What determines the financial literacy of young people? An analysis from PISA 2012*

María Jesús Mancebón‡, Domingo P. Ximénez-de-Embún§♮, and José María Gómez-Sancho‡

‡Department of Applied Economics, University of Zaragoza

♮Department of Economic Analysis, University of Zaragoza

mjmance@unizar.es, dpxe@unizar.es, jmgomez@unizar.es

February 5, 2015

Abstract

This paper aims to disentangle the factors determining the financial skills of young people in order to inspire effective policies aimed at improving the financial literacy of the population. PISA 2012 data is used. Special attention is paid to the sample selection and simultaneity biases that threaten the internal validity of the estimations. Our results show that the most important determinants of financial literacy of students are mathematical skills. Household socioeconomic

*M.J. Mancebón wishes to thank the financial support from INEE (Instituto Nacional de Evaluación Educativa). M.J. Mancebón and J.M. Gómez-Sancho are grateful for support from the Spanish Ministry of Economy and Competitiveness (EDU2013-42480-R) and from the Spanish Regional Government of Aragón and from the European Social Fund. D.P. Ximénez-de-Embún gratefully acknowledges financial support from the Fundación Ramón Areces. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of these institutions.

§Corresponding author at: University of Zaragoza, Gran Vía 2, Facultad de Economía y Empresa, 50005, Zaragoza, Spain. Tel.: +34 876 554 785; fax: +34 976 761 996

level also has a statistically significant effect. School management model (public versus private) does not display any significant effect on the promotion of the financial culture of students.

Keywords: Financial literacy, mathematical performance, school choice, selection bias, simultaneity bias, multilevel models, propensity score matching

1 Introduction

Over the past ten years there has been considerable international interest in the measurement and analysis of the economic and financial knowledge of the population, which may be explained by a variety of factors. On the one hand, the baby boom generation is drawing nearer to retirement age, leading to rising concern regarding the savings levels of the elderly population, given the increasing limitations affecting the public social security system. Consequently, many studies have aimed to disentangle the determinants of domestic savings in the long term, with financial culture being one of the main factors of interest in this literature. On the other hand, the current economic crisis has demonstrated the inability of many citizens to make optimal financial investments. Some evidence of this reality is the acquisition of complex financial products, such as preferred stocks, by groups of citizens with an inappropriate investor profile, and the excessive debt levels of many low-income households (Bover et al., 2014). The complexity of financial assets currently offered by the capital markets requires small investors to be financially qualified in order to make well-informed decisions that maximize their economic wellbeing. Indeed, some authors have stated that such a lack of financial skills is one of the primary causes of the current economic crisis (Gerardi et al., 2010; President's Advisory Council on Financial Literacy, 2008). Finally, the financial culture of the population influences not only its personal wellbeing but is also a source of positive externalities for society as a whole, as discussed by Gnan et al. (2007) and Lusardi and Mitchell (2011), among others. Awareness of this situation on the part of public authorities is another factor underlying recent concern over the assessment and improvement of the financial literacy of the population. Proof of this concern is the recent publication of the Financial Literacy Assessment conducted by the OECD in 2012 (OECD, 2014). This last wave of PISA constitutes the first large-scale international assessment of financial literacy around the world.

Most studies measuring economic-financial competency have focused on the role of the financial skills of the population in stimulating diverse economic outcomes. Some have attempted to evaluate the distribution of economic knowledge based on ethnicity (Crossan et al., 2011), age, gender, educational level or employment status (Fornero and Monticone, 2011). Other research has focused on the influence of financial culture on the probabilities of having a pension plan (Fornero and Monticone, 2011; Klaper and Panos, 2011), on savings levels (Behrman et al., 2010)[1] , on participation in the stock market (van Rooij et al., 2011a,b), on the risk of defaulting on bank loans (Gerardi et al., 2010; Grinstein-Weiss et al., 2012), on the ability to make optimal investments (Lusardi and Tufano, 2009) or on the potential of financial literacy to prevent social exclusion (Robson, 2012). In this literature financial culture is regarded as another input in the economic process.

By contrast, a second line of research into financial literacy has focused on the internal processes through which individuals develop economic and financial skills. Such studies aim to identify the factors involved in the promotion of financial performance, in order for them to serve as the basis for successful public policies aimed at improving such skills (see Lusardi et al., 2010; Monticone, 2010; Romagnoli and Trifilidis, 2013; Shim et al., 2010; Walstad et al., 2010). In these studies, financial skills are described as the output of a complex process in which several influences participate (individual attitudes, aptitudes for learning, the family context, social networks, schools, etc.).

Our study falls within this second research line. Its main contributions to the previous literature are based on three points: our use of an internationally validated database barely explored to date (PISA 2012), our use of the lessons supplied by the literature on the determinants of cognitive skills as the principal reference in the specification of empirical models[2], and the consideration of financial literacy as a skill acquired simultaneously with other cognitive skills.

In particular, our work focuses on the PISA 2012 data corresponding to Spain, one of the 13 countries participating in the first international financial literacy assessment[3]. Specifically we aim to examine which factors contribute to the acquisition of financial skills by 15-year-old Spanish students.

Two hypotheses are proposed for consideration:

Hypothesis 1: The math skills of individuals are the main predictor of their degree of financial literacy; such as these skills are evaluated by PISA 2012.

Hypothesis 2: The school management model (public versus private[4]) indirectly influences the degree of financial literacy of young people through its influence on the knowledge acquired from classes where the official educational curriculum is taught (specifically mathematics-based concepts).

The first hypothesis is based on the following:

Firstly, at the age of 15, Spanish students have received barely any type of formal education regarding economic/financial skills[5]. For this reason, their competencies in these areas must mainly come from factors external to the school (the family environment, personal interest and motivation, social relationships, etc.) or from the education offered by schools in other courses (with mathematics being the area that most likely influences financial literacy, as measured by PISA 2012[6]). Secondly, the exploratory analysis of the data provided for Spain in PISA 2012 shows a very high correlation coefficient between math and financial scores obtained by students (0.79). Thirdly, 73% of the schools participating in the fifth wave of PISA include financial education within their "mathematics" classes (as shown by the responses given by school principals to question 37 of the Schools Questionnaire).

With regard to the second hypothesis, this is based on the following:

Firstly, as the majority of 15-year-old Spanish students do not take any economics courses at school, the impact of the school, and specifically of the school management model, on financial literacy, if it exists, must operate indirectly, through its influence on other skills that are simultaneously acquired by students during their stay in schools.

Secondly, the review of the prolific literature on the role of school type (public versus private) on students' performance, dating back from Coleman et al. (1982), has produced inconclusive results (Toma and Zimmer, 2012). In some studies, the effect of privately run schools on test scores is positive (Bedi and Garg, 2000), in others it is negative (Bifulco and Ladd, 2006; Lefebvre et al., 2011; Morgan, 2001; Pfeffermann and Landsman, 2011) while in yet others it is neutral (Mancebón et al., 2012). Finally, in numerous studies, the statistical associations found in the raw data between school type and educational scores vanish after introducing various methodological controls into the analysis (Bettinger, 2005; Betts et al., 2006; Chudgar and Quin, 2012; Witte et al., 2007)[7]. In this context, and given that the data from PISA 2012 show a statistical association between school management model (public/private) and student scores in both the mathematical and financial skills assessment (see Table 3), it is interesting to test whether this association is a reflection of a true influence or if it is a spurious effect of the fact that students having more favorable learning attributes tend to be more likely to attend Spanish PFPrRS.

2 Empirical analysis strategy

In order to achieve the objective of our study, three technical factors must be considered.

Firstly, the data from PISA 2012 have a hierarchical structure, due to the fact that the sample selection of individuals occurs at two levels (students and schools). Thus, data are nested. Consequently, some of the characteristics of students attending the same school are correlated, violating the hypothesis of independence of the observations upon which traditional regression models are based. The application of ordinary least squares (OLS) to these data structures produces an underestimation of the true standard errors, leading to spurious results (Hox, 2002).

Secondly, it should be underlined that the "mathematical skills" predictor and the endogenous variable in the present study (financial literacy) are interdependent, since both are affected by a set of common influences (at least those operating at the student level) and determined simultaneously over time. These characteristics lead to a violation of the hypothesis of non-correlation between regressors and the random term required by conventional econometric estimates based on OLS, causing the expected values of the estimated structural coefficients to differ from the real values and leading to inconsistency in the estimates obtained. This is known as the simultaneity bias (Dougherty, 2011).

Finally, when assessing the impact of school type (PFRS versus PFPrRS), it should be noted that in Spain schools are freely chosen by families[8], family socioeconomic characteristics being one of the main determinants of the selection pattern (Escardíbul and Villarroya, 2009; Mancebón-Torrubia and Ximénez-de Embún, 2014). The "school type" predictor is therefore an endogenous variable. This gives rise to correlations between this predictor and the residuals of the regressions, creating biased parameter estimates. This is what Heckman (1979) defined as sample selection bias.

The characteristics described immediately above are the basic factors conditioning the empirical strategy employed here. This strategy takes material shape in a two-level analysis.

First, a Propensity Score Matching (PSM) analysis was conducted, in order to define a homogenous student subsample in terms of the observable characteristics which may simultaneously influence the selection of school type and educational scores.

