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Abstract

This research aims to expand the literature regarding the determinants of educational output by exploring the relationship that there is between cognitive and non-cognitive skills. To do this, we use a large dataset from a sample of students enrolled in their last year of lower secondary education in the region of Asturias. This dataset was built especially for the purpose of this research. This information can be used to measure non-cognitive skills such as student effort, motivation or responsibility. Besides, we had access to information from student academic records. This can be used as a proxy for cognitive skills. Many other variables related to family background, study habits, leisure activities or their relationship with their parents were also available. Assuming that both dimensions of educational output are closely interrelated, we adopt an econometric approach based on a bivariate ordered probit model with an endogenous regressor. In this manner, we can simultaneously estimate the determinants of both educational outputs and the link between them. The results of the empirical analysis show that there is a positive and significant relationship between non-cognitive skills and academic achievement. However, this relationship is not significant when considering different groups of students. Specifically, we observe that there is no significant relationship between the two analysed variables for male students or students belonging to large families only. Another interesting finding is that the main determinants identified for each educational output are substantially different.

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Key words: Non-cognitive skills, Academic achievement, Secondary education, Determinants of educational output, Probit, Endogenous variables.

Resumen

La presente investigación pretende contribuir a la literatura sobre los factores determinantes del output educativo tratando de explorar la relación existente entre las competencias cognitivas y no cognitivas. Para ello disponemos de una amplia base de datos sobre una muestra de alumnos del último curso de educación secundaria obligatoria del Principado de Asturias construida para el objetivo concreto de la presente investigación, con la que resulta posible medir aspectos no cognitivos tales como el esfuerzo, la motivación o la responsabilidad de los estudiantes. Asimismo, se dispone de información relativa al expediente académico de los alumnos, a través del cual se pueden aproximar sus competencias cognitivas, y multitud de variables relativas al entorno familiar de los estudiantes, sus hábitos de estudio, las actividades de ocio o la relación que tienen con sus padres. Partiendo de la premisa de que las dos dimensiones del output educativo consideradas están interrelacionadas entre sí, se utiliza un enfoque econométrico basado en un modelo probit bivariante ordenado con variable endógena, con el que resulta posible estimar simultáneamente los factores determinantes de los dos indicadores del output educativo, así como el vínculo existente entre ellos. Los resultados de nuestras estimaciones ponen de manifiesto la existencia de una relación positiva y estadísticamente significativa entre dichas habilidades y los resultados académicos. No obstante, la relación existente entre ambas dimensiones del output para el conjunto de la muestra no se mantiene cuando consideramos diferentes subgrupos de estudiantes. Concretamente, se observa que la significatividad de la relación entre las dos dimensiones desaparece cuando consideramos únicamente a los estudiantes varones o pertenecientes a familias numerosas. Otro resultado interesante es que existen importantes divergencias a la hora de identificar los principales factores determinantes de cada output educativo.

Palabras clave: Habilidades no cognitivas, Rendimiento académico, Educación secundaria, Determinantes del output educativo, Probit, Variables endógenas.

Introduction

One of the key lines of research within the field of education economics is the exploration of the determinants of educational achievement using what is known as the educational production function (Todd and Wolpin, 2003). Since the first empirical studies were published in the 1970s, most papers have focused on the analysis of factors associated with cognitive skills, usually measured by means of a standardized test of knowledge, making a distinction between factors associated with student socioeconomic environment and school resources (Coleman et al., 1966). Researchers generally tend to agree about the significance of socioeconomic factors (Sirin, 2005), whereas there are bigger differences of opinion with respect to school resources (Hanushek, 2003).

There has been a growing trend in recent years to explore the determinants of other dimensions of educational output, such as social skills, attitudes or student maturity (Borghans, Duckworth, Heckman and ter Weel, 2008). These are considered to be key developmental factors and should therefore be encouraged by schools (Levin, 2012). While initiatives developed within the school environment designed to improve the development of such non-cognitive skills among students have attracted a lot of interest (Durlak, Weissberg, Dymnicki, Taylor and Schellinger, 2011), it is also true that school factors have a relatively small impact compared with personal and family environment (Opdenakker and Van Damme, 2000).

The purpose of this research is first and foremost to identify the key determinants of two dimensions of educational output as far apart as cognitive and non-cognitive skills, focusing primarily on student behavioural habits and the characteristics of their environment. Secondly, we aim to explore the possibility of there being an interconnection between the acquisition of non-cognitive skills and the development of cognitive skills. In doing so, we take up a line of research that, after the publication of several empirical studies, is now booming in the United States (Lleras, 2008; Cunha and Heckman, 2008), which we apply in Spain.

