How does pre-school attendance affect school performance ? An application of Gini-BMA methodology on PISA 2018 dataset

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Abstract. Evidence flourishes in the literature of a direct link between pre-primary education and achievement test scores in the primary school. However, children tend to reap the greatest benefits if preschool programmes are of high quality. Premised on this commonality between pre-primary education and academic achievement in the primary school, and considering variations in pre-schooling quality, this study mainly investigates the effect of universal pre-school education on the students' academic results in 22 OECD and non-OECD countries. Data are obtained from the OECD Programme for International Student Assessment (PISA) 2018. Employing a Gini Regression Bayesian Model Averaging (BMA) approach to account for theory uncertainty we find that attendance of pre-primary institutions has a salutary impact on PISA test scores for 15-year-old students in most of the countries. However, there are cases where early childhood coincides with a decline in students' outcomes in both science and reading.

Keywords: students' performance, pre-primary education, Gini regression coefficient, BMA methodology, PISA.
JEL classification: *C11; C38; I21; J24*

1 Introduction

This study investigates the effect of universal pre-school education on the students' academic results in 22 OECD and non-OECD countries using a large data set obtained from the OECD Programme for International Student Assessment (PISA) 2018. We want to emphasize from the outset that our findings regarding the associations between students' performance in reading literacy and science and the set of variables related to attendance in pre-primary education from 15 years earlier and refer to the state of pre-school education standards of that period. There is an emerging consensus that early childhood education interventions provide a cognitively simulating environment that enhance school readiness, academic performance, social integration and long-term skill development (Myers (1995), Entwisle and Alexander (1993), Waldfogel (2002), Brooks-Gunn (2003), Carniero and Heckman (2003)). In compliance with human capital theory the skills acquired during pre-primary schooling years form the basis for the development of future skills (Heckman (2006)). Becker (1964) is of the view that early childhood investments bring higher returns compared to future investments because recipients have a longer time to enjoy the benefits. Along the same lines, a study by Heckman (2006) reveals that pre-primary education generates the highest possible annual return that gradually fades at higher levels of education program. In addition, apart from the contributions to human capital evolution, pre-primary experience offers to a country's social and economic development in the long run.

Evidence flourishes in the literature of a direct link between pre-primary education and achievement test scores in the primary school. There is a broad opinion in the sense that the comprehensive early preschool exposure conduces to cognitive development in the short run while in the long term increases academic achievement and reduces grade retention. (Waldfogel (2002), Brooks-Gunn (2003)). However, children tend to reap the greatest benefits if preschool programmes are of high quality (Carneiro and Heckman (2003)). Most of the economic research on this topic recognizes that pre-primary education of exclusive quality is a high-yield investment with longstanding benefits (Gormley et. al. (2005), Heckman and Lochner (2000), Reynolds et. al. (2011)). Thus, policies that encourage childcare expansion should consider that improvements in both quantity and quality issues are crucial (Hanushek and Woessmann (2007)).

Pre-primary education comprises many distinct structures of coordinated and maintained center-based activities such as pre-school, kindergartens, and day care centers aiming to foster children's development (OECD 2011). Several studies have been attempted to appraise the gains of another category of early childhood environment, namely "special programmes". The Perry Preschool Project (Schweinhart and Weikart (1981), Heckman, Pinto, and Savelyev (2013)), the Carolina Abecedarian Project (Ramey (1974)) and the Chicago Child-Parent Center Programme (Reynolds (2000)) are the three most notorious early intervention programmes that address to children up to 5 years old age coming from economically disadvantaged family backgrounds with purpose to compensate the detrimental influence of this situation/condition and create educational opportunities. The salutary results of these programmes on their beneficiaries are related in producing short and medium-to-long term gains in terms of scholastic success and later labor market outcomes. Meantime, however, there are many limitations to what these early intervention programmes can achieve. Parental involvement, parents' education, family features and many other factors are responsible, to some extent, for variations in early years, and these factors cannot eagerly be controlled by policy instruments. Besides, high-quality early intervention programmes are costly, not all of them are evenly compelling and even the most auspicious model programs may not attribute the most when they delivered on a large-scale. There are also many concerns regarding the extent to which these early interventions are best delivered universally or targeted only to disadvantaged groups.

All told, most of the evidence does demonstrate positive effects of early childhood programs targeted to at risk children, with the size and the strength of these effects being quite modest, reflecting the differences in the quality of education provided (Karoly, Kilburn and Cannon (2005), Reynolds et. al. (2011)). In contrast, there are surprisingly fewer studies that examine the impact of large-scale universal pre-school programs. Berlinski et. al. (2008), Aguilar and Tansini (2012), Taiwo and Tyolo (2002), Pholphirul (2017) are among those who examine the effects of universal pre-primary schooling expansion in developing countries. Results reveal positive and, in some cases, long-lasting effects of preschool attendance. Similar research has been conducted for developed countries too (Cascio (2009), Goux and Maurin (2008), Baker et. al. (2005), Dickson (2012), Gormley and Gayer (2005), Akabayashi and Tanaka (2013)). The findings emerge from this literature vary. The bulk of evidence suggests that high-quality pre-primary education leads to positive short- and long-term benefits but these tend to be larger and more lasting for disadvantaged children. Many are the studies that witness a positive effect of pre-school schooling on achievement test scores, but, in most cases, this academic impact quickly dissipates. There are also several research papers that find no or even negative effects.

While there is a number of single-country studies that examine the effects of expansion of pre-schooling for the child population in general, much less are the nation-wide studies that have attempted to make comparisons among different countries. Complementary to that, there exist (as far as we aware) no single study which also considers variations in pre-school programs' quality. In light of the above, this paper aims at explaining the academic performance of a sample of children aged between 15 years 3 months and 16 years and 2 months, having completed at least 6 years of formal education. Premised on the commonality between pre-primary education and academic achievement in the primary school, this study mainly investigates the effect of universal pre-school education on the students' academic results in 22 OECD and non-OECD countries. Data are obtained from the OECD Programme for International Student Assessment (PISA) 2018. The dataset consists of the students' test scores in reading literacy and 33 quality indicators relative to students', families' and schools' characteristics. Among those quality indicators, 6 represent the attendance in pre-primary schooling. For reasons of comparison, students' test scores in science are applied too. Prior research has displayed that test scores are robust predictors for future educational and labor market outcomes (Connolly, Micklewright and Nickell (1992), Currie and Thomas (2001)). The information for the quality indicators is derived from the student and school questionnaire released by PISA 2018.

To investigate how pre-primary attendance and other determinants affect students' performance in reading and science, Gini-BMA approach is employed by calculating the weighted average of model specific estimates using Gini estimates. The weights attached to each estimate is identical to posterior model probabilities. As a baseline estimation, a universe of all potential models using 33 covariates is taken into consideration. Results are provided for each of the selected countries that participated in PISA 2018. Being totally agnostic about whether any of these regressors is included in the true model, a prior probability of 0.5 is attached to each one, implying a uniform model prior. Regarding the parameter space, the unit information prior (UIP) is adopted, where the integrated likelihood is proxied by the Schwarz Information Criterion (SIC).

Exploiting the information found in the student questionnaire, a detailed description regarding the years of attendance in pre-primary schooling is provided for each country. It should be noted that all this institutional background information is dated back to 2006, when most of the sampled students were at the age of three. Surprisingly, it is found that, although the duration of the pre-primary cycle is more than one year in most of the countries, most students report a pre-primary experience shorter than the official one. This can be attributed to the fact that pre-primary education was not compulsory for students below the age of five and/or six for most of the countries in the sample.

Regression results show that attendance of pre-primary institutions has a salutary impact on PISA test scores for 15-year-old students in many countries. Czech Republic (Czechia), Costa Rica, Germany, Hong Kong and Kazakhstan are among those countries who benefit the most with more years of experience in pre-primary schooling. Korea, in contrast does not seem to benefit with five or more years of attendance in pre-schooling. In Finland, early childhood education seems to have positive effect on both science test scores and on reading performance. This positive effect on reading test scores appears to hold in Singapore too. In Bosnia and Herzegovina is optimal to attend pre-primary schooling at the age between three and four years old since it creates positive externalities for students' science and reading performance. However, the extension of early childhood education in Canada and the United Sates coincides with a decline in students' outcomes in both science and reading (a result confirmed by Schulman et. al. (1999), Barnett et.al (2004), Baker et. al. (2005), Manguson et. al. (2007), Cascio (2009)). Most of the findings arrived at in this study are in accordance with the existing literature (Fredriksson (2006), Niikko and Havu-Nuutinen (2009), Lorence and Dworkin (2006), Black et.al. (2011), Ting (2007), Li (2004)), Baker et. al. (2005), Berlinski et. al. (2008), Cascio (2009), Schütz (2009), Kupiainen et.al. (2009), Turunen (2012)).

The contribution of this paper to the current literature is fourfold. First, it is an important contribution to the narrow literature that focuses on the factors that affect students' performance in reading literacy and science, and particularly is the first study that analyzes extensively the preschool landscape universally. Most importantly, it tempts to shed a light on the following question: Does pre-primary education consist a crucial factor for students' performance in reading and science, and if yes, in which countries and under what conditions? Second, this is among the very first studies that exploit OECD's PISA 2018 dataset. It should be noted, however, that all this institutional background information related to pre-primary education is dated back to 2006, when most of the sampled students were at the age of three. So, all the conclusions derived from this paper regarding the associations between students' performance in reading literacy and science and the set of variables related to attendance in pre-primary education, are placed 15 years ago. To examine how is the situation in 2021 and if there is an improvement or not, future research and the upcoming PISA 2033 dataset are necessary and will give the answer. Third, this paper is one of the few studies to use Bayesian Model Averaging framework to answer the aforementioned research questions. Due to the substantial number of possible explanatory variables provided by PISA 2018 questionnaires and to the weakness of the existing literature to present a model specification guide and a set of possible explanatory variables, this framework permits to consider a wider range of possible explanatory variables and to end up with those that can effectively explain the relationship, by addressing model uncertainty in the model selection process sussessfully. Finally, it is the first time that Gini regression methodology is incorporated into the BMA one, to calculate the variables' coefficients.

The rest of the paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 presents the BMA methodology and details the theory for Gini regression coefficient. Section 4 describes the data and documents background information on students' experience in pre-primary education. Section 5 lays the empirical strategy and reports the estimated effects. Section 6 evaluates the robustness of the main findings. Section 7 concludes.

2 Literature Review

A growing literature is increasingly acknowledging the importance of early childhood interventions as an indispensable tool in nations building, as it has been argued that early interventions determine educational and labour market outcomes later in life (Cunha, Heckman, Lochner and Masterov,2006). As early childhood is considered a susceptible period for brain development and language acquisition (Heckman, Krueger and Friedman (2002); Knudsen, Heckman, Cameron and Shonkoff (2006)), pre-primary education assures a smooth transition to primary education and establishes the basis for later learning. A study by Carniero and Heckman (2003) points out that investments in human capital have dynamic complementarities and that skills obtained early in the child's lifetime expedite the development of additional future skills. So, early learning makes subsequent learning easier and generates important benefits in terms of medium and long-term schooling and socio-economic outcomes.

Early exposure to pre-primary schooling engenders supportive environment for the new intakes to easily adjust to formal school and develop essential social skills that lead to peer acceptance and academic achievement. (Myers 1992; Knight and Hughes 1995). Evidence abounds in the literature of the direct link between pre-school experience and academic performance. Entwisle and Alexander (1993) relate later school achievements to the children's academic skills obtained at school entry, while Berlinski et. al. (2009) links pre-primary school education to short-term gains in test scores and behavioral outcomes (e.g. attention, class participation, effort, and discipline). However, as is indicated by Behrman and Birdsall (1983), focusing exclusively on the quantity of pre-schooling might lead to misleading results because the variation in quality is substantial too. Using five different structural quality indicators, Bauchmüller et. al. (2014) find persistent, although modest, positive relationships between high quality early childhood care and children's test outcomes at the end of the primary school's 9th grade. In contrast, Chetty et.al. (2011) argues that high quality has a positive impact in cognitive development but is not lasting, since it fades out after few years. Goodman and Sianasi (2005) find that early education is related to improvements in cognitive skills at age 7, but the impact is short-lived since it remains important throughout the schooling years up to age 16. Similarly, using data from the Early Childhood Longitudinal Study, Manguson et. al. (2007) show that pre-school enrolment in the United States is associated with higher reading and mathematics skills at the time of entry into the first grade, but these effects dissipate for most children by the end of the first grade.

There are several reasons that justify the diminishing trend of/in gains from early childhood interventions. Esping-Andersen et. al. (2012) and Reynolds (1993,2000) state that children at risk due to family's low-income, poverty and other related factors cannot secure a continuous development if there is no a coherent, continual and adequate support provided by government funded preschool and primary grade intervention programs. Specifically, Zigler and Berman (1983) mention that a one-year intervention cannot "inoculate a child against continuing disadvantage" (p.898). Barnett (2011) mentions that interventions are not compelling when graduates from the early educational intervention programs attend public schools with limited efficiency. Further, Schulman et. al. (1999) and Barnett et.al (2004) acknowledge that although most of the states, across the United States, have established prekindergarten curriculum standards, they differ in terms of quality, accessibility and availability of resources. Most importantly, few of them have established mechanisms to implement these comprehensive standards/prekindergarten initiatives.

Along with the early childhood interventions, many studies have found that home conditions are another crucial determinant of child's educational achievement (Bjorklund and Salvanes,2011). Both Velez et.al (1993) and Wößmann (2005) agree that, apart from preschool attendance, parental involvement and family features are key components in students' performance. A child's development begins within the family and depends on the parents' educational and cultural levels (Wößmann, 2005). Waldfogel and Washbrook (2011, and press b) support that parents that are educated and receive high income, spend more time to prepare their children's reading skills. In contrast, parents with lower income and less education have more possibilities to engage in harsh and incompatible parenting teaching behaviours that may negatively affect child's progress. Becker (1981, 1985) and Becker and Tomes (1986) embrace the theory of family to provide a reasonable justification for the failure of preschool education. Many authors correlate family's income with the quality of pre-school education too (Bainbridge et al., 2005; Magnuson and Waldfogel, 2005; Meyers et al.,2004). Low-income families are less likely to enrol their children to pre-school care, and if they do, they are most likely to be characterized by low-quality. In contrast, children from prosperous families are more likely to be registered in high-quality pre-schools. Attending systematically poorer quality pre-schools is an additional reason why gains from pre-school may eventually fade (Esping-Andersen et. al.,2012).

Expanding pre-primary education is an effective instrument to improve school progression and raise average achievement for less advantaged children. Extensive research has been conducted both on the short-run and long-run effects (see among others Barnett (1992), Barnett (1995), Danziger and Waldfogel (2000), Currie (2001), Blau and Currie (2006), Ludwig and Miller (2007)). Dumas and Lefranc (2010) find that extending pre-school enrolment in France is beneficial in terms of schooling outcomes, including test scores, for children from disadvantaged households. Heckman et. al. (2013) evaluate the results of the early childhood education Perry Preschool program that targeted to children from economically disadvantaged families. Outcomes reveal that children who participated in this program tended to create improvements in personality skills and enhance academic motivation. In particular, there is a boost in the long-term achievement test scores, with the effect being stronger for girls than for boys. Research suggests that disadvantaged children take the greatest advantage if, these special programs are of high quality (Gormley et al. (2005), Heckman and Lochner (2000), Neuman, Kamerman, Waldfogel, and Brooks-Gunn (2003), Reynolds et al. (2011), Waldfogel (2006)). Although there is ample empirical evidence that early childhood intervention programs have significant positive effects on the results of children from disadvantaged or minority background, it is not clear whether such pre-school programs influence the outcomes of children in the population as a whole. As typical preschool or prekindergarten programs vary in the quality of learning environments they provide and in the availability of financial resources, little is known about whether universal intervention can promote children's cognitive and academic outcomes (Gilliam and Zigler (2001)).

Many recent papers document the effects of universal preschool enrolment on the education of children in the entire population in a variety of other counties. Estimates obtained for developing counties testify positive and in some cases long-lasting effects of preschool attendance. Exploiting the information given by the Uruguayan Household Survey, Berlinski et. al. (2008) notice that attendance in pre-primary education reduces the probability for grade retention, grade failure and early drop-out during the primary and secondary schooling years. Aguilar and Tansini (2012) recognize that early exposure to pre-primary education has a positive effect on children's performance in the first year at public schools in Montevideo, Uruguay, and this effect remains positive but weakens after six years. Berlinski et.al. (2009) study the effects of Argentina's expansion of universal pre-primary schooling and find that pre-primary education positively affects third grade standardized Spanish and Mathematics test scores as well as students' behavioral skills. Taiwo and Tyolo (2002) notice that first grade Botswana students with pre-school experience achieve higher scores in English language, mathematics and science compared to students without such an experience. Using data for Thailand obtained from the Programme of International Student Assessment (PISA) for the years 2009 and 2012, Pholphirul (2017) reveals that pre-schooling attributes positively on cognitive skills in reading, mathematics and science with the mother's education attainment being a decisive factor on child's enrollment to preschool. According to this information, early exposure to pre-primary schooling appears as a successful and cost-effective policy to prevent late entry, early drop-out rates and early grade failure in poor countries, where large share of young population is excluded from compulsory education already at an early age (UNESCO, 2005).

There is considerable evidence for the impact of universal early childhood schooling in developed countries too. Using Census data, Cascio (2009) examines the long-run results of an expansion in universal kindergarten in the late 60s and early 70s across the United States. She reports no effect on the labour market outcomes and regarding the educational ones, the only positive influence is the reduction in grade retention. Goux and Maurin (2008) apply a difference-in-difference approach and find that one additional year in pre-elementary school in French has no important effect on children's subsequent educational skills. Baker et. al. (2005) show that the establishment of full-time and highly- subsidized kindergartens in the Canadian province of Quebec in the late 1990s, corresponds to an increase in the labour supply by married women and a decline in children's outcomes. Similarly, Dickson (2012) displays that the extension of free early education in the UK to all three -year- olds does not have any impact on reading, writing and mathematics when children reach the age seven. Only for deprived Local Education Authorities the results turn to be positive. In contrast Gormley and Gayer (2005) find that Oklahoma's universal pre-school program contributes positively to cognitive scores. In Japan, the expansion of both kindergartens and nursery schools is associated with higher achievement rates both in high school and college (Akabayashi and Tanaka (2013)).

A subject of considerable debate in recent years has been the age of starting school. While most counties recognize the age of six years old as the staring age of the compulsory education, several others allow individual children to enter school either before compulsory school age or after. Those in favour of children starting school at an early age argue that young children can get a head start in learning because they are able to understand the formal skills intrinsic in the school curriculum. Especially children from disadvantaged households can get the maximum advantage from early start. Leuven et. al. (2010) confirm that one additional month of education in school system in the Netherlands, increases language and math scores of children from less advantaged backgrounds while for non-disadvantaged students there is no effect. Unlike, many papers have shown a consistent pattern that children who start school later tend to score higher on school tests. However, a distinction between school starting age effect and direct age -at- test effect in needed. Children who start school with a delay, achieve higher test scores because they are simply older compared to their counterparts and being older provides an advantage or because starting school at an older age provides direct benefits. Black et.al. (2011) separate these two effects and find that starting school younger has a small positive effect on IQ test scores at the age 18 and on earnings, but this second effect fades by the age of 30. It seems that school starting age have both short and long run effects on children's outcomes, but the sing of its effect is theoretically ambiguous.

3 A combination of BMA methodology and Gini Regression Coefficient

Classical Statistical Analysis disregards the theory and specification uncertainty, which jointly refer to as model uncertainty. As indicated by Leamer (1983), whimsical decisions about choice of functional forms and control variables leads to fragile inferences based on economic data. Bayesian Model Averaging (BMA) has successfully addressed model uncertainty in the model selection process, providing a comprehensible mechanism to embody ambiguity into conclusions about parameters. To construct estimates, it does not condition on a specific set of theories and covariates, but rather extracts information from a universe of candidate models. The result is a weighted average of model specific estimates, where posterior model probabilities are employed as weights.

Bayesian Model Averaging (BMA) methodology is applied on this dataset, which moves the focus of analysis from estimates obtained from a given model, to estimates that do not depend on a particular model specification but rather use information from all candidate models. Thus, inference is averaged over models, forming a weighted average of model specific estimates where the weights are given by the posterior model probabilities. Due to the substantial number of possible explanatory variables provided by PISA 2018 questionnaires and to the weakness of the existing literature to present a model specification guide and a set of possible explanatory variables, this framework permits to consider a wider range of possible explanatory variables and to end up with those that can effectively explain the relationship. To estimate the coefficients, Gini regression methodology is incorporated into the BMA. The Gini methodology is a rank-based regression methodology that takes into consideration both the variate values and their ranks and it is based on the Gini Mean Difference (GMD) as a measure of dispersion. Among the two types of Gini regression coefficients that can be attributed to GMD, the focus has been on the semi-parametric approach. The semi-parametric nature of the Gini regression coefficient is justified because it does not rely on the linearity assumption nor on any distributional assumptions and the regression coefficients can simply be interpreted as weighted average of slopes. Even though both the OLS and Gini share an underlining linear structure, they differ in that the estimated marginal responses (estimated beta coefficients) are generated differently and in the case of the Gini in a much more robust fashion. This fits well in using a BMA approach that relies on the uncertainty that surrounds the estimates of beta coefficients. Using alternative semi-parametric methods based on local smoothers (Pagan and Ullan (1999)) would not lend themselves directly to the use of BMA since the estimation of marginal effects would not be expressed in a single coefficient as in the case of both OLS and Gini.

3.1 Bayesian Model Averaging (BMA) Methodology

BMA provides a probabilistic framework to simultaneously deal with model and parameter uncertainty.To describe the relationships between all the unknown parameters and the data, a joint probability distribution is needed. To construct estimates, instead of conditioning on a single model, a model space M= $\{M_1,\ldots,M_k\}$ is taken into consideration, whose elements cover all the possible regressors suggested by the literature. For multiple model setups, it proceeds by assigning prior probability distributions to each model and to the parameters of each model. Combining those priors with the distribution for the data and conditioning on the data, results in the posterior distribution of model uncertainty, which allows for model selection and inferences[1].

Considering the case of normal linear regression models, model uncertainty occurs from the selection of the "best'' model, or alternatively, from the selection of the explanatory variables to include in the right-hand side:

$$Y = \beta_0 + \sum_{j=1}^{q} \left(\beta_j X_j + \varepsilon\right) = XB + \varepsilon \ , \ \varepsilon \sim N(0, \sigma^2 I_n) \qquad (1)$$

where Y and ε are nx1 vectors of the dependent variable and the error term respectively, X is a nxq matrix of candidate regressors that may or may not be included in the model, B is an nxq matrix with the parameters to be estimated and n is the total number of observations. If some of the elements of the parameter vector, $\beta = (\beta_1, \beta_2, \ldots \beta_q)$ equal zero, there are 2^q candidate models in total to be estimated, indexed by M_k for k= 1,….,2^q . Each of these models offers to explain the data and represents a distinct subset of the candidate regressors. For instance, model M_k takes the form:

$$Y = \sum_{j=1}^{q_k} \beta_j^{(k)} X_j^{(k)} + \varepsilon \qquad (2)$$

where Y is the dependent variable, ε is the normal error term, $X_1^{(k)},\ldots, X_{q_k}^{(k)}$ is a subset of $X_1,..X_q$ and $\beta = (\beta_1^{(k)},\ldots, \beta_{qk}^{(k)})$ is a vector of regression coefficients to be estimated. The vector $\theta_k = (\beta_0, \beta^{(k)}, \sigma)$ summarizes the parameters for the given model M_k. . By attaching a prior probability $p(M_k)$ to each model and a prior probability distribution $p(\theta_k \mid M_k)$ to the parameters of each model, a joint distribution over the models, the data and the parameters can be expressed as follows:

$$p(D, \theta_k, M_k) = p(D|\theta_k, M_k)p(\theta_k|M_k)p(M_k) \qquad (3)$$

where $p(D \mid \theta_k, M_k)$ represents the likelihood function of model M_k which embodies all the information about the vector θ_k that is given by the data, D[2].

