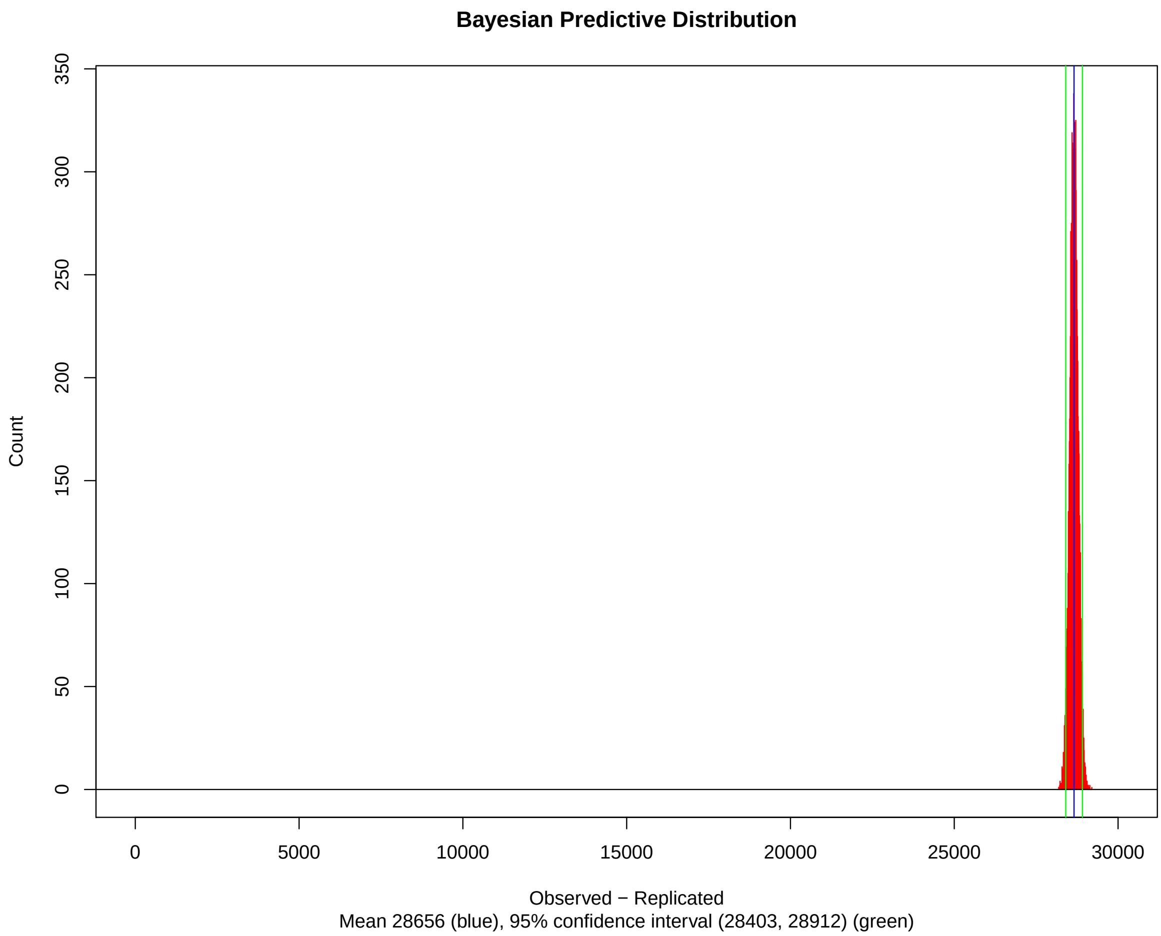
1 4 7 11 15 19 23 27



Bayesian Predictive Scatter Plot
Replicated
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)