The source of the information used for this study is a broad database of students enrolled in their last year of lower secondary education in the region of Asturias. Based on a questionnaire especially designed for this research, we can gain an understanding of issues that are hard to measure, such as effort, motivation and responsibility. We also have access to information from student academic records and many other variables related to their environment. They can be considered explanatory factors of either or both of the dimensions of educational output.

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The methodology used in our empirical analysis is based on the use of a bivariate ordered probit model with fixed effects. We use this model to simultaneously estimate the determinant factors of both dependent variables and also take into account the potentially endogeneity of non-cognitive skills with respect to academic achievement. To the best of our knowledge, the field of education economics has made scant use of this technique. Noteworthy examples of papers that have previously applied this method are a study by Jiménez and Vilaplana (2014) examining the relation between test scores of Spanish students in financial literacy and mathematics in PISA 2012, or a study by Kalb and Van Ours (2014) about the impact of reading habits at an early age on the future reading skills of students.

The remainder of the paper is organized as follows. Section 2 reviews the literature on the relationship between cognitive and non-cognitive skills. Section 3 explains the methodology applied, whereas Section 4 describes the database used and the model variables. Section 5 reports the key results. The paper ends with some conclusions.

Literature review

Many studies draw attention to the role played by non-cognitive skills in educational achievement among young people (Chamorro-Premuzic and Furnham, 2003; Lleras, 2008), where non-cognitive skills are taken to mean aspects related to student personality, such as their intrinsic motivation or perseverance[1]. The main problem posed by this field of research is that it is hard to identify such non-cognitive skills.

Students that receive proper non-cognitive training (i.e. are stimulated to learn such concepts as motivation, joy of learning, hardworkingness, etc.) are more open to learning and take better advantage of the educational process (Cunha and Heckman, 2008), making activities related to curricular skills learning more effective (Heckman and Kautz, 2012). This impact extends to the entire cohort, irrespective of family socioeconomic and cultural level (Carneiro, Crawford and Goodman, 2007).

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(1) Rosen, Glennie, Dalton, Lennon and Bozick (2010) provide a classification of such non-cognitive skills, whereas Almlund, Duckworth, Heckman and Kautz (2011) give an exhaustive review of evidence as to the relationship between personality and non-cognitive skills.

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As skills learning is a dynamic process, the importance and effect of non-cognitive skills on curricular outcomes grow over time, that is, any deficits developed at early ages would ultimately lead to academic problems during adulthood (Farkas, 2003), even controlling by exogenous factors (Segal, 2008). On the other hand, adequate non-cognitive skills supplement and directly boost any efforts aimed at improving cognitive learning (Heckman and Kautz, 2013). According to Carneiro et al. (2007), young people with the best non-cognitive outcomes at age 11 are more likely to continue studying after the age of 16 and achieve a higher educational level. This finding was confirmed in a well-known study by Cunha and Heckman (2008), which shows how the level of non-cognitive skills during one period has an effect on the learning of cognitive skills in later periods. Additionally, deficient non-cognitive training could, by way of low job remuneration, weigh negatively against satisfactory cognitive skills in the future (Heckman y Rubinstein, 2001).

Carneiro et al. (2007) highlight the fact that non-cognitive skills may be more malleable than cognitive skills, especially among seven- to 11-year-olds. If this were true, it would suggest that educational policy potentially has a broader scope of action, stretching beyond the direct promotion of cognitive skills. In this respect, a great deal of literature, mainly in the United States (Knudsen, Heckman, Cameron and Shonkoff, 2006), focuses on analysing the effects of early intervention on children's non-cognitive skills[2]. The best known experimental intervention is the Perry Preschool Program, conducted in the United States with Afro-American students aged from three to four years with below average cognitive abilities. It found that motivation or effort had a bigger influence on academic achievement than student cognitive ability (measured by an intelligence test).

This close relationship between cognitive and non-cognitive skills has led to both having been recognized in the literature as key determinants of academic achievement and of the personal and professional prospects of students (Heckman, Stixrud and Urzua, 2006; Levin, 2012). However, the influence of non-cognitive skills on curricular achievement has been dealt with from different viewpoints. Some authors have focused on the influence of non-cognitive skills confined to performance in curricular

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(2) See Heckman and Kautz (2013) for a review of the most noteworthy experiments.

