Rising above their circumstances: What makes some disadvantaged East and South-East Asian students perform far better in science than their background predicts?

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The Programme for International Student Assessment, carried out every three years by the Organisation for Economic Co-operation and Development across a large number of countries and economies, assesses the extent to which 15-year-old students have acquired the knowledge and skills that their societies need. Socioeconomically disadvantaged students are almost three times more likely than advantaged students not to attain the baseline level of proficiency in science. However, academic resilience, an attribute measured in the assessments, appears in a significant proportion of disadvantaged students. Using data from 2015's science-focused assessment and a logistic multilevel model analysis, this study examined the relationships between academic resilience and other non-cognitive skills measured by the assessment across seven East Asian countries and regions. Although there are significant disparities between the countries and regions, the results indicate that enjoyment of and interest in science are positively related to science resilience. By contrast, when the student has an instrumental motivation for learning science (he or she is interested in science because it is useful for his or her career plans), the relationship is negative. This provides useful guidance for policymakers, educators, parents, and students on how to foster better science results for students, and especially for disadvantaged students.

Keywords: resilience; science attitudes; PISA 2015; multilevel logistic models; East Asian students; non-cognitive skills

1. Introduction

According to PISA 2015 socioeconomically disadvantaged students across the countries of the Organisation for Economic Co-operation and Development (OECD) are almost three times more likely than advantaged students not to attain the baseline level of proficiency in science and, maybe due to this fact, they do not envisage themselves working in science-related occupations (OECD, 2016). Fortunately, some of those disadvantage students beat the odds and perform better than expected according to their low socioeconomic background. They are called resilient students. In this paper, we analyse who those resilient students are and how resilience can be developed stressing the importance of the non-cognive skills.

We found interesting the purpose of our study because resilient students are a sign of hope: their performance is an indication that poverty does not necessarily replicate itself. It is evidence that poor parents will not necessarily have poor children with poor academic performances and consequently poor jobs that lead to them being poor parents themselves (Heckman, 2011).

We used the large-scale PISA 2015 assessment to study the relationships between resilience and several other non-cognitive skills. If resilience is an attitude, it must be related to other attitudes towards science. These attitudes towards science, provided that they are related with academic resilience in science, are more easily changeable than other aspects that influence academic achievement, such as socioeconomic background, type of school, or the student/teacher ratio (see OECD, 2016). If our findings are right, there is a shortcut to improve science results, given that competency in science is not only based on knowledge about science, but also on attitudes towards science, and these attitudes can be more easily changed for the better.

Given the outstanding results consistently reached by some East Asian and South-East Asian countries or regions, and the high percentage of resilient students they have, we decided to base our study on the PISA 2015 results in seven countries or regions of that region: Hong Kong, Japan, the Republic of Korea, Singapore, Macao, the Chinese provinces of Beijing, Shanghai, Jiangsu, and Guangdong (hereafter QCH), and Chinese Taipei.

The rest of the paper is structured as follows. In Section 2, we briefly present a literature review. Section 3 provides a description of the material and methods: we describe how non-cognitive skills were measured through the PISA 2015 questionnaires and how we augment our analysis by adding other information available in the PISA background variables, such as demographics, school conditions and management, and classroom and teacher factors. Given that the information comes from two sources (students' questionnaire and principals' questionnaire) and two levels of attribution (student level and school level), we chose a logistic regression because of the dependent variable analysed (resilient or non-resilient student) and we chose the multilevel approach due to the hierarchical structure of the data. Section 4 reports the main results. Finally, in Section 5 we discuss our main conclusions.

2. Literature Review

Resilience is one of the non-cognitive skills related not only to academic performance but also to other life outcomes (Heckman & Rubinstein, 2001), (Farrington et al., 2012). These non-cognitive skills include a set of behaviours, skills, attitudes, and strategies (Clavel, 2018) that are crucial to students but may not be reflected in their scores on cognitive tests. These skills form part of the knowledge that is not valued in our narrow measures of ability, especially given the pressure on students to perform in tests and the incorrect assumption that test performance must determine their intelligence and identity (Chua, 2009).