Second, a multilevel simultaneous equation model (MSEM) is estimated to allow for the consideration of: a) the possible simultaneous production of financial and math skills in students, and b) the hierarchical structure of the data supplied by PISA 2012. This model permits the examination of the joint production process conducted in schools. In addition, the multi-level model will permit differentiation between those influences acting on the student and those acting on the school.

It is expected that this empirical strategy will lead to more accurate estimations and reduced bias.

3 Methodological issues

This section offers a brief examination of the techniques used to obtain the estimates. Firstly, the foundations of the PSM calculation are described. Secondly, the functioning of the multi-level models of simultaneous equations is presented.

3.1 Propensity score matching (PSM)

The main challenge faced in evaluating the impact of a public intervention, experienced in a non-random manner by the individuals evaluated, is to approximate a credible value for the counterfactual condition of each individual in the treatment group (hereinafter TG). That is to say, to find a value that appropriately reflects the outcomes that would have been attained by the individuals treated in the absence of the intervention (see Rubin, 1974). In this specific case, as we wish to evaluate the differential impact of attending a PFPrRS versus attending a PFRS, the challenge is to proxy for each individual attending a PFPrRS (TG) the financial score he or she would have obtained had he or she attended a PFRS (control group, CG)[9].

When it comes to putting into practice the appropriate imputation strategy for these counterfactual values for each TG individual, it should be remembered that the only information available in the database on the outcomes attained in the absence of intervention are records corresponding to individuals who have not received the treatment (CG). Therefore, the problem is to find a procedure allowing each TG individual to be matched to one or various similar CG individuals, in the sense that all of them share the relevant characteristics in the determination of the evaluated result. The outcome obtained by the individual/s from the CG subsample thereby constitutes a good approximation of the counterfactual for each of the individuals belonging to the TG. The correct implementation of this empirical strategy ensures that the potential outcomes of individuals from both groups are identical, which allows the ignorable treatment assignment hypothesis to be fulfilled (Rosenbaum and Rubin, 1983), as required by the PSM technique. The subsample so defined contains homogenous individuals with regard to the characteristics influencing educational outcomes and school choice, thus avoiding the sample selection bias associated with the original data. Below, an explanation is provided of how the matching techniques and, specifically, the PSM are useful in achieving this objective.

Matching techniques consist of one of the three procedures proposed by the literature in order to define homogenous samples of individuals[10]. This methodology bases its calculations on the creation of matchings between individuals from the TG with members of the CG who have similar observable characteristics (X), which are simultaneously predictors of the outcome of interest (Y) and of the principal study predictor (W)[11]. Specifically, matching techniques match each individual from the TG (W=1) with one or n individuals from the CG (W=0), using the X variables (Caliendo and Kopeinig, 2008). Therefore, the resulting subsample is free of the sample selection bias due to observable characteristics[12].

Within these matching techniques the PSM is notable. Its origins date back to the ground-breaking work of Rosenbaum and Rubin (1983). The main advantage of this methodology lies in its ability to deal with a large number of covariates (X). This is significant as the probability of finding valid matchings between the TG and the CG is inversely proportional to the number of variables of the X vector. This is known as the matching dimensionality problem.

Rosenbaum and Rubin (1983) solved this problem by proposing a single magnitude, the propensity score (hereinafter, ps) on which the necessary matchings are based for the delimitation of the unbiased subsample. The ps is a synthetic indicator of the information contained in the X variables, calculated on the basis of a logistical regression model (or similar). Unlike other synthetic indicators, such as those resulting from discriminant analysis, the ps, far from being a construct void of content, has a very clear significance. It is simply the conditional probability of participating in the evaluated intervention for each individual in the sample, given their observable characteristics X; that is:

$$ps = P(W = 1|X) \tag{1}$$

This gives the ps a special value in terms of correcting sample selection bias. In fact, as previously stated, the identification of a valid empirical counterfactual value requires CG individuals to present a high degree of similarity to TG in all the observable characteristics affecting outcomes (X). This is the only way to ensure that the differences in outcomes between the two groups are not contaminated by differences in X. In other words, it complies with the hypothesis of ignorable treatment assignment. The calculation of the ps allows identification of the (X) outcomes which determine participation in the intervention and are also influential in the determination of the result of interest (Y), that is to say the variables which potentially cause sample selection bias.

The key to PSM functioning lies in the creation of good matching, namely in finding the CG individuals having a ps similar to that of the TG individuals. In other words, finding $\forall i \in W = 1$ one (some) $j \in W = 0$ such that $P_i(W = 1) \approx P_j(W = 1)$. This requires that $P(W = 1|X) < 1$ and $P(W = 1|X) > 0 \forall X$. The fulfillment of these two relations ensures that the two groups (TG and CG) contain similar individuals regarding observable characteristics (which is known as the common support assumption). The matching process may be conducted using different algorithms. Guo and Fraser (2009) offer a detailed description of the topic. Several of these algorithms have been used in our empirical work to test the sensitivity of our estimates to the employed algorithm.

3.2 Multi-level models of simultaneous equations (MSEM)

As indicated, PSM allows for a subsample of comparable individuals with respect to the observable variables (X) which influence school choice and which are also potentially significant in determining the outcome of interest (Y).

However, potential influences on educational outcomes may consist of more variables than those considered when constructing the ps. Therefore, the calculation of the net effect of an intervention, such as (W) (i.e. attending a PFPrRS) requires testing for the influence of other factors (X’) that are potentially important in determining (Y) but which do not affect the reception of the treatment (W). Therefore, a post-matching analysis should also be conducted. Two types of influence deserve attention: a) characteristics of the school in which students have studied, and b) student attributes that are not incorporated in the calculation of the propensity score.

The study of the significance of these characteristics to the educational outcomes of interest (i.e. financial skills) may be performed via the estimation of a regression model applied to the matched sample. Indeed, since the subsample defined by PSM is not affected by the selection bias issue affecting the original sample, the regression analysis is now fully relevant in terms of identifying the effect of the treatment (W) on outcomes.

The selection of the ideal regression model to conduct the estimates is conditioned by two peculiarities that affect the present study and have been mentioned previously. The first is the presumably simultaneous nature of the development of financial and mathematical performance. The second is the hierarchical structure of the PISA data.

Of all the available regression models, the multi-level models of simultaneous equations (MSEM) adapt best to these peculiarities[13]. Their main advantage is that they allow for differentiation between those influences acting at the student level (first level of analysis) and those acting at the school level (second level), while also allowing for the simultaneous determination of math and financial skills (i.e. the potential cross effects between the two types of cognitive skills evaluated in our study)[14].

The creation of a model of simultaneous equations presents certain challenges to estimation (see Gujarati, 2004). These models have a complex structure and their functioning is based on certain assumptions which should be verified prior to their application. The two most important assumptions are the conditions of completeness and identification. The first assumption is that the number of equations should equal the number of endogenous variables to be estimated (i.e. math and financial skills). As for identification, this requires that the conditions of order and range are satisfied. The first, order, requires that in each equation the number of excluded regressors is greater than the number of endogenous variables included minus one. The range condition requires the second equation to contain at least one exogenous variable not included in the first equation. The specification proposed in the next section fulfills the three above-mentioned assumptions[15].

Multi-level models are especially appropriate for working with data nested at various levels, for example those data supplied by almost all educational databases. This is because this data structure, as well as the intra-group correlation, causes the characteristics and outcomes of students attending different schools to vary (Hox, 1995). These models permit the analysis of variables acting at different levels (individuals and schools, for example) and they allow the identification of the proportion of the total variance of an outcome that is attributed to each of the specified levels[16]. In analytical terms, the level 1 equation is determined as follows:

$$Y_{ik} = \pi_{0k} + \sum_{p=1}^{P} \pi_{pk} a_{pk} + e_{ik} \text{ with } e_{ik} \sim \left(0, \sigma^2\right) \tag{2}$$

where Y_{ik} is the expected result for individual i in school k; a_{pk} is an explanatory variable p of level 1 for the individual i from school k, π_{pk} are the level 1 coefficients $(p = 0, 1, \ldots, P)$ and e_{ik} is the random effect of level 1. For level 2 (schools), the coefficients π are treated as variables to be estimated, and thus:

$$\pi_{pk} = \beta_{0pk} + \sum_{q=1}^{Q_p} \beta_{qpk} X_{qpk} + r_{qpk} \tag{3}$$

where β_{0pk} $\left(q = 0, 1, \ldots, Q_p\right)$ are the level 2 coefficients, X_{qpk} is a level 2 predictor and r_{qpk} is a random effect. The model assumes that, for each unit k, the vector $\left(r_{q0k}, r_{q1k}, \ldots, r_{qPk}\right)'$ is distributed based on a normal multivariate where each element has a mean of zero and a covariance matrix T_π, with a maximum dimension of $(P+1) \times (P+1)$.

4 Results

This section explains the results obtained from the application of the two methodologies described above to the data for Spain obtained from PISA 2012. Firstly, the results of the PSM are presented. Secondly, estimates from the multi-level model of simultaneous equations are offered.