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tests (Blanden, Gregg and Macmillan, 2007; Balart and Cabrales, 2014), revealing the impact of non-cognitive factors, like motivation and the effort put into test performance by the student, on outcomes. Other experts highlight the importance of these skills as predictors (and causes) of success in life beyond what such exams can reflect. Therefore, this type of tests are not completely valid either as a strict measure of cognitive skills (as they also capture the impact of non-cognitive skills) or as global indicators of educational achievement (Heckman and Kautz, 2012)[3].

Despite evidence reported in the literature, the relation between the many attributes making up the set of non-cognitive competences and academic outcomes is still very ambiguous because of the many concepts that may be taken into account. In the field of personality psychology, non-cognitive skills have been grouped for the purposes of definition and measurement in what is the quite widely accepted *Big Five* categorization (Costa and McCrae, 1992). Of the five factors covered by the above taxonomy, the tendency to be perseverant, responsible and hardworking, embodied by the term *conscientiousness* has turned out to be the most predictive factor for educational outcomes[4] (Heckman and Kautz, 2012). This is not surprising, as, apart from student behaviour in the classroom (study habits, attitude to effort, prosocial behaviour) directly related to this factor, educational achievement requires hard work and perseverance. If we break this factor down, aspects like effort, motivation or responsibility are directly related to the learning of problem-solving strategies, which has a direct impact on better educational achievement. In the same respect, Duckworth and Seligman (2005) show that responsibility and self-discipline are a superb predictor of academic outcomes, whereas Duckworth, Peterson, Matthews and Kelly (2007) report a similar finding for motivation and perseverance.

Exploring this breakdown further, two of the most cited aspects with respect to their influence on curricular results are motivation and effort. Despite having been considered in two senses in the literature (broadly speaking, as the desire to perform a task correctly or, strictly speaking, as the desire to succeed academically), motivation is directly related to

(3) Since some non-cognitive skills, like sociability and empathy, do not directly affect curricular outcomes, but do affect job and social prospects.

(4) It was just as good a predictor as intelligence tests with respect to the number of years of schooling (Almlund et al., 2011).

educational achievement in both senses (Marchand and Skinner, 2007). The distinction between intrinsic and extrinsic motivation may be more significant for these purposes (Eccles, Wigfield and Shiefele, 1998). Intrinsic motivation refers to the inherent pleasure of carrying out a task correctly, whereas extrinsic motivation is based on external incentives, such as rewards or social pressure. As regards their effect[5] on the curricular outcome, experts have shown that intrinsic motivation has a more positive and long-lasting influence than extrinsic motivation (McInerney and Ali, 2006).

As regards the concept of effort, educational research has covered a wide range of behaviours, and there is no generally accepted model to be found in the literature. Within this spectrum, the usual thing has been to focus on student effort defined as "*behaviour that exhibits dynamism, enthusiasm and positive feelings as part of the interaction of the individual with academic activities*" (Kindermann, 2007). This meaning would include both procedural effort, i.e., the work done to complete a task, and substantive effort, i.e., an active attitude to learning that goes beyond the ordinary performance requirements for completing an academic task[6].

With regard to the notion of responsibility, it refers, educationally speaking, to a range of student social behaviours related to autonomy and self-learning ability (self-assessment tasks, revision of educational strategies used, time management, etc.), as well as to other minor issues, such as time spent on homework or appropriate classroom attitude. For example, the literature suggests that responsibility with regard to homework is very significantly related to educational outcomes (Ramdass and Zimmerman, 2011). Additionally, a sizeable number of the recommended educational practices for improving the classroom environment and teacher-student interaction involve inculcating students with higher levels of responsibility in order to facilitate a truly collaborative learning process (Gordon, 2010).

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(5) Most studies are based on questionnaires administered to students to build a variable that rates their level of motivation (Rosen et al., 2010). To do this, it is usually based on their level of agreement/disagreement with statements like "One important reason for doing my school work is that I learn new things" or "I work hard because I like to learn new things".

(6) Surveys of both teachers and students, including questions about whether it plays a more or less active role in learning or whether they put more time or work into tasks that they personally find harder, have been used to rate effort in the literature (Agbuga and Xiang, 2008).