Generally speaking, resilience is the ability to cope with adversity and to reach outstanding goals. Academic resilience is just a facet of resilience itself. Perhaps the first document on academic resilience and PISA was OECD (2011), which is based on PISA 2006. The report examined the influence of three sets of factors on resilience: approaches to learning; participation in science courses and time spent learning science at school; and school characteristics. It was found that taking more science courses benefits disadvantaged students even more than it does their more advantaged peers. In addition, it was suggested that exposing disadvantaged students to science learning at school might help close performance gaps. The report also provides evidence that resilient students enjoy learning science and display a series of positive attitudes towards learning science.

The most recent report on PISA and academic resilience may be the one by Agasisti et al. (2018). This paper, based on the PISA 2015 results, focuses on school-level correlates of resilience, looking for the school characteristics that contribute more to the probability that disadvantaged students will be academically resilient, and how much these factors vary across countries. They found that resilient students attend schools with a positive school climate, and that this climate, after accounting for demographic and social differences, is more easily found in schools where the turnover of teachers is low and where principals adopt a transformational leadership style (Tajasom & Ahmad, 2011).

In every study on resilience (see for example Banerjee, 2016), the research methodology includes two measures: how the disadvantaged situation is defined (the resilient student may grow up in a lower socioeconomic environment, face a language barrier, belong to an ethnic minority, or be an immigrant) and how the top performance is calculated; most of the time there is some sort of test or exam that provides the results.

Previous studies focusing on East Asian education systems have found diverse results depending on the type of resilience being measured and the instruments being used. For example, using the TIMSS[1] dataset, it was found that high academic expectation and time spent on mathematics at home have a differential effect between disadvantaged and non-disadvantaged students in Singapore (Sandoval-Hernández & Bialowolski, 2016). For Korea, a study involving more than four hundred students that received support from social welfare agencies, Kim et al. (2005) point out that hope, teacher support, and what students consider the meaning of life distinguished resilient students from their counterparts. Using data from PISA 2009, Shen (2012) found that compared with disadvantaged low-achievers, resilient students tend to enjoy reading, develop reading strategies, and have more high-quality reading activities at school. Li (2017), using a questionnaire among 693 11th-grade students in China participating in the competitive college entrance examination, found three factors from family and school settings that promote resilience: parental supervision, school involvement and recognition, and school expectation of behaviour. He found that parents' supervision and school involvement and recognition are significantly and negatively associated with low school commitment and individual conflict attitude, thus they promote academic resilience. By way of summary, studies generally show that disadvantaged students develop academic resilience if they grew up in supportive families and it tended to be associated with better psychologic well-being and social-emotional behaviours (Cheung et al., 2014).

Our paper attempts to add to the current evidence on students' academic resilience in two ways: first, following Sandoval-Hernandez, we focus on several countries that, although there are differences between them, share some similar background (Sandoval-Hernández &

[1] TIMSS: Trends in International Mathematics and Science Studies.

Bialowolski, 2016); second, combining school and student level, we focus on non-cognitive skills and their relationships with resilience. It is easier to foster these skills than to try and change biographic or collective factors that depend on high-level policymaking or cannot be changed at all. (Gorard et al., 2012). These skills have better "treatment" than biographic or collective factors that depend on higher decision-offices or cannot be modified at all.

There are many non-cognitive skills that influence students' science performance. Some of them are measured in the PISA 2015 context questionnaire. A group of non-cognitive skills is especially related to science, such as the students' interest in scientific knowledge or the students' pleasure when studying science. Other measured non-cognitive skills are common mental dexterities, in the sense that they influence a broad spectrum of young people's capacities, not only science performance. In this second group of attitudes, students' self-motivation and their ability to deal with test anxiety are included, for example.

Previous studies have already shown the influence of these non-cognitive skills on students' performance. See for example Humphries and Kosse (2017) for an overview of what these non-cognitive skills are influencing and why it matters, the literature review by Gutman and Schoon in 2013 for the Institute of Education, or Farrington et al. (2012). These skills form a group of interconnected mental dexterities that helps the student to reach his or her goals. If there is one species of bird in a forest, there are likely to be other species as well. If a student is resilient, he or she will also be more likely to have skills such as persistence, self-contentment, and motivation. The relationships within this set of non-cognitive skills are what we analyse in this paper.