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[1] For an excellent and detailed explanation of Bayesian model averaging see Raftery, Madigan, Hoeting (1997), Hoeting, Madigan, Raftery and Volinsky (1999), Sala-i-Martin (1997), Clyde and George (2004), Chipman, George, McCulloch (2001) and Steel (2020).

[2] According to Chipman et.al. (2001) and Clyde and George (2004), this prior information incorporates all these different models into one hierarchical mixture model (or, full model otherwise). The procedure to realize the data consists of three phases: first, the prior model distributions $p(M_1), \ldots p(M_k)$ are used to generate the model M_k. After deciding for the model, the parameter vector θ_k is generated using the prior probability distribution $p(\theta_k \mid Mk)$. In the last step, the likelihood function $p(D \mid \theta_k, M_k)$ of the selected model M_k is employed to generate the data D.

Establishing this prior formulation, the model uncertainty problem becomes that of finding the model M_k that was generated by the prior model probabilities $p(M_1),\ldots,p(M_k)$ and actually generated the data D. Conditioning on the observed data and applying Bayes' theorem, the probability that M_k is the true model is given by the posterior model probability:

$$p(M_k|D) = \frac{p(D|M_k)\, p(M_k)}{\sum_k p(D|M_k) p(M_k)} \qquad (4)$$

where p (D | M_k) is the marginal or integrated likelihood of model M_k, given, after applying the law of total probability, by[3]:

$$p(D|M_k) = \int p(D|\, \theta_k, M_k)\, p(\theta_k|M_k) d\theta k \qquad (5)$$

The posterior model probability summarizes all the information contained in the data and presents a complete and consistent outline of post-data uncertainty. Thus, it can be treated as a measure of support for model M_k and it can be used as a model weight in BMA.

The posterior distribution of a quantity of interest, Δ, which is not model-specific, given the data D, is obtained through mixing the model-specific posterior distribution from each individual model:

$$p(\Delta|D) = \sum_{k=1}^{2^q} p(\Delta|M_k, D) p(M_k|D) \qquad (6)$$

where p (Δ| M_k, D) is the posterior distribution of Δ given a particular model M_k.

Taking into consideration the above framework, the Bayesian model average estimator for the slope parameters is determined by the posterior mean, defined by:

$$E\left[\beta_j^{BMA}\right] = \sum_{\kappa=1}^{2^q} p(\Delta|M_\kappa, \Delta) p(M_\kappa|D) \qquad (7)$$

where $\beta_j^{(k)}$ is the posterior mean under model M_k and equals zero if X_j is not included in the model M_k[4]. That is, the posterior mean is the weighted-average of the model-specific posterior means, where the posterior model probabilities are employed as weights.

The posterior variance for the Bayesian model average estimator is expressed as:

$$Var\left[\beta_j^{BMA}\right] = \sum_{k=1}^{2^q} \left(Var\left[\beta_j^{BMA}|D, M_\kappa\ \right] + \beta_j^{(k)}\right) p(\,M_\kappa|D) - E\left[\beta_j^{BMA}|D\right]^2 \qquad (8)$$

where the first term captures the average of the posterior variances within models and the second one captures the variance of the posterior means across models (defined as the weighted average of the squared deviations of the model specific from the model averaged estimates). This implies,

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[3] When the prior probability distribution of parameters p (θ_k | Mk) is discrete, then summation replaces integration.

[4] According to Raftery (1993) and Drapper (1995), $\beta_j^{(k)} = E(\beta_j^{(k)}|\, D, M_k)$

that even if accurate estimates are calculated in all candidate models, there might be substantial uncertainty about the slope parameters, if those estimates differ across alternative specifications.

3.2 Gini Regression Coefficient

Although Least Squares methodology ranks as one of the most popular practices for estimating the relationship between a set of regressors on the conditional expected value of the dependent variable, it relies on certain assumptions, whose violations might result in non-robust estimates. The Gini regression, introduced by Olkin and Yitzhaki (1992), is proposed as an alternative. Its utilization is justified whenever the investigator wants to relax the traditional assumptions, such as the convenient world of normality and the linearity of the model. The Gini methodology is a rank-based methodology that takes into consideration both the variate values and their ranks and it is based on the Gini Mean Difference (GMD) as a measure of dispersion[5].

Between the at least 14 distinct presentations that exist for GMD, the focus has been on the formula that relies on covariances (Lerman and Yitzhaki (1984))[6]. That is, if F(X) is the cumulative distribution function (cdf) which is uniformly distributed on [0,1], the GMD is expressed as:

$$G = 4\,E\{X(F(X) - E[F(X)])\} = 4\,cov[X, F(X)] \qquad (9)$$

which is four times the covariance between a random variable X and its cumulative distribution function F(X).

There are two types of Gini regressions related to GMD. The first one, known as the R-regression (Hettmansperger (1984)), is based on the minimization of the GMD of the residuals. The second one, known as the semi-parametric approach (Olkin and Yitzhaki (1992)), imitates the OLS methodology by replacing the variance-based expressions by the equivalent GMD terms[7]. The combination of these two allows one to identify and test whether the implicit assumptions about the underlying distributions are supported by the data or not. Gini estimators are robust to the existence of extreme values or measurement errors and to the asymmetry of the distribution. Under that case, heavy tailed distributions can be used (Serfling (2010)) and only the first moment conditions are needed for the Gini methodology to be implemented (Stuart and Ord (1987, p.58)). Focusing on the second approach, and assuming a simple regression, the population semi-parametric Gini regression coefficient is based on the covariance presentation of the GMD and is obtained by replacing the covariance expressions in the OLS regression coefficient by the corresponding Gini covariances:

$$\beta^N = \frac{cov[Y, F(X)]}{cov[X, F(X)]} \qquad (10)$$

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[5] The GMD as a measure of spread/variability was first initiated by Corrado Gini (1912).

[6] For a complete overview of the Gini methodology, the reader is referred to Yitzhaki and Schechtman (2013).

[7] The Gini estimator taken by the second approach cannot be characterized as “the best” because it is not derived by solving a minimization problem. In contrast, the one derived by the first approach is optimal but it does not have an explicit presentation and it is only expressed numerically.

where F(X), the cdf of X, is represented by R(X), the regressor's rank[8].
For the case of multiple Gini regression coefficients, a set of linear equations composed of simple Gini regression coefficients must be solved. Starting from the multiple regression model, expressed in population parameters:

$$Y = a + \beta_1 X_1 + .. + \beta_K X_K + \varepsilon \tag{11}$$

and defining K random variables $R(X_1)$, $R(X_2)$,..,$R(X_k)$, the following identities hold:

$$cov(Y, R(X_1)) = \beta_1 cov(X_1, R(X_1)) + .. + \beta_K cov(X_K, R(X_1)) + cov(\varepsilon, R(X_1)) \tag{12}$$

$$cov(Y, R(X_2)) = \beta_1 cov(X_1, R(X_2)) + .. + \beta_K cov(X_K, R(X_2)) + cov(\varepsilon, R(X_2))$$

$$\vdots$$

$$cov(Y, R(X_K)) = \beta_1 cov(X_1, R(X_K)) + .. + \beta_K cov(X_K, R(X_K)) + cov(\varepsilon, R(X_K))$$

Setting

$$\beta_{\varepsilon j} = \frac{cov(\varepsilon, R(X_j))}{cov(X_j, R(X_j))}, \quad \beta_{kj} = \frac{cov(X_k, R(X_j))}{cov(X_j, R(X_j))}, \quad \beta_{0j} = \frac{cov(Y, R(X_j))}{cov(X_j, R(X_j))} \tag{13}$$

with k,j=1,2,…,K and dividing the three last equations by, respectively, $cov(X_1,R(X_1))$, $cov(X_2,R(X_2))$, and $cov(X_k,R(X_k))$, under the assumption that $cov(X_k,R(X_k)) \neq 0$, (k= 1,2,..,K), yields:

$$\beta_{01} = \beta_1 1 + .. + \beta_K \beta_{K1} + \beta_{\varepsilon 1} \tag{14}$$

$$\beta_{02} = \beta_1 \beta_{12} + .. + \beta_K \beta_{K2} + \beta_{\varepsilon 2}$$

$$\vdots$$

$$\beta_{0K} = \beta_1 \beta_{1K} + .. + \beta_K \beta_{KK} + \beta_{\varepsilon K}$$

where the index 0 illustrates the dependent variable, $\beta_{\varepsilon j}$ and $\beta_{kj}$are the regression coefficients in the simple regressions of X_k on $R(X_k)$ and β_{0j} are the semi-parametric Gini regression coefficients as given in presentation (10).
Rearranging, defining the following column vectors β_0= (β_{01} , β_{02},…, β_{0K}), β_ε= ($\beta_{\varepsilon 1}$, $\beta_{\varepsilon 2}$,.., $\beta_{\varepsilon k}$) and provided that the rank of the matrix that consists of the β_k's coefficients is K, it comes:

$$\begin{bmatrix} \beta_1 \\ \vdots \\ \beta_K \end{bmatrix} = \begin{bmatrix} 1 & \beta_{21} & \dots & \beta_{K1} \\ \vdots & \vdots & & \vdots \\ \beta_{K1} & \cdots & & 1 \end{bmatrix}^{-1} \begin{bmatrix} \beta_{01} - \beta_{\varepsilon 1} \\ \vdots \\ \beta_{0K} - \beta_{\varepsilon K} \end{bmatrix} = A^{-1} [\beta_0 - \beta_\varepsilon] \tag{15}$$

[8] Empirically the regressor's rank R_x is computed by the formula $R(X) = \frac{\sum_{i=1}^{N} R(X_i)}{N}$.

where A^{-1} is a K x K matrix while the β's are K x 1 vectors.
Imposing the set of restrictions, known as "orthogonality conditions", described by:

$$\beta_{\varepsilon k} = 0\,,\; for\; k = 1,2,..,K \tag{16}$$

the identities of (15) turn into:

$$\begin{bmatrix}\beta_1\\ \vdots\\ \beta_K\end{bmatrix} = \begin{bmatrix}1 & \beta_{21} & \cdots & \beta_{K1}\\ \vdots & \vdots & & \vdots\\ \beta_{K1} & \cdots & & 1\end{bmatrix}^{-1}\begin{bmatrix}\beta_{01}\\ \vdots\\ \beta_{0K}\end{bmatrix} = A^{-1}\beta_0 \tag{17}$$

or equivalently

$$\beta^{GINI} = \begin{bmatrix}1 & \beta_{21} & \cdots & \beta_{K1}\\ \vdots & \vdots & & \vdots\\ \beta_{K1} & \cdots & & 1\end{bmatrix}^{-1}\begin{bmatrix}\beta_{01}\\ \vdots\\ \beta_{0K}\end{bmatrix} = A^{-1}\beta_0$$

The previous expression shows the Gini estimator β^{GINI} is a function of slope coefficients of semi-parametric simple Gini regressions β_0. Consequently, it is a semi-parametric Gini estimator.
Since, most of the concepts and parameters in the Gini framework are parallel in structure to the OLS framework, it is natural to view presentation (10) as an OLS instrumental variable (IV), where F(X)=R(X) serves as an instrument[9]. According to Olkin and Yitzhaki (1992), when the model is given by:

$$Y = X\,B^{GINI} + \varepsilon \tag{18}$$

where Y is the dependent variable (N x 1 vector), X ≡ $[x_{ik}]$ is the matrix of regressors (N x K with the first column of ones), B^{GINI} is the vector of parameters to be estimated (K x 1) and ε is the vector of errors (N x1), the semi-parametric Gini regression yields an estimator of β^{GINI},

$$\beta^{GINI} = (R_x'\,X)^{-1}\,R_x'\,Y \tag{19}$$

where R_x = R(X).

4 Data

Employing the database of the 2018 round of the Programme for International Student Assessment (PISA 2018), this paper evaluates the impact of pre-primary education and quality indicators on the later schooling outcomes, approximated by science and reading test scores.

[9] Although the Gini regression framework can imitate the OLS concepts, they differ in interpretations and properties. Under the Gini IV analysis, the concept of IV is applied twice. As a first step, the sample's empirical cumulative distribution function replaces the variable, without questioning the validity of the rank to serve as an IV. As a next step, another variable that satisfies all the conditions from an IV perspective is required (Yitzhaki and Schechtman (2004)).

4.1 The PISA 2018 Database

The OECD Programme for International Student Assessment (PISA) 2018 is conducted in 79 developed and emerging countries and economies, including all 37 OECD member countries. It evaluates the students' problem-solving skills, concept understanding and their ability to use the acquired key knowledge to meet social and economic life-challenges. It is a triennial survey, where science, reading and mathematics are one of the major domains in each study. In 2018 (2009 and 2000, respectively), the focus is in reading literacy[10] with less detailed testing in science and mathematics (OECD,2018). For this reason, this paper employs the achievement on reading literacy as the dependent variable.

A total number of 602,004 students completed the computer-based assessment[11], which was designed as a two-hour test. The target population consists of students aged between 15 years 3 months and 16 years 2 months, having completed at least 6 years of formal education. Choosing age instead of grade level as a criterion for students' qualification to participate in this assessment, PISA ensures a consistent comparison among students' skills, who are at the end of their compulsory schooling. To provide a broader and more clear view of the student background, school characteristics and institutional performance, students, the principal of their school, and optionally teachers and parents, are asked to respond to questionnaires[12]. This additional information extracted from the questionnaires, is used in this paper to determine the quality indicators that explain variation in student achievement.

A two-stage stratified sampling practice is employed by most countries to draw a representative sample of the total 15-year-old students tested in each country. As a first step, a random sample of at least 150 schools is selected. In the case where the number of schools is less than 150 in a country, all the schools are taken into consideration. The methodology applied is referred to as Probability Proportional to Size (PPS), where the school's size depends on the estimated number of 15-year-old students enrolled in each school. As a second step of this sampling procedure, approximately 42 15-year-old students that belong to the sampled schools, are chosen. The probability of each 15-year-old student in a sampled school to sit the PISA test is equal. In the sampled schools with the targeted age group consisting of less than 42 students, all these students are included into the sample. Both schools and individual students are subject to eligibility requirements and exclusion principles to assure systematic inclusion of the focus group[13].

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[10] According to PISA 2018 (OECD,2019, p.34) reading literacy is understanding, using, evaluating, reflecting on and engaging with texts in order to achieve one's goals, to develop one's knowledge and potential, and to participate in society.

[11] Only 9 countries used paper-based delivery to sit the PISA assessment. Among those are: Argentina, Jordan, Lebanon, the Republic of Moldova, the Republic of North Macedonia, Romania, Saudi Arabia, Ukraine and Viet Nam.

[12] The five additional optional questionnaires offered in PISA 2018 assessment are: computer-family questionnaire, well-being questionnaire, educational career questionnaire, parent questionnaire, teacher questionnaire.

[13] A more detailed description of the PISA Sampling design can be found in PISA 2018, Technical report, Chapter 4.

4.2 The Student-Level Micro Database

Apart from the achievement data in reading literacy, science and mathematics for the target population of 15-year-old students in the participating countries, PISA 2018 releases/presents additional background information on both students and schools. Two separate questionnaires are provided: 1) a student questionnaire answered by each individual student, with questions that refer to personal characteristics and family background and 2) a school questionnaire answered by the school principals, with questions that refer to educational and organisational characteristics of each school. Besides these two, in PISA 2018 assessment, five additional and optional questionnaires are provided. However, due to the substantial amount of missing observations in these auxiliary questionnaires, only the student and the school questionnaires are used as a supplementary source of information.

The dataset consists of the students' test scores in reading literary and 33 quality indicators relative to students', families' and schools' characteristics. All the qualitative variables are transformed into dummy variables for estimation purposes and all missing observations (7,475 in number) on the questionnaire items are discarded. In total 22 countries are taken into consideration with the final data sample containing 177,813 students. This includes 127,917 students in 17 OECD countries and 49,896 students in 6 Non-OECD countries. Table 3 summarizes all the variables employed in this paper. In particular, it includes description of the variables, the original variable names, the original versus missing data for each variable and the belonging questionnaire that are extracted from. The abbreviation STXXX corresponds to student questionnaire while the SCXXX corresponds to school questionnaire.

4.3 Pre-Primary Attendance and International Standard Classification of Education (ISCED 0)

According to revised International Standard Classification of Education (ISCED 2011), ISCED 0 refers to the early childhood education and includes all the early childhood programmes that aim to develop cognitive, physical and socio-emotional skills necessary for participation in school and society (p.19, Education at a Glance 2018: OECD Indicators). All these programmes that belong to this initial stage of organized instruction are often discriminated by the typical entrance age. Usually they are designed for children aged at least three years old. However, there are countries where children at age two can participate in pre-primary education[14]. In this paper, all the essential information on students' experience in pre-primary education is collected from the student questionnaire. In question ST125Q01, students are asked the following question: "How old were you when you started <ISCED0>?". The following 8 answer categories are provided: "1 year or younger"; "2 years"; "3 years"; "4 years"; "5 years"; "6 years or older"; "I did not attend <ISCED0>"; "I do not remember".

A detailed description on the repetitiveness/frequency for each answer category regarding the attendance in pre-primary education is shown in Table 1. This information is accompanied by the total number of students who sit the PISA 2018 assessment in each country, the number and the

[14] See Table 1 for a detailed description.

percentages of missing observations and the remaining number of student observations for which information on pre-primary education is available. Among these 23 countries, Canada is the one with the highest number of students (21,434 in total) who provide information on their pre-primary experience. Kazakhstan, Argentina and Australia follow with 19,109, 18,495 and 12,784 students respectively. Regarding the percentage of missing observations, Singapore retains the first position with 17,37% of students not having reply. Then follow Germany (13,48%), Australia (10,43%), Bosnia and Herzegovina (6,74%) and Canada (5,38%). For the remaining countries, the percentage of missing observations fluctuates below 5%. Since this variable is crucial for the analysis that follows, all the students with missing observations are excluded from the data sample.

Regarding the non-attendance in pre-primary education, presented in the first column of Table 1, Bosnia and Herzegovina appear to have the highest percentage (50,8%) since 3,070 out of 6,043 students do not have any pre-primary experience. Non-attendance is still significant in Kazakhstan but already below 50% (38,56%). In Poland and the USA non-attendance rates are still above the 10 percent level (13,89% and 13,08% respectively), but for the rest countries the percentages move below that level.

Columns 2 to 8 demonstrate the seven categories related to pre-primary attendance accompanied with the students' shares in each one. Students who attend pre-primary education at the age one or less are a minority compared to students who attend pre-primary education at age two or older. In the first case and for most of the countries, the percentage rates are below 5%. Only in Sweden and Singapore, the rate is above that limit reaching the 21% and 26% respectively. In the second case, all the countries report a percentage rate above 50% with only exception Bosnia and Herzegovina which reports a rate equal to 37,81%. This might be related to the fact that half of the students in that country do not have pre-primary experience. Among the categories presented in columns 3 to 7, the one with the highest frequency is the attendance in pre-primary school at the age between three and four years old with twelve out of twenty-three countries displaying a rate above 50%. Attendance in pre-primary school at the age between two and three years old occurs most regularly in seven of the remaining countries, with the rate ranging between 44% and 75%. The last four countries, Singapore, Bosnia and Herzegovina, Korea and Costa Rica, report higher student shares for the category attendance in pre-primary school at the age between four and five years old, with rates 14,77%, 19,18%, 45,74% and 47,76% respectively.

Table 2 demonstrates how many students with pre-primary experience attend pre-primary education for one year or less or for more than one year. Evidences show that for most of these students, participation expands up to one year or less. For this category, most countries report a percentage rate that ranges between 76% and 97%. The only exceptions to this rule are Sweden and the United States, with the percentages still being sizeable but lower (60% and 68% respectively).

Structural qualities of pre-primary education are also illustrated in the last three columns of Table 2. These refer to the entrance age into the pre-primary education, the duration of pre-primary experience and the entrance age into the primary schooling. This institutional background information is dated back to 2006, when most of the sampled students were at the age of three. Surprisingly, although the duration of the pre-primary cycle is more than one year in most of the countries, the majority of students report a pre-primary experience shorter than the official one. This can be attributed to the fact that pre-primary education was not compulsory for students below the age of five and/or six for most of the countries in the sample. For instance, Poland introduced the compulsory pre-school education at the age of 6 in 2004 (OECD, 2006). Australia, Canada and Ireland are among the very few countries where the official duration of pre-primary schooling is one year. The percentages displayed are 77%, 81% and 81% respectively.

5 Pre-primary attendance and PISA Achievement

This section presents the empirical results on the relationship between pre-primary education and PISA science test scores. This relationship is estimated separately for each of the 22 countries by using the same sets of control variables. However, for some countries few of the variables are excluded due to the lack of observations. Pre-primary education is defined as the attendance in pre-primary schooling for more than one year.

5.1 Empirical Specification – Baseline Exercises

To investigate how pre-primary attendance and other determinants affect students' performance in science, Gini-BMA approach is employed by calculating the weighted average of model specific estimates using Gini estimates[15]. The weights attached to each estimate is identical to posterior model probabilities. As a baseline estimation, a universe of all potential models using 33 covariates is taken into consideration. Results are provided for each of the selected countries that participated in PISA 2018. Being totally agnostic about whether any of these regressors is included in the true model, a prior probability of 0.5 is attached to each one, implying a uniform model prior. Regarding the parameter space, the unit information prior (UIP) is adopted, where the integrated likelihood is proxied by the Schwarz Information Criterion (SIC).

Table 4 and Table 5 display the findings for the Gini-BMA analysis for the students' performance in science and reading respectively. For each country, the first column shows the posterior inclusion probability that each of the covariates is included in the truth model, while the second and the third columns present the BMA unconditional posterior mean (PSE) and posterior standard deviation (PSD) for each regressor. A covariate is identified as a "robust" determinant, if the posterior inclusion probability exceeds 50%[16]. Apart from the candidate regressors that refer to the number of years attending pre-primary education, the rest reveal information on the students' and their families' backgrounds and on the schools' resource endowments and location.

5.1.1 Empirical Results for Science

The Program for International Student Assessment (PISA, 2018) results ranks 15-year old Finnish comprehensive school students among the top performers in reading, mathematics and science

[15] An alternative extension for the calculation of the estimates can be found in Kourtellos, Stengos and Tan (2013), Durlauf, Kourtellos and Tan (2012) and Eicher, Lenkoski and Raftery (2009), who incorporate the 2SLS estimator into the BMA methodology.

[16] In the paper " Trade Creation and Diversion Revisited: Accounting for model uncertainty and natural trading partner effects", Eicher, Henn and Papageorgiou (2012), following Kass and Raftery (1995), classified the strength of evidence of a regressors' effect into the following categories, sorted by the PIP: if PIP<50%, there is lack of evidence for the effect, if 50%<PIP<75% there is weak evidence for the effect, if 75%<PIP<95% there is positive evidence for the effect, 95%<PIP<99% there is strong evidence for the effect, if 99%<PIP<100% there is decisive evidence for the effect. These cut-offs form an approximation and are not based strictly in statistical theory.

among the 79 countries included in PISA. Finland also records lower gap between the lowest and highest performing students in science compared to the average across OECD countries[17] and has small between-school variations (OECD, 2019). Complementary to these outcomes, and emphasising more to the factors that influence students' performance in science, as presented in Table 4, it seems that in Finland, among the 6 candidate regressors that represent attendance in pre-primary schooling, attending at the age between two and three is a robust determinant for later school success. As discussed by Fredriksson (2006), background family characteristics, a homogeneous Finnish school system and high qualified teaching staff are part of the reason for exceptional students' performance, while heavy investments in pre-primary schooling can also be an explanation to this. Also, in an evaluation of the Finnish national core curriculum for pre-schooling, during the academic year of 2002-2003, Niikko and Havu-Nuutinen (2009), find that pre-school teachers gave more emphasis on the academic skills such as reading, writing and mathematics.