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Finally, of the four items related to non-cognitive skills that are employed in this study, critical thinking is the one that has received least attention in the educational literature, despite the fact that it was considered as long as a century ago to be one of the key educational goals by scholars like Dewey (1910). Strictly speaking, critical thinking was defined in psychology as *"the ability to form a considered opinion about what to do or what to think"* (Facione, 1990). Generally speaking, critically thinking students have all or most of the following characteristics (Popil, 2011): they are open to new ideas, flexible, ready to change, innovative, creative, assertive, perseverant, dynamic, daring, informed, observant, and intuitive. All these traits are associated with beneficial effects on educational achievement. As a result, the literature has recommended active strategies to encourage critical thinking by students because of its positive effects on their cognitive outcomes (Youngblood and Beitz, 2001). Indeed, some authors attribute underperformance in higher education to a failure to encourage critical analysis at school during adolescence (Mendelman, 2007).

Data and variables

To make up for the shortage of objective data on aspects related to personality and student behaviour, we had to design and conduct a special-purpose survey. This survey was used to gather information on the non-cognitive skills of the evaluated students and their academic record, as well as different aspects that may be considered as potential determinants of both.

The surveyed population was composed of all fourth-year lower secondary education students enrolled at both public and private government-dependent schools in the region of Asturias for the 2010/11 academic year. To assure the utmost rigour of the enacted procedure, a professional company operating in the sector was engaged to carry out the field work. Interviewers received training beforehand from the authors of the study. Additionally, the survey was administered during teaching hours at either the start or the end of any of the classes scheduled for the day with a view to gathering as many responses as possible. The census of the population to be surveyed was composed of 7,072 students from 136 schools, of which 80 were public schools (4,676 students) and 56 private government-dependent schools (2,396 students). The response ratio was very high (78.9% of the potential census) and similar at both public schools (76.10%) and private government-dependent schools (84.30%). The final database after processing the questionnaires was composed of 5,493 students.

Domain experts advised on the design of the questionnaire completed by all the students in order to guarantee that the included items tied in with the non-cognitive skills dimension that we aimed to evaluate. These questionnaires included items related to the personality dimension known in the literature as *conscientiousness*, signifying the feeling of responsibility, motivation, effort and critical thinking. Specifically, two questions were added for each of these concepts with four possible behavioural options in such a manner as one could be unquestionably classed as the best option for each concept. Based on this information, we designed an additive outcome index (*NOCOG*) derived from assigning a value of one to each of the questions that the student answered correctly. The tests carried out to check the consistency of this index returned satisfactory results[7].

As a measure of the cognitive output based on the academic outcome of the students *(COG)*, we used the average grade attained in the previous academic year, building a four-category variable[8].

The selected explanatory variables are related to the characteristics of the students and their family background that are usually considered in studies on the educational production function, like gender, immigrant status, family structure and number of siblings, educational level and occupation of parents, family income or household possessions (books, computers, etc.). Likewise, we have knowledge of students' study habits, relationships with friends and parents' engagement in the learning process. We also have access to information which we can use to build variables that are uncommon in this type of studies such as parents' age, religious beliefs or leisure pursuits. Table I defines the explanatory variables mentioned above, and Table II shows the main descriptive statistics. As all the variables are dichotomous, the measures can be interpreted as proportions.

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(7) The value of Cronbach's alpha was 0.70 and the correlations between the items and the aggregate index were statistically significant at a confidence level of 99%.

(8) This measure is used as an approximation of the cognitive output because there is no standardized measure of knowledge at this educational level in Spain (the only source of information is from the diagnostic tests conducted in the second year of lower secondary education).

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TABLE I. Definition of explanatory variables

VARIABLES	DEFINITION
Gender	Male=0, Female=1
Grade retention	The student has repeated at least once=1, otherwise=0
First-generation immigrant	Born overseas=1, otherwise=0
Second-generation immigrant	Born in Spain to foreign parents=1, otherwise=0
Mother's educational level	Higher education=1, other=0
Father's educational level	Higher education=1, other=0
Mother's job qualifications	Highly qualified job=1, other=0
Father's job qualifications	Highly qualified job=1, other=0
Father aged under 35	Father aged under 35=1, other=0
Father aged over 45	Father aged over 45=1, other=0
Mother aged under 35	Mother aged under 35=1, other=0
Mother aged over 45	Mother aged over 45=1, other=0
Single child	Yes=1, no=0
Siblings	Two or more=1, other=0
Single-parent family	Yes=1, other=0
Mixed family	Yes=1, other=0
Household income	Greater than 2,000 euros=1, other=0
Practising Catholic student	Yes=1, no=0
Practising Catholic parents	Yes=1, no=0
Computer in room	Yes=1, no=0
Social network user	Connects daily=1, other=0
Videogame user	More than two hours per day=1, other=0
Reading for pleasure	Reads in spare time=1; other=0
Individual sport player	Yes=1, other=0
Team sport player	Yes=1, other=0
Friends' grades	Get good grades=1, other=0
Does less than 3 hours homework per week	Yes=1, other=0
Does more than 9 hours homework per week	Yes=1, other=0
Does homework daily	Yes=1, other=0
Parents check up on homework	Monitor child's homework daily=1, other=0
Rules	There are clear rules at home and they are met=1, other=0
Parents know child's friends	Parents know their child's friends=1, no=0
Parents know how child spends spare time	Yes=1, no=0
Parents spend time with their child	Parents spend time with their child daily=1, other=0