2. Materials and methods

In the present study, there are two kinds of predictors of academic resilience: externally measurable predictors such as grade repletion or school type and self-reported predictors such as interest or teaching behaviour. These serve as covariates in the logistic regression analyses in order to control for the effects of demographic variables on the probability of a disadvantaged student being classified as resilient in science literacy.

Three issues are dealt with in this section: (1) the characteristics of the large-scale PISA 2015 relevant to this study, (2) the definition of the dependent variable (i.e. a resilient student), and finally, (3) which are the variables that do have some influence on a student's resilience and how are they measured.

2.1. The sample: PISA 2015

Data were drawn from PISA 2015, conducted by the OECD. The target for PISA was the 15-year-old student population across 72 countries and economies. In addition to all OECD countries, the survey has been conducted in the following Asian regions: Beijing, Shanghai, Jiangsu, and Guangdong (China), Hong Kong (China), Indonesia, Macao (China), Malaysia, Singapore, Taipei, Thailand, and Vietnam.

The sample used for this study includes only socioeconomically disadvantaged students. It is intended to compare disadvantaged students who are "resilient" with disadvantaged students who are "non-resilient."

As stated previously, in addition the assessment of science, reading comprehension, and maths, PISA also covers information about the characteristics of schools, teachers, parents, and students. In PISA 2015, the main focus was science, which provides extra information on science instruction, including the measurement of some character skills that will be used in the analysis.

For the purpose of this study, analysis was limited to science performance in seven Asian countries and regions: Hong Kong, Japan, the Republic of Korea, Singapore, Macao, QCH, and Taipei.

The students were not only tested on their knowledge of science, maths, and reading comprehension, but also completed several questionnaires that provide interesting contextual information. The precise combination of several sets of information collected in PISA provides an index, the Economic, Social, and Cultural Status (ESCS), which is widely accepted as a measure of the socioeconomic background of the student. The ESCS was created on the basis of the following variables: the International Socio-Economic Index of Occupational Status (ISEI); the highest level of education of the student's parents, converted into years of schooling; the PISA index of family wealth; the PISA index of home educational resources; and the PISA index of possessions related to "classical" culture in the family home. See OECD (2017) for detailed information.

PISA information is collected following several procedures that must be taken into account: the sampling weights, the replicates of the estimation for computing the standard errors, and the use of plausible values (see OECD, 2017). This is worth mentioning here, because these procedures make the analysis of the PISA datasets more sophisticated. In our case, a multilevel analysis has been used as it includes the hierarchical structure of the data.

The weights used in this work were recalculated so that the sum of the weights of each student corresponded to the total of disadvantage students in the analyzed sample. In this way, the weight of each school is the sum of the weights of its disadvantaged students. In this work, the weight of the student within the school was used in level 1 of the analysis, and the weight of the school in the second level (Rutkowski et al., 2010).

2.2. Dependent variable: who is a resilient student?

In this paper, a student who is resilient in science is someone with an ESCS in the lowest quarter within his or her country and with a performance in science in the highest quarter, once the effect of the ESCS has been considered.

From the PISA perspective, academically resilient students are those who come from an socioeconomic disadvantaged background but somehow perform much higher than what is predicted by their ESCS (OECD, 2011). Operationally, there are three steps in the identification of academic resilient students. First, students located at the bottom quarter (i.e. below Q1, the twenty-fifth percentile) of the PISA ESCS index within their own countries or economies are identified as ESCS-disadvantaged students (see for example OECD 2019, pag. 66 where the same criterion is used). Second, science performance scores as assessed in PISA are regressed on students' ESCS across all participating countries or economies to find out the international ESCS-performance relationship. Third, a student's residual performance is obtained by comparing the actual performance of each student with the performance predicted by the international ESCS-performance relationship.

Academically resilient students are identified as those ESCS-disadvantaged students whose residual performance is amongst the top quarter (i.e. above Q3, the seventy-fifth percentile) of students' residual performance from all countries or economies.