Continuing the analysis for Finland, it seems that the regressors "*Repeat a grade*" and the "*Entrance age in primary education*" affect performance distinctly and in the same direction. Both appear to adversely influence science test scores. The results about the ineffectiveness of grade retention can be supported by other studies (Holmes and Matthews (1984), Meisels and Liaw (1993), McCoy and Reynolds (1999), Bonvin et. al. (2008), Hughes et. al. (2018)). Regarding the second factor, our results indicate that children who start primary school earlier tend to score higher on school tests in science. Recent work conducted by Leuven et. al. (2010) confirms this outcome. Unlike, many papers have shown a consistent pattern that children who start school later tend to score higher on school tests. However, a distinction between school starting age effect and direct age -at- test effect is needed**.** Children who start school with a delay, achieve higher test scores because they are simply older compared to their counterparts and being older provides an advantage or because starting school at an older age provides direct benefits. It seems that school starting age have both short and long run effects on children's outcomes, but the sing of its effect is theoretically ambiguous (Black et.al. (2011)).

At the "top of the class" on many of the internationally benchmarked tests on academic achievement, Singapore's exceptional/extraordinary performance in PISA 2018 has placed it among the world's best performing education systems. Singaporean students have the second highest mean performance in all three subjects (i.e. reading, mathematics, science) with their mean scores lay more than 50 score points above the average scores across OECD countries. Also, the number of very poorly performing students in science (under level 1) is among the lowest ones while the number of students with excellent records (above level 6) is the second highest compared to any other country (OECD, 2019). For Singapore, pre-primary experience appears to play a negative role on students' science test scores. Attendance for five years or more (i.e. "*Attendance at the age of one year or less*"), or for less years (i.e. "*Attendance at the age between two and three, four and five, five years old or more*") enter with high inclusion probabilities and negative Gini

[17] In science, the difference between high-achieving students (represented by the 95th percentile of performance) and low- achieving students (represented by the 5th percentile of performance) is more than 220 score points in all countries and economies, with the OECD average being equal to 323 score points. The smallest differences fount amongst countries with the lowest mean scores (e.g. Morocco, Dominican Republic, Albania, Turkey).

coefficients. Regarding the regressors "*Repeat a grade*" and the "*Entrance age in primary education*", the results are similar to Finland's.

The interest of raising the quality standards of pre-school education in Singapore and the introduction of new policies and key reforms might be a possible explanation for the negative role of pre-school experience on students' performance in science. Before 2003, Singapore's pre-school curriculum followed a traditional teaching method of instructional academic rote learning aiming to prepare children for primary school by enhancing academic skills in reading, writing and arithmetic through repetitious exercises and worksheets (Wong (2000), Ting (2007)). In January 2003, the Ministry of Education (MOE) commiteed to a new national pedagogical framework that geared towards more child-centered teaching with an empahsis on play, aimed to develop lifelong skills and learning and promote creativity through experiential and exploratory activities (Tharman (2005), Ng (2008)). Of course, this dramatic educational change in pre-school curriculum included a shift in teachers' roles, since teachers are key players in education (MOE,2003a). The goal was to reinforce the professional standard of preschool teachers by modifying their pedagogical approaches, skill development, teacher's education and qualifications. (IMIG (2004), MOE (2003a), MOE (2003c)). However, the new teacher-training framework requirements demanded a significant amount of effort and time from teachers' perspective. As a result, due to the pressures faced and the lack of time, teachers were faced with a persistent sense of more need to be done which threfore resulted in low quality work (Liew (2008)).

Two additional East Asian countries that consistently emerge top of the ranking league across the international comparative measures on academic performance are Hong Kong and Korea. In both countries, students score above the OECD average in all three courses. In Hong Kong, 11.8% of students reach either level 6 (top) or 5 (excellent) in science performance, while in Korea the percentage is 7.8% (OECD, 2019). For these countries, the factors that seems to enhance science test scores is the attendance in pre-primary schooling at the age between one and two years old. However, attendance for more than five years in pre-primary education (i.e. "*Attendance at the age of one year or less*"), the "*Repetition of a grade*" and the "*Entrance age in primary education*" have a considerable negative impact on science performance. It is interesting to note that parents in Hong Kong have overwhelming concerns about their children's academic progress. They embrace the belief that hard work is synonym to academic success and that academic achievement is the road for future prosperity and life enhancement (C.C. Lam et.al (2002), Li (2004)). Especially, a study directed by Fung and Lam (2008) confirms similar parental concerns in the academic year 2006-2007. Parental expectations and concerns are so strong and intense that not only they become more involved in the education of their children but also, they intervene in the professional mission of pre-school education and in the pedagogical practices adapted by teachers. However, this intervention creates an inconsistency between pedagogical practices and official expectations, since teachers emphasize more on intellectual matters and mastering learning skills and fail to take into consideration children's needs and interests, capabilities and levels of development (EMB, (2001), (2005)).

Canada and Costa Rica are the only countries where most of the regressors for pre-primary attendance enter with high posterior inclusion probabilities. For Canada, all the 6 variables referring to pre-primary experience play a negative role on students' test scores. Negative impacts have also been found in Baker et. al. (2005) who show that the establishment of full-time and highly- subsidized kindergartens in the Canadian province of Quebec in the late 1990s, corresponds to an increase in the labour supply by married women and a decline in children's outcomes. For Costa Rica, 5 out of 6 are robust determinants of students' performance in science, with attendance in pre-primary schooling for one year or less (i.e. "*Attendance at the age of five or more*") being excluded. While attendance for five years or more (i.e. "*Attendance at the age of one or less*") adversely influences students' performance, attendance for four, three or two years (i.e. "*Attendance at the age between one and two, two and three, three and four, four and five*") is highly beneficial. Our results are in line with the literature that uncovers positive and in some cases long-term impacts of preschool attendance for developing countries (Berlinski et. al. (2008), Berlinski et.al. (2009), Aguilar and Tansini (2012), Taiwo and Tyolo (2002), Pholphirul (2017)). According to OECD 2019 outcomes, Canada is included in the highest-performing OECD countries while Costa Rica scores below OECD average in reading, mathematics and science[18]. In contrast, in the United States, attendance in pre-primary schooling for five years or more (i.e. "*Attendance at the age or one year or less*") is the only robust determinant among the 6 potential ones and affects negatively the students' performance in science. Although the US scores above the OECD average in science[19], it does not belong to the group of highest-performing countries (OECD, 2019). In an evaluation study of the impact of the expansion in universal kindergarten in the late 60s and early 70s across the United States carried out by Cascio (2009), the researcher reports no effect on the labour market outcomes and regarding the educational ones, the only positive influence is the reduction in grade retention.

Two non-OECD countries located in South-East Europe and Central Asia respectively that underperform in all three courses in comparison to OECD average are Bosnia and Herzegovina and Kazakhstan, with the first one performing better compared to the second one. Focusing on the impact of pre-primary schooling on science test scores, the results are ambiguous. While attendance for more than five years (i.e. "*Attendance at the age of one year or less*") has a considerable negative impact in Bosnia and Herzegovina, it appears with a positive Gini coefficient in the case of Kazakhstan. However, attendance at the age between three and four years old has exactly the opposite effects. While it is beneficial for the first country, it adversely influences science test scores in the second one. In contrast, attendance for two years or less (i.e. "*Attendance at the age between four and five, attendance at the age of five years old or more"*) affects students' performance negatively in both countries.

Based on the above results, attendance in pre-primary schooling at the age between three and four years old creates positive externalities for students' science performance in Bosnia and Herzegovina. However, it should be mentioned that this country appears to have the highest percentage (50,8%) of non-attendance in pre-primary education among the rest of the countries, since 3,070 out of 6,043 students do not have any pre-primary experience (as presented in the first column of Table 1). Low levels of preschool enrollment are also confirmed by the Ministry of Civil Affairs of Bosnia and Herzegovina (2012) for the year 2011, when the country pocessed the second place in a list of countries with negative child preschool participation rates, while in 2013 the

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[18] In PISA 2018 assessment, the OECD average for reading, mathematics and science is equal to 485, 478, 486 respectively. For Costa Rica the mean score is equal to 426, 402 and 416.

[19] According to PISA 2018 assessment, the US average for science is equal to 502 score points while the OECD average is 486 score points.

country had the lowest participation rates in Europe and Central Asia (UNICEF 2013a).Camovic and Hondzic (2017) recognize that poverty and economic instability in this post-war transition country are among the basic factors that affect the infrastructure and the quality of kindergartens. It was only recently, in 2008, that the government began the process of declaring the strategic goals of its preschool system adapting the "Strategic directions for the development of education in Bosnia and Herzegovina with implementation plan 2008-2015" and building the Framework Law on preschool education in 2007.

For Kazakhstan, non-attendance is still significant in but already below 50% (38,56%) (as presented in the first column of Table 1). As mentioned above, our results imply that in this country, emphasis has been given in the quantity and not in the quality of education, since more years of pre-primary experience are beneficial for later outcomes. Indeed, Aitken (2012) acknowledges a reduction in the availability of kindergartens and a decline in the qulity in the period after/following Kazakstan's independence. However, children tend to reap the greatest benefits if preschool programmes are of high quality (Carneiro and Heckman (2003)). Most of the economic research on this topic recognizes that pre-primary education of exclusive quality is a high-yield investment with longstanding benefits (Gormley et. al. (2005), Heckman and Lochner (2000), Reynolds et. al. (2011)). Thus, policies that encourage childcare expansion should consider that improvements in both quantity and quality issues are crucial (Hanushek and Woessmann (2007)).

Czech Republic (Czechia) and Germany are two OECD countries located in Europe that outperform in science in comparison to OECD average. Based on OECD results, Germany's science mean score is higher compared to the science mean score of the first country. For Czech Republic (Czechia), pre-primary experience for five or more than five years (i.e. "*Attendance at the age between one and two years old*", and "*Attendance at the age of one year or less*"), or for two years (i.e. "*Attendance at the age between four and five years old*") are positively effective in science performance. Our positive estimates confirm prior research conducted by Schütz (2009). In Germany, more years of pre-primary education (i.e. "*Attendance at the age of one year of less*") appear to be beneficial. However, attendance in pre-primary schooling for one year or less (i.e. "*Attendance at the age between five years or more*") has a negative impact on primary schooling. This negative result might be attributed to the fact that the official duration of the pre-primary education cycle in Germany is 3 years (as presented in the third column of Table 2). So, even if students attended pre-school for one year or less, this is still a short time span as compared to the official one.

Additional robust determinants are also identified for students' performance in science. The variables "*Average time spent for mathematics*" and the "*Average time of class periods*" also enter with high inclusion probabilities and positive Gini coefficients for most of the countries. However, performance in Kazakhstan and Sweden is not affected by the first regressor and in the US and Singapore, it is not affected by the second one, while in Australia, Greece and Luxembourg it is adversely influenced by those two. Among the regressors that adversely influence science performance in more than half of the countries are the "*Repeat a Grade*"[20], "*Entrance age in*

[20] In Czech Republic (Czechia), Germany, Greece, Kazakhstan and Poland, the regressor "*Repeat a grade*" is excluded from the set of candidate regressors.

primary education", "*Not having a computer per student*" and the "*Average time spent for foreign language*".

"*Worrying about what others think of me in a case of a failure"* and "*Trying hard at school because it is helpful to get a good job*" are two regressors that have a positive impact on test scores in half of the countries. Only in Kazakhstan and Korea they appear with a negative Gini coefficient. Similarly, "*Having doubts for future plans in a case of a failure*" is another variable that positively influences performance in Australia, Canada, Czech Republic (Czechia), Finland, Poland and the United States. In contrast, "*Trying harder when I am in competition with other people*" is a factor with contradicting results on test scores. While in Finland, Hong Kong, Korea and Sweden it appears with a positive posterior mean in Belgium, Czech Republic (Czechia), Costa Rica, Greece, Italy, Netherlands and Singapore it appears with a negative one. The last regressor refers to the immigrant status of the student. Except from Australia and Singapore, in more than half of the countries, the variable "*Non-native students*" enters with an inclusion probability that ranges between 74% and 100% and its' marginal effect is considerable and negative.

Ultimately, it seems that early education and other influential indicators of quality have a higher pay-off in terms of test scores in some countries than in others. A detailed description on the posterior inclusion probabilities and Gini coefficients is provided in the Appendix.

5.1.2 Empirical Results for Reading

According to PISA outcomes, Finland holds a position among the highest-performing OECD countries in reading. Over 85% Finnish students performed at least Level 2 proficiency in reading, indicating their ability to make a distinction between fact and opinion, think in a critical way and make reliable/consistent judgements. Their way of reading is characterized as an efficient one, since Finnish students score above average levels of proficiency by dedicating less time to learning compared to 15-year-old students on average across OECD countries (OECD, 2019). Analyzing the results of the effect of pre-primary experience on reading test scores, it appears that attendance in pre-primary schooling between the age of two and three years old has a considerable positive impact on students' reading performance. This outcome comes in agreement with the results found for science. Based on prior research, national pre-school curriculum promotes a more child-centered teaching method with a priority on play, so as to foster children's physical, psychological, cognitive, social and emotional development while, at the same time, strengthens children's reading and mathematical skills through age-appropriate preparatory activities (Kupiainen et.al. (2009), Turunen (2012)). Regarding the regressor "*Repeat a grade*", the results hold the same, since it continues affecting negatively reading test scores. However, the regressor "*Entrance age in primary education*" does not appear as a robust determinant anymore.

Singaporean students possess the second highest performance in reading compared to all other participants in PISA 2018. About 26% of the Singaporean students belong to top performers in reading, when only the 8.7% of the students on average across OECD countries perform at Level 5 or above. Almost 90% of the 15-year-old students in Singapore, that are registered in grade 7 and above, reach a minimum level of proficiency in reading (i.e. Level 2 or above on the PISA scale). However, Singapore has one of the broadest variations in reading performance, because of the differences in linguistic backgrounds among the students (OECD, 2019). For Singapore, attendance in pre-primary schooling for five years or more adversely influences reading test scores, while attendance for less years (i.e. “*Attendance at the age between two and three years old*”) seems to positively affect students’ outcomes. The results found for science come in agreement with the first part of the outcomes, while there is a contradiction for the second part, since the effect is still negative. The negative impact on reading performance can be attributed to the fact that the official official duration of the pre-primary education cycle in Singapore is 3 years (as presented in the third column of Table 2). So, even if students attended pre-school for five years or more, this is still a long-time span as compared to the official one. Also, prior research confirms our positive estimates. As mentioned earlier, in 2003, the government of Singapore decided to enhance preschool’s quality by shifting from an overly structured and academic oriented curriculum, aimed merely for academic readiness in reading, writing and arithmetic to a play curriculum (MOE (2012b), Pre-school education Branch (2008)). However, the transition from the old teaching method to the new one required time. To promote more evenness in the quality of teaching and learning across child-care centers and to better support preschool teachers in operationalizing the NEL framework (Ang (2014)), the MOE launched in 2008 a practical curriculum guide that described in detail the planning process and included models of learning activities and suggestions for children’s development and learning (Pre-school education Branch (2008)). It should be noted, however, that, most of the sampled Singaporean students that attended pre-primary education were at the age of three in the year 2006, so they were influenced mostly by the old curriculum. Regarding the regressors “*Repeat a grade*” and the “*Entrance age in primary education*”, the effect is substantial, and both appear with the same negative sign.

In Korea, students score significantly higher in reading than the OECD mean. The share of 15-year-old Korean students who reach at least Level 4 proficiency ranges between 35% and 42%, with the average across OECD counties being equal to 28%. However, in recent period, Korea has observed a declining trend in all three domains including students’ performance in reading (OECD, 2019). Among the factors that seem to adversely influence reading test scores is the repetition of a grade. Similarly, among the 6 candidate regressors that proxy pre-primary schooling, only the attendance for five years or more (i.e. “*Attendance at the age of one year or less*”) enters as a robust determinant and has a negative impact on reading test scores. Similar results are confirmed by Schütz (2009). Also, this outcome coincides with the findings for science performance. Negative is also the effect of the variable “*Entrance age in primary education*” on reading results, confirming again the results found for science scores.

Two countries located in North and Central America respectively that retain different ranking positions according to mean performance in reading are Canada and Costa Rica. While Canada belongs among the highest performing OECD countries in reading, Costa Rica achieves reading test sores below the OECD average[21]. For these two countries, most of the regressors for pre-primary attendance still enter with high inclusion probabilities. The results for reading performance are the same with the ones that refer to science performance. For Canada, all the 6 variables referring to pre-primary experience play a negative role on students’ reading test scores, a result which is in accordance with Baker et. al. (2005). For Costa Rica, 5 out of 6 are robust determinants

[21] While Canada belongs among the highest-performing OECD countries in reading, it records high differences within the country, that are often as large as the differences that are recorded between countries. (OECD, 2019, What students know and can do, p.63).

of students' performance in reading, with attendance in pre-primary schooling for one year or less (i.e. "*Attendance at the age of five or more*") being excluded. While attendance for five years or more (i.e. "*Attendance at the age of one or less*") adversely influences students' performance, attendance for four, three or two years (i.e. "*Attendance at the age between one and two, two and three, three and four, four and five*") is highly beneficial. Also, the results found for reading performance in the United States confirm the ones referring to science performance and the existing literature (e.g. Cascio (2009), Manguson et.al. (2007)). In the United States, attendance in pre-primary schooling for five years or more (i.e. "*Attendance at the age or one year or less*") is the only robust determinant among the 6 potential ones and affects negatively the students' performance in reading.

Bosnia and Herzegovina and Kazakhstan are two non-OECD countries that underperform in reading compared to OECD average. For both countries, most of the students perform at Level 1a[22], when, on average across OECD countries, only 15% of students display proficiency at that level (OECD, 2019). For Bosnia and Herzegovina, 3 out of 6 regressors that represent pre-primary experience are robust determinants for students' reading test scores, confirming the outcomes found for science. Attendance for more than five years (i.e. "*Attendance at the age of one year or less*") or for one year or less (i.e. "*Attendance at the age of five years old or more*") have a considerable negative impact on reading performance, while attendance at the age between three and four years old has exactly the opposite effect. However, in Kazakhstan, the impact of pre-primary schooling on reading test scores is positive only, contradicting the findings for science. That is, attendance in pre-primary schooling for five years or more, or attendance for four or three years (i.e. "*Attendance at the age between one or less, one and two, and two and three years old*") enter with positive Gini coefficient and are highly beneficial. It is characteristic that after the commencement of economic and political transition independence of Kazakhstan, the government gave great emphasis on the expansion of childcare in both the Kazakn and Russian languages and stressed the necessity for all children to master in both by improving their skills in reading, speaking and writing (UNESCO, 2004).

Czech Republic (Czechia) and Germany are two European OECD countries that achieve a mean score in reading above and close to OECD average respectively. For Czech Republic (Czechia) all the 6 variables that represent pre-primary experience are robust determinants for reading test scores. Excluding pre-primary experience for five years or more (i.e. "*Attendance at the age of one year or less*"), all the rest play a negative role in students' reading performance. These findings contradict the ones referring to science, where three of these regressors are robust determinants and appear to have a positive impact. However, the outcomes for reading in Germany confirm the science ones. That is, more years of pre-primary education (i.e. "*Attendance at the age of one year of less*") appear to be beneficial.

Among the factors that continue having a considerable and positive impact on students' performance in most of the countries are the regressors "*Average time spent for mathematics*" and "*Average time of class periods*". The inclusion probability ranges between 95% and 100%.

[22] The PISA 2018 reading assessment identified three proficiency levels below Level 2. PISA considers students who scored at or below these three levels to be low performers in reading (OECD, 2019, What students know and can do, p. 94).

Performance in Sweden and Kazakhstan continues being unaffected by the first regressor, with Germany being the new addition to this list of countries. Also, test scores in Singapore are still not influenced by the second regressor and, for reading performance, the same appears to hold for Australia. In contrast, "*Repeat a grade*"[23], "*Entrance age in primary education*", "*Not having a computer per student*" and the "*Average time spent for foreign language*" remain, for more than half of the countries, among the variables with a negative impact on students' achievements.

The outcomes for the regressors "*Worrying about what others think of me in a case of a failure*" and "*Trying hard at school because it is helpful to get a good job*" are same as before. Both appear to have a positive impact on reading test scores. However, only the first is a robust determinant for half of the countries, while the second one is a significant regressor only for 7 countries. Again, Kazakhstan and Korea are affected negatively by those two respectively. "*Having doubts for future plans in a case of a failure*" is another variable with positive impact in reading performance in Australia, Canada, Czech Republic (Czechia), Finland, Luxemburg, Poland and the United States. Entering with high inclusion probability, the variable "*Trying harder when I am in competition*" continues being a robust determinant for test scores but only in 7 countries. As before the effect is positive in Finland, Korea and Sweden while it is negative in Belgium, Czech Republic (Czechia), Italy and Greece.

Under the science performance outcomes, "*Residence in a particular area*" is among the regressors with beneficial effects on students' performance. The same holds for the reading outcomes too. In Australia, Costa Rica, France, Greece, Italy, Korea, Luxemburg, Poland and Singapore, the variable appears with a positive Gini coefficient. Only in Kazakhstan it has a negative posterior mean. Also, "*Mandatory internal evaluation/self-evaluation*" (e.g. based on district or ministry policies) has a significant negative marginal effect on reading scores in 12 countries. "*Non-native students*" is another robust variable for more than half of the countries which enters with a posterior inclusion probability that ranges between 51% and 100% and has a significant negative marginal effect on reading test scores. However, Australia and Canada are excluded since for these two the impact is positive.

A more detailed description on the posterior inclusion probabilities and Gini coefficients is provided in the Appendix.

6 Robustness Checks

To examine the sensitivity of the baseline results, further robustness exercises are considered. Specifically, four separate model averaging specification sets were run for the new dataset, obtained by pooling the original individual data from the 22 different countries. The specifications are based on the mother's high school education (existence or not), while a further breakdown between female and male occurs for the students whose mothers have high school education. Moreover, the Gini results are compared to the OLS ones, taken by default when applying BMA methodology. Table 6 and Table 7 summarize the main findings for science and reading test scores, respectively. Columns (1)- (4) and (5)-(8) present the OLS-MA and Gini-MA results of the "kitchen sink" models, respectively. Each column contains the posterior inclusion probabilities and

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[23] In Czech Republic (Czechia), Germany, Greece, Kazakhstan and Poland, the regressor "*Repeat a grade*" is excluded from the set of the candidate regressors.

the posterior means (i.e. the second ones are presented in brackets). In all the MA exercises reported in the table, a uniform model prior and a prior probability of 0.5 attached to each regressor are assumed (as discussed in Section 5.1), and country dummies in all specifications are retained to capture the fixed country effects, while country-school id clustered posterior standard errors are obtained by applying the jackknife method.

Apart from the "kitchen" (largest) regression models, Tables 8 - 15 summarize the outcomes of the top three models for each specification set. From the Bayesian perspective, if a researcher prefers to select a model from the model space rather than engage in model averaging, these models would be the ones that are best supported by the data. However, as the PMP in Tables 8-15 show, even these models do not enjoy overwhelming support; they have a posterior model probability of only just slightly more than 9% for the OLS outcomes, while for the Gini estimates are, in some cases, rather higher. Nevertheless, the conclusions made from the BMA exercises reported in Table 4 and Table 5 are borne out in the findings for the top models for both cases. Yet, if the researcher insists on selecting a model from the model space, Gini regressions are preferrable since the goodness of fit, in all cases, is slightly more that 50%, while for OLS regressions, R^2 is no more than 35%.