4.1 PSM results

As previously noted, the PSM estimation strategy is based on the identification of a group of students attending a PFRS that is comparable to a group of students attending a PFPrRS, in terms of all the variables which may condition school choice and scores for the financial skills assessed in PISA 2012 [17]. To do this, firstly, the selection equation should be determined; that is, an equation allowing for the prediction of the ps and, secondly, students belonging to the TG and CG should be balanced for this indicator. The determination of the selection equation is of decisive importance, since the correctness of its specification affects the acquisition of credible and unbiased estimates of the impact of the intervention evaluated. It should be noted that in this equation all variables which may simultaneously influence school choice and outcomes must be considered to be predictors (Caliendo and Kopeinig, 2008)[18]. Econometric literature offers various methods of estimating the conditional probability of receiving treatment (namely, of attending a private school): logistic regression, probit models and discriminant analysis (Guo and Fraser, 2009). The present study uses a logistic regression model.

[Insert Table 1 here]

Table 1 shows the results of this regression (selection equation), which allows for the prediction of a ps value for each individual from the sample. The variables having the greatest influence on the probability of attending a PFPrRS are the following: immigrant status (39%), household possessions (TV and dishwasher), years of education of the mother and occupation of the father (8% and 1%, respectively), followed by student gender (with girls having a lower probability of attending a private school). The number of books in the household also has a major influence (the greater the number of books, the higher the probability of attending a PFRS). Although in these models the resulting R^2 is low, the percentage of correct predictions of the estimated model (almost 60%) is considered in the literature to be a relatively high degree of reliability.

Figures 1 and 2 display the distribution of the ps. As the two figures show, there is a wide area of common support. That is, individuals in the TG have individuals in the CG with whom they can be compared, as their ps scores are the same.

[Insert Figure 1 here]

[Insert Figure 2 here]

After estimating the ps the matching process is then undertaken. Various algorithms can be found in the literature regarding the performance of this process: greedy matching, optimal matching and fine balance (Guo and Fraser, 2009). The present study uses the first of these, which may be applied via a range of variants (Smith and Todd, 2005). The two most commonly used algorithms are nearest neighbor matching (hereinafter, NNM), which allows for diverse variants, and methods based on kernel functions (hereinafter, KM). The first of these matches each individual from the TG with that/those from the CG having the most similar ps value. KM constructs matches using all the individuals in the potential control sample in such a way that it takes more information from those who are closer matches and less from distant observations. In so doing, KM uses comparatively more information than other matching algorithms (Guo and Fraser, 2009, chapter 7). In the present study, these two algorithms were applied, as well as several of the options permitted by NNM (with and without replacement, with caliper and without caliper, 1 to 1, 1 to 2 and 1 to 3). The KM, in turn, was applied with different bandwidths. This was done in an attempt to test the sensitivity of the matching to the different estimation methods.

The analysis led us to opt for the Epanechnikov kernel type KM with a bandwidth of 0.06, since it best equates the individuals from the TG and the CG. The sample was only reduced by 3 individuals from the CG who were not paired with any individual from the TG[19]. The remaining individuals from the CG received a weight in function of the number of times that they are matched with individuals from the TG. These weights were required to be used in the subsequent analyses. Figures 2a and 2b display the distribution of the ps in the original sample and in the matched subsample. In the latter, it is observable that there is an almost perfect overlap in the distribution for PFRS and PFPrRS. Figure 3 shows the matching used between students from PFRS and PFPrRS.

[Insert Figure 3 here]

Table 2 shows the differences in means in the ps and the discriminant variables for the overall sample and the matched sample, as well as the reduction in bias achieved through the matching. This table illustrates the effectiveness of matching in reducing bias between groups (i.e. the means of the variables are compared before and after matching and the percentage of bias reduction is determined). The variables do not display significant differences between PFRS and PFPrRS in the matched sample. The percentage of bias for each variable has been reduced considerably, in almost all cases, to under 5%.

[Insert Table 2 here]

Similar conclusions may be reached from observation of Figure 4. The circles represent the bias between PFRS and PFPrRS in the sample before matching, while the crosses represent these biases for the matched sample. The crosses are clearly closer to zero, while in many cases the circles display higher values.

[Insert Figure 4 here]

Figure 5 displays the distribution of some of the variables used in the PSM for the overall sample (left-hand figures) and for the matched sample (right-hand figures). In the latter, the matched sample clearly has a much closer distribution of variables; in many cases it is virtually identical for the two school types.

[Insert Figure 5 here]

Finally, Table 3 compares the scores in math and financial performance for the unmatched and matched samples. It shows that PFPrRS have a positive effect on the outcomes attained by

Spanish students on the math and financial tests for the unmatched sample. However, those differences vanish for the matched samples. In any event, a more precise estimation of the effect than that offered by the data directly collected for PISA 2012 would require a refined approach which took into account the following three issues: the variables which may influence the evaluated skills not included in the PSM, simultaneity biases potentially affecting the "financial skills" and "math performance" variables, and the hierarchical structure of the database supplied by PISA. Consequently, a post-matching analysis was undertaken, with results to be shown in the following section.

[Insert Table 3 here]

4.2 Results of the MSEM

This section offers the results from the application of the MSEM to the data subsample created from the PSM. This subsample consists of 131 schools and 468 students. The analysis conducted in this section has a dual objective: a) to explore the interrelationships existing between financial and math skills of 15-year-old Spanish students and b) to contribute to disentangling the determinants of the degree of financial literacy, as measured by PISA 2012.

The development of the empirical model is performed in two stages, applied sequentially. Firstly, simultaneity in the production of financial and math competencies is evaluated via the resolution of a simultaneous equations model, presented at student level. Secondly, and based on the conclusions of the first stage, a model of these characteristics is recalculated at two levels (student and school). This multi-level model of simultaneous equations permits the identification of the determinants of financial skills of those individuals evaluated in PISA 2012, differentiating between the influences operating at school level from those functioning at student level. The following two sections show the results obtained.

4.2.1 Analysis of simultaneity between financial and math performance

This section presents the results of the application of a simultaneous equation model at student level. Table 4 corroborates the overlapping relationship existing in the creation of financial and math skills in the Spanish students evaluated by PISA 2012. Financial skills are explained by mathematical performance. The sign of the effect is positive and significant at 1%. As for the mathematical competencies equation, the relationship with financial skills is also statistically significant (up to 5%). The Hausman test value (11.28 in the explanatory equation for financial competencies and 25.05 for that of math competencies) indicates that there is an overlap in the production of the two types of cognitive skills examined.

[Insert Table 4 here]

4.2.2 Analysis of the determinants of financial literacy

After verifying that the financial and math skills of 15-year-old Spanish students are determined simultaneously, this section presents the results of the MSEM model. This type of model, as previously explained, permits the identification of the proportion of the total variance of the outcomes obtained by students which may be attributed to the different estimation levels. In our case, level 1 is represented by the student while level 2 is represented by the school.

The main advantage of the MSEM models is that, as previously noted, they consider the hierarchical structure of the data supplied by PISA 2012, while at the same time allowing for integration of the simultaneous relationship existing between financial and math skills. The appropriateness of applying a multi-level model is justified empirically by the intra-class correlation (ICC) values of the null model of financial (0.123) and mathematics (0.238) performance (see Table 5). Its values highlight the fact that school level explains some 12.3% and 23.8% of the variance of the outcomes for each of the two cognitive skills respectively, thereby recommending the implementation of a multi-level regression model[20].

[Insert Table 5 here]

Table 6 displays the results of the MSEM model. The dependent variables in the regression are the scores attained by the 15-year-old Spanish students in the math and financial assessment tests of PISA 2012[21]. The predictors of the two regressions are grouped by levels.

Based on Hausman (1983), the estimates were obtained through the application of the two-stage least squares method (2SLS). The final specification of the two equations estimated is the result of a parsimonious analysis that began with a broad model which was subsequently reduced, on the basis of the non-statistical significance of the variables. The models were estimated by imposing fixed effects on the parameters (with the exception of the independent term)[22]. Before estimating the simultaneous equation model, it was verified that the specification of equations fulfills the conditions of completeness and identification (order and range) that the resolution of this type of model requires, as previously explained. It should also be noted that the estimates were obtained taking into account the special statistical treatment that must be given to the plausible values and the weights obtained in the PSM. The first three columns of Table 6 show the results for math performance. The last three columns display the values corresponding to the financial performance regression. The pseudo-R^2 returns values of 0.39 and 0.32 respectively.

[Insert Table 6 here]

The most relevant predictors of math scores at level 1 are those of "Repeater" and "Self-efficacy in mathematics". The effect of the former is negative, demonstrating that the policy of repeating grades does not lead to improved educational outcomes. This result is similar to that obtained in the works of Alet (2010); Brophy (2006); Greene and Winters (2007) and Morrison and Ieong On No (2007). The positive effect of the "Self-efficacy in mathematics" shows that self-esteem in the solving of math problems contributes to obtaining higher scores. This result suggests the need to incorporate non-cognitive aspects into educational math programs, given the potential influence of non-cognitive skills on the improvement of cognitive skills (see Garcia-Garcia, 2013). The positive sign of the "Motivation in mathematics" variable leads to similar conclusions, although in this case the parameter is not significant.

Another result of interest, related to the equation of math scores, is the positive effect of household socioeconomic environment and family culture in the improvement of scores in this area. These variables were approximated by the professional level of the father (BFMJ2), the mother's educational level and the number of books in the household. The sign of the effect, coinciding with that obtained in all previous studies carried out in this area, is positive, although only the parameter of the variable corresponding to the years of study of the mother is found to be statistically significant.

It is worth noting the negative sign of the variable gender, indicating worse math skills for girls in comparison to boys.