We replicated this identification strategy. First, we estimated the ordinary least squares linear regression by country or region that we have studied and the average regression within all those estimated results. The dependent variable was the 10 plausible values in science performance of each student. The independent variable was the ESCS index. The equation thus is:

$$PVSCIE_i = \beta_0 + \beta_1 ESCS_i + \varepsilon_i \tag{1}$$

where ε_i are the random errors that follow a distribution with mean equal to zero and variance equal to σ^2. The estimated coefficients are denoted as $\hat{\beta}_0$ and $\hat{\beta}_1$. Thus, the expected students' performance given their level of ESCS could be estimated as:

$$E\left[P\widehat{VSCI}E_i\right] = \hat{\beta}_0 + \hat{\beta}_1 \cdot ESCS_i \tag{2}$$

In the second step, we translate the regression estimated to the third quartile, moving the centroid to a new position on the horizontal axis: the third quartile of all the participant countries, Q3PVSCIE. The model becomes:

$$\widehat{Q3}_{PVSCIE_i} = Q3_{PVSCIE} + \hat{\beta}_1 \cdot ESCS_i + \varepsilon_i \tag{3}$$

Thus, the expected value is:

$$E\left[\widehat{Q3}_{PVSCIE_i}\right] = Q3_{PVSCIE} + \hat{\beta}_1 \cdot ESCS_i \tag{4}$$

From now on, we use $E\left[\widehat{Q3}_{PVSCIE_i}\right]$ to obtain the cut point as a function of the ESCS. We designate as resilient those students with an ESCS in the lowest quartile of the students in their country and at least six out of the ten plausible values are above the expected value ($E\left[\widehat{Q3}_{PVSCIE_i}\right]$) according to their ESCS.

2.3. Independent variables

In addition to science performance, PISA provides extra information obtained through the context questionnaires that we will use as independent variables in our analysis. This kind of information can be used as it is presented (i.e. gender or immigration status) or summarised in an index (i.e. science self-efficacy or enjoyment of science). These transformed variables are constructed through the scaling of multiple items. The index was scaled using the item response theory and the values of the index correspond to Warm likelihood estimates. For details of how each scale index was constructed, see OECD (2017).

A second classification of the independent variables is related to where they are embedded. Some of them are located at the student level, while others are located at the school level. The first level (student level or Level 1) includes variables that collect information about student demographic characteristics and students' perception of personal aspects, including their attitudes towards science and their school environment. The second level (school level or Level 2) information is collected from the principals of the schools. It includes information on school management and the student/teacher ratio. We will describe each of these variables, which basic statistics are presented on Table 1, for the entire dataset.

[Table 1 near here]

2.3.1. Independent variables at student level (Level 1): Science related non-cognitive skills

Student attitudes towards science collected in PISA 2015 have been summarised in four indices. Three of them relate to students' motivation for learning science: enjoyment of science, interest in broad science topics, and instrumental motivation for learning science. A fourth index, students' science self-beliefs, reflects student's perceived ability to use their knowledge of science in real-world situations.

Enjoyment of science (*Joyscie*) is an index constructed from students' responses to a four-point Likert scale containing the categories "strongly agree", "agree", "disagree", and "strongly disagree". Higher values on the index reflect greater levels of agreement with these statements. The second self-measurement of students' science attitudes is the index of instrumental motivation to learn science (*Intscie*). Students reported on a four-point Likert scale with the categories "strongly agree", "agree", "disagree", and "strongly disagree" about the statements like "Making an effort in my science subject(s) is worth it because this will help me in the work I want to do later on" or "What I learn in my science subject(s) is important for me because I need this for what I want to do later on". Responses were reverse-coded, so that higher values of the index correspond to higher levels of instrumental motivation.

The index of science self-efficacy (*Scieeff*) was constructed with a similar four-point Likert scale. The statements “I could do this easily”, “I could do this with a bit of effort”, “I would struggle to do this on my own”, and “I could not do this”, were used to rate how they would perform in some science tasks, like recognising the science question that underlies a newspaper report on a health issue, explaining why earthquakes occur more frequently in some areas than in others, or describing the role of antibiotics in the treatment of disease. Responses were reverse-coded so that higher values of the index correspond to higher levels of science self-efficacy.