6.1 Robustness for science

Referring to the regressors that proxy pre-primary experience, the results grounded in Gini coefficients suggest that attendance in pre-primary schooling for five years or more (i.e., "*Attendance at the age of one year or less*") is a robust determinant of students' performance in science. In particular, more years in pre-primary education are advantageous, especially for females whose mothers have high school education or for students whose mothers do not have high school education. Regarding the rest regressors of this category, they appear to be robust only under the OLS case, with negative effects on students' performance of the first specification.

Although the number of significant variables implied by the "kitchen sink" and the top models in Table 6 and Tables 8-11,respectively, is smaller than the one in the baseline estimations (i.e. Table 4), the variables "*Repeat a grade*" and "*Entrance age in primary education*" still appear to be vital. While the first one exhibits important and negative effects on students' performance, results are contradicting for the second one. That is, according to Gini-MA results its' marginal effect is considerable and negative, especially for those whose mother does not appear with high school education. This result comes in accordance with the baseline results and the existing literature. However, OLS-MA outcomes are exactly the opposite, implying that male students who start school at an older age provide direct benefits to later test scores.

Focusing on female students, a comparison between the Gini-MA results and the OLS-MA ones, presented in Columns (2) and (6) of Table 6 and in Table 9, suggests that the determinants that are important under Gini analysis are not necessarily similar to the ones that are important under OLS analysis. "*Having doubts for future plans in a case of a failure*", "*Trying harder when being in competition with other people*", "*Class size*", "*Average time spent for mathematics*" and "*The percentage of student fees or school charges paid by parents*" are those variables with a positive impact on girls' performance under OLS. "*Achievement data tracked over time by an administrative authority*" is also positively effective under both OLS and Gini analysis. Among the factors that affect performance distinctly but have negative impacts are the variables "*Not* *having doubts for future plans in a case of a failure*", "*Residence in a particular area*" and being a "*Non-native student*". The first one is found robust under the Gini analysis while the rest under the OLS one. It should be noted, that the conclusions about the variables identified as robust as well as the sign of the regression coefficients are in agreement with baseline results of Table 4.

It seems that the regressors "*Being in competition with other people*", "*The percentage of student fees or school charges paid by parents*" and the "*Average time spent for science and mathematics*" are highly advantageous for male's performance, under both Gini-MA and OLS-MA approach. Also, the extra time spent for science contributes positively to students' test scores whose mothers do not have high school education. Further, "*Worrying about what others think of me in a case of a failure*" appears to be robust and greatly beneficial for students that belong to the first specification (i.e. mother with high school education). In contrast, the "*Average time spent for language-in-instruction*" or the "*Average time of class periods*" and being "*First generation student*" has a negative impact on accomplishments. However, these last conclusions are only supported by the OLS approach.

6.2 Robustness for reading

Comparing these results to the ones that refer to science performance, and focusing on the regressors that proxy attendance in pre-primary schooling, it seems that attendance for more than five years (i.e. "*Attendance at the age of one year old or less*") continues to be the only regressor among the 6 potential/promising ones, which affects students' performance under Gini-MA approach. However, now, it appears to have a negative effect in all four specifications, according to Table 7. Regarding the OLS-MA analysis, negative also remains the effect of attendance for one year or less (i.e. "*Attendance at the age of five years or more*") in all four categories.

Among the factors that continue having a considerable and negative impact on students' performance in all for classifications are the regressors "*Repeat a grade*" and the "*Entrance age in primary education*". However, now, the second one turns to be robust only under the Gini-MA analysis. In contrast, the OLS results reveal that the factors "*Being in competition with other people*", the "*Average time spent for science and a foreign language*" and the "*Class size*" enjoy strong posterior support for being important explanations for students' accomplishments. All appear to have positive marginal effect on reading test scores for all students, and this conclusion comes in line with the results found above and the baseline results found in Table 5.

Concerning female students, the regressors "*Having doubts for future plans in a case of a failure*", "*Achievement data tracked over time by an administrative authority*", "*Not having doubts for future plans in a case of a failure*" and being a "*Non-native student*" continue affecting performance distinctly but have opposite impacts. The first two are highly beneficial while the rest have a negative effect on test scores. These outcomes conform to the ones found above. For male students, "*Not having a computer*" seems to contribute negatively on their reading performance. For students, whose mothers do not have high school education, the extra time spent on mathematics contributes positively on their marks while being non-native student is found to be strongly robust with a negative effect.

7 Conclusions

The importance of pre-school education has gained great attendance by many studies in the economics of early childhood education as it is asserted that lays the foundation for lifelong learning. Several studies demonstrate that investment in pre-school education guarantees long-term benefits and is thus presented as a high-yield investment. Most importantly, children tend to reap the greatest benefits if preschool programmes are of high quality. Evidence abounds in the literature of the direct link between pre-school experience and academic performance too. However, the outcomes mainly concern disadvantaged children while there are surprisingly fewer studies that examine the impact of large-scale universal pre-school programs. This study aims to investigate the effect of universal pre-school education on the students' academic results in 22 OECD and non-OECD countries.

Data are obtained from the OECD Programme for International Student Assessment (PISA) 2018. The dataset consists of the students' test scores in reading literacy and 33 quality indicators relative to students', families' and schools' characteristics. Among those quality indicators, 6 represent the attendance in pre-primary schooling. For reasons of comparison, students' test scores in science are applied too. To investigate how pre-primary attendance and other determinants affect students' performance in reading and science, Gini-BMA approach is employed by calculating the weighted average of model specific estimates using Gini estimates.

Regression results show that attendance of pre-primary institutions has a salutary impact on PISA test scores for 15-year-old students in some countries. Czech Republic (Czechia), Costa Rica, Germany, Hong Kong and Kazakhstan are among those countries who benefit the most with more years of experience in pre-primary schooling. Korea, in contrast does not seem to benefit with five or more years of attendance in pre-schooling. In Finland, early childhood education seems to have positive effect both on science test scores and on reading performance. This positive effect on reading test scores appears to hold in Singapore too. In Bosnia and Herzegovina is optimal to attend pre-primary schooling at the age between three and four years old since it creates positive externalities for students' science and reading performance. However, the extension of early childhood education in Canada and the United Sates coincides with a decline in students' outcomes in both science and reading (a result confirmed by Schulman et. al. (1999), Barnett et.al (2004), Baker et. al. (2005), Manguson et. al. (2007), Cascio (2009)). Most of the findings arrived at in this study are in accordance with the existing literature (Fredriksson (2006), Niikko and Havu-Nuutinen (2009), Lorence and Dworkin (2006), Black et.al. (2011), Ting (2007), Li (2004)), Baker et. al. (2005), Berlinski et. al. (2008), Cascio (2009), Schütz (2009), Kupiainen et.al. (2009), Turunen (2012)).

Apart from the regressors that proxy attendance in pre-primary schooling, additional robust determinants are also identified for students' performance in science and reading, indicating that the quality of pre-primary education indeed pays off in terms of increased test scores for 15-year-old students. Although, preschool quality comprises of a wide range of factors, only 27 quality indicators relative to students', families' and schools' characteristics are employed and the strength of these indicators lies in them being comparable across preschools and countries. The variables "*Average time spent for mathematics*", "*Average time of class periods*", "*Worrying about what others think of me in a case of a failure*" and "*Trying hard at school because it is helpful to get a good job*" stand among the rest for their positive influence on students' performance in most of the countries. The findings from our analysis have some useful policy implications and suggest some further investigation on both quality and quantity issues related to childcare expansion by policy makers is warranted, especially as new evidence of PISA outcome data become available covering more recent periods.

8 Appendix

8.1 Appendix A- Detailed Analysis of the empirical baseline findings

8.1.1 The effect of pre-primary education on science test scores

Referring to the regressors that proxy pre-primary experience, of the 6 potential/promising ones only 1 affects the students' performance in science under the Gini analysis in Albania, Austria, Belgium, France, Ireland, Sweden and the US. The results grounded in Gini coefficients, suggest that attendance in pre-primary schooling for five years or more (i.e. "*Attendance at the age of one year or less*") is a robust determinant of students' performance in science, with posterior inclusion probabilities 74%, 100%, 100%, 100%, 99%, 94% and 100% respectively. In particular, more years in pre-primary education adversely affects students' performance with the posterior means ranging between 10.63 and 75.49, with the lowest observed in Albania and the highest in France.

In contrast, Canada and Costa Rica are the only countries where most of the regressors for pre-primary attendance enter with high posterior inclusion probabilities. For the first one, all the 6 variables referring to pre-primary experience have posterior inclusion probabilities around 99% and 100% and play a negative role on students' test scores. Attendance for one year or less (i.e. "*Attendance at the age of five or more*") enters with a considerable negative coefficient equal to 81.81, while attendance for five years or more (i.e. "*Attendance at the age of one or less*") exhibits a negative posterior mean equal to 55.58. For Costa Rica, 5 out of 6 are robust determinants of students' performance in science, with attendance in pre-primary schooling for one year or less (i.e. "Attendance at the age of five or more") being excluded. However, most of them enter with positive Gini coefficients. While attendance for five years or more (i.e. "*Attendance at the age of one or less*") adversely influences students' performance, attendance for four, three or two years (i.e. "*Attendance at the age between one and two, two and three, three and four, four and five*") is highly beneficial.

For the rest countries, the effect of pre-primary experience on science test scores for more than five years (i.e. "*Attendance at the age of one or less*") is ambiguous. In Czech Republic (Czechia), Germany, Greece, Kazakhstan and Poland[24] the variable is positively effective in performance, appearing with an posterior inclusion probability equal to 100% in all cases, and posterior mean that takes values from 294.71 and 516.89. However, in Australia, Bosnia and Herzegovina, Hong Kong, Italy, Korea, Luxembourg, Netherlands and Singapore it has a negative impact, entering with high inclusion probability (100% and 99% only for Korea), and a posterior mean equal to 31.24, 0.36, 40.16, 54.08,22.48, 54.58, 57.28 and 46.28 respectively.

Although "*Attendance at the age between one and two years old*" contributes negatively in performance for Netherlands, having a Gini coefficient equal to 26.85 and 100% inclusion

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[24] The fact that the variable "*Attendance at the age of one or less*'' appears with high Gini coefficient for these countries, might attributed to the exclusion of the regressor "*Repeat a grade*" from the set of the candidate regressors.

probability, it plays a positive role for Czech Republic (Czechia), Greece, Hong Kong and Korea: it enters with an inclusion probability of 99%, 54%, 88% and 57% and a posterior mean of 10.10, 5.01, 9.14 and 4.25 respectively. "*Attendance at the age between two and three years old*" appears with an inclusion probability above 95% for Australia and Italy but lower for Singapore (57%), and with a negative Gini coefficient equal to 12.42,14.68 and 14.64 respectively. In Poland, however, this variable still appears with high inclusion probability (89%) but it has a positive impact on science performance, with a posterior mean equal to 14.55.

For Kazakhstan, "*Attendance at the age between three and four years old*" adversely influences students' performance, entering with a posterior mean equal to 18.64. Although "*Attendance at the age between four and five years old*" is advantageous for performance in Czech Republic (Czechia) and Luxembourg, its marginal effect is substantial but negative in Bosnia and Herzegovina, Kazakhstan and Singapore. Pre-primary experience for one year or less (i.e. "*Attendance at the age of five or more*") negatively affects science performance in Bosnia and Herzegovina, Germany, Kazakhstan and Singapore with the Gini coefficient equal to 24.46, 41.18 and 22.73 respectively. In Finland, only one (i.e. "*Attendance at the age between two and three years old*") out of the 6 candidate regressors that represent attendance in pre-primary schooling is a robust determinant for later school success.

8.1.1.1 Other factors

Additional robust determinants are also identified for student's performance in science. The regressors "*Average time spent for mathematics*" and the "*Average time of class periods*" are robust determinants of science performance for most of the countries. All these three enter with an inclusion probability that ranges between 88% and 100% and are highly beneficial. However, performance in Kazakhstan and Sweden is not affected by the first regressor and in the US and Singapore, it is not affected by the second one, while in Australia, Greece and Luxembourg it is adversely influenced by those two.

"*Achievement data being posted publicly (e.g. in the media)*", "*Achievement data being tracked over time by an administrative authority*" and "*Achievement data being provided directly to parents*" are three variables that are positively effective in performance in less than 10 countries, appearing with an posterior inclusion probability that ranges between 50% and 100% and posterior means that take values from 1.84 and 26.15. Only in Australia and in Czech Republic (Czechia), the first and the third regressor enter with a negative coefficient, equal to 1.25 and 13.63, respectively. "*Class size*" is another variable which enters with high inclusion probability (i.e. 98%-100%) and its marginal effect on test scores is substantial and positive. In contrast, "*Student's record of academic performance (including placement tests)*" and "*The percentage of student fees or school charges paid by parents*" have an ambiguous effect on performance. While, in Czech Republic (Czechia), Hong Kong, Kazakhstan, Korea and Poland, these two variables have a positive impact, in Australia, Greece, Italy and Luxembourg the influence is negative. Singapore is affected only by the first variable, and the impact is negative.

Among the regressors that adversely influence science performance in more than half of the countries are the "*Repeat a grade*"[25], "*Entrance age in primary education*", "*Not having a computer per student*" and the "*Average time spent for foreign language*". The second one, appears with high inclusion probability and a Gini coefficient that ranges between 27.91 and 124.98, while for the rest two the inclusion probability is still significant, but the marginal effect is actually/substantially low. In particular, for the third regressor, the Gini coefficient is either 0.01 or 0.02, while for the fourth one, it takes values between 0.04 and 0.38. The "*Average time spent for language-in-instruction"* has a positive influence on science results in Australia, Belgium, Bosnia and Herzegovina, Italy and Kazakhstan, while it appears with negative Gini coefficient in Austria, Germany and Ireland. "*Average time spent for science*" has similar behavior. While it has a positive impact on science scores in Albania, Austria, Bosnia and Herzegovina and Kazakhstan, the opposite holds for Australia and Ireland.

"*Worrying about what others think of me in a case of a failure*" and "*Trying hard at school because it is helpful to get a good job*" are two regressors that have a positive impact on test scores in half of the countries, with posterior means ranging between 4.90 - 16.33 and 0.02 - 20.10 respectively. Only in Kazakhstan and Korea they appear with a negative Gini coefficient equal to 17.55 and 0.16 respectively. Similarly, "*Having doubts for future plans in a case of a failure*" is another variable that positively influences performance in Australia, Canada, Czech Republic (Czechia), Finland, Poland and the United States. In contrast, "*Trying harder when I am in competition with other people*" is a factor with contradicting results on test scores. While in Finland, Hong Kong, Korea and Sweden it appears with a positive posterior mean equal to 15.69, 7.36,15.95 and 23.43, in Belgium, Czech Republic (Czechia), Costa Rica, Greece, Italy, Netherlands and Singapore it appears with a negative one. "*Not having doubts for future plans in a case of a failure*" is a robust determinant only for two countries, Costa Rica and Kazakhstan but it has opposite effects: the posterior mean is negative for the first one and positive for the other one.

"*Residence in a particular area*" belongs to the regressors with beneficial effects on test scores. Only for Ireland and Kazakhstan it is recorded with a negative Gini coefficient. "*Internal evaluation/self-evaluation based on school-initiative*" plays also a positive role in Albania, Czech Republic (Czechia), Italy and Korea, while its impact is negative for science performance in Kazakhstan. However, "*Mandatory internal evaluation/self-evaluation (e.g. based on district or ministry policies)*" has a considerable negative effect on science scores in 15 countries. Hong Kong is excluded from this list of countries, since for this one the impact is positive. For "*External evaluation/self-evaluation based on school-initiative*" and "*Mandatory external evaluation*" the results are ambiguous. The first regressor enters with a positive posterior mean in Costa Rica and Sweden, while its effect is negative for Albania and Korea. Similarly, the second variable is beneficial for Albania, Germany, Italy and Sweden, while it adversely affects test scores in Belgium, France and Netherlands.

The last two regressors refer to the immigrant status of the student. Except from the Australia and Singapore, in more than half of the countries, the variable "*Non-native students*" enters with

[25] In Czech Republic (Czechia), Germany, Greece, Kazakhstan and Poland, the regressor "*Repeat a grade*" is excluded from the set of candidate regressors.

an inclusion probability that ranges between 74% and 100% and its' marginal effect is considerable and negative. In contrast, "*First generation students*" has both positive and negative effects. For Germany, Italy and Kazakhstan, it exhibits a positive Gini coefficient equal to 9.94, 6.95 and 14.39 respectively. However, it appears to negatively affect science performance in Hong Kong, Korea and Sweden, having a posterior mean equal to 4.51, 6.13, and 0.01.

8.1.2 The effect of pre-primary education on reading test scores

Comparing these results to the ones that refer to science performance, and focusing on the regressors that proxy attendance in pre-primary schooling, it seems that attendance for more than five years (i.e. "*Attendance at the age of one year old or less*") continues to be the only regressor among the 6 potential/promising ones, which affects students' performance in Austria, Belgium, France, Sweden and the United States. Korea and Luxemburg are the two new countries added to this list while Albania and Ireland are now excluded. The impact on reading test scores is still negative with the posterior inclusion probability and the posterior mean ranging between 77% - 100% and 10.04 – 77.78 respectively[26].

Not only Canada and Costa Rica but also Czech Republic (Czechia) and Italy are now the countries which are affected by most of the variables for pre-primary schooling. For Canada, all the 6 pre-primary variables have a negative impact on reading performance. The same holds for Czech Republic (Czechia), with the only exclusion that attendance for five years or more (i.e. "*Attendance at the age of one year old or less*") enters with a positive Gini coefficient. While the results for Canada coincide with the previous findings, this is not the case for Czech Republic (Czechia). Under the science performance outcomes, only attendance for five years or more (i.e. "*Attendance at the age of one year old or less*") and attendance for four and two years (i.e. "*Attendance between the age of one and two, and four and five*") are robust determinants with beneficial effects on performance. For Italy and Costa Rica, 5 out of 6 are robust determinants of students' performance in reading, with "*Attendance at the age between three and four years old*" and "*Attendance at the age between five years or more*" being excluded respectively. For the first country, only "*Attendance at the age between one and two years old*" enters with positive Gini coefficient, while the rest play a negative role on test scores. For the second country, the same outcome as before holds: While attendance for five years or more (i.e. "*Attendance at the age of one or less*") adversely influences students' performance, attendance for four, three or two years (i.e. "*Attendance at the age between one and two, two and three, three and four, four and five*") is highly beneficial.

For the remaining countries, the impact of attending pre-primary schooling for five years or more (i.e. "*Attendance at the age of one year old or less*") coincides with the findings for science test scores. In Germany, Greece, Kazakhstan and Poland the variable continues to have a considerable positive impact on reading performance with posterior inclusion probability equal to 100% and the posterior mean ranging between 288.28 and 513.67. Further, in Australia, Bosnia

[26] Under the reading performance analysis, Hong Kong is excluded from the sample of countries due to technicality issues.

and Herzegovina, Ireland, Netherlands and Singapore the impact continues to be negative, with the variable entering with high inclusion probability and a posterior mean equal to 28.41, 31.69, 20.42, 53.62 and 57.57 respectively.

The effect of "*Attendance at the age between one and two years old*" remains negative for Netherlands, with a Gini coefficient equal to 34.49 and 100% inclusion probability. However, for Greece and Kazakhstan the variable appears to be highly beneficial with the Gini coefficient equal to 5.68 and 9.87 and posterior inclusion probability equal to 53% and 93%, confirming the results found for science performance. Although "*Attendance at the age between two and three years old*" continues to have a negative contribution to students' performance in Australia, having a Gini coefficient equal to 11.93, it plays a positive role for a new set of countries including Finland, Ireland, Kazakhstan and Singapore: it enters with an inclusion probability of 76%, 68%, 93% and 67% and a posterior mean of 11.77, 8.51, 15.45 and 6.23 respectively.

The findings for "*Attendance at the age between three and four years old*" contradict the ones referring to science test scores. Even though the variable is not a robust determinant for science performance in Bosnia and Herzegovina and in Czech Republic (Czechia), now it appears to have a significant positive marginal effect on reading performance in the first country, while it is detrimental for reading test scores in the second one. For Poland, attendance in pre-primary schooling for two years (i.e. "*Attendance at the age between four and five years old*") has a negative impact on performance, entering with a posterior mean equal to 27.71. Negative also remains the effect of attendance for one year or less (i.e. "*Attendance at the age of five years or more*") in Bosnia and Herzegovina, Germany and Poland, with the Gini coefficient equal to 8.19, 36.07 and 22.40 respectively.

8.1.2.1 Other factors

Among the factors that continue having a considerable and positive impact on students' performance in most of the countries are the regressors "*Average time spent for mathematics*" and "*Average time of class periods*". The inclusion probability for these ranges between 95% and 100%. Performance in Sweden and Kazakhstan continues being unaffected by the first regressor, with Germany being the new addition to this list of countries. Also, test scores in Singapore are still not influenced by the second regressor and, for reading performance, the same appears to hold for Australia.

The regressors "*Achievement data being posted publicly (e.g. in the media)*", "*Achievement data being tracked over time by an administrative authority*" and "*Achievement data being provided directly to parents*" still have a positive impact on students' performance but now in less than 7 countries. The inclusion probability ranges between 58% and 99% for the first one, 74% and 100% for the second and 62% and 100% for the third one. The Gini coefficient takes values between 4.56 and 30.09 for the first one, 7.39 and 23.76 for the second and 6.13 and 27.44 for the third. As in the case for science results, Australia and Czech Republic (Czechia) are the only countries which are adversely influenced by the first and third regressor, respectively. Another variable with significant positive impact on reading test scores is "*Class size*". For Albania, Australia, Czech Republic (Czechia), Greece and Poland, this variable sustains high inclusion probability (i.e. 82% - 100%) and a Gini coefficient equal to 10.73, 8.93, 15.69, 23.87, and 22.68

respectively. In contrast, "*Student's record of academic performance (including placement tests)*" has a negative impact in reading test scores in Albania, Greece, Sweden and Singapore while its effect is positive only in Kazakhstan. Similarly, "*The percentage of student fees or school charges paid by parents*" is beneficial for Korea and Poland, but it adversely influences performance in Italy and Luxemburg.

"*Repeat a grade*[27]", "*Entrance age in primary education*", "*Not having a computer per student*" and the "*Average time spent for foreign language*" remain, for more than half of the countries, among the variables with a negative impact on students' achievements. All the four appear with high inclusion probability, but only for the first two the marginal effect is substantially high. In particular, the Gini coefficient ranges between 0.01 and 0.03 for the third regressor and 0.04 and 0.40 for the fourth one. The "*Average time spent for language-in-instruction*" has a positive impact on reading scores in 5 countries (i.e. Australia, Belgium, Greece, Italy and Kazakhstan), while it appears with a negative Gini coefficient only in Austria and Czech Republic (Czechia). "*Average time spent for science*" behaves similarly. While it is beneficial for reading performance in Albania, Bosnia and Herzegovina and Kazakhstan, its' effect is negative in Australia, Canada, Ireland, Poland and Sweden.