Finally, the fact that none of the variables introduced in level 2 are statistically significant deserves special attention. School type (PFPrRS) always has a negative sign. This indicates that, after discounting all the effects and correcting for the bias threatening the relationship between school type and math skills, students attending privately run schools obtain worse scores in mathematics than those attending PFRS. The positive effect associated with PFPrRS detected in Table 3 disappears once the statistical tools which the literature currently requires to treat the data are applied. The quality of school infrastructure (SCMATBUI) also fails to demonstrate an influence on the math skills of students.

With regard to the results of the regression of financial skills (the last three columns of Table 6), the variable showing the greatest influence on this type of skill is the "mathematics" variable, which reflects scores obtained in the PISA math test. The parameter value (0.88) indicates that for each additional point in mathematics the score for the financial test increases by 0.88 points. If it is taken into consideration that the correlation between the two skills is 0.79, it may be concluded that the effect is strong (see Cohen, 1988). Therefore, it may be stated that education in financial issues is acquired by individuals through the acquisition of math skills. This supports the confirmation of hypothesis 1, described at the beginning of this study.

Together with this result, Table 6 also leads to the conclusion that household socioeconomic level and family culture have a statistically significant effect on the degree of the financial literacy of students, similar to results reached regarding math performance. Moreover, the effect of the family on financial skills is independent of the effect that this variable has on math skills. Clearly, the significant effects shown by these variables in the financial literacy regression (which includes mathematics as a predictor) show that the family influences the acquisition of financial skills, not only via mathematics education, but also in an autonomous way. Additionally, it should be noted that this influence is positive for the HISEI variable, although the mother's years of education have a negative sign. These results are in line with the conclusions other studies have reached on the influence of parents on their children's financial knowledge (see Friedline et al., 2011; Grinstein-Weiss et al., 2012; Gudmunson and Danes, 2011; Shim et al., 2010; Webley and Nyhus, 2006, among others). However, while the mother's educational level is usually a key positive factor in the case of reading, mathematics and science skills (see Baker et al., 2002), its effect on financial literacy shows a negative influence in our study. The same result is shown by the number of books (the other variable used to proxy the cultural capital in the household). However, the effect of this last variable is not statistically significant.

Student gender is also a factor affecting the degree of financial literacy, although unlike the effect of this variable on mathematics performance, here girls have better scores than boys.

With regard to the school level variables, school type displays, as in the regression of math competencies, a negative and statistically insignificant effect on financial performance. This offers evidence disproving hypothesis 2. As occurred in the analysis of math performance, the introduction of rigorous statistical controls to deal with sample selection bias and simultaneity bias, as well as the specific treatment of the PISA nested data by means of MSEM cancels out the raw differences in scores between PFRS and PFPrRS displayed in Table 3.

Another result to be highlighted is the negative influence of the "Financial education not available in the school for 15-year-old students" variable, which shows that students attending schools which do not offer education on financial topics (during the fourth year of secondary education) obtain worse scores. Although the effect of this variable is not statistically significant[23], this result highlights the need to reflect more deeply on the appropriateness of incorporating financial courses into the official secondary education curriculum. Our results are consistent with other studies that have found a positive influence of diverse economic/financial educational programs on the financial skills of participating students (see ANZ, 2004, 2005; ANZ and Commission for Financial Literacy and Retirement Income, 2013; García Bohórquez, 2012; Grimes et al., 2010; Romagnoli and Trifilidis, 2013; Russell et al., 2006).

5 Conclusions

The analysis performed in the previous sections leads to various conclusions that may contribute to enriching the debate about interventions to improve the population's economic and financial knowledge. Such improvements are very important, as they would enhance the ability of individuals to make economic decisions that might boost their financial well-being. In addition, successful interventions in this area could contribute to an increased confidence in the financial system, so recently damaged as a result of the crisis, while also strengthening economic growth.

An initial conclusion of the present study is that the development of financial abilities of young people is mediated by their mathematical skills, supporting hypothesis 1. This result suggests that an improvement in financial skills might be attained by improving the population's math knowledge, thereby questioning whether it is really necessary, as some authors propose, to increase the supply of specific economic/financial subjects in the official school curriculum for primary and secondary students' classes. Adding hours to mathematics classes and modifying the orientation of teaching in this area towards a positive student attitude to this subject[24] may be a more effective strategy, while also being easier and less costly to implement than the introduction of specific financial courses. In any case, this conclusion, which is the result of initial research into this topic in Spain, should be placed in the context of other studies where a positive impact on financial skills has been achieved by the implementation of school programs on economics. As an example, the evaluation of a Spanish pilot program on financial education (applied to students attending the third year of secondary education during 2010-2011 and sponsored by the Central Bank of Spain, the National Stock Market and the Spanish Ministry of Education, Culture and Sport) has shown a positive impact on students' technical knowledge (see Banco de España and CNMV, 2013). The non-significant statistical effect of financial training in the fourth year of secondary education students, as found here, may result from not only the lack of effectiveness of the education provided in itself, but from the teaching methodology applied. Whatever the case, new assessments need to be made in order to gain further knowledge as to how schools may improve the financial culture of their students.

A second conclusion, in accordance with those of other international studies, is the importance of the family on the financial literacy of 15-year-old Spanish students. The family, a first-order determinant in reading, science and math scores, is a key variable in the development of financial skills. Our results show that its influence is produced dualistically. On the one hand, the educational level of the mother positively conditions adolescents' math skills. On the other hand, the parents' professional status influences the financial skills of their children. With regard to these financial skills, the educational level of the mother, as well as the number of books in the home, shows a negative influence, which may indicate a special idiosyncrasy of financial skills as opposed to other cognitive dimensions in which parental education tends to have positive effects.

Finally, school type does not display any effect on either the financial or math performance of Spanish students. This is particularly true for the school management model (public versus private). The differences observed in the comparison of raw data supplied by PISA 2012 of the students attending to PFRS and PFPrRS vanish when the analysis includes all the statistical controls necessary according to the technical peculiarities of this study[25]. The most important differences in scores are between schools themselves, as evidenced by the multi-level model, but not between the two main educational systems coexisting in Spain (the public system versus the publicly financed and privately run system). It is important not to lose sight of the considerable effort the present study has made to homogenize samples between students attending each type of school through the application of the PSM. This can explain the non-significant effects found in the regression analysis between some of the variables showing the greatest differences between Spanish PFRS and PFPrRS (this is the case of immigrant versus native status).

Notes

[1]The pioneer study analyzing the relationship between training in financial areas and the level of savings was conducted by (Bernheim et al., 2001). It was shown that adults who received a course in financial management during their secondary education studies had increased savings rates. Other studies belonging to this research line include the works published in the case study on Financial Literacy and Planning Retirement in the Journal of Pension Economics and Finance, vol. 10 (4).

[2]This allows us to link two research lines that have traditionally remained separate: the economics of education and financial economics.

[3]The PISA 2012 financial literacy assessment was administered to approximately 29,000 students in 13 OECD countries and economies (Australia, the Flemish Community of Belgium, the Czech Republic, Estonia, France, Israel, Italy, New Zealand, Poland, the Slovak Republic, Slovenia, Spain and the United States) and five partner countries and economies (Colombia, Croatia, Latvia, the Russian Federation and Shanghai-China), representing 40% of world GDP. These 15-year-old students were evaluated in addition to those who participated in the core PISA assessment. In general, eight additional 15-year-old students were chosen at random from each participating school to undertake the financial literacy assessment. Questions about students' experiences with money matters were included at the end of the financial literacy test booklets. Students who took the assessment of financial literacy also answered the PISA student questionnaire about themselves, their homes, their school and learning experiences and attitudes. School principals received

a questionnaire that asked standard questions about school policies and the learning environment, and also included questions about the provision of financial education in school.

[4]One of the defining characteristics of the compulsory schooling system in Spain is its dual nature, consisting of predominantly public sector provision but with a substantial private sector. The largest segment of the latter are publicly financed privately run schools (hereinafter PFPrRS). These schools were formerly fully private and run by the Catholic Church. While these schools remain privately owned and run, they are now financed by regional education authorities and the central government. The distribution of students enrolled in secondary education among different school types in Spain in 2012 was as follows: publicly financed and run schools (hereinafter PFRS) 66%, PFPrRS 31%, while there is a smaller completely independent sector 3% (Spanish Ministry of Education (MECD), 2013). In this paper, we focus on comparing the PFRS with the PFPrRS.

[5]In the questionnaire completed by Spanish school principals only 15.8% indicated that they offer financial education to 15-year-old students in their schools (question 35 of the Schools Questionnaire). This is due to the fact that financial literacy is an optional course in the Spanish compulsory education system.

[6]Indeed, the resolution of many of the financial questions proposed in the evaluation undertaken by the OECD requires the use of math-like instruments (see OECD, 2014).