Finally, the interest in broad science topics (*Intbrsc*) was obtained from the interest expressed by the students (“not interested”, “hardly interested”, “interested”, or “highly interested”) on several topics relating to science like the biosphere (e.g. ecosystem services, sustainability), or motion and forces (e.g. velocity, friction, magnetic and gravitational forces). A fifth response offered students the possibility to report that “[they] do not know what this is”.

More information on the variables described above can be found in the PISA Technical Report (OECD, 2017).

2.3.2. Independent variables at student level (and school level): control variables

At student level, in addition to science attitudes, we worked with control variables. They include gender, grade repetition (*Repeat*), the level of anxiety shown by students before a test or when solving a school task (*Anxtest*), and achieving motivation (*Motivat*). We did away with *Grade* because of its very low variance in the countries included in the analysis and its expected reiteration with the information provided by *Repeat*.

In relation to their teachers, students were asked about the adaptation of the instruction to the students’ needs and knowledge (*Adinst*), about the level of support, interest, and help in students' learning (*Teachsup*), and the level of discipline in science classes (*Disclisci*).

Finally, as the countries and regions analysed chose to implement an international ICT familiarity questionnaire (ICQ), we used, among the variables related to familiarity in ICT[2], the students' ICT interest (*Intict*) and the students' use of ICT as a topic in social interaction (*Soiaict*).

2.3.3. Independent variables at school level:

At the school level (Level 2), we included four variables related to school environment: one to distinguish whether it is a public or private school (*Schtype*); a second variable reporting the student/teacher ratio (*Stchratio*); a third variable reporting the behaviour of a teacher making learning difficult (*Teachbeha*), including teacher absenteeism, teacher resisting change, teachers who are too strict with students, teachers who are not well prepared, and teachers who do not adequately meet the needs of students. Finally, a fourth variable reports the students' behaviour that hinders their learning (*Stubeha*), including students' absenteeism, students who do not respect teachers, the use of alcohol or illegal drugs, and if students intimidate or bully other students.

2.4. Statistical analysis

First, the sample characteristics (i.e. demographic and other characteristics elucidated earlier) for the resilient vs. non-resilient students in each of the seven East Asian countries or regions were examined. Secondly, a logistic multilevel regression was carried out for the student classification, as a function of the demographic and school characteristics.

[2] ICT: Information and Communications Technology

A multilevel regression analysis was used to determine and distinguish the factors relating to resilience. Readers interested in this method will find a complete but accessible explanation in De Leeuw and Meijer (2008) or in Goldstein (2011).

Obviously, the students are nested within classes, which are nested within schools, which could be nested within school districts or countries or regions. All these relations often imply a hierarchical structure. In this paper we will consider only two levels: students and schools. We are interested in the variables that cause a student to be resilient. It also makes sense that different school characteristics can have an impact. Different schools with different characteristics would affect students differently.

Multilevel modelling provides a useful framework that recognises the existence of such a hierarchical data structure by allowing for residual components at each level in the hierarchy. Observations are not independent within clusters. Students within schools tend to share similar characteristics. One of the benefits of this methodology is that it distinguishes effects between and within schools. The multilevel models account this clustered sample design. It was used as an alternative to the replicate weights provided by the PISA database.

The hierarchical logistic regression, based on maximum likelihood estimates, does not make assumptions regarding normality, homoscedasticity, and measurement level of the variables. However, it does require observations to be independent, and quite large sample sizes are needed for the estimation of the parameters. To find out whether there is evidence of an association between predictor variables and academic resilience or slackening, an odds ratio has been calculated to describe the probability of the event occurring for each predictor variable in the logistic regression equation. This ratio will be used as an effect-size measure to compare the influences of risk and protective factors of academic resilience across countries and regions.