The outcomes for the regressors "*Worrying about what others think of me in a case of a failure*" and "*Trying hard at school because it is helpful to get a good job*" are same as before. Both appear to have a positive impact on reading test scores, with the Gini coefficient taking values between 6.75 - 15.38 and 0.02 – 0.24. However, only the first is a robust determinant for half of the countries, while the second one is a significant regressor only for 7 countries. Again, Kazakhstan and Korea are affected negatively by those two respectively. "*Having doubts for future plans in a case of a failure*" is another variable with positive impact in reading performance in Australia, Canada, Czech Republic (Czechia), Finland, Luxemburg, Poland and the United States. Entering with high inclusion probability, the variable "*Trying harder when I am in competition*" continues being a robust determinant for test scores but only in 7 countries. As before the effect is positive in Finland, Korea and Sweden while it is negative in Belgium, Czech Republic (Czechia), Italy and Greece. "*Not having doubts for future plans in a case of a failure*" is another robust determinant but now, it affects test scores in more than 2 countries. It appears with a positive posterior mean in Finland, Greece, Kazakhstan, Singapore and the United States, while it affects negatively performance only in Costa Rica.

Under the science performance outcomes, "*Residence in a particular area*" is among the regressors with beneficial effects on students' performance. The same holds for the reading outcomes too. In Australia, Costa Rica, France, Greece, Italy, Korea, Luxemburg, Poland and Singapore, the variable appears with a positive Gini coefficient that ranges between 0.06 and 4.35. Only in Kazakhstan it has a negative posterior mean equal to 0.66. Also, "*Internal evaluation/self-evaluation based on school-initiative*" plays a positive role in Albania, Austria, Greece, Italy and Korea but it adversely affects reading performance in Kazakhstan. "*Mandatory internal evaluation/self-evaluation (e.g. based on district or ministry policies)*" has a significant negative marginal effect on reading scores in 12 countries. Both "*External evaluation/self-evaluation based*

[27] In Czech Republic (Czechia), Germany, Greece, Kazakhstan and Poland, the regressor "*Repeat a grade*" is excluded from the set of the candidate regressors.

on school-initiative” and “*Mandatory external evaluation*” have a questionable effect on performance. The first variable has a positive posterior mean in Czech Republic (Czechia) and Sweden while it enters with a negative Gini coefficient in Albania and Korea. Likewise, the second variable is valuable in Albania, Austria, Germany and Italy while it has a negative effect on reading test scores in Belgium, France and Netherlands.

“*Non-native students*” is another robust variable for more than half of the countries which enters with a posterior inclusion probability that ranges between 51% and 100% and has a significant negative marginal effect on reading test scores. However, Australia and Canada are excluded since for these two the impact is positive. Also, “*First generation students*” is the second variable that describes the immigration status of the student. In Korea and Sweden, it appears with a negative posterior mean equal to 5.89 and 0.02 respectively, while it is beneficial for reading performance in Kazakhstan, since it appears with a positive posterior mean equal to 12.19.

8.2 Appendix B-Tables

Table 1: Attendance of Pre-Primary Education

Countries	ATTENDANCE (students attend pre-school at the age of)											
	No-pre-primary education	One years old or less	One and two years old	Two and three years old	Three and four years old	Four and five years old	Five years old or more	More than one year old	No. of non-missing students	Percentage of missing observations	Total number of students	Missing observations
ALB	289 or 4.64%	76 or 1.22%	287 or 4.6%	2,098 or 33.68%	3,116 or 50%	2,427 or 38.96%	2,223 or 35.68%	5,548 or 89.10%	6,230	2.03%	6,359	129
ARE	1,038 or 5.61%	566 or 3.10%	1,719 or 9.29%	5,267 or 28.48%	9,774 or 52.85%	7,556 or 40.85%	2,594 or 14.02%	13,521 or 73.11%	18,495	4.06%	19,277	782
AUS	292 or 2.28%	538 or 4.21%	1,497 or 11.71%	3,868 or 30.26%	6,444 or 50.41%	5,435 or 42.51%	2,183 or 17.08%	9,586 or 74.98%	12,784	10.43%	14,273	1,489
AUT	96 or 1.44%	234 or 3.52%	1,095 or 16.48%	3,252 or 48.94%	3,732 or 56.16%	1,774 or 26.69%	587 or 8.83%	5180 or 77.95%	6,645	2.31%	6,802	157
BEL	81 or 0.97%	125 or 1.50%	3,400 or 40.93%	6,208 or 74.73%	3,223 or 38.80%	382 or 4.60%	150 or 1.81%	6,647 or 80.02%	8,307	1.98%	8,475	168
BIH	3,070 or 50.80%	132 or 2.18%	403 or 6.67%	807 or 13.35%	1,047 or 17.33%	1,159 or 19.18%	967 or 16%	2,285 or 37.81%	6,043	6.74%	6,480	437
CAN	571 or 2.66%	830 or 3.87%	2,400 or 11.20%	5,854 or 27.31%	10,660 or 49.73%	10,526 or 49.11%	4,710 or 21.97%	16,940 or 79.03%	21,434	5.38%	22,653	1,219
CRI	435 or 6.10%	83 or 1.16%	225 or 3.16%	441 ot 6.18%	1,405 or 19.70%	3,406 or 47.76%	3,637 or 51%	5,184 or 72.70%	7,131	1.25%	7,221	90
CZE	98 or 1.41%	43 or 0.62%	548 or 7.91%	4,197 or 60.59%	4,765 or 68.79%	1,394 or 20.12%	488 or 7.04%	5,758 or 83.12%	6,927	1.31%	7,019	92
FIN	58 or 1.05%	341 or 6.15%	1,051 or 18.94%	1,751 or 31.56%	1,864 or 33.59%	1,665 or 30%	1,642 or 29.59%	4,216 or 75.98%	5,549	1.77%	5,649	100
FRA	65 or 1.05%	104 or 1.69%	1,541 or 24.97%	4,715 or 76.39%	3,563 or 57.73%	350 or 5.67%	112 or 1.84%	5,112 or 82.83%	6,172	2.16%	6,308	136
GER	77 or 1.63%	223 or 4.73%	907 or 19.23%	2,888 or 61.24%	2,663 or 56.47%	579 or 12.28%	190 or 4.03%	3,537 or 75%	6,927	1.31%	5,451	735
GRC	99 or 1.56%	229 or 3.62%	778 or 12.29%	1,810 or 28.60%	3,225 or 50.96%	3,171 or 50.11%	1,398 or 22.09%	5,172 or 81.73%	6,328	1.17%	6,403	75
HKG	25 or 0.43%	178 or 3.03%	1,226 or 20.90%	4,013 or 68.41%	3,319 or 56.58%	459 or 7.82%	155 or 2.64%	4,522 or 77.09%	5,866	2.83%	6,037	171
IRL	342 or 6.21%	312 or 5.66%	1,307 or 23.72%	3,104 or 56.33%	3,007 or 54.57%	1,060 or 19.24%	193 or 3.50%	4,195 or 76.13%	5,510	1.20%	5,577	67
ITA	184 or 1.61%	0 or 0%	2037 or 17.80%	8,065 or 70.46%	7,037 or 61.47%	1,362 or 11.90%	545 or 4.76%	9,619 or 84.03%	11,447	2.87%	11,785	338
KAZ	7,369 or 38.56%	387 or 2.03%	2,374 or 12.20%	5,718 or 29.92%	5,863 or 30.68%	3,529 or 18.47%	1,864 or 9.75%	9,714 or 50.83%	19,109	2.04%	19,507	398
KOR	111 or 1.68%	58 or 0.87%	371 or 5.60%	1,404 or 21.21%	2,653 or 40.08%	3,028 or 45.74%	2,290 or 34.59%	5,256 or 79.40%	6,620	0.45%	6,650	30
LUX	149 or 2.91%	130 or 2.54%	507 or 9.91%	1823 or 35.62%	2,837 or 55.43%	1,803 or 35.23%	622 or 12.15%	3,836 or 74.95%	5,118	2.14%	5,230	112
NLD	80 or 1.72%	19 or 0.41%	78 or 1.67%	513 or 11.00%	3,558 or 76.32%	3,356 or 71.99%	298 or 6.39%	3,915 or 83.98%	4,662	2.16%	4,765	103
POL	772 or 13.89%	22 or 0.39%	331 or 5.96%	1,439 or 25.89%	1,986 or 35.73%	1,690 or 30.41%	1,573 or 28.30%	3,868 or 69.59%	5,558	1.19%	5,625	67
SGP	60 or 1.09%	1,455 or 26.37%	1,165 or 21.12%	431 or 7.81%	545 or 9.88%	815 or 14.77%	69 or 1.25%	5289 or 95.87%	5,517	17.37%	6,677	1,160
SWE	161 or 2.99%	1,129 or 20.99%	2,803 or 52.12%	2,383 or 44.31%	1,016 or 18.89%	560 or 10.41%	442 or 8.22%	3132 or 58.24%	5,378	2.29%	5,504	126
USA	623 or 13.08%	183 or 3.84%	514 or 10.79%	1,266 or 26.59%	2,098 or 44.06%	1,506 or 31.63%	393 or 8.25%	2,822 or 59.26%	4,762	1.57%	4,838	76

Note: The table reports the students' responses on the question: "How old were you when you started <ISCED0>?". The following 8 answer categories are provided: "1 year or younger"; "2 years"; "3 years"; "4 years"; "5 years"; "6 years or older"; "I did not attend <ISCED0>"; "I do not remember". The number and the percentage of missing observations are presented in the last two columns. Only the students who provide information on their pre-primary education are taken into consideration.

Table 2: Attendance Rates and Structural Qualities

Countries	Of those who attended pre-primary education:			Structural qualities of pre-primary education (2006)		
	Total number	**One-year or less**	**More than one year**	**Entrance age in pre-primary education**	**Duration of pre-primary education**	**Entrance age in primary education**
ALB	5,941	5,548 or 93,38%	393 or 6,62%	3	3	6
ARE	17,457	13,521 or 77,45%	3,936 or 22,55%	4	2	6
AUS	12,492	9,586 or 76,74%	2,906 or 23,26%	4	1	5
AUT	6,549	5,180 or 79,10%	1,369 or 20,9%	3	3	6
BEL	8,226	6,647 or 80,80%	1,579 or 19,20%	3	3	6
BIH	2,973	2,285 or 76,86%	688 or 23,14%	3	3	6
CAN	20,863	16,940 or 81,20%	3,923 or 18,80%	5	1	6
CRI	6,696	5,184 or 77,42%	1,512 or 22,58%	4	2	6
CZE	6,829	5,758 or 84,32%	1,071 or 15,68%	3	3	6
FIN	5,491	4,216 or 76,78%	1275 or 23,22%	3	4	7
FRA	6,107	5,112 or 83,71%	995 or 16,29%	3	3	6
GER	4,639	3,537 or 76,24%	1,102 or 23,76%	3	3	6
GRC	6,229	5,172 or 83,03%	1,057 or 16,97%	4	2	6
HKG	5,841	4,522 or 77,42%	1,319 or 22,58%	3	3	6
IRL	5,168	4,195 or 81,17%	973 or 18,83%	4	1	5
ITA	11,263	9,619 or 85,40%	1,644 or 14,60%	3	3	6
KAZ	11,740	9,714 or 82,74%	2026 or 17,26%	3	4	7
KOR	6,509	5,256 or 80,75%	1,253 or 19,25%	5	2	7
LUX	4,969	3,836 or 77,20%	1,133 or 22,80%	3	3	6
NLD	4,582	3915 or 85,44%	667 or 14,56%	3	3	6
POL	4,786	3,868 or 80,82%	918 or 19,18%	3	4	7
SGP	5,457	5,289 or 96,92%	168 or 3,08%	3	3	6
SWE	5,217	3,132 or 60,03%	2,085 or 39,97%	3	4	7
USA	4,139	2,822 or 68,18%	1,317 or 31,82%	3	3	6

Note: The first three columns display students' answers related to the duration of their pre-primary experience (see also Table 2). The rest columns present information on structural qualities in 2006. Source for entrance age in pre-primary and primary education and duration of pre-primary education: UNESCO Institute for Statistics http://data.uis.unesco.org/#

Table 3: Description of the variables

Variable	Acronyms	Data (PISA 2018 OECD)	Description	N	QST
		Test Scores			
Reading		pv1read - pv10read	Quantitative	102,776	STU
			The final variable is the average of these 10 variables		
Science		pv1scie-pv10scie	Quantitative	102,776	STU
			The final variable is the average of these 10 variables		
		Attendance in pre-primary schooling			
Attendance at the age of one years old or less	OneOrLess	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		
Attendance between the age of one and two years old	OneAndTwo	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		
Attendance between the age of two and three years old	TwoAndThree	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		
Attendance between the age of three and four years old	ThreeAndFour	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		
Attendance between the age of four and five years old	FourAndFive	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		
Attendance between the age of five years or more	FiveOrMore	ST125Q01NA	Qualitative	102,776	STU
			1-one year or younger		
			2-two years		
			3- three years		
			4-four years		
			5-five years		
			6-six years or older		
			7-I did not attend		
			8-I do not remember		

Table 3 (continue): Description of the variables

Variable	**Acronyms**	**Data (PISA 2018 OECD)**	**Description**	**N**	**QST**
		Student Characteristics			
Repeat a grade	Repeat	ST127Q01TA02,03	Qualitative	76,085	ST
			1-No never		
			2-Yes, once	(Total missing	
			3 - Yes, twice or more	observations	
				26,691	
		ST127Q02TA02,03	Qualitative	from CZE, GER,	
			1-No never	GRC, KAZ,POL)	
			2-Yes, once		
			3 - Yes, twice or more		
Average time spent	MathTime	ST059Q02TA	Quantitative	102,776	ST
for mathematics (per		ST061Q01NA	Quantitative		
week)					
Average time spent	ForeignTime	ST059Q04HA	Quantitative	102,776	ST
for foreign language		ST061Q01NA	Quantitative		
(per week)					
Average time spent	LanguageTime	ST059Q01TA	Quantitative	102,776	ST
for language-in-instruction		ST061Q01NA	Quantitative		
(per week)					
Average time spent	ScienceTime	ST059Q03TA	Quantitative	102,776	ST
for science (per		ST061Q01NA	Quantitative		
week)					
External evaluation	ExternalMandatory	SC037Q02TA01	Qualitative	102,776	SC
(mandatory)			1- Yes, this is mandatory,		
			e.g. based on district		
			or ministry policies		
			2- Yes, based on school		
			initiative		
			3- No		
Inernal or self- evaluation	InternalMandatory	SC037Q01TA01	Qualitative	102,776	SC
(mandatory)			1- Yes, this is mandatory,		
			e.g. based on district		
			or ministry policies		
			2- Yes, based on school		
			initiative		
			3- No		
External evaluation	ExternalSchool	SC037Q02TA02	Qualitative	102,776	SC
(school initiative)			1- Yes, this is mandatory,		
			e.g. based on district		
			or ministry policies		
			2- Yes, based on school		
			initiative		
			3- No		
Inernal or self- evaluation	InternalSchool	SC037Q01TA02	Qualitative	102,776	SC
(school initiative)			1- Yes, this is mandatory,		
			e.g. based on district		
			or ministry policies		
			2- Yes, based on school		
			initiative		
			3- No		
Achievement data are posted	DataPublic	SC036Q01TA(Yes)	Qualitative	102,776	SC
publicly (e.g. in the media)			1-Yes		
			2-No		
Achievement data are tracked	DataAuthority	SC036Q02TA (Yes)	Qualitative	102,776	SC
over time by an administrative			1-Yes		
authority			2-No		
Achievement data are provided	DataParents	SC036Q03NA (Yes)	Qualitative	102,776	SC
directly to parents			1-Yes		
			2-No		

Table 3 (continue): Description of the variables

Variable	Acronyms	Data (PISA 2018 OECD)	Description	N	QST
Percentage of student fees or school charges paid by parents	SchoolExpenses	SC016Q02TA01	Quantitative	85,551 (Total missing observations 17,225 from BEL, IRL, SWE, USA)	SC
Trying hard at school will help me get a good job	GoodJob	ST036Q05TA	Qualitative 1-Stronlgy agree 2- Agree 3-Disagree 4-Strongly disagree	102,776	ST
When I am failing, I worry about what others think for me	Worry	ST183Q01HA	Qualitative 1- Strongly disagree 2- Disagree 3- Agree 4-Stronly agree	102,776	ST
When I am failing, this makes me doubt my plans for future	FututeDoubts	ST183Q03HA	Qualitative 1- Strongly disagree 2- Disagree 3- Agree 4-Stronly agree	102,776	ST
When I am failing, this makes me not doubt my plans for future	NoFututeDoubts	ST183Q03HA	Qualitative 1- Strongly disagree 2- Disagree 3- Agree 4-Stronly agree	102,776	ST
I try harder when I am in competition with other people	InCompetition	ST181Q04HA	Qualitative 1- Strongly disagree 2- Disagree 3- Agree 4-Stronly agree	102,776	ST
Students' record of academic performance (including placement tests)	RecordForAdmission	SC012Q01TA03 (Always)	Qualitative 1- Never 2- Sometimes 3-Always	102,776	SC
Age entrance at primary schooling	AgeEntrance	ST125Q01NA	Qualitative 1-one year or younger 2-two years 3- three years 4-four years 5-five years 6-six years or older 7-I did not attend 8-I do not remember	102,776	ST
		ST126Q01TA	Qualitative 1- three or younger 2- four 3- five 4-six 5-seven 6-eight 7- nine or older		
		Immigration status			
Non-native students	Non-native	ST019AQ01T	Qualitative 1- Country of test 2- Other country	102,776	ST
First generation students	FirstGeneration	ST019AQ01T	Qualitative 1- Country of test 2- Other country	102,776	ST

Table 3 (continue): Description of the variables

Variable	Acronyms	Data (PISA 2018 OECD)	Description	N	QST
		School characteristics			
Computers per student	NoComputer	SC004Q01TA	Quantitative	99,884	SC
		SC004Q02TA	Quantitative	(Total missing observations 2,892 from USA)	
Class periods (average time, total)	ClassPeriods	ST060Q01NA	Quantitative	102,776	ST
		ST061Q01NA	Quantitative		
Class size	ClassSize			98,448	SC
				(Total missing observations 4,328 from SWE)	
Residence in a particular area	Residence	SC012Q06TA	Qualitative 1-Never 2-Sometimes 3-Always	102,776	SC