[7]Numerous studies suggest that the private school effect depends on school type (Catholic or non-Catholic, private independent or subsidized), on the type of output analyzed (mathematics, reading, sciences or school satisfaction) and on student type (ethnicity, family background or prior achievement). See, for example, Altonji et al. (2005); Green et al. (2014); Imberman (2011) and Zimmer et al. (2012)

[8]LODE (1985): Organic Law 8/1985, 3 July, regulating Education. Spanish Official State Bulletin 159. Since the approval of this Law, the Spanish schooling system has comprised three types of schools: publicly financed and run schools (PFRS), publicly financed and privately run schools

(PFPrRS) and private independent schools. The distribution of students enrolled in secondary education among these three different school types in Spain in 2012 was as follows: PFRS 66%, PFPrRS 31% and 3% of students in a completely independent sector (Spanish Ministry of Education (MECD), 2013). In this paper, we focus on comparing the PFRS with the PFPrPS due to the very poor coverage of the fully independent sector in our data. A more detailed analysis of the structure of the Spanish educational System and of the main differences between PFRS and PFPrRS can be seen in Green et al. (2014)

[9]The analysis of the impact of school type, public or private, on educational outcomes requires an analysis to be conducted prior to the selection of comparable individuals based on the original sample supplied by PISA 2012. This is due to the fact that the "school type" predictor is an endogenous variable. School choice is made by families on the basis of diverse characteristics of households such as income and wealth, socio-cultural profile, etc. (Burgess and Briggs, 2010; Escardíbul and Villarroya, 2009; Gallego and Hernando, 2009; Mancebón-Torrubia and Ximénez-de Embún, 2014; Tamm, 2008, among others); many of these constitute, in turn, determinants of students' educational outcomes. In these cases, the value of the coefficient associated to the variable "school type" which supplies a conventional regression through the application of the OLS method is biased, as it violates one of the principal assumptions of this method. The PSM technique allows us to address this limitation, as we shall explain.

[10]The other techniques are conventional regression and stratification (see Guo and Fraser, 2009, chapter 3 and Murname and Willett, 2011, chapter 12).

[11]In our case, W refers to the school type attended by the evaluated students, with W=1 being the student group enrolled in a PFPrRS and W=0 the student group enrolled in a PFRS.

[12]In any case, the potential risk that individuals from the TG and CG may differ in non-observable characteristics remains. The analysis of this issue extends beyond the scope of this study. Possible corrections of this problem may be found in Caliendo and Kopeinig (2008)

[13]A wide range of these models may be found in Steele et al. (2007)

[14]Despite the fact that the knowledge production process is an ideal example of joint production, models of simultaneous equations have been surprisingly underutilized in the literature on the functioning of educational production and even less so in conjunction with multi-level models. However, the application of simultaneous equation models in this area of research is not only natural but essential. As Goldberger (1991) indicates, the problems of simultaneity, reciprocal causation and feedback are ubiquitous in education. Studies by Levin (1970) Boardman et al. (1977) and Garcia-Garcia (2013) offer three contributions of interest regarding the potentiality of simultaneous equation models in the study of the process of educational production. The application of multi-level models to the educational context has been considerably more numerous. For example, there are the studies of Somers et al. (2004) and Mancebón et al. (2012), with the latter applying to Spanish data from the PISA 2006 survey. To our knowledge, the application of MSEM models to the educational field has only been performed by Steele et al. (2007)

[15]This document does not provide the results of the verification of these three assumptions, but they are available upon request. Specifically, the equation of financial competencies is an over-identified equation; this explains why a two-stage least squares model (2SLS) was applied in the empirical estimation. Regarding the equation for mathematical competencies, its specification excludes financial competencies as predictors (see footnote 21 for further explanation). Consequently, the analysis of the identification condition lost relevance. In fact, the final model to be estimated is a recursive model and not a model of simultaneous equations in the strictest sense. We shall address this issue later.

[16]Bryck and Raudenbusch (1988) recommend the use of this type of general model when analyzing the effects of schools on educational outcomes.

[17]The specification of the logistic regression model is based on the review of both the literature on the determinants of school choice and the literature on the determinants of academic perfor-

mance. This is due to the fact that in the logit model only the variables that affect both school choice and academic performance must be included. In addition, only those regressors which are potential predictors of educational outcomes and which occur prior to the school choice (or were stable between the time of the school choice and the time of the outcome assessment) should be included in the logit model as explanatory variables (Caliendo and Kopeinig, 2008). This is due to the fact that PSM aims to match students with common characteristics at the time of school entry.

[18]Based on this limitation, neither the variables potentially contributing to the explanation of differences in financial skills but not influencing school choice (such as school absence) nor those which may be determinants of school choice but which do not influence financial competencies (school admission policy, for example) are considered.

[19]The final sample consists of 131 schools and 468 students.

[20]The intra-class correlation (ICC) is the proportion of the total variance explained by the differences between schools (level 2). If the ICC were zero, a hierarchical model would not be necessary, since in this case the total variance of the scores would not be explained by the differences existing between students attending different schools.

[21]Mathematical skills were excluded from the equation of financial literacy. This decision responds to the belief that overlap between mathematical and financial knowledge does not imply causation. In the present authors' view, there are more reasons to assume that the causal direction is from mathematics skills to financial competencies, rather than in the opposite direction. On the one hand, the resolution of many of the issues regarding financial assessment requires the handling of mathematical tools, while the resolution of the mathematics questions is very technical and does not require the handling of financial concepts. On the other hand, as mathematics forms part of the official school curriculum of 15-year-old Spanish students, their potential predictors are school, personal aptitudes and attitudes of students and family variables. However, financial knowledge is not formally acquired in schools, although there is no doubt that general cognitive development

in other knowledge areas, particularly in that of mathematics, undeniably conditions differences in the financial literacy of students.

[22]The model with randomized effects for the parameters for which these effects were statistically significant was also estimated. The results were very similar and are available upon request.

[23]Nevertheless, it should be noted that the majority of schools in Spain do not offer financial education to 15-year-old students, so that the variability of the variable "Financial education not available" was very low.

[24]It should be remembered that one of the variables displaying a very significant influence on the mathematics scores was that referring to self-confidence in this area.

[25]In fact, examination of the sign of the parameter of the school type variable shows that publicly run schools display an advantage. Other studies by Field et al. (2007) and OECD (2010) have also failed to conclude that the autonomy of schools significantly improves their efficiency.

References

Alet, E. (2010). Is grade repetition a second chance? In *Journées de Microéconomie Appliquée (JMA)*, number January.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, 113(1):151–184.

ANZ (2004). Making a difference to financial literacy. Technical report.

ANZ (2005). ANZ Financial Literacy & Inclusion. Global Benchmarking Report (2005). Technical report.

ANZ and Commission for Financial Literacy and Retirement Income (2013). Financial Knowledge and Behaviour Survey Key Point Summary. Technical report, ANZ and Comission for Financial Literacy and Retirement Income.

Baker, D. P., Goesling, B., and LeTendre, G. K. (2002). Socioeconomic Status, School Quality, and National Economic Development: A Cross National Analysis of the "Heyneman-Loxley Effect" on Mathematics and Science Achievement. *Comparative Education Review*, 46(3):291–312.

Banco de España and CNMV (2013). Plan Nacional de Educación Financiera 2013-2017. Technical report, Madrid.

Bedi, A. S. and Garg, A. (2000). The effectiveness of private versus public schools: the case of Indonesia. *Journal of Development Economics*, 61(2):463–494.

Behrman, J., Mitchell, O., Soo, C., and Bravo, D. (2010). Financial Literacy, Schooling, and Wealth Accumulation.

Bernheim, B., Garrett, D. M., and Maki, D. M. (2001). Education and Saving: The long term effects of high school financial curriculum mandates. *Journal of Public Economics*, 80(3):435–465.

Bettinger, E. P. (2005). The effect of charter schools on charter students and public schools. *Economics of Education Review*, 24(2):133–147.

Betts, J. R., Rice, L. A., Zau, A. C., Tang, Y. E., and Koedel, C. R. (2006). *Does School Choice Work ? Effects on Student Integration and Achievement*. Public Policy Institute of California, San Francisco, CA.

Bifulco, R. and Ladd, H. F. (2006). The Impacts of Charter Schools on Student Achievement: Evidence from North Carolina. *Education Finance and Policy*, 1(1):50–90.

Boardman, A. E., Davis, O. A., and Sanday, P. R. (1977). A simultaneous equations model of the educational process. *Journal of Public Economics*, 7(1):23–49.

Bover, O., Casado, J. M., Costa, S., Caju, P. D., Mccarthy, Y., Sierminska, E., Tzamourani, P., Villanueva, E., and Zavadil, T. (2014). The Distribution of Debt Across Euro Area Countries The Role of Individual Characteristics, Institutions and Credit Conditions.

Brophy, J. (2006). Grade repetition.

Bryck, A. and Raudenbusch, S. (1988). Toward a More Appropriate Conceptualization of Research on School Effects: A Three-Level Hierarchical Linear Model. *American Journal of Education*, 97(1):65–108.

Burgess, S. and Briggs, A. (2010). School assignment, school choice and social mobility. *Economics of Education Review*, 29(4):639–649.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of Propensity Score Matching. *Journal of Economic Surveys*, 22(1):31–72.

Chudgar, A. and Quin, E. (2012). Relationship between private schooling and achievement: Results from rural and urban India. *Economics of Education Review*, 31(4):376–390.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Lawrence Erlbaum Associates, Publixhers, NJ: Lawrence, second edi edition.

Coleman, J. S., Hoffer, T., and Kilgore, S. (1982). *Secondary school achievement. Public, catholic and private schools compared*. Basic Books, New York.

Crossan, D., Feslier, D., and Hurnard, R. (2011). Financial literacy and retirement planning in New Zealand. *Journal of Pension Economics and Finance*, 10(04):619–635.