TABLE II. Descriptive statistics

VARIABLES	Minimum	Maximum	Mean	S.D.
Dependent variables				
Non-cognitive outcome (NOCOG)	1	5	3.78	2.14
Cognitive outcome (COG)	1	4	2.55	0.80
Explanatory variables				
Gender	0	1	0.48	0.50
Grade retention	0	1	0.08	0.28
First-generation immigrant	0	1	0.02	0.15
Second-generation immigrant	0	1	0.29	0.45
Mother's educational level	0	1	0.28	0.45
Father's educational level	0	1	0.30	0.46
Mother's job qualifications	0	1	0.43	0.50
Father's job qualifications	0	1	0.41	0.49
Father aged under 35	0	1	0.07	0.26
Father aged over 45	0	1	0.50	0.50
Mother aged under 35	0	1	0.12	0.32
Mother aged over 45	0	1	0.33	0.47
Single child	0	1	0.72	0.44
Siblings	0	1	0.22	0.42
Single-parent family	0	1	0.25	0.43
Mixed family	0	1	0.06	0.24
Household income	0	1	0.38	0.49
Practising Catholic student	0	1	0.19	0.39
Practising Catholic parents	0	1	0.20	0.40
Computer in room	0	1	0.53	0.50
Social network user	0	1	0.67	0.47
Videogame user	0	1	0.12	0.32
Reading for pleasure	0	1	0.56	0.50
Individual sport player	0	1	0.24	0.43
Team sport player	0	1	0.29	0.46
Friends' grades	0	1	0.26	0.44
Does less than 3 hours homework per week	0	1	0.51	0.50
Does more than 9 hours homework per week	0	1	0.06	0.25
Does homework daily	0	1	0.33	0.47
Parents check up on homework	0	1	0.47	0.50
Rules	0	1	0.77	0.42
Parents know friends	0	1	0.88	0.32
Parents know how child spends spare time	0	1	0.93	0.24
Parents spend time with child	0	1	0.24	0.42

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Methodology

The aim of this paper is to identify the determinants of educational output, approximated by means of two measures that are presumed to be correlated with each other. To do this, we need to apply some sort of econometric technique to simultaneously estimate the determinant factors of both dependent variables on academic performance, taking into account the potential endogeneity of non-cognitive skills, as both variables may be similarly affected by the same non-observable factors.

We have to estimate an ordered probit model because the configuration of the two dependent variables considered in this research is discrete (they have more than two categories). Models with a limited number of dependent variables and endogenous regressors pose certain challenges that require the application of more complex methods (Angrist, 2001). On this ground, we estimated a bivariate ordered probit model with an endogenous variable (Greene and Hensher, 2010) computed using Stata as proposed by Sajaia (2008). To be precise, we estimated a bivariate ordered probit with fixed effects to assure that the possible effect of non-cognitive skills on academic achievement is equal for all the individuals in the sample. The model specification is represented by the system of equations (1)-(2):

$$NOCOG_i = \beta_1 x'_{1i} + \varepsilon_{1i} \tag{1}$$

$$COG_i = \alpha NOCOG_i + \beta_2 x'_{2i} + \varepsilon_{2i} \tag{2}$$

where the influence of non-cognitive skills on academic outcomes is given by α, the explanatory variables of each of the dependent variable are included in vectors χ'_{1i} and χ'_{2i}, respectively, and the error terms ε_{1i} and ε_{2i} are assumed to be correlated according to a bivariate normal distribution (Equation 3):

$$\begin{pmatrix}\varepsilon_{1i}\\ \varepsilon_{2i}\end{pmatrix} \sim N\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right] \tag{3}$$