Table 4: Empirical results for Science test scores using the Gini-MA methodology

Variables	ALB	ARE	AUS	AUT	BEL	BIH	CAN	CRI	CZE	FIN	FRA	GER	GRC	HKG	IRL	ITA	KAZ	KOR	LUX	NLD	POL	SGP	SWE	USA
Repeat	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00		1,00	1,00			0,93	1,00	1,00		1,00	1,00	1,00		1,00	1,00	1,00
	(-39.2)	(-34.87)	(-45.57)	(-50.38)	(-50.1)	(-398.2)	(-53.75)	(-42.59)		(-48.7)	(-41.81)			(-37.92)	(-52.11)	(-43.94)		(-48.17)	(-45.74)	(-57.41)		(-50.33)	(-50.21)	(-50.01)
OneOrLess	0,74	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,33	1,00	1,00	1,00	1,00	0,99	1,00	1,00	0,99	1,00	1,00	1,00	1,00	0,94	1,00
	(-10.63)	(-49.21)	(-31.24)	(-41.00)	(-64.28)	(-0.36)	(-55.58)	(-43.20)	(-487.28)	(-4.08)	(-75.49)	(-516.89)	(-506.56)	(-40.16)	(-20.24)	(-54.08)	(-294.71)	(-22.48)	(-54.58)	(-57.28)	(-465.38)	(-46.28)	(-12.55)	(-70.25)
OneAndTwo	0,46	0,99	0,49	0,02	0,03	0,03	0,99	0,99	0,99	0,02	0,18	0,16	0,54	0,88	0,02	0,11	0,09	0,57	0,02	1,00	0,48	0,33	0,04	0,07
	(-3.68)	(-7.91)	(-4.07)	(-0.03)	(-0.06)	(-0.03)	(-16.12)	(-15.12)	(-10.1)	(-0.07)	(-1.04)	(-1.49)	(-5.01)	(-9.14)	(-0.04)	(-0.41)	(-7.12)	(-4.25)	(-0.03)	(-26.85)	(-4.73)	(-9.90)	(-0.29)	(-0.53)
TwoAndThree	0,03	1,00	0,95	0,10	0,08	0,04	1,00	1,00	0,07	0,55	0,03	0,36	0,08	0,18	0,36	0,99	0,10	0,03	0,17	0,02	0,89	0,57	0,12	0,11
	(-0.03)	(-33.06)	(-12.42)	(-0.75)	(-0.28)	(-0.2)	(-41.41)	(-30.92)	(-3.91)	(-7.59)	(-0.10)	(-5.53)	(-0.62)	(-1.71)	(-3.72)	(-14.68)	(-1.29)	(-0.13)	(-1.67)	(-0.06)	(-14.55)	(-14.64)	(-7.66)	(-1.13)
ThreeAndFour	0,04	1,00	0,03	0,03	0,01	0,29	1,00	0,99	0,11	0,04	0,02	0,04	0,07	0,03	0,03	0,03	0,91	0,06	0,02	0,03	0,14	0,34	0,02	0,07
	(-0.42)	(-30.60)	(-0.19)	(-0.1)	(-0.01)	(-4.49)	(-51.55)	(-22.76)	(-6.81)	(-0.24)	(-0.12)	(-0.35)	(-0.71)	(-0.14)	(-0.19)	(-0.13)	(-18.64)	(-0.58)	(-0.03)	(-0.24)	(-0.07)	(-27.81)	(-0.01)	(-0.62)
FourAndFive	0,16	1,00	0,08	0,04	0,10	0,62	1,00	0,99	0,99	0,04	0,02	0,03	0,03	0,08	0,02	0,05	0,91	0,05	0,85	0,03	0,18	0,79	0,02	0,04
	(-2.63)	(-35.40)	(-0.89)	(-0.18)	(-0.61)	(-6.20)	(-54.82)	(-12.44)	(-17.99)	(-0.18)	(-0.02)	(-0.06)	(-0.1)	(-0.63)	(-0.06)	(-0.81)	(-25.73)	(-0.45)	(-12.49)	(-0.12)	(-4.21)	(-45.75)	(-0.03)	(-0.21)
FiveOrMore	0,41	1,00	0,32	0,04	0,07	0,88	1,00	0,01	0,11	0,08	0,02	0,88	0,02	0,06	0,02	0,09	0,99	0,01	0,03	0,02	0,33	0,80	0,04	0,02
	(-10.01)	(-58.40)	(-8.01)	(-0.43)	(-0.80)	(-24.46)	(-81.81)	(-0.01)	(-7.87)	(-0.94)	(-0.02)	(-41.18)	(-0.04)	(-0.84)	(-0.01)	(-2.45)	(-22.73)	0	(-0.25)	(-0.06)	(-1.13)	(-53.53)	(-0.27)	(-0.04)
AgeEntrance	0,07	1,00	0,99	0,80	0,99	0,99	1,00	0,01	0,10	0,97	0,04	0,05	0,41	0,98	0,02	0,92	1,00	0,99	0,38	0,02	0,86	0,98	0,99	0,03
	(-3.83)	(-72.03)	(-58.41)	(-56.31)	(-46.02)	(-87.10)	(-124.98)	(-0.11)	(-13.19)	(-75.98)	(-0.84)	(-4.62)	(-17.19)	(-44.81)	(-0.25)	(-37.39)	(-82.32)	(-33.04)	(-10.77)	(-0.04)	(-27.91)	(-99.18)	(-66.54)	(-0.61)
DataPublic	0,88	0,99	0,50	0,38	0,02	0,87	1,00	0,02	0,08	0,69	0,03	0,05	0,03	0,06	0,10	0,10	0,91	0,01	0,07	0,03	0,63	0,49	0,99	0,06
	(-3.16)	(-5.11)	(-1.25)	(-1.05)	(-0.01)	(-3.87)	(-12.72)	0	(-1.71)	(-2.06)	(-0.03)	(-0.08)	(-0.03)	(-0.14)	(-0.19)	(-0.33)	(-5.56)	0	(-0.10)	(-0.02)	(-1.84)	(-8.52)	(-4.36)	(-0.07)
DataAuthority	0,04	1,00	0,59	0,04	0,22	0,09	0,20	0,24	0,98	0,04	0,19	0,03	0,03	0,99	0,99	0,01	0,01	1,00	0,02	0,02	0,99	1,00	0,03	0,06
	(-0.12)	(-8.9)	(-3.99)	(-0.32)	(-5.58)	(-0.43)	(-0.81)	(-1.10)	(-11.69)	(-0.62)	(-1.1)	(-0.22)	(-0.07)	(-12.46)	(-11.92)	(-0.01)	(-0.01)	(-26.15)	(-0.06)	(-0.02)	(-11.23)	(-23.51)	(-0.11)	(-0.42)
DataParents	0,02	0,03	0,17	0,98	0,02	0,03	0,01	0,02	0,99	0,03	0,04	0,04	0,07	0,99	0,02	0,91	1,00	0,03	0,99	0,02	0,02	0,09	0,07	0,02
	(-0.03)	(-0.2)	(-1.36)	(-12.15)	(-0.02)	(-0.13)	(-0.03)	(-0.05)	(-13.63)	(-0.05)	(-0.17)	(-0.21)	(-0.32)	(-11.86)	(-0.03)	(-6.24)	(-24.93)	(-0.11)	(-17.46)	(-0.03)	(-0.07)	(-0.95)	(-0.41)	(-0.09)
RecordForAdmission	0,44	0,10	0,96	0,03	0,05	0,02	0,01	0,49	0,78	0,04	0,04	0,03	0,99	0,99	0,07	0,11	1,00	0,01	0,02	0,44	0,02	1,00	0,11	0,09
	(-7.84)	(-0.7)	(-11.90)	(-0.06)	(-0.16)	(-0.04)	0	(-5.92)	(-11.26)	(-0.17)	(-0.21)	(-0.04)	(-47.64)	(-13.27)	(-0.33)	(-0.75)	(-41.43)	(-0.01)	(-0.02)	(-5.19)	(-0.34)	(-12.17)	(-0.76)	(-1.14)
ClassSize	0,98	0,99	0,99	0,02	0,02	0,08	0,01	0,02	1,00	0,05	0,02	0,03	0,99	0,99	0,15	0,02	0,02	0,02	0,02	0,05	1,00	0,02		0,02
	(-11.12)	(-8.55)	(-10.05)	(-0.05)	(-0.04)	(-0.37)	0	(-0.03)	(-16.75)	(-0.6)	(-0.02)	(-0.03)	(-34.77)	(-22.68)	(-1.25)	(-0.06)	(-0.03)	(-0.07)	(-0.01)	(-0.19)	(-19.95)	(-0.07)		(-0.05)
GoodJob	0,03	1,00	1,00	0,42	0,03	0,04	0,01	0,51	0,07	0,03	1,00	0,18	0,97	1,00	0,97	1,00	1,00	0,86	0,11	0,10	1,00	1,00	0,91	0,99
	0	(-0.18)	(-0.14)	(-0.02)	0	0	0	(-0.02)	0	0	(-0.14)	(-0.02)	(-0.11)	(-0.44)	(-0.12)	(-0.1)	(-0.22)	(-0.16)	0	0	(-0.21)	(-0.19)	(-20.1)	(-0.03)
InCompetition	0,03	0,01	0,11	0,22	1,00	0,37	0,01	1,00	1,00	0,99	0,04	0,24	1,00	0,79	0,01	0,99	0,13	1,00	0,04	0,69	0,02	0,68	1,00	0,17
	(-0.09)	0	(-0.46)	(-1.50)	(-12.35)	(-2.40)	0	(-12.13)	(-18.39)	(-15.69)	(-0.13)	(-2.46)	(-14.59)	(-7.36)	(-0.01)	(-9.79)	(-0.38)	(-15.95)	(-0.14)	(-6.12)	(-0.04)	(-4.59)	(-23.43)	(-1.18)
Worry	0,96	1,00	1,00	0,04	0,95	0,07	1,00	1,00	0,37	0,24	0,03	0,08	0,06	0,40	0,99	0,97	1,00	0,07	0,99	0,10	0,99	0,12	0,60	0,62
	(-10.06)	(-14.82)	(-16.33)	(-0.17)	(-8.1)	(-0.33)	(-14.9)	(-11.77)	(-2.98)	(-2.28)	(-0.07)	(-0.56)	(-0.24)	(-3.07)	(-12.17)	(-7.41)	(-17.55)	(-0.32)	(-13.71)	(-0.69)	(-11.98)	(-0.52)	(-4.9)	(-6.08)
FutureDoubts	0,03	0,56	1,00	0,03	0,01	0,08	0,99	0,05	0,94	0,96	0,02	0,09	0,02	0,28	0,02	0,03	0,05	0,16	0,08	0,06	0,91	0,01	0,02	0,99
	(-0.11)	(-3.39)	(-16.4)	(-0.10)	(-0.03)	(-0.62)	(-9.59)	(-0.23)	(-12.65)	(-20.56)	(-0.04)	(-0.92)	0	(-1.95)	(-0.02)	(-0.10)	(-2.66)	(-0.97)	(-0.48)	(-0.4)	(-11.09)	(-0.01)	(-0.06)	(-23.2)
NoFutureDoubts	0,02	0,05	0,02	0,02	0,01	0,02	0,06	0,77	0,02	0,07	0,17	0,03	0,42	0,03	0,02	0,01	1,00	0,07	0,02	0,16	0,08	0,01	0,02	0,06
	(-0.01)	(-0.17)	(-0.03)	(-0.01)	(-0.02)	(-0.05)	(-0.25)	(-5.78)	(-0.02)	(-0.8)	(-1.06)	(-0.12)	-4.05	(-0.09)	(-0.04)	(-0.02)	(-15.65)	(-0.42)	(-0.06)	(-1.71)	(-0.54)	(-0.01)	(-0.05)	(-0.35)
ScienceTime	0,97	0,16	0,94	0,80	0,03	0,98	0,12	0,20	0,02	0,02	0,03	0,03	0,02	0,04	0,95	0,02	0,99	0,23	0,02	0,06	0,02	0,02	0,06	0,22
	(-12.21)	(-0.86)	(-12.70)	(-8.6)	(-0.15)	(-11.57)	(-0.73)	(-0.91)	(-0.04)	(-0.02)	(-0.13)	(-0.05)	(-0.05)	(-0.24)	(-15.10)	(-0.07)	(-8.11)	(-1.85)	0	(-0.31)	(-0.08)	(-0.04)	(-0.32)	(-2.56)
MathTime	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,01	0,99	1,00	1,00	1,00	1,00	0,25	0,99
	(-0.04)	(-0.11)	(-0.15)	(-0.11)	(-0.08)	(-0.11)	(-0.06)	(-0.06)	(-0.18)	(-0.27)	(-0.16)	(-0.22)	(-0.21)	(-0.06)	(-0.17)	(-0.11)	0	(-0.12)	(-0.12)	(-0.07)	(-0.15)	(-0.29)	(-0.01)	(-0.09)
LanguageTime	0,06	0,99	1,00	0,72	1,00	0,99	0,02	0,03	0,03	0,07	0,03	0,99	0,40	0,08	0,98	1,00	1,00	0,02	0,05	0,37	0,01	0,37	0,02	0,25
	0	(-0.04)	(-0.21)	(-0.05)	(-0.3)	(-0.14)	0	0	0	(-0.01)	0	(-0.26)	(-0.03)	0	(-0.19)	(-0.16)	(-0.19)	0	0	(-0.03)	0	(-0.02)	0	(-1.06)
ForeignTime	0,82	1,00	0,99	1,00	1,00	0,06	0,01	1,00	1,00	0,91	0,53	1,00	0,99	0,06	0,99	1,00	1,00	0,37	0,07	1,00	0,02	1,00	1,00	0,02
	(-0.05)	(-0.07)	(-0.12)	(-0.33)	(-0.17)	0	0	(-0.12)	(-0.25)	(-0.16)	(-0.04)	(-0.24)	(-0.08)	0	(-0.19)	(-0.10)	(-0.13)	(-0.03)	0	(-0.22)	0	(-0.38)	(-0.14)	0
ClassPeriods	0,99	1,00	0,94	1,00	1,00	0,88	0,20	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,02	1,00	0,45
	(-0.1)	(-0.05)	(-0.03)	(-0.2)	(-0.15)	(-0.05)	0	(-0.07)	(-0.16)	(-0.14)	(-0.16)	(-0.23)	(-0.16)	(-0.06)	(-0.12)	(-3.44)	(-6.95)	(-11.38)	(-9.01)	(-9.3)	(-0.16)	0	(-0.15)	(-0.01)
NoComputer	1,00	1,00	0,99	0,07	1,00	1,00	1,00	0,01	1,00	0,46	0,49	0,15	0,99	0,98	0,19	1,00	0,99	0,02	1,00	0,99	1,00	0,05		0,99
	(-0.01)	(-0.01)	(-0.02)	0	(-0.02)	(-0.02)	(-0.01)	0	(-0.02)	(-0.01)	0	0	(-0.01)	(-0.01)	0	(-0.02)	0	0	(-0.02)	(-0.02)	(-0.02)	0		(-0.01)
FirstGeneration	0,06	1,00	0,21	0,04	0,11	0,05	0,01	0,14	0,03	0,03	0,09	0,82	0,04	0,57	0,09	0,82	1,00	1,00	0,04	0,07	0,04	0,02	0,99	0,09
	(-0.23)	(-28.87)	(-0.88)	(-0.1)	(-0.27)	(-0.37)	0	(-1.01)	(-0.05)	(-0.09)	(-0.40)	(-9.94)	(-0.48)	(-4.51)	(-0.71)	(-6.95)	(-14.39)	(-6.13)	(-0.06)	(-0.30)	(-0.22)	(-0.03)	(-0.01)	(-0.33)
Non-native	0,05	1,00	0,98	1,00	1,00	0,41	0,06	0,74	0,99	0,98	1,00	0,99	1,00	0,02	0,37	1,00	0,12	0,05	1,00	1,00	0,99	0,99	1,00	0,06
	(-1.35)	(-25.77)	(-12.06)	(-37.71)	(-29.61)	(-8.81)	(-0.27)	(-6.87)	(-37.41)	(-45.84)	(-40.18)	(-27.98)	(-27.48)	(-0.01)	(-4.65)	(-24.19)	(-0.86)	(-1.17)	(-27.24)	(-49.76)	(-66.45)	-15.66	(-0.51)	(-0.4)
InternalMandatory	0,56	1,00	0,01	1,00	1,00	0,79	0,01	0,05	0,99	1,00	0,99	0,97	0,99	0,65	0,16	1,00	1,00	0,02	0,99	0,98	0,11	0,01	1,00	0,07
	(-31.48)	(-42.79)	(-0.01)	(-45.65)	(-46.10)	(-24.88)	(-0.01)	(-0.33)	(-54.75)	(-63.73)	(-35.96)	(-44.56)	(-45.72)	(-7.64)	(-1.66)	(-36.76)	(-0.21)	(-0.59)	(-18.82)	(-49.56)	(-6.75)	(-0.01)	(-0.63)	(-0.89)
InternalSchool	0,99	0,05	0,09	0,09	0,04	0,03	0,02	0,02	0,04	0,04	0,03	0,05	0,69	0,08	0,03	1,00	0,69	0,58	0,04	0,20	0,03	0,02	0,05	0,09
	(-48.91)	(-0.13)	(-0.18)	(-1.54)	(-0.26)	(-0.09)	(-0.05)	(-0.05)	(-0.22)	(-0.18)	(-0.05)	(-0.01)	(-10.47)	(-0.41)	(-0.14)	(-34.65)	(-5.17)	(-7.21)	(-0.16)	(-3.58)	(-0.35)	(-0.06)	(-0.28)	(-0.61)
ExternalMandatory	0,96	0,05	0,31	0,09	0,97	0,02	0,01	0,02	0,19	0,04	0,66	0,83	0,04	0,06	0,04	0,99	0,31	0,20	0,02	0,81	0,04	0,02	0,97	0,14
	(-40.54)	(-0.17)	(-2.16)	(-1.61)	(-9.55)	(-0.03)	(-0.02)	(-0.04)	(-1.67)	(-0.12)	(-5.27)	(-12.78)	(-0.15)	(-0.26)	(-0.23)	(-25.86)	(-1.99)	(-1.61)	0	(-15.07)	(-0.51)	(-0.04)	(-14.19)	(-1.01)
ExternalSchool	0,99	0,01	0,01	0,09	0,01	0,03	0,01	0,85	0,25	0,06	0,06	0,05	0,10	0,16	0,03	0,01	0,03	0,92	0,04	0,10	0,02	0,02	0,82	0,07
	(-32.75)	(-0.03)	0	(-0.53)	(-0.01)	(-0.09)	(-0.01)	(-5.6)	(-1.69)	(-0.31)	(-0.23)	(-0.26)	(-1.29)	(-31.42)	(-0.14)	0	(-0.1)	(-11.93)	(-0.33)	(-0.53)	(-0.07)	(-0.05)	(-6.91)	(-0.45)
SchoolExpenses	0,03	0,01	0,03	0,03		0,02	0,01	0,85	0,02	0,29	0,04	0,03	0,02	0,16		0,93	0,01	0,99	0,99	0,22	0,98	0,18		
	(-0.18)	(-0.01)	(-0.14)	(-0.14)		(-0.01)	(-0.03)	(-8.47)	(-0.03)	(-4.84)	(-0.25)	(-0.03)	(-0.1)	(-29.31)		(-9.49)	(-0.04)	(-20.34)	(-128.95)	(-1.55)	(-33.38)	(-2.32)		
Residence	0,12	1,00	1,00	0,30	0,03	0,07	0,02	0,06	0,04	0,08	1,00	0,03	1,00	0,04	0,55	0,99	1,00	1,00	1,00	0,06	0,97	0,99	0,10	0,02
	(-0.01)	(-0.41)	(-0.78)	(-0.08)	(-0.11)	(-0.02)	0	(-0.04)	(-0.01)	(-0.28)	(-0.74)	(-0.01)	(-0.34)	0	(-7.96)	(-0.24)	(-0.72)	(-0.49)	(-3.06)	(-0.03)	(-1.25)	(-0.42)	(-0.95)	(-0.03)

Note: The table presents the posterior inclusion probabilities and the posterior means (in brackets) for the Gini-MA methodology. Country-school id clustered posterior standard errors are obtained by applying the jackknife method and can be provided upon request. Following Kass and Raftery (1995), classified the strength of evidence of a regressors' effect into the following categories, sorted by the PIP : if PIP<50%, there is lack of evidence for the effect(white colour), if 50%<PIP<75% (blue colour) there is weak evidence for the effect, if 75%<PIP<95% (yellow colour) there is positive evidence for the effect, 95%<PIP<99% (red colour) there is strong evidence for the effect, if 99%<PIP<100% (deep red colour) there is decisive evidence for the effect.