Dougherty, C. (2011). *Introduction to Econometrics*. Oxford University Press, New York, fourth edi edition.

Escardíbul, J. O. and Villarroya, A. (2009). The inequalities in school choice in Spain in accordance to PISA data. *Journal of Education Policy*, 24(6):673–696.

Field, S., Kuczera, M., and Pont, B. (2007). *No more failures: Ten steps to equity in education*. OECD Publishing, Paris.

Fornero, E. and Monticone, C. (2011). Financial literacy and pension plan participation in Italy. *Journal of Pension Economics and Finance*, 10(04):547–564.

Friedline, T. L., Elliott, W., and Nam, I. (2011). Predicting Savings from Adolescence to Young Adulthood: A Propensity Score Approach. *Journal of the Society for Social Work and Research*, 2(1):1–22.

Gallego, F. and Hernando, A. (2009). School Choice in Chile: Looking at the Demand Side.

García Bohórquez, N. (2012). El impacto de la educacion economica y financiera en los jóvenes: el caso de finanzas para el Cambio.

Garcia-Garcia, E. (2013). *What we learn in school: Cognitive and non-cognitive skills in the educational production function*. PhD thesis, Columbia University.

Gerardi, K., Goette, L., and Meier, S. (2010). Financial Literacy and Subprime Mortgage Delinquency: Evidence from a Survey Matched to Administrative Data.

Gnan, E., Silgoner, M. A., and Weber, B. (2007). Economic and Financial Education: Concepts, Goals and Measurement. *Monetary Policy & the Economy*, (Q3):28–49.

Goldberger, A. S. (1991). *A Course in Econometrics*. Harvard University Pres, Cambridge, MA.

Green, C. P., Navarro-Paniagua, M., Ximénez-de Embún, D. P., and Mancebón, M.-J. (2014). School choice and student wellbeing. *Economics of Education Review*, 38(6):139–150.

Greene, J. P. and Winters, M. A. (2007). Revisiting Grade Retention: An Evaluation of Florida's Test-Based Promotion Policy. *Education Finance and Policy*, 2(4):319–340.

Grimes, P. W., Rogers, K. E., and Smith, R. C. (2010). High School Economic Education and Access to Financial Services. *Journal of Consumer Affairs*, 44(2):317–335.

Grinstein-Weiss, M., Spader, J. S., Yeo, Y. H., Key, C. C., and Freeze, E. B. (2012). Loan Performance among Low-Income Households: Does Prior Parental Teaching of Money Management Matter? *Social Work Research*, 36(4):257–270.

Gudmunson, C. G. and Danes, S. M. (2011). Family Financial Socialization: Theory and Critical Review. *Journal of Family and Economic Issues*, 32(4):644–667.

Gujarati, D. N. (2004). *Basic Econometrics*. Tata McGraw Hill, New Delhi, 4th editio edition.

Guo, S. and Fraser, M. W. (2009). *Propensity Score Analysis. Statistical Methods and Applications*. SAGE Publications, London.

Hausman, J. A. (1983). Specification and estimation of simultaneous equation models. In Griliches, Z. and Intriligator, M., editors, *Handbook of Econometrics (volume 1)*, pages 391–498. Elsevier.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1):153–161.

Hox, J. J. (1995). *Applied Multilevel Analysis*. TT-Publikaties, Amsterdam.

Hox, J. J. (2002). *Multilevel analysis. Techniques and applications*. Lawrence Erlbaum Associates, Inc., Publishers, Mahwah, New Jersey.

Imberman, S. A. (2011). Achievement and Behavior in Charter Schools: Drawing a More Complete Picture. *The Review of Economics and Statistics*, 93(2):416–435.

Klaper, L. and Panos, G. A. (2011). Financial literacy and retirement planning: the Russian case. *Journal of Pension Economics and Finance*, 10(04):599–618.

Lefebvre, P., Merrigan, P., and Verstraete, M. (2011). Public subsidies to private schools do make a difference for achievement in mathematics: Longitudinal evidence from Canada. *Economics of Education Review*, 30(1):79–98.

Levin, H. M. (1970). A Cost-Effectiveness Analysis of Teacher Selection. *The Journal of Human Resources*, 5(1):24–33.

Lusardi, A. and Mitchell, O. S. (2011). Financial literacy and retirement planning in the United States. *Journal of Pension Economics and Finance*, 10(04):509–525.

Lusardi, A., Mitchell, O. S., and Curto, V. (2010). Financial Literacy among the Young. *Journal of Consumer Affairs*, 44(2):358–380.

Lusardi, A. and Tufano, P. (2009). Debt Literacy, Financial Experiences, and Overindebtedness.

Mancebón, M.-J., Calero, J., Choi, A., and Ximénez-de Embún, D. P. (2012). The efficiency of public and publicly subsidized high schools in Spain: Evidence from PISA-2006. *Journal of the Operational Research Society*, 63(11):1516–1533.

Mancebón-Torrubia, M. J. and Ximénez-de Embún, D. P. (2014). Equality of school choice: a study applied to the Spanish region of Aragón. *Education Economics*, 22(1):90–111.

Monticone, C. (2010). How Much Does Wealth Matter in the Acquisition of Financial Literacy? *Journal of Consumer Affairs*, 44(2):403–422.

Morgan, S. L. (2001). Counterfactuals, causal effect, heterogeneity and the Catholic school effect on learning. *Sociology of Education*, 74:341–374.

Morrison, K. and Ieong On No, A. (2007). Does repeating a year improve performance? The case of teaching English. *Educational Studies*, 33(3):353–371.

Murname, R. J. and Willett, J. B. (2011). *Methods Matter: Improving Causal Inference in Educational and Social Science Research*. Oxford University Press, New York.

OECD (2010). *PISA 2009 Results : What Students Know and Can Do*, volume I. OECD Publishing, Paris.

OECD (2014). *PISA 2012 Results: Students and Money. Financial Literacy Skills for the 21st Century (Volume VI)*. OECD Publishing, Paris.

Pfeffermann, D. and Landsman, V. (2011). Are Private Schools Better Than Public Schools? Appraisal for Ireland by Methods for Observational Studies. *The Annals of Applied Statistics*, 5(3):1726–1751.

President's Advisory Council on Financial Literacy (2008). Annual Report to the President. Technical report.

Robson, J. (2012). The Case for Financial Literacy. . Assessing the effects of financial literacy interventions for low income and vulnerable groups in Canad. Technical report, Canadian Centre for Financial Literacy.

Romagnoli, A. and Trifilidis, M. (2013). Does financial education at school work? Evidence from Italy.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5):688–701.

Russell, R., Brooks, R., and Nair, A. (2006). Evaluation of the Youth Financial Literacy Trial Program. Technical Report April, RMIT University.

Shim, S., Barber, B. L., Card, N. A., Xiao, J. J., and Serido, J. (2010). Financial socialization of first-year college students: the roles of parents, work, and education. *Journal of youth and adolescence*, 39(12):1457–1470.

Smith, J. A. and Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1-2):305–353.

Snijders, T. a. B. and Bosker, R. J. (1994). Modeled Variance in Two-Level Models. *Sociological Methods & Research*, 22(3):342–363.

Somers, M. A., McEwan, P. J., and Willms, J. D. (2004). How Effective Are Private Schools in Latin America? *Comparative Education Review*, 48(1):48–69.

Spanish Ministry of Education (MECD) (2013). Estadística de Enseñanzas no Universitarias - Resultados Detallados - Curso 2011-2012. Technical report.

Steele, F., Vignoles, A., and Jenkins, A. (2007). The effect of school resources on pupil attainment: a multilevel simultaneous equation modelling approach. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 170(3):801–824.

Tamm, M. (2008). Does money buy higher schooling?: Evidence from secondary school track choice in Germany. *Economics of Education Review*, 27(5):536–545.

Toma, E. and Zimmer, R. (2012). Two decades of charter schools: Expectations, reality, and the future. *Economics of Education Review*, 31(2):209–212.

van Rooij, M. C., Lusardi, A., and Alessie, R. J. (2011a). Financial literacy and retirement planning in the Netherlands. *Economics of Education Review*, 32(4):593–608.

van Rooij, M. C., Lusardi, A., and Alessie, R. J. (2011b). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2):449–472.

Walstad, W. B., Rebeck, K., and MacDonald, R. A. (2010). The Effects of Financial Education on the Financial Knowledge of High School Students. *Journal of Consumer Affairs*, 44(2):336–357.

Webley, P. and Nyhus, E. K. (2006). Parents' influence on children's future orientation and saving. *Journal of Economic Psychology*, 27(1):140–164.

Witte, J., Weimer, D., Shober, A., and Schlomer, P. (2007). The performance of charter schools in Wisconsin. *Journal of Policy Analysis and Management*, 26(3):557–578.

Zimmer, R., Gill, B., Booker, K., Lavertu, S., and Witte, J. (2012). Examining charter student achievement effects across seven states. *Economics of Education Review*, 31(2):213–224.