Both dependent variables, $NOCOG_i$ and COG_i, are ordered categorical variables built based on latent continuous variables, and, respectively. Thus, the variable measuring non-cognitive skills, $NOCOG_i$, classifies students into five categories based on their responses to the different survey items as shown in Equation 4:

$$NOCOG_i = \begin{cases} 1\ si\ NOCOG_i^* < 1 \\ 2\ si\ 1 \leq NOCOG_i^* \leq 2 \\ 3\ si\ 2 < NOCOG_i^* \leq 4 \\ 4\ si\ 4 < NOCOG_i^* \leq 6 \\ 5\ si\ 6 < NOCOG_i^* \leq 8 \end{cases} \tag{4}$$

On the other hand, the variable measuring student academic performance, COG_i, is ordered based on the average grade attained in the previous academic year as outlined in Equation 5:

$$COG_i = \begin{cases} 1\ si\ COG_i^* < 5 \\ 2\ si\ 5 \leq COG_i^* \leq 6 \\ 3\ si\ 6 < COG_i^* \leq 8 \\ 4\ si\ 8 < COG_i^* \leq 10 \end{cases} \tag{5}$$

As many of the control variables are correlated with each other, we have to take care to select only the ones that have the biggest influence on the two analysed outputs. To do this, we conducted a preliminary exploratory analysis where we applied Bayesian model averaging (BMA) to estimate the effect of each prospective variable on the dependent variable, taking into account all possible models and the uncertainty with respect to the model estimates (Moral-Benito, 2013).

Essentially, this technique involves estimating a weighted mean of estimates of all the models resulting from the possible combinations of all available explanatory variables ($\beta\hat{}_1 MA = \Sigma_1 (j = 1)^{\uparrow} J \equiv [\omega_1 j\ (\beta_1 j\ )\hat{}\ ]$) .. According to the parameters of the Bayesian analysis, the weighting assigned to each model depends on the actual data and the a priori probability of each model set by the researcher. Based on this probability, we can compute the a posteriori probability of the model *i*, that is, a measure of goodness of fit from a Bayesian viewpoint. Once we have the a posteriori probability of each model, we can calculate the a posteriori inclusion probability (PIP) of each variable, that is, the probability that the coefficient accompanying the variable is not zero. This probability, which can be construed as a measure of the variable's importance in the model, is calculated as the sum of the probabilities of all the models including the variable in question (Equation 6):

$$PIP_k = P(\theta_k \neq 0|D) = \sum_{\theta_k \neq 0} P(M_j|D) \tag{6}$$

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The variables with the highest PIP values will be the ones that best explain the variability of the dependent variable and can, therefore, be considered as the most robust explanatory variables. The criterion established by Kass and Raftery (1995) is usually used in order to facilitate the interpretation of this indicator. According to this criterion, the influence of a variable is decisive if the value of the PIP is greater than 0.99, strong if it is from 0.95 to 0.99, positive if it is from 0.75 to 0.95 or weak if it is from 0.5 to 0.75. For values under 0.5, the variable is considered to have no impact whatsoever.

We chose to use the well-known Markov Chain Monte Carlo Model Composition (MCMC), developed by Madigan, York and Allard (1995), to implement BMA in practice. This method can reduce the computational workload when there are a high number of explanatory variables and a priori probabilities are fixed according the criterion established by Eicher, Papageorgiou and Raftery (2011)[9].

Having identified the factors that most influence each dependent variable, we estimate the bivariate probit model using the maximum likelihood method. Assuming that all the observations are independent, the log-likelihood function for the total sample would be:

$$\ln L = \sum_{i=1}^{N} \sum_{j=1}^{5} \sum_{k=1}^{4} I(NOCOG_i = j, COG_i = k) \ln Pr(NOCOG_i = j, COG_i = k) \qquad (7)$$

Although the system of equations (1)-(2) is not linear, constraints are introduced in order to improve the identificative properties of the model to assure that the vectors χ'_{1i} and χ'_2 do not contain the same variables.

Results

First, Table III shows the results of applying the BMA method considering all the potential explanatory variables and the two dependent variables. The two models were estimated using the BMS package, implemented in R (Feldkircher and Zeugner, 2009). According to Kass and Raftery's selection criteria (1995), our probit model included all the variables that

(9) See Moral-Benito (2013) for a detailed description.

have a significant impact on the dependent variables, that is, any with PIP values over 0.75.

The explanatory variables that turned out to have the biggest influence in the case of the non-cognitive skills (NOCOG) include student-related variables, like gender, whether they read for pleasure, whether they do homework on a daily basis, whether they are regular social network or videogame users or whether their friends get good grades. On the other hand, other key indicators are related to the family environment like parents' age (father aged under 35 years or mother aged over 45 years), whether they monitor their children's homework, whether they know their children's friends and how they spend their spare time or whether there are rules that have to be complied with at home. With regard to cognitive outcomes (COG), some of the variables that have the biggest impact are the same as for non-cognitive skills (gender, reading for pleasure, regular social network and videogame user and friends that get good grades, parents who check up on homework and know their friends), but there are others like grade retention, time spent on homework per week, educational level and mother's job qualifications and family income.