Table 5: Empirical results for Reading test scores using the Gini-MA methodology

Variables	ALB	ARE	AUS	AUT	BEL	BIH	CAN	CRI	CZE	FIN	FRA	GER	GRC	IRL	ITA	KAZ	KOR	LUX	NLD	POL	SGP	SWE	USA
Repeat	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00		1,00	1,00			1,00	1,00		1,00	1,00	1,00		1,00	1,00	1,00
	(-42.65)	(-34.49)	(-44.98)	(-48.7)	(-49.04)	(-41.53)	(-54.37)	(-43.46)		(-50.16)	(-40.80)			(-55.47)	(-45.4.4)		(-47.92)	(-45.42)	(-55.00)		(-48.80)	(-52.2)	(-50.85)
OneOrLess	0,36	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,21	1,00	1,00	1,00	0,99	1,00	1,00	0,99	1,00	1,00	1,00	1,00	0,77	1,00
	(-4.61)	(-54.58)	(-28.41)	(-38.29)	(-63.54)	(-31.69)	(-61.88)	(-45.89)	(-508.74)	(-2.34)	(-77.78)	(-513.13)	(-513.67)	(-20.42)	(-62.02)	(-288.28)	(-26.77)	(-62.36)	(-53.62)	(-471.88)	(-57.57)	(-10.04)	(-78.62)
OneAndTwo	0,05	0,99	0,30	0,02	0,14	0,02	0,59	0,33	0,98	0,03	0,21	0,42	0,53	0,05	0,61	0,93	0,08	0,03	1,00	0,32	0,03	0,01	0,03
	(-0.2)	(-9.21)	(-2.34)	(-0.02)	(-0.57)	(-0.03)	(-7.46)	(-2.86)	(-24.89)	(-0.04)	(-1.36)	(-5.18)	(-5.68)	(-0.37)	(-3.85)	(-9.87)	(-0.38)	(-0.08)	(-34.49)	(-4.31)	-0.14	(-0.01)	(-0.18)
TwoAndThree	0,06	1,00	0,92	0,02	0,06	0,02	0,88	0,99	0,83	0,76	0,02	0,09	0,02	0,68	0,60	0,93	0,02	0,40	0,04	0,32	0,67	0,03	0,05
	(-0.32)	(-34.78)	(-11.93)	(-0.05)	(-0.22)	(-0.04)	(-27.24)	(-23.7)	(-70.25)	(-11.77)	(-0.04)	(-0.90)	(-0.01)	(-8.51)	(-14.76)	(-15.45)	(-0.05)	(-5.29)	(-0.65)	(-5.42)	(-6.23)	(-0.12)	(-0.48)
ThreeAndFour	0,02	1,00	0,03	0,03	0,01	0,74	0,88	0,91	0,83	0,09	0,02	0,06	0,05	0,02	0,45	0,08	0,07	0,03	0,03	0,40	0,02	0,06	0,06
	(-0.06)	(-33.04)	(-0.08)	(-0.13)	(-0.01)	(-12.5)	(-34.36)	(-18.24)	(-108.44)	(-1.01)	(-0.04)	(-0.67)	(-0.44)	(-0.01)	(-6.97)	(-1.54)	(-0.66)	(-0.19)	(-0.35)	(-4.42)	(-0.03)	(-0.32)	(-0.55)
FourAndFive	0,02	1,00	0,42	0,06	0,01	0,31	0,87	0,28	0,99	0,03	0,02	0,04	0,02	0,02	0,55	0,14	0,01	0,17	0,02	0,75	0,15	0,03	0,02
	(-0.03)	(-38.37)	(-7.47)	(-0.42)	(-0.02)	(-2.28)	(-34.99)	-1.99	(-110.34)	(-0.11)	(-0.08)	(-0.28)	(-0.10)	(-0.05)	(-17.25)	(-2.58)	(-0.03)	(-1.84)	(-0.01)	(-27.71)	(-1.41)	(-0.17)	(-0.01)
FiveOrMore	0,03	1,00	0,26	0,22	0,04	0,61	0,87	0,04	0,83	0,03	0,02	0,80	0,03	0,03	0,51	0,45	0,04	0,05	0,02	0,81	0,04	0,26	0,02
	(-0.24)	(-57.65)	(-7.11)	(-4.43)	(-0.34)	(-8.19)	(-54.87)	(-0.56)	(-158.06)	(-0.21)	(-0.05)	(-36.07)	(-0.22)	(-0.53)	(-33.15)	(-0.02)	(-0.28)	(-0.60)	(-0.13)	(-22.40)	(-0.24)	(-3.54)	(-0.09)
AgeEntrance	0,03	1,00	0,99	0,96	0,98	0,44	0,99	0,04	0,84	0,34	0,05	0,08	0,16	0,02	0,89	1,00	0,99	0,63	0,03	0,95	0,80	0,99	0,02
	(-0.66)	(-88.93)	(-61.28)	(-80.22)	(-42.61)	(-22.03)	(-98.80)	(-0.71)	(-223.75)	(-17.24)	(-1.25)	(-10.07)	(-5.94)	(-0.17)	(-69.40)	(-50.74)	(-38.71)	(-23.13)	(-0.57)	(-62.41)	(-28.94)	(-70.71)	(-0.34)
DataPublic	0,10	0,99	0,58	0,15	0,02	0,15	0,90	0,04	0,83	0,08	0,02	0,06	0,04	0,02	0,54	0,11	0,05	0,03	0,08	0,89	0,06	0,99	0,02
	(-0.16)	(-5.79)	(-1.63)	(-0.36)	0	(-0.21)	(-8.58)	(-0.08)	(-30.09)	(-0.14)	(-0.01)	(-0.14)	(-0.05)	(-0.02)	(-5.25)	(-0.54)	(-0.05)	(-0.01)	(-0.14)	(-6.41)	(-0.07)	(-4.56)	(-0.01)
DataAuthority	0,05	1,00	0,03	0,02	0,15	0,03	0,11	0,33	0,74	0,04	0,46	0,05	0,02	0,99	0,02	0,22	1,00	0,03	0,02	0,99	1,00	0,02	0,12
	(-0.21)	(-11.61)	(-0.12)	(-0.14)	(-3.85)	(-0.06)	(-0.44)	(-1.88)	(-7.39)	(-0.64)	(-3.53)	(-0.47)	0	(-12.85)	(-0.06)	(-0.82)	(-29.04)	(-0.13)	(-0.01)	(-11.64)	(-23.76)	(-0.06)	(-1.29)
DataParents	0,05	0,25	0,03	0,62	0,01	0,02	0,01	0,03	0,94	0,02	0,04	0,03	0,06	0,03	0,99	1,00	0,06	0,13	0,02	0,07	0,30	0,02	0,02
	(-0.31)	(-3.04)	(-0.15)	(-6.13)	(-0.02)	0	(-0.02)	(-0.19)	(-10.13)	(-0.01)	(-0.15)	(-0.1)	(-0.32)	(-0.09)	-8.7	(-27.44)	(-0.28)	(-1.12)	(-0.05)	(-0.42)	(-4.95)	0	(-0.07)
RecordForAdmission	0,95	0,48	0,36	0,03	0,02	0,02	0,01	0,23	0,23	0,04	0,02	0,04	0,99	0,02	0,01	1,00	0,02	0,06	0,40	0,05	1,00	0,60	0,16
	(-25.61)	(-5.66)	(-3.42)	(-0.11)	(-0.05)	0	0	(-2.85)	(-2.53)	(-0.19)	(-0.03)	(-0.13)	(-47.78)	(-0.05)	0	(-37.25)	0	(-0.42)	(-4.97)	(-1.29)	(-18.28)	(-6.71)	(-2.35)
ClassSize	0,92	0,02	0,94	0,02	0,01	0,19	0,01	0,02	0,99	0,10	0,02	0,04	0,82	0,04	0,01	0,01	0,08	0,02	0,10	0,99	0,02		0,02
	(-10.73)	(-0.03)	(-8.93)	(-0.01)	0	(-1.24)	(-0.01)	(-0.03)	(-15.69)	(-1.56)	(-0.01)	(-0.15)	(-23.87)	(-0.19)	0	(-0.02)	(-0.37)	(-0.06)	(-0.56)	(-22.68)	(-0.03)		(-0.03)
GoodJob	0,08	1,00	1,00	0,17	0,01	0,12	0,01	0,63	0,19	0,02	1,00	0,13	0,99	0,90	1,00	1,00	0,74	0,42	0,07	1,00	1,00	0,25	0,94
	0	(-0.21)	(-0.14)	(-0.01)	0	0	0	(-0.02)	(-0.01)	0	(-0.16)	(-0.01)	(-0.16)	(-0.1)	(-0.11)	(-0.23)	(-0.16)	(-0.02)	0	(-0.24)	(-0.22)	(-4.27)	(-0.03)
Incompetition	0,03	0,01	0,03	0,13	1,00	0,04	0,02	0,40	1,00	0,99	0,02	0,07	0,99	0,03	0,99	0,28	1,00	0,05	0,14	0,02	0,10	1,00	0,03
	(-0.04)	(-0.01)	(-0.1)	(-0.85)	(-11.03)	(-0.15)	(-0.06)	(-2.14)	(-16.71)	(-15.74)	(-0.01)	(-0.47)	(-15.10)	(-0.11)	(-9.33)	(-1.02)	(-14.82)	(-0.21)	(-0.89)	(-0.05)	(-0.53)	(-25.24)	(-0.13)
Worry	0,99	1,00	0,99	0,06	0,12	0,02	0,94	0,99	0,03	0,09	0,02	0,07	0,02	0,81	0,27	1,00	0,04	0,76	0,16	0,07	0,02	0,03	0,10
	(-15.38)	(-21.37)	(-13.39)	(-0.32)	(-0.62)	(-0.03)	(-6.75)	(-8.99)	(-0.12)	(-0.69)	(-0.05)	(-0.44)	(-0.01)	(-7.78)	(-1.45)	(-19.74)	(-0.16)	(-8.02)	(-1.31)	(-0.40)	(-0.02)	(-0.12)	(-0.69)
FutureDoubts	0,03	0,41	1,00	0,02	0,04	0,06	0,99	0,04	0,98	0,99	0,02	0,25	0,06	0,49	0,02	0,04	0,47	0,96	0,11	0,99	0,12	0,31	0,99
	(-0.07)	(-3.00)	(-22.54)	(-0.02)	(-0.21)	(-0.42)	(-11.57)	(-0.17)	(-16.01)	(-32.03)	(-0.05)	(-3.59)	(-0.45)	(-4.92)	(-0.03)	(-0.20)	(-3.78)	(-14.42)	(-1.03)	(-18.93)	(-0.8)	(-3.00)	(-23.18)
NoFutureDoubts	0,02	0,95	0,39	0,02	0,07	0,06	0,01	0,99	0,05	0,59	0,02	0,09	0,87	0,27	0,03	0,99	0,09	0,02	0,33	0,15	0,75	0,02	0,80
	(-0.03)	(-8.11)	(-3.12)	(-0.01)	(-0.43)	(-0.36)	0	(-11.98)	(-0.39)	(-11.45)	(-0.02)	(-1.04)	(-12.66)	(-2.36)	(-0.08)	(-13.56)	(-0.64)	(-0.06)	(-4.68)	(-1.22)	(-6.25)	(-0.04)	(-11.92)
ScienceTime	0,77	0,07	0,99	0,13	0,02	0,74	0,99	0,08	0,33	0,04	0,02	0,03	0,14	0,99	0,02	0,99	0,02	0,03	0,34	0,63	0,02	0,58	0,18
	(-8.92)	(-0.38)	(-25.43)	(-0.91)	(-0.03)	(-7.32)	(-14.83)	(-0.32)	(-3.25)	(-0.19)	(-0.01)	(-0.12)	(-1.21)	(-24.88)	(-0.08)	(-7.05)	(-0.02)	(-0.11)	(-3.29)	(-7.64)	(-0.05)	(-6.64)	(-2.16)
MathTime	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,99	0,99	0,01	0,95	1,00	1,00	1,00	1,00	0,43	0,99
	(-0.11)	(-0.1)	(-0.12)	(-0.1)	(-0.08)	(-0.11)	(-0.05)	(-0.06)	(-0.18)	(-0.26)	(-0.16)	(-0.9)	(-0.22)	(-0.12)	(-0.08)	0	(-0.11)	(-0.13)	(-0.05)	(-0.15)	(-0.32)	(-0.03)	(-0.09)
LanguageTime	0,07	0,77	0,99	0,99	1,00	0,08	0,03	0,02	0,98	0,17	0,02	1,00	0,68	0,43	1,00	1,00	0,02	0,02	0,03	0,02	0,08	0,02	0,05
	0	(-0.03)	(-0.14)	(-0.12)	(-0.29)	0	0	0	(-0.12)	(-0.02)	0	(-0.26)	(-0.06)	(-0.06)	(-0.11)	(-0.21)	0	0	0	0	0	0	0
ForeignTime	0,99	0,99	0,36	1,00	1,00	0,02	0,01	1,00	1,00	0,91	0,58	1,00	0,99	0,99	0,99	1,00	0,43	0,09	1,00	0,01	1,00	1,00	0,02
	(-0.09)	(-0.06)	(-0.03)	(-0.33)	(-0.14)	0	0	(-0.13)	(-0.23)	(-0.17)	(-0.04)	(-0.27)	(-0.11)	(-0.26)	(-0.07)	(-0.15)	(-0.04)	0	(-0.23)	0	(-0.40)	(-0.14)	0
ClassPeriods	0,99	1,00	0,10	1,00	1,00	1,00	0,95	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,02	1,00	0,99
	(-0.11)	(-0.05)	0	-0.27	(-0.17)	(-0.1)	(-0.02)	(-0.08)	(-0.2)	(-0.15)	(-0.19)	(-0.27)	(-0.20)	(-0.14)	(-4.29)	(-6.88)	(-12.14)	(-10.15)	(-10.93)	(-0.17)	0	(-0.15)	(-0.05)
NoComputer	1,00	1,00	0,99	0,11	1,00	1,00	1,00	0,02	1,00	0,82	0,62	0,05	0,99	0,95	1,00	1,00	0,02	1,00	0,99	1,00	0,03		0,99
	(-0.02)	(-0.01)	(-0.02)	0	(-0.03)	(-0.01)	(-0.01)	0	(-0.02)	(-0.02)	0	0	(-0.01)	(-0.01)	(-0.03)	0	0	(-0.03)	(-0.02)	(-0.03)	0		(-0.01)
FirstGeneration	0,03	1,00	0,04	0,08	0,01	0,07	0,01	0,05	0,02	0,03	0,02	0,39	0,05	0,09	0,01	1,00	1,00	0,05	0,20	0,04	0,02	1,00	0,10
	(-0.04)	(-30.42)	(-0.13)	(-0.26)	(-0.01)	(-0.76)	(-0.01)	(-0.27)	(-0.01)	(-0.11)	(-0.04)	(-3.84)	(-0.95)	(-0.76)	(-0.01)	(-12.19)	(-5.89)	(-0.02)	(-1.31)	(-0.2)	(-0.02)	(-0.02)	(-0.44)
Non-native	0,07	1,00	0,99	1,00	1,00	0,05	0,99	0,76	0,59	0,96	1,00	0,29	0,99	0,98	0,99	0,02	0,51	1,00	1,00	0,92	0,68	1,00	0,10
	(-2.58)	(-31.13)	(-13.92)	(-30.57)	(-23.26)	(-0.57)	(-12.9)	(-8.47)	(-15.59)	(-42.33)	(-28.99)	(-4.28)	(-28.40)	(-19.66)	(-22.71)	(-0.11)	(-24.35)	(-22.33)	(-39.61)	(-54.09)	(-9.44)	(-43.12)	(-0.97)
InternalMandatory	0,12	1,00	0,09	1,00	1,00	0,05	0,01	0,03	0,99	1,00	0,99	0,99	0,99	0,04	0,99	1,00	0,01	0,75	0,99	0,08	0,18	1,00	0,04
	(-5.19)	(-46.76)	(-0.59)	(-46.51)	(-47.00)	(-0.75)	0	(-0.22)	(-52.74)	(-73.63)	(-32.21)	(-50.31)	(-51.42)	(-0.27)	(-29.26)	(-28.19)	(-0.07)	(-9.33)	(-54.06)	(-4.81)	(-1.65)	(-76.08)	(-0.48)
InternalSchool	0,81	0,01	0,07	0,61	0,40	0,06	0,03	0,08	0,05	0,06	0,09	0,06	0,97	0,15	0,99	0,70	0,60	0,04	0,25	0,11	0,02	0,15	0,06
	(-30.62)	(-0.02)	(-0.08)	(-17.44)	(-3.66)	(-0.3)	(-0.09)	(-0.34)	(-0.04)	(-0.29)	(-0.64)	(-0.4)	(-21.17)	(-0.94)	(-35.19)	(-5.91)	(-8.71)	(-0.21)	(-3.52)	(-1.08)	(-0.02)	(-1.10)	(-0.34)
ExternalMandatory	0,62	0,01	0,22	0,61	0,63	0,03	0,04	0,12	0,35	0,04	0,63	0,78	0,02	0,32	0,99	0,31	0,19	0,02	0,75	0,23	0,01	0,77	0,09
	-23.85	(-0.03)	(-1.45)	(-17.54)	(-5.58)	(-0.05)	(-0.14)	(-0.6)	(-3.17)	(-0.2)	(-5.60)	(-11.69)	(-0.06)	(-3.01)	(-28.94)	(-2.37)	(-2.04)	(-0.02)	(-11.46)	(-2.97)	(-0.01)	(-7.88)	(-0.67)
ExternalSchool	0,99	0,01	0,01	0,02	0,02	0,20	0,01	0,35	0,96	0,02	0,04	0,03	0,17	0,02	0,02	0,03	0,94	0,08	0,04	0,05	0,02	0,99	0,14
	(-36.93)	(-0.02)	(-0.02)	(-0.05)	(-0.02)	(-1.25)	(-0.01)	(-1.81)	(-10.43)	(-0.01)	(-0.16)	(-0.12)	(-2.86)	(-0.02)	(-0.04)	(-0.08)	(-13.01)	(-0.78)	(-0.16)	(-0.54)	(-0.18)	(-13.04)	(-1.17)
SchoolExpenses	0,03	0,01	0,02	0,07		0,11	0,01	0,03	0,03	0,39	0,04	0,03	0,03		0,99	0,01	0,83	0,99	0,14	0,77	0,07		
	(-0.34)	(-0.01)	(-0.12)	(-0.48)		(-0.97)	(-0.01)	(-0.14)	(-0.1)	(-7.23)	(-0.36)	(-0.02)	(-0.16)		(-13.63)	(-0.01)	(-14.65)	(-217.15)	(-0.90)	(-23.02)	(-1.01)		
Residence	0,06	1,00	1,00	0,41	0,03	0,23	0,02	0,51	0,06	0,08	1,00	0,07	1,00	0,13	0,99	1,00	1,00	1,00	0,11	0,76	0,99	0,33	0,03
	0	(-0.34)	(-0.78)	(-0.12)	(-0.11)	(-0.08)	0	(-0.06)	(-0.02)	(-0.31)	(-0.91)	(-0.07)	(-0.46)	(-1.46)	(-0.32)	(-0.66)	(-0.47)	(-4.35)	(-0.08)	(-0.89)	(-0.45)	(-4.6)	(-0.09)

Note: The table presents the posterior inclusion probabilities and the posterior means (in brackets) for the Gini-MA methodology. Country-school id clustered posterior standard errors are obtained by applying the jackknife method and can be provided upon request. Following Kass and Raftery (1995), classified the strength of evidence of a regressors' effect into the following categories, sorted by the PIP : if PIP<50%, there is lack of evidence for the effect(white colour), if 50%<PIP<75% (blue colour) there is weak evidence for the effect, if 75%<PIP<95% (yellow colour) there is positive evidence for the effect, 95%<PIP<99% (red colour) there is strong evidence for the effect, if 99%<PIP<100% (deep red colour) there is decisive evidence for the effect.

Table 6: Heatmap-Robustness checks for Science test scores using pooled data

	OLS				GINI			
Variables (SCIENCE)	**Mother with high school education**	**Mother with high school education (FEMALE)**	**Mother with high school education (MALE)**	**Mother without high school education**	**Mother with high school education**	**Mother with high school education (FEMALE)**	**Mother with high school education (MALE)**	**Mother without high school education**
Repeat	1.00(-44.42)	1.00(-43.18)	1.00(-46.25)	1.00(-42.24)	1.00(-62.95)	1.00(-32.53)	1.00(-49.82)	0.33(-7.20)
OneOrLess	0.21(-1.10)	0.10(0.42)	1.00(0.02)	0.07(0.32)	1.00(27.89)	1.00(23.76)	1.00(28.31)	1.00(36.69)
OneAndTwo	0.96(-13.18)	0.10(-0.69)	0.01(-6.83)	0.17(-1.36)	0.05(0.17)	0.02(0.03)	0.01(0.00)	0.04(0.12)
TwoAndThree	0.64(-12.93)	0.03(-0.29)	0.11(-0.06)	0.10(-0.98)	0.05(-0.21)	0.07(-0.36)	0.11(-0.82)	0.12(-0.91)
ThreeAndFour	0.64(-14.31)	0.03(-0.34)	0.01(0.03)	0.04(0.20)	0.01(0.00)	0.01(0.03)	0.01(-0.03)	0.06(-0.51)
FourAndFive	0.65(-21.00)	0.39(-4.11)	0.04(0.00)	0.02(-0.04)	0.02(0.04)	0.04(0.16)	0.04(0.17)	0.03(0.12)
FiveOrMore	1.00(-57.29)	1.00(-36.86)	0.01(-33.04)	1.00(-34.77)	0.04(-0.21)	0.10(-0.73)	0.01(0.02)	0.03(-0.10)
AgeEntrance	0.64(3.53)	0.03(0.07)	1.00(0.02)	0.02(0.00)	1.00(-47.87)	1.00(-38.11)	1.00(-50.02)	1.00(-36.97)
DataPublic	0.02(0.02)	0.05(0.19)	0.04(-0.01)	0.19(0.97)	0.01(0.00)	0.02(0.00)	0.04(0.04)	0.02(0.00)
DataAuthority	0.31(1.52)	0.74(5.70)	0.04(0.03)	0.22(1.67)	0.82(4.21)	1.00(8.71)	0.04(0.13)	0.37(2.17)
DataParents	0.02(-0.05)	0.01(0.01)	0.05(-0.63)	0.02(0.03)	0.12(-0.50)	0.01(-0.01)	0.05(-0.24)	0.09(-0.46)
RecordForAdmission	0.07(0.19)	0.01(0.01)	0.02(1.64)	0.02(0.01)	0.02(-0.06)	0.01(0.01)	0.02(-0.04)	0.03(0.12)
ClassSize	1.00(0.06)	1.00(0.05)	0.06(0.06)	0.47(0.01)	0.05(0.12)	0.03(0.06)	0.06(0.23)	0.06(-0.22)
GoodJob	0.03(-0.07)	0.02(-0.02)	0.05(-0.12)	0.05(-0.16)	0.17(0.02)	0.02(0.00)	0.05(0.00)	0.67(-0.08)
InCompetition	1.00(11.29)	0.99(8.68)	0.78(12.11)	1.00(9.16)	0.98(-5.43)	0.05(-0.16)	0.78(-5.32)	0.04(-0.14)
Worry	0.43(2.28)	0.08(0.44)	1.00(0.05)	0.01(0.01)	1.00(7.98)	0.05(0.16)	1.00(10.62)	0.48(2.98)
FutureDoubts	0.14(0.61)	0.97(9.43)	0.02(-0.01)	0.03(-0.12)	0.02(0.04)	0.19(1.16)	0.02(0.02)	0.02(-0.02)
NoFutureDoubts	0.01(0.00)	0.02(-0.04)	0.57(0.03)	0.19(1.15)	0.01(0.00)	0.47(3.22)	0.57(-5.32)	0.06(-0.26)
ScienceTime	1.00(0.05)	1.00(0.07)	0.66(0.04)	1.00(0.08)	0.02(0.03)	0.05(-0.23)	0.66(5.31)	0.62(5.02)
MathTime	1.00(0.04)	0.67(0.03)	0.09(0.04)	0.04(0.00)	0.05(0.00)	0.02(0.00)	0.09(0.00)	1.00(0.07)
LanguageTime	1.00(-0.06)	1.00(-0.05)	1.00(-0.06)	1.00(-0.07)	1.00(0.14)	1.00(0.16)	1.00(0.14)	0.89(0.07)
ForeignTime	1.00(0.02)	0.95(0.03)	0.03(0.01)	0.94(0.02)	0.01(0.00)	0.01(0.00)	0.03(0.00)	0.03(0.00)
ClassPeriods	1.00(-0.01)	1.00(-0.01)	0.01(-0.01)	1.00(-0.01)	0.08(0.00)	0.99(0.06)	0.01(0.00)	0.03(0.00)
NoComputer	0.01(0.00)	0.02(0.00)	0.91(-0.02)	0.02(0.00)	1.00(0.02)	0.04(0.00)	0.91(-0.02)	0.03(0.00)
FirstGeneration	1.00(-14.66)	1.00(-13.72)	0.02(-13.27)	0.02(0.03)	0.03(-0.01)	0.01(0.00)	0.02(-0.03)	0.03(-0.01)
Non-native	0.90(-9.02)	0.69(-8.07)	1.00(-1.25)	0.03(-0.10)	1.00(-16.89)	1.00(-17.79)	1.00(-17.35)	0.07(0.33)
InternalMandatory)	0.72(3.67)	0.06(0.19)	0.11(3.28)	0.02(0.02)	1.00(-11.85)	1.00(-17.94)	0.11(-0.88)	0.04(-0.21)
InternalSchool	0.18(-0.80)	0.05(-0.18)	0.05(-0.47)	0.02(0.01)	0.16(0.61)	0.35(-1.77)	0.05(-0.16)	0.02(-0.02)
ExternalMandatory	0.02(0.05)	0.06(0.23)	0.05(0.00)	0.02(-0.02)	0.52(-2.28)	0.11(0.44)	0.05(0.18)	0.02(0.00)
ExternalSchool	0.01(-0.02)	0.03(-0.09)	0.04(0.00)	0.02(0.03)	0.02(-0.02)	0.01(-0.01)	0.04(-0.16)	0.62(-4.11)
SchoolAdmission	1.00(0.39)	1.00(0.34)	0.12(0.41)	0.66(0.08)	0.06(0.22)	0.02(0.04)	0.12(0.76)	0.02(0.03)
Residence	0.79(-3.92)	0.73(-4.68)	0.15(-0.18)	0.20(-1.00)	0.02(0.00)	0.01(0.00)	0.15(-0.03)	0.05(-0.01)

Note: The table presents the posterior inclusion probabilities and the posterior means (in brackets) for the OLS-MA and Gini-MA methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method and can be provided upon request. Following Kass and Raftery (1995), classified the strength of evidence of a regressors' effect into the following categories, sorted by the PIP : if PIP<50%, there is lack of evidence for the effect, if 50%<PIP<75% there is weak evidence for the effect, if 75%<PIP<95% there is positive evidence for the effect, 95%<PIP<99% there is strong evidence for the effect, if 99%<PIP<100% there is decisive evidence for the effect.

Table 7: Heatmap-Robustness checks for Reading test scores using pooled data

	OLS				GINI			
Variables (READ)	Mother with high school education	Mother with high school education (FEMALE)	Mother with high school education (MALE)	Mother without high school education	Mother with high school education	Mother with high school education (FEMALE)	Mother with high school education (MALE)	Mother without high school education
Repeat	1.00 (-49.29)	1.00(-46.92)	1.00(-48.19)	1.00(-46.33)	1.00(-60.03)	0.97(-29.49)	1.00(-51.45)	0.58(-24.57)
OneOrLess	0.02(-0.05)	0.03(0.07)	0.01(0.00)	0.03(0.12)	1.00(-31.37)	1.00(-26.13)	1.00(-29.80)	1.00(-40.44)
OneAndTwo	0.77(-6.23)	0.24(-1.85)	0.29(-2.53)	0.14(-1.21)	0.02(0.05)	0.01(0.00)	0.01(-0.01)	0.05(0.23)
TwoAndThree	0.03(-0.40)	0.01(-0.03)	0.01(-0.04)	0.07(-0.67)	0.04(-0.17)	0.12(-0.82)	0.03(-0.13)	0.10(-0.83)
ThreeAndFour	0.03(-0.45)	0.02(-0.15)	0.03(0.14)	0.02(0.06)	0.01(0.01)	0.03(0.20)	0.01(-0.03)	0.05(-0.41)
FourAndFive	0.07(-0.92)	0.72(-8.81)	0.02(0.04)	0.02(0.03)	0.01(0.02)	0.03(0.12)	0.06(0.35)	0.02(0.04)
FiveOrMore	1.00(-38.38)	1.00(-40.52)	1.00(-33.09)	1.00(-39.35)	0.04(-0.21)	0.17(-1.57)	0.02(0.04)	0.02(-0.01)
AgeEntrance	0.03(0.10)	0.02(0.02)	0.12(0.15)	0.02(0.01)	1.00(-51.31)	1.00(-41.01)	1.00(-52.54)	1.00(-42.46)
DataPublic	0.04(0.11)	0.03(0.09)	0.01(0.02)	0.07(0.30)	0.01(0.00)	0.02(0.01)	0.15(0.22)	0.01(0.00)
DataAuthority	0.15(0.69)	0.72(5.87)	0.01(0.03)	0.52(5.30)	0.96(6.38)	0.99(8.49)	0.13(0.64)	0.14(0.74)
DataParents	0.01(-0.01)	0.01(0.01)	0.06(-0.31)	0.01(0.00)	0.26(-1.33)	0.01(0.00)	0.05(-0.26)	0.07(-0.39)
RecordForAdmission	0.04(0.11)	0.01(0.01)	0.27(1.58)	0.02(0.01)	0.01(-0.01)	0.01(0.02)	0.02(-0.03)	0.03(0.09)
ClassSize	1.00(0.07)	1.00(0.06)	1.00(0.08)	0.29(0.01)	0.02(0.04)	0.02(0.04)	0.05(0.21)	0.20(-1.09)
GoodJob	0.01(0.00)	0.01(0.00)	0.02(-0.03)	0.01(-0.01)	0.04(0.00)	0.04(0.00)	0.08(0.01)	0.47(-0.07)
InCompetition	1.00(10.54)	1.00(10.48)	1.00(14.37)	0.98(9.12)	0.16(-0.60)	0.02(-0.03)	0.20(-1.06)	0.01(0.00)
Worry	0.54(4.04)	0.14(0.99)	0.01(0.03)	0.02(0.05)	0.97(6.67)	0.13(0.65)	1.00(13.54)	0.17(0.94)
FutureDoubts	0.53(3.83)	0.91(8.95)	0.01(-0.02)	0.02(0.03)	0.09(0.41)	0.21(1.39)	0.01(0.01)	0.01(0.00)
FutureDoubts	0.05(-0.19)	0.02(-0.07)	0.01(0.01)	0.04(0.20)	0.02(0.05)	0.37(2.63)	0.83(-9.19)	0.01(0.00)
ScienceTime	1.00(0.04)	1.00(0.06)	1.00(0.03)	1.00(0.07)	0.03(-0.08)	0.07(-0.41)	0.11(0.65)	0.21(1.54)
MathTimw	0.67(0.02)	0.33(0.01)	0.34(0.01)	0.02(0.00)	0.01(0.00)	0.01(0.00)	0.02(0.00)	0.88(0.05)
LanguageTime	1.00(-0.06)	0.98(-0.04)	1.00(-0.06)	1.00(-0.07)	1.00(0.12)	1.00(0.15)	0.98(0.10)	0.99(0.11)
ForeignTime	1.00(0.04)	1.00(0.04)	0.97(0.03)	1.00(0.03)	0.03(0.00)	0.01(0.00)	0.02(0.00)	0.02(0.00)
ClassPeriods	1.00(-0.01)	1.00(-0.01)	1.00(-0.01)	1.00(-0.01)	0.40(0.01)	0.98(0.06)	0.01(0.00)	0.11(0.00)
NoComputer	0.01(0.00)	0.01(0.00)	0.02(-0.01)	0.02(0.00)	0.99(-0.02)	0.06(0.0)	0.98(-0.02)	0.34(-0.01)
FirstGeneration	1.00(-12.31)	0.67(-6.96)	0.70(-7.74)	0.15(1.01)	0.02(-0.01)	0.01(0.00)	0.02(-0.04)	0.03(-0.02)
Non-native	0.84(-8.99)	0.39(-4.32)	0.08(-0.76)	0.16(-1.39)	1.00(-14.67)	1.00(-15.12)	0.98(-13.65)	0.67(6.78)
InternalMandatory)	0.10(0.34)	0.02(0.03)	0.12(0.66)	0.02(-0.04)	0.97(-11.74)	1.00(-18.26)	0.05(-0.41)	0.34(-3.65)
InternalSchool	0.04(-0.10)	0.02(-0.03)	0.03(-0.05)	0.06(0.29)	0.73(-4.21)	0.61(-3.91)	0.08(-0.36)	0.04(-0.15)
ExternalMandatory	0.03(0.08)	0.07(0.27)	0.01(0.00)	0.01(0.00)	0.24(1.31)	0.18(0.94)	0.15(0.78)	0.03(0.11)
ExternalSchool	0.03(-0.09)	0.05(-0.25)	0.01(0.00)	0.02(0.04)	0.01(-0.01)	0.01(0.00)	0.03(-0.08)	0.23(-1.43)
SchoolExpenses	1.00(0.36)	1.00(0.31)	1.00(0.39)	0.08(0.01)	0.02(0.04)	0.01(0.01)	0.09(0.54)	0.05(0.28)
Residence	0.31(-1.37)	0.67(-4.54)	0.02(-0.07)	0.07(-0.27)	0.04(0.00)	0.01(0.00)	0.16(-0.03)	0.06(-0.01)

Note: The table presents the posterior inclusion probabilities and the posterior means (in brackets) for the OLS-MA and Gini-MA methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method and can be provided upon request. Following Kass and Raftery (1995), classified the strength of evidence of a regressors' effect into the following categories, sorted by the PIP : if PIP<50%, there is lack of evidence for the effect, if 50%<PIP<75% there is weak evidence for the effect, if 75%<PIP<95% there is positive evidence for the effect, 95%<PIP<99% there is strong evidence for the effect, if 99%<PIP<100% there is decisive evidence for the effect.