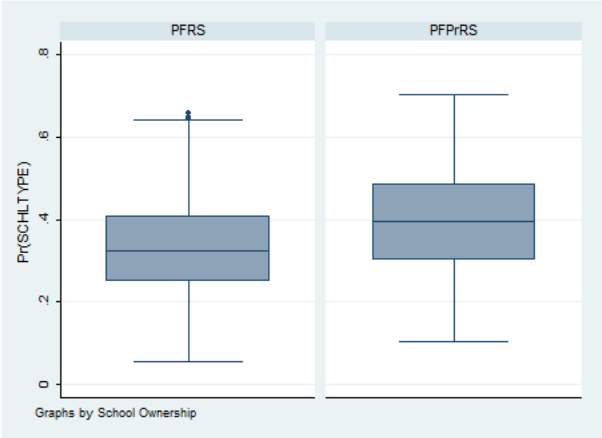
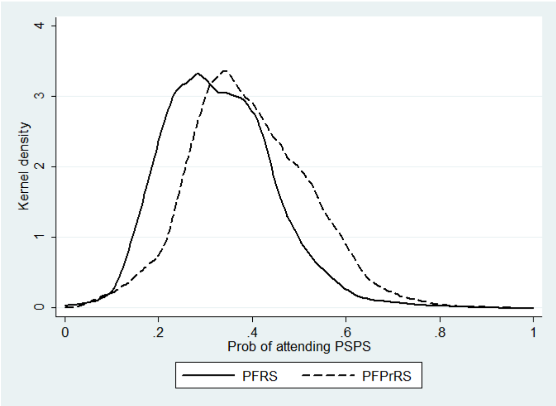
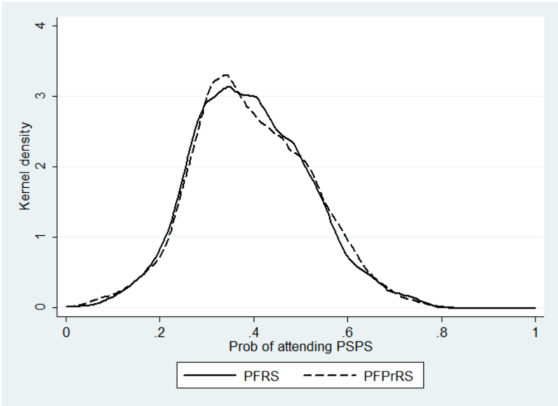


Figure 1: Boxplot ps scores



(a) Unmatched sample



(b) Matched sample

Figure 2: Propensity score distribution by school type

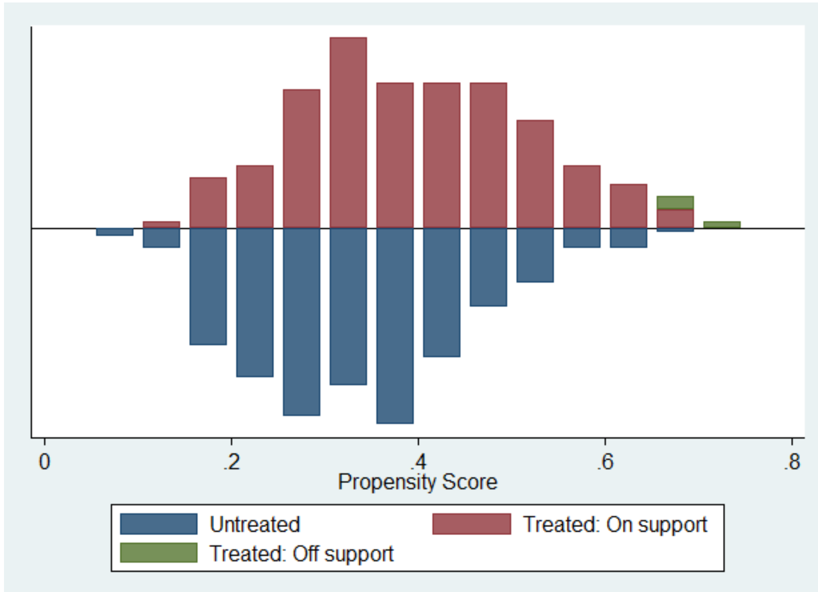


Figure 3: Boxplot ps scores

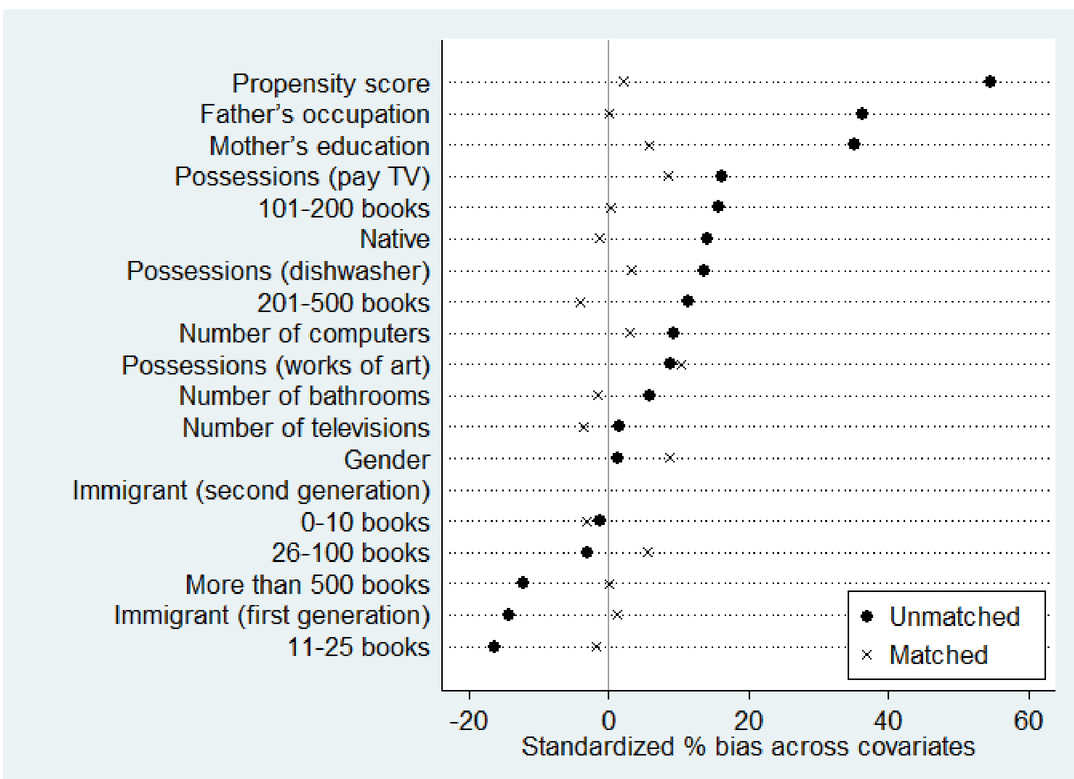
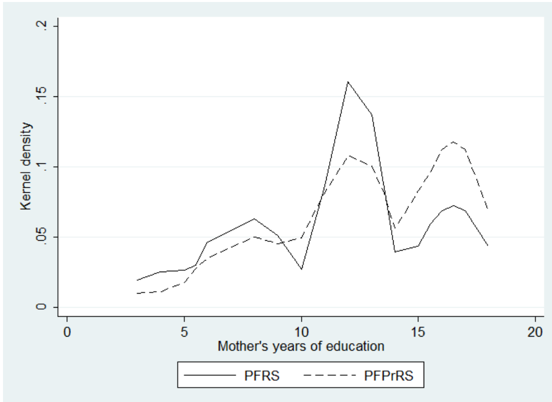
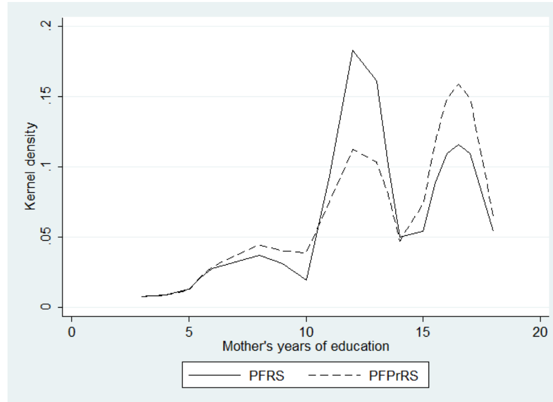


Figure 4: Pre- and post-matching bias between public and private schools

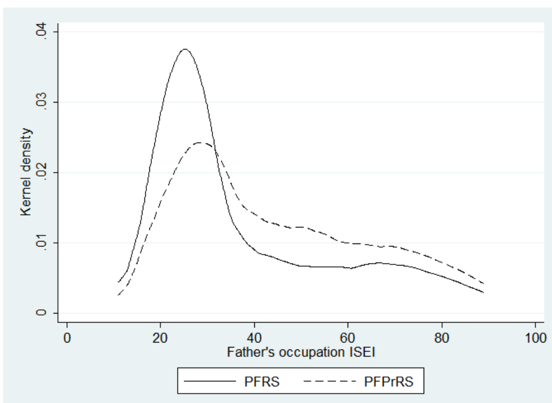


(a) Unmatched sample

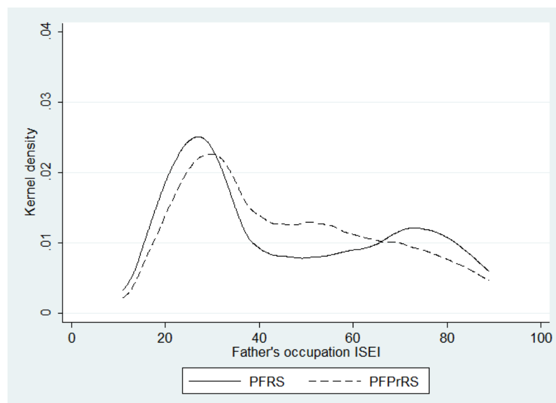


(b) Matched sample

Mother's education (in years)