Table IV reports the result of the bivariate ordered probit model with fixed effects, including the above control variables, plus the indicator representing non-cognitive skills.

First note the value of the statistic yielded by the likelihood ratio (LR) test for independent equations, which shows that the null hypothesis of independence is strongly rejected. This gives the reason for estimating a bivariate model instead of a simple ordered probit model, which would not take into account the endogeneity of non-cognitive skills and thus generate biased results.

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TABLE III. Results of Bayesian model for both dependent variables

COGNITIVE OUTCOME		NON-COGNITIVE OUTCOME	
VARIABLES	**PIP**	**VARIABLES**	**PIP**
Grade retention	1.0000	Gender	1.0000
Mother's education level	1.0000	Father aged under 35	1.0000
Household income	1.0000	Social network user	1.0000
Social network user	1.0000	Videogame user	1.0000
Reading for pleasure	1.0000	Reading for pleasure	1.0000
Parents check up on homework	1.0000	Does homework daily	1.0000
Gender	0.9910	Parents check up on homework	1.0000
Does more than 9 hours of homework per week	0.9780	Parents know how child spends spare time	1.0000
Friends' grades	0.9580	Rules	0.9907
Parents know friends	0.7970	Parents know friends	0.9373
Mother's job qualifications	0.7900	Mother aged over 45	0.9030
Videogame user	0.4050	Friends' grades	0.8623
Parents know how child spends spare time	0.3090	Father's job qualifications	0.3930
Rules	0.2610	Grade retention	0.3503
Practising Catholic parents	0.1750	Individual sport player	0.2343
Father aged under 35	0.1050	First-generation immigrant	0.2117
Father's job qualifications	0.0800	Single-parent family	0.1363
Single-parent family	0.0790	Mother aged under 35	0.1247
Individual sport player	0.0460	Does less than 3 hours of homework per week	0.1127
Does homework daily	0.0460	Practising Catholic parents	0.1087
Mother aged over 45	0.0440	Second-generation immigrant	0.0880
Parents spend time with child	0.0430	Mixed family	0.0640
Computer in room	0.0350	Practising Catholic students	0.0483
Second-generation immigrant	0.0250	Father's educational level	0.0410
Father's educational level	0.0240	Household income	0.0200
First-generation immigrant	0.0220	Parents spend time with child	0.0200
Practising Catholic students	0.0220	Mother's job qualifications	0.0167
Mother aged under 35	0.0200	Does more than 9 hours of homework per week	0.0110
Does less than 3 hours of homework per week	0.0160	Team sport player	0.0027
Team sport player	0.0140	Mother's educational level	0.0010
Mixed family	0.0120	Father aged over 45	0.0000
Father aged over 45	0.0100	Computer in room	0.0000

TABLE IV. Estimation of the bivariate ordered probit model with fixed effects

VARIABLES	Coefficient	S.D.
Cognitive Outcomes		
Non-cognitive outcomes	0.2002	0.0730***
Gender	0.0791	0.0359**
Grade retention	-0.7870	0.0361***
Social network user	-0.0965	0.0349***
Reading for pleasure	0.1813	0.0412***
Does more than 9 hours of homework per week	0.2117	0.0620***
Friends' grades	0.1272	0.0361***
Parents check up on homework	0.0952	0.0439**
Parents know friends	0.1018	0.0554*
Mother's educational level	0.1862	0.0383***
Mother's job qualifications	0.1265	0.0352***
Household income	0.1732	0.0332***
Non-cognitive Outcomes		
Gender	0.2210	0.0298***
Social network user	-0.1546	0.0312***
Videogame user	-0.2103	0.0462***
Reading for pleasure	0.3364	0.0300***
Does homework daily	0.2840	0.0317***
Friends' grades	0.1067	0.0334***
Parents check up on homework	0.3711	0.0300***
Parents know friends	0.1818	0.0498***
Parents know how child spends spare time	0.2918	0.0610***
Rules at home	0.1610	0.0354***
Father's age (<35)	-0.2976	0.0602***
Mother's age (>45)	0.0993	0.0310***
Chi-square LR test of independence (p-value)		
119.56 (0.000)		
N	5,493	

(*** level of significance 1%; ** level of significance 5%)

With regard to the aim of this paper, we can state that non-cognitive skills have a statistically significant and positive effect on academic achievement, increasing the likelihood of students attaining better outcomes. This finding is aligned with other empirical evidence available on this question (Duckworth and Seligman, 2005).