Table 8: Top 3 models for Science test scores-1st specification: Mother with High school education

Variables (SCIENCE)-MoHighScience	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	401.12(4.54) ***	400.75(4.54) ***	400.66(4.57) ***	478.33(7.09) ***	478.79(6.74) ***	478.17(7.55) ***
Repeat	-44.25(1.92) ***	-44.35(1.92) ***	-44.42(1.92) ***	-48.48(1.96) ***	-48.5(1.96) ***	-48.49(1.96) ***
OneOrLess				4.20(1.63) *	4.2(1.63) *	4.2(1.63) *
OneAndTwo	-15.27(2.47) ***	-15.23(2.47) ***	-7.66(2.12) ***			
TwoAndThree	-18.32(3.80) ***	-18.30(3.80) ***				
Three and four	-20.09(3.95) ***	-20.12(3.95) ***				
Four and five	-30.07(4.93) ***	-30.14(4.93) ***				
FiveOrMore	-67.12(7.26) ***	-67.08(7.26) ***	-34.22(4.65) ***			
AgeEntrance	5.14(0.89) ***	5.15(0.89) ***		-0.34(0.38)	-0.35(0.38)	-0.34(0.38)
DataAuthority				5.1(2.93) ●	5.16(2.89) ●	5.15(2.89) ●
ClassSize	0.06(0.01) ***	0.06(0.01) ***	0.06(0.01) ***			
InCompetition	11.67(1.40) ***	10.99(1.42) ***	11.61(1.40) ***	11.27(1.47) ***	11.28(1.47) ***	11.28(1.47) ***
Worry		5.38(1.78) ***		5.23(1.86) *	5.24(1.86) *	5.23(1.86) *
MathTime	0.04(0.01) ***	0.04(0.01) ***	0.04(0.01) ***			
ScienceTime	0.05(0.01) ***	0.05(0.01) ***	0.05(0.01) ***			
LanguageTime	-0.06(0.01) ***	-0.06(0.01) ***	-0.06(0.01) ***	-0.03(0.01) ***	-0.03(0.01) ***	-0.03(0.01) ***
ForeignTime	0.02(0.01) ***	0.02(0.01) ***	0.03(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***			
NoComputer				-2.27(1.46)	-2.25(1.46)	-2.26(1.46)
FirstGeneration	-14.89(2.34) ***	-14.71(2.34) ***	-14.98(2.34) ***			
Non-native	-9.85(2.92) ***	-9.67(2.92) ***	-10.54(2.93) ***	-4.44(3.01)	-4.44(3.01)	-4.45(3.01)
InternalMandatory	5.19(2.07)	5.18(2.07)	5.09(2.07)	3.03(2.16)	3.06(2.15)	3.76(5.02)
InternalSchool						0.77(5.14)
ExternalMandatory				0.57(2.47)		
SchoolExpenses	0.39(0.05) ***	0.38(0.05) ***	0.39(0.05) ***			
Residence	-4.91(1.94)	-4.93(1.94)	-5.02(1.95)			
PMP (Exact)	**0.051**	**0.048**	**0.043**	**0.186**	**0.128**	**0.042**
PMP (MCMC)	**0.053**	**0.051**	**0.040**	**0.185**	**0.127**	**0.042**
R^2 adjusted	**35%**	**35%**	**35%**			
GR				**57%**	**57%**	**57%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 9: Top 3 models for Science test scores-2nd specification: Girls whose Mothers have High school education

Variables (Science)-MoHighFemaleScience	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	391.66(5.69) ***	392.04(5.69) ***	392.68(5.70) ***	480.56(7.80) ***	479.78(7.78) ***	481.93(8.58) ***
Repeat	-43.15(2.69) ***	-43.03(2.70) ***	-42.72(2.67) ***	-48.40(2.72) ***	-48.50(2.72) ***	-48.41(2.72) ***
OneOrLess				4.97(2.19) *	5.04(2.19) *	4.98(2.19) *
FourAndFive		-9.39(3.11) ***				
FiveOrMore	-35.55(7.74) ***	-36.71(7.49)	-35.88(7.46) ***			
AgeEntrance				-0.52(0.55)	-0.54(0.55)	-0.52(0.55)
DataAuthority	7.80(3.24)	7.78(3.24) ***	7.79(3.25) *	8.10(3.43) *	8.10(3.43) *	8.12(3.44) *
ClassSize	0.06(0.01) ***	0.06(0.01) ***	0.05(0.01) ***			
InCompetition	8.67(1.97) ***	8.67(1.97) ***	8.83(1.98) ***			
FutureDoubts	9.75(2.31) ***	9.70(2.31) ***	9.90(2.31) ***			
NoFutureDoubts				-4.73(2.54) ●		-4.73(2.54) ●
MathTime	0.04(0.02) ***	0.04(0.02)				
ScienceTime	0.07(0.01) ***	0.07(0.01) ***	0.07(0.01) ***			
LanguageTime	-0.06(0.01) ***	-0.06(0.01) ***	-0.04(0.01) ***	-0.01(0.01)	-0.01(0.01)	-0.01(0.01)
ForeignTime	0.03(0.01) ***	0.03(0.01) ***	0.03(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***	0.00(0.00) ●	0.00(0.00) ●	0.00(0.00) ●
FirstGeneration	-14.30(3.08) ***	-14.24(3.08) ***	-14.29(3.09) ***			
Non-native	-11.66(3.81) ***	-11.28(3.81) ***	-11.90(3.81) ***	-6.19(3.91)	-6.04(3.91)	-6.17(3.91)
InternalMandatory				1.84(2.59)	1.85(2.59)	0.30(5.60)
InternalSchool						-1.70(5.72)
SchoolExpenses	0.34(0.06) ***	0.33(0.06) ***	0.33(0.06) ***			
Residence	-6.46(2.40)	-6.44(2.39)	-6.28(2.39) *			
PMP (Exact)	**0.076**	**0.043**	**0.041**	**0.138**	**0.097**	**0.088**
PMP (MCMC)	**0.078**	**0.043**	**0.042**	**0.137**	**0.097**	**0.087**
R^2 squared	**35%**	**35%**	**35%**			
GR				**57%**	**57%**	**57%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 10: Top 3 models for Science test scores-3rd specification: Boys whose Mothers have High school education

Variables (Science)-MoHighMaleScience	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	402.91(5.51) ***	408.55(5.04) ***	400.34(5.56) ***	473.7(6.64) ***	472.88(6.66) ***	478.86(6.70) ***
Repeat	-46.35(2.56) ***	-46.26(2.56) ***	-46.39(2.56) ***	-49.33(2.77) ***	-49.3(2.77) ***	-49.78(2.63) ***
OneOrLess				3.00(2.41)	3.03(2.41)	3.41(2.39)
OneAndTwo	-9.73(3.10) ***	-9.77(3.10)	-9.69(3.08) ***			
FiveOrmore	-33.42(5.84) ***	-33.43(5.84) ***	-33.71(5.84) ***			
AgeEntrance				-0.07(0.51)	-0.07(0.51)	-0.11(0.51)
ClassSize	0.06(0.01) ***	0.06(0.01) ***	0.06(0.01) ***			
RecordForAdmission			5.41(2.58)			
InCompetition	12.08(1.97) ***	12.07(1.97) ***	12.08(1.96) ***	12.62(2.5) ***	12.39(2.06) ***	12.41(2.08) ***
Worry				1.94(2.86)	2.38(2.91)	2.34(2.93)
NoFutureDoubts					2.95(2.40)	2.71(2.43)
MathTime	0.05(0.01) ***	0.05(0.01) ***	0.05(0.01) ***			
ScienceTime	0.04(0.01) ***	0.04(0.01) ***	0.04(0.01) ***	0.09(0.01) ***	0.09(0.01) ***	
LanguageTime	-0.06(0.01) ***	-0.06(0.01) ***	-0.06(0.01) ***	-0.09(0.01) ***	-0.09(0.01) ***	-0.05(0.01)* **
ForeignTime						
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***			
NoComputer				-2.07(2.12)	-2.1(2.12)	-1.72(2.14)
FirstGeneration	-13.22(3.19) ***	-13.04(3.19) ***	-13.34(3.19) ***			
Non-native				-1.77(4.28)	-1.75(4.28)	-2.76(4.26)
InternalMandatory	6.24(2.61)		6.34(2.61)			
ExternalMandatory						
SchoolExpenses	0.42(0.06) ***	0.41(0.06) ***	0.41(0.06) ***			
PMP (Exact)	**0.088**	**0.072**	**0.041**	**0.103**	**0.095**	**0.063**
PMP (MCMC)	**0.088**	**0.072**	**0.041**	**0.102**	**0.094**	**0.061**
R^2 squared	**34%**	**34%**	**32%**			
GR				**58%**	**58%**	**58%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 11: Top 3 models for Science test scores-4th specification: Mother without High school education

Variables (Science)-MoWithoutHighScience	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	408.95(9.58) ***	413.86(9.01) ***	416.54(9.03) ***	454.73(8.05) ***	440.56(8.63) ***	439.6(8.35) ***
Repeat	-42.32(2.22) ***	-42.39(2.22) ***	-42.07(2.21) ***	-42.31(2.28) ***		
OneOrLess				5.52(2.73) *	5.53(2.83) ●	5.65(2.83) ●
FiveOrMore	-34.58(5.72) ***	-34.94(5.73) ***	-34.78(5.72) ***			
AgeEntrance				-0.55(0.49)	-0.89(0.50) ●	-0.88(0.50) ●
DataAuthority						7.76(5.40)
ClassSize	0.03(0.01) ***					
GoodJob					-1.88(2.21)	-1.92(2.20)
InCompetition	9.16(1.90) ***	9.28(1.90) ***	9.20(1.91) ***			
MathTime				0.03(0.02)	0.00(0.02)	0.00(0.02)
ScienceTime	0.07(0.01) ***	0.08(0.01) ***	0.08(0.01) ***	0.1(0.01) ***	0.12(0.01) ***	0.12(0.01) ***
LanguageTime	-0.07(0.01) ***	-0.07(0.01) ***	-0.07(0.01) ***	-0.12(0.02) ***	-0.12(0.02) ***	-0.12(0.02) ***
ForeignTime	0.02(0.01) ***	0.02(0.01) ***	0.02(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***			
ExternalSchool				3.19(4.10)	2.46(4.39)	2.5(4.39)
SchoolExpenses	0.12(0.05)	0.11(0.05)				
PMP (Exact)	**0.076**	**0.065**	**0.030**	**0.186**	**0.128**	**0.042**
PMP (MCMC)	**0.076**	**0.064**	**0.030**	**0.185**	**0.127**	**0.042**
R^2 squared	**33%**	**33%**	**33%**			
GR				**59%**	**54%**	**54%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 12: Top 3 models for Reading test scores-1st specification: Mother with High school education

Variables (Reading)-MoHighRead	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	393.01(4.24) ***	393.07 (4.23) ***	393.71 (4.23) ***	477.26 (8.14) ***	481.39 (8.08) ***	481.95 (8.30) ***
Repeat	-49.28(2.18) ***	-49.37 (2.18) ***	-49.03 (2.17) ***	-53.84 (2.26) ***	-53.40 (2.23) ***	-53.41 (2.23) ***
OneOrLess				2.94 (1.83)	2.95 (1.82)	2.95 (1.82)
OneAndTwo	-7.81(2.29) ***	-7.72 (2.29) ***	-7.92 (2.28) ***			
FiveOrMore	-37.77(5.25) ***	-37.83 (5.25) ***	-37.73 (5.24) ***			
AgeEntrance				-0.76 (0.43) ●	-0.79 (0.43) ●	-0.79 (0.43) ●
DataAuthority				5.08 (3.06)	5.03 (3.05)	5.06 (3.05)
DataParents						-0.84 (3.36)
ClassSize	0.07(0.01) ***	0.07 (0.01) ***	0.07 (0.01) ***			
InCompetition	10.57 (1.56) ***	10.44 (1.57) ***	10.71 (1.56) ***			
Worry		7.88 (1.96) ***		9.52 (2.03) ***	9.96 (2.03) ***	9.97 (2.03) ***
FutureDoubts	7.75 (1.92) ***		7.72 (1.93) ***			
MathTime	0.03(0.01)	0.03 (0.01) ***				
ScienceTime	0.04 (0.01) ***	0.04 (0.07) ***	0.04 (0.01) ***			
LanguageTime	-0.06 (0.01) ***	-0.06 (0.01) ***	-0.05(0.01) ***	-0.04 (0.01) ***	-0.01 (0.01)	-0.01 (0.01)
ForeignTime	0.04 (0.01) ***	0.04 (0.01) ***	0.04 (0.01) ***			
ClassPeriods	-0.01 (0.00) ***	-0.01 (0.00) ***	-0.01 (0.00) ***		-0.01 (0.00) ***	-0.01 (0.00) ***
NoComputer				-4.09 (1.68) *	-3.95 (1.65) *	-3.95 (1.65) *
FirstGeneration	-12.78 (2.55) ***	-12.48 (2.55) ***	-12.64 (2.56) ***			
Non-native	-10.75 (3.25) ***	-10.47 (3.25) ***	-11.03 (3.24) ***	-5.36 (3.37)	-5.73 (3.34)	-5.73 (3.34) ●
InternalMandatory				4.24 (5.39)	4.25 (5.37)	4.36 (5.38)
InternalSchool				2.47 (5.54)	2.59 (5.51)	2.69 (5.53)
SchoolExpenses	0.36 (0.05) ***	0.36 (0.50) ***	0.36 (0.05) ***			
PMP (Exact)	**0.071**	**0.064**	**0.048**	**0.171**	**0.092**	**0.051**
PMP (MCMC)	**0.070**	**0.065**	**0.048**	**0.172**	**0.092**	**0.052**
R^2 squared	**32%**	**32%**	**32%**			
GR				**54%**	**54%**	**54%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 13: Top 3 models for Reading test scores-2nd specification: Girls whose Mothers have High school education

Variables (Reading)-MoHighFemaleRead	OLS			GINI		
	TOP MODEL 1	**TOP MODEL 2**	**TOP MODEL 3**	**TOP MODEL 1**	**TOP MODEL 2**	**TOP MODEL 3**
Intercept	382.76 (5.96) ***	390.28(6.01) ***	390.47(6.03) ***	486.38(8.51) ***	487.29(8.49) ***	484.38(8.47) ***
Repeat	-46.79(2.93) ***	-46.31(2.94) ***	-46.97(2.94) ***	-52.36(2.99) ***	-52.25(2.99) ***	-52.07(2.98) ***
OneOrLess				3.62(2.38)	3.54(2.38)	3.48(2.37)
FourAndFive	-11.91(3.37) ***	-11.5(3.37) ***	-11.90(3.36) ***			
FiveOrMore	-40.73(7.79) ***	-40.2(7.78)	-40.59(7.83) ***			
AgeEntrance				-0.93(0.59)	-0.9(0.59)	-0.97(0.59)
DataAuthority	8.22(3.34)	8.24(3.33) ***	8.33(3.35)	8.6(3.53) *	8.61(3.53) *	8.30(3.52) *
ClassSize	0.06(0.01) ***	0.06(0.01) ***	0.06(0.01) ***			
InCompetition	10.61(2.13) ***	0.53(2.13) ***	10.53(2.13) ***			
FutureDoubts	9.91(2.47) ***	9.91(2.46) ***	9.99(2.46) ***			12.45(2.53) ***
NoFutureDoubts					-5.38(2.81) ●	
ScienceTime	0.06(0.01) ***	0.06(0.01) ***	0.06(0.01) ***			
LanguageTime	-0.04(0.01) ***	-0.04(0.01) ***	-0.04(0.01) ***	0.01(0.02)	0.01(0.02)	0.01(0.02)
Foreign	0.04(0.00) ***	0.04(0.01) ***	0.04(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***	0.00(0.00) *	0.00(0.00) *	0.00(0.00) *
FirstGeneration	-9.36(3.16) ***	-11.18(3.26) ***				
Non-native		-11.4(4.03)		-6.99(4.11) ●	-7.17(4.11) ●	-7.03(4.08) ●
InternalMandatory				-0.32(5.83)	-0.37(5.82)	-0.48(5.80)
InternalSchool				-0.82(5.95)	-0.85(5.94)	-0.97(5.94)
SchoolExpenses	0.3(0.06) ***	0.31(0.06) ***	0.29(0.06) ***			
Residence	-6.78(2.50)	-6.60(2.49)	-6.76(2.51)			
PMP (Exact)	**0.034**	**0.031**	**0.029**	**0.111**	**0.094**	**0.055**
PMP (MCMC)	**0.034**	**0.031**	**0.029**	**0.112**	**0.095**	**0.056**
R^2 squared	**32%**	**33%**	**32%**			
GR				**54%**	**54%**	**54%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 14: Top 3 models for Reading test scores-3rd specification: Boys whose Mothers have High school education

Variables (Reading)-MoHighMaleRead	OLS			GINI		
	TOP MODEL 1	**TOP MODEL 2**	**TOP MODEL 3**	**TOP MODEL 1**	**TOP MODEL 2**	**TOP MODEL 3**
Intercept	382.61(5.16)***	381.96(5.18) ***	382.87(5.17) ***	464.15(6.59)***	460.91(6.56)***	465.38(7.04) **
Repeat	-48.17(2.87) ***	-48.34(2.87) ***	-48.19(2.88) ***	-52.89(2.96) ***	-52.02(2.97) ***	-52.91(2.96)***
OneOrLess				1.5(2.65)	1.46(2.64)	1.53(2.66)
FiveOrMore	-32.14(6.79) ***	-32.38(6.81) ***	-31.82(6.81) ***			
AgeEntrance				0.17(0.57)	0.21(0.57)	0.17(0.57)
ClassSize	0.08(0.01) ***	0.08(0.01) ***	0.08(0.01) ***			
InCompetition	14.41(2.21) ***	14.3(2.21) ***	14.35(2.21) ***		14.86(2.33) ***	
Worry				5.17(3.16)	1.59(3.24)	5.2(3.17)
NoFutureDoubts				3.2(2.64)	1.77(2.65)	3.24(2.64)
MathTime		0.03(0.01)				
ScienceTime	0.03(0.01) ***	0.03(0.01) ***	0.03(0.01) ***			
LanguageTime	-0.05(0.01) ***	-0.07(0.01) ***	-0.05(0.01) ***	-0.05(0.01) ***	-0.05(0.01) ***	-0.05(0.01) ***
ForeignTime	0.04(0.01) ***	0.03(0.01) ***	0.04(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***			
NoComputer				-4.32(2.30) ●	-4.27(2.29) ●	-4.27(2.30) ●
FirstGeneration	-10.65(3.64) ***	-11.00(3.64) ***				
Non-native				-2.91(4.90)	-3.60(4.86)	-2.92(4.90)
Externalmandatory						-1.44(3.15)
SchoolExpenses	0.39(0.07)	0.39(0.07) ***	0.39(0.07) ***			
PMP (Exact)	**0.113**	**0.063**	**0.061**	**0.162**	**0.042**	**0.038**
PMP (MCMC)	**0.113**	**0.063**	**0.059**	**0.162**	**0.042**	**0.038**
R^2 squared	**30%**	**31%**	**31%**			
GR				**53%**	**53%**	**53%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

Table 15: Top 3 models for Reading test scores-4th specification: Mother without High school education

Variables (Reading)-MoWithoutHighRead	OLS			GINI		
	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3	TOP MODEL 1	TOP MODEL 2	TOP MODEL 3
Intercept	398.79(11.68) ***	408.99(10.51) ***	374.58(12.26)***	458.42(9.26) ***	456.59(9.34)***	444.46(9.50) ***
Repeat	-46.43(2.56) ***	-46.43(2.56) ***	-46.34(2.58) ***	-51.10(2.62) ***	-50.24(2.65) ***	
OneOrLess				4.72(3.16)	4.53(3.14)	4.31(3.28)
FiveOrMore	-39.55(6.45) ***	-39.54(6.51) ***	-39.20(6.44)			
AgeEntrance				-0.71(0.56)	-0.68(0.56)	-1.07(0.57) ●
DataAuthority	10.33(5.32)		10.12(5.31) ***			
ClassSize			0.03(0.01) ***			
GoodJob						1.86(2.46)
InCompetition	9.36(2.21) ***	9.28(2.21) ***	9.23(2.21) ***			
MathTime				0.08(0.02) ***	0.08(0.02) ***	0.06(0.02) *
ScienceTime	0.07(0.01) ***	0.07(0.01) ***	0.07(0.01) ***			
LanguageTime	-0.07(0.01) ***	-0.07(0.01) ***	-0.07(0.01) ***	-0.10(0.02)	-0.10(0.02) ***	-0.1(0.02) ***
ForeignTime	0.03(0.01) ***	0.03(0.01) ***	0.03(0.01) ***			
ClassPeriods	-0.01(0.00) ***	-0.01(0.00) ***	-0.01(0.00) ***			
NoComputer					2.08(2.14)	
Non-native					-9.78(4.52) *	-16.93(4.49) ***
InternalMandatory				-1.42(3.41)		
PMP (Exact)	**0.125**	**0.095**	**0.040**	**0.031**	**0.030**	**0.020**
PMP (MCMC)	**0.125**	**0.096**	**0.040**	**0.031**	**0.030**	**0.019**
R^2 squared	**28%**	**28%**	**28%**			
GR				**51%**	**51%**	**44%**

Note: The table presents the coefficients and the robust standard errors (in brackets) for the OLS and Gini methodology. Country dummies in all specifications are retained to capture the fixed country effects. Country-school id clustered posterior standard errors are obtained by applying the jackknife method. Asterisks denote significance at *** 0%, **0.1%, *1%, while • at 5%.

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