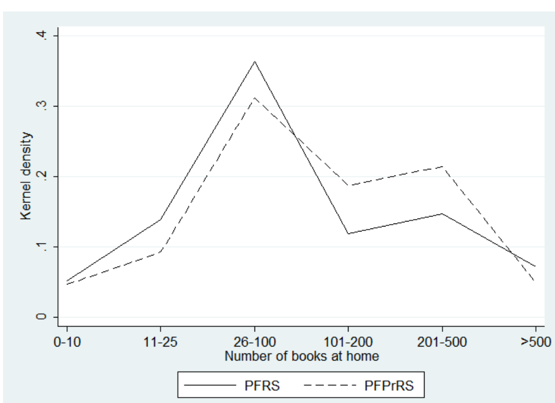


(c) Unmatched sample

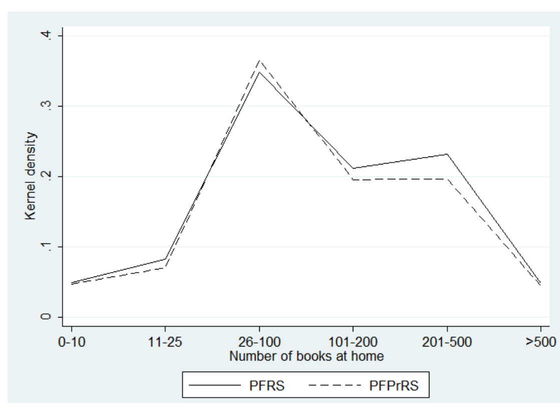


(d) Matched sample

Father's occupation (ISEI)



(e) Unmatched sample



(f) Matched sample

Number of books in the household

Figure 5: Distribution of the variables in the unmatched and matched samples

Table 1: Results of the logistical regression (logit model)

Variable	Coeff.	Std. error	P>|z|
Gender (girls)	-0.09***	0.01	0.00
Immigrant	-0.39***	0.02	0.00
Occupation of father (ISEI)	0.01***	0.00	0.00
Education of mother (years of study)	0.08***	0.00	0.00
Possessions (objects of art)	-0.06***	0.01	0.00
Possessions (dishwashers)	0.05***	0.01	0.00
Possessions (pay TV)	0.24***	0.01	0.00
Number of televisions	0.21***	0.01	0.00
Number of computers	-0.12***	0.01	0.00
Number of bathrooms	0.01*	0.01	0.06
Number of books (ref. 0-10 books)			
11-25 books	-0.64***	0.03	0.00
26-100 books	-0.38***	0.03	0.00
101-200 books	-0.03	0.03	0.19
201-500 books	-0.27***	0.03	0.00
Over 500 books	-1.00***	0.03	0.00
Constant	-2.22***	0.05	0.00

N=471, R^2=0.05, % correctly predicted probabilities =58.02%

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 2: Average differences based on school type for the variables in the pre- and post-matching samples and bias reduction

Variable	Sample	Mean		% bias	% bias	t-test	
		TG	CG		reduction	t	p>|t|
Propensity score (ps)	Unmatched	0.40	0.33	54.6		5.82	0.00
	Matched	0.40	0.39	2.1	96.1	0.20	0.84
Gender (girls)	Unmatched	0.48	0.47	1.4		0.15	0.88
	Matched	0.48	0.44	8.8	-527.7	0.83	0.41
Native	Unmatched	0.94	0.90	14.2		1.46	0.15
	Matched	0.94	0.94	-1.2	91.4	-0.13	0.90
Immigrant	Unmatched	0.06	0.10	-14.2		-1.46	0.15
	Matched	0.06	0.06	1.2	91.4	0.13	0.90
Father's occupation (ISEI)	Unmatched	47.02	39.34	36.4		3.84	0.00
	Matched	46.52	46.49	0.1	99.7	0.01	0.99
Mother's education (years of study)	Unmatched	12.90	11.59	35.1		3.71	0.00
	Matched	12.84	12.62	5.9	83.2	0.58	0.57
Possessions (works of art)	Unmatched	0.61	0.57	9.0		0.94	0.35
	Matched	0.61	0.56	10.4	-16.7	0.98	0.33
Possessions (dishwasher)	Unmatched	0.80	0.74	13.7		1.43	0.15
	Matched	0.80	0.78	3.4	75.6	0.32	0.75
Possessions (pay TV)	Unmatched	0.56	0.47	16.3		1.72	0.09
	Matched	0.55	0.51	8.6	47.4	0.80	0.42
Number of televisions	Unmatched	3.48	3.47	1.5		0.16	0.87
	Matched	3.47	3.49	-3.5	-128.5	-0.33	0.74
Number of computers	Unmatched	3.17	3.10	9.4		0.98	0.33
	Matched	3.17	3.14	3.1	66.4	0.29	0.77
Number of bathrooms	Unmatched	2.78	2.73	5.8		0.61	0.54
	Matched	2.79	2.80	-1.5	74.5	-0.14	0.89
Number of books (ref. 0-10 books)	Unmatched	0.06	0.06	-1.2		-0.13	0.90
	Matched	0.06	0.06	-3.0	-144.0	-0.28	0.78
11-25 books	Unmatched	0.09	0.15	-16.4		-1.69	0.09
	Matched	0.10	0.10	-1.8	89.0	-0.18	0.85
26-100 books	Unmatched	0.32	0.34	-3.1		-0.33	0.75
	Matched	0.33	0.30	5.6	-81.9	0.53	0.59
101-200 books	Unmatched	0.24	0.18	15.7		1.68	0.09
	Matched	0.23	0.22	0.3	97.8	0.03	0.98
201-500 books	Unmatched	0.21	0.16	11.4		1.21	0.23
	Matched	0.21	0.22	-3.9	65.5	-0.35	0.73
Over 500 books	Unmatched	0.08	0.12	-12.2		-1.26	0.21
	Matched	0.08	0.08	0.1	99.6	0.01	1.00
Abs (bias)	Unmatched			15.1			
	Matched			3.6			

Table 3: Comparison of financial and mathematics performance, based on school type in the original and matched samples

Variable	Sample	TG	CG	Difference	S.E.	T-stat
Financial performance	Unmatched	500.2	478.2	22.03	7.31	3.01
	Matched	505.3	497.3	7.99	17.68	0.45
Math performance	Unmatched	499.1	469.5	29.61	7.66	3.87
	Matched	500.3	493.6	6.74	37.60	0.18

Table 4: Model of the simultaneous equations model at student level with only Math (Financial literacy) performance as predictors

	Dependent variable	
Independent variable	Financial performance	Math performance
Math performance	0.863***	
	(0.041)	
Financial performance		1.052**
		(0.047)
Observations	350	350
R^2	0.68	0.69
Hausman test	11.28	25.05
Hausman test (p-value)	0.001	0.000

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5: Percentage of variance explained and pseudo-R^2 in the multi-level models with simultaneous equations

	Math competencies		Financial competencies	
	Null model	Complete model	Null model	Complete model
Schools	1672.6	995.2	748.5	337.2
Students	5357.1	3090.1	5357.1	3156.0
Total	7029.7	4085.4	6105.6	3493.2
Intra-class correlation (ICC)	23.8%	24.4%	12.3%	9.7%
% total variance explained by the variables		41.9%		42.8%
% variance (students) explained by the variables		42.3%		41.1%
% variance (schools) explained by the variables		40.5%		55.0%
Pseudo-R^2*		39.8%		32.1%

*Calculation based on the reduction of squared prediction errors (Snijders and Bosker, 1994)

Table 6: Results of the multi-level model with simultaneous equations

Variables	Mathematics (1st stage)			Financial literacy (2nd stage)		
	Coeff.	Std. Error	t-ratio	Coeff.	Std. Error	t-ratio
Level 1 (students)						
Gender (female)	-20.19**	8.34	-2.42	12.68**	6.55	1.94
Father's occupation (BFMJ2)	0.26	0.17	1.51			
Highest occup. status of parents (HISEI)				0.38**	0.17	2.18
Mother's education (years of study)	1.86*	1.06	1.76	-2.85***	0.87	-3.27
Over 200 books	16.86	10.53	1.60	-2.51	7.65	-0.33
Native	4.73	16.56	0.29	-8.55	11.82	-0.72
Math motivation (INSTMOT)	4.37	3.89	1.12			
Self-efficacy in mathematics (MATHEFF)	20.81***	5.27	3.95			
Repeater	-88.32***	10.48	-8.43	-7.48	13.24	-0.56
Math scores				0.88***	0.11	8.28
Level 2 (schools)						
Constant	517.64***	19.92	25.99	508.66***	17.09	29.76
Financial education not available	-2.94	9.47	-0.31	-4.57	8.25	-0.55
Private school	-5.14	9.92	-0.52	-7.45	6.31	-1.18
Infrastructure quality (SCMATBUI)	8.79	6.06	1.45			

Standard errors calculated based on Gujarati (2004)
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$