However, we want to check whether the effect of non-cognitive skills is also significant considering different genders or family settings. To do this, we again estimate the above model dividing the total sample into different subsets. The first division differentiates between boys and girls

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in order to check whether there are divergences as to the effects of the non-cognitive component on the cognitive component between the two sexes. Additionally, we also conducted a separate estimation for students who are single children and students who have siblings, as we suspect that upbringing, especially as regards questions related to responsibility, effort and motivation may vary between the two groups. Similarly, we estimated the model making a distinction between students that are part of a large family (three or more children) and students who are not. Table V reports the results, only illustrating the values for the variable of interest as the control variables exhibit similar values in all specifications[10].

TABLE V. Estimation of the bivariate probit model by subsets

Variables **Cognitive Outcomes**	**Coef.**	**S.D.**	**Coef.**	**S.D.**
By gender:	**Girls**		**Boys**	
Non-cognitive skills	0.4026	0.1102 ***	0.0414	0.0909
Chi-square LR test of independence (p-value)	66.27 (0.0000)		57.22 (0.0000)	
N	2.570		2.923	
By number of siblings I :	**Single child**		**Siblings**	
Non-cognitive skills	0.2065	0.0917 **	0.1055	0.1202
Chi-square LR test of independence (p-value)	74.55 (0.0000)		42.56 (0.0000)	
N	3.903		1.493	
By number of siblings II:	**Large family**		**Non-large family**	
Non-cognitive skills	0.2363	0.1595	0.2001	0.0855 **
Chi-square LR test of independence (p-value)	8.34 (0.0039)		108.32 (0.0000)	
N	1.207		4.189	

Table V above shows that, when differentiating by gender, non-cognitive skills do have a positive and significant effect on cognitive skills in the case of girls, whereas no statistically significant effect is found for boys. This gender-related divergence is a new finding, as very few papers have explored this differentiation with respect to the link between the two dimensions of educational output. In this regard, DiPrete and Jennings (2012) point out that girls are significantly better than boys at learning non-cognitive skills as of the early stages of education. This

(10) Full results are available upon request.

largely accounts for their better academic outcomes (Buchmann and DiPrete, 2006).

Focusing on the number of siblings, we found that non-cognitive skills do have a statistically significant influence on cognitive skills only if students are single children or are not members of a large family, where the effect is similar in both cases.

Conclusions

This paper provides empirical evidence about the statistically significant and positive relation that there is between the non-cognitive dimension of educational output and the academic performance of secondary school students. This result is aligned with the previous literature on this question, developed primarily in the United States, according to which more motivated young people with a greater sense of responsibility and ability to work hard are more likely to learn and benefit from the educational process. Despite this being a rather obvious relation, there is hardly any evidence in this country, except for research by Krüger, Formichella and Lekuona (2015) and Méndez, Zamarro, García and Hitt (2015), because it is difficult to gather information in this regard. In this respect, most of the value added of this research is down to the design of a special-purpose questionnaire which gave access to a large volume of information regarding non-cognitive issues.

A much more remarkable result is that the relationship between both dimensions of the output for the sample does not hold when considering different subgroups of students. Specifically, we found that the relationship between the two dimensions is not significant for only male students. Neither is this relationship to be found among students from large families. In both cases, it would be necessary to more thoroughly explore the psychological and sociological reasons why these two factors are not linked. This is beyond the scope of this paper.

Besides these results, the empirical work highlights that there are notable differences when identifying the key determinant factors of one of the two dimensions of educational output considered. In this respect, note that the variables related to student socioeconomic background appear to play a very minor role with respect to the non-cognitive dimension compared with their huge importance as predictors of

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academic performance. Interestingly, parents' maturity level approximated by age has a major impact on the non-cognitive component, whereas this factor does not appear to influence the cognitive dimension at all.

Finally, we must conclude by saying that the results should be interpreted with caution, as they were sourced from a database for a single academic year and for a single region of Spain. To get more robust results that could be extrapolated to the entire population, it would be necessary to gather more information on the development of non-cognitive aspects throughout the different stages of the education system. This is an increasingly more widespread concern internationally, as attested to by the fact that they are now being considered for inclusion in international tests like the well-known PISA report.

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