The multilevel analysis was performed, following OECD standards, using HLM6: Hierarchical Linear and Nonlinear Modeling (Raudenbush et al., 2004). A two level logistic regression analysis was carried out, with students serving as level 1, schools as level 2. The model coefficients and statistics were estimated using a full maximum likelihood procedure. Normalized student final weights were used, so that the sum of the weights was equal to the number of students in the dataset, and each country contributed equally to the analysis. An uncentered model was used as second-level coefficients provide correct estimates of the individual and the contextual effects when the contextual predictor variable is included in the second-level model (Kreft et al., 1995). Measure of model fit was assessed using the negative log-likelihood and the Cox-Snell statistics. These two goodness-of-fit statistics are testing whether one can do even better by making the model more elaborate and complicated. The negative log-likelihood is an entropy-based measure (Theil, 1970), and the Cox-Snell's pseudo-R-squared attempts to mimic the OLS R-squared statistic as a measure of improvement from the null model (i.e. a model with no predictor variable) to the fitted model (Cox & Snell, 1989). A significance level of $\alpha = 0.05$ was chosen as the criterion for evaluating the statistical significance of the results. Because of the complicated rotated PISA 2015 questionnaire design, special treatment of missing data was needed. Based on the iterative Markov Chain Monte Carlo (MCMC) method, missing values were imputed by the SPSS multiple regression imputation procedures. Multiple imputations of five datasets were done in accordance with Rubin (1987).

The intra-class correlation coefficient (ICC) measures the degree of data dependence. It describes how strongly units in the same group resemble each other. If ICC = 0, the responses of students within schools are uncorrelated; if ICC = 1, responses within schools are identical. Given that the variance of the random variable depends on the values of the explanatory variables, some adaptation is needed in our case. Following Hosmer and Lemeshow, 2005 we fix that variance in $\pi^2/3$, thus the ICC is:

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + {}^{\pi^2}/_3}$$

where σ_u^2 is the residual variance in the second level of the general model:

$$logit\{\Pr(y_{ij} = 1|\boldsymbol{x}_{ij}, \xi_j)\} = \beta_{oj} + \sum_k \beta_{1k} x_{k,ij} + \varepsilon_{ij} \tag{L1}$$

$$\beta_{oj} = \gamma_{00} + \sum_m \gamma_{01,m} g_{m,j} + u_{0j} \tag{L2}$$

where $x_{k,ij}$ are the factors related to students' characteristics (Level 1) and $g_{m,j}$ variables related with school characteristics (Level 2). Random disturbances u_{0j} are supposed to be independent and identically distributed, following a $N(0,\psi)$ distribution, independent of $\boldsymbol{x}_{ij}$. Given u_{0j} and $\boldsymbol{x}_{ij}$, we consider that y_{ij} response from student *i,* in school *j* follows a Bernoulli distribution independent of the others.

The intra-class correlation coefficients (ICC) for the null model were obtained for each country or region. We observed some variability between the results obtained, the ICC of Singapore (0.061) being the lowest, which would indicate that there is practically no correlation between the responses of the students within a school. On the opposite side is Japan, whose ICC is 0.294, indicating a moderate correlation between the responses of students from the same school.

3. Results

3.1 Descriptive analysis

Table 2 includes, for each country and region, some descriptive statistics of the variables included in the analysis: sample size of students and schools used for calculations, percentages of resilient students, male students, students who had repeated at least one grade, and percentage of privately-owned schools.

[Table 2 near here]

For the rest of variables included in our analysis, we used the indices built through the responses of students and principals (see Table 2) that are part of the PISA outcomes (OECD, 2017). Each index is constructed with mean 0 and standard deviation 1 for all OECD countries and economies, and Table 2 shows the mean of each index for the countries and regions analysed.

High variability can be observed between countries or regions in almost all variables used in the analysis. The percentages of resilient students range from 44% in Korea to 69% in Hong Kong, whereas the share of students who have repeated at least a grade is practically nil in Japan but reaches 45% of students in Macao.

As we have pointed out in the methodological description, it is resilience variability within countries that we want to explain, using mainly the non-cognitive skills. The differences within countries and regions are summarised in Table 2. Beginning with science-related non-cognitive skills, all countries and regions analysed show on average low levels of self-efficacy in science (*Scieeff*), ranging from -0.72 in Japan to -0.14 in Taipei. High variability between countries or regions can be observed with respect to the other variables related with science and, in some case, also within a country or region. For example, students in Korea show a high level of interest only in broad science topics (*Intbrsc*) but not in enjoyment of science (*Joysci*) or in instrumental motivation (*Intscie*) whereas Singapore shows positive figures in these variables.

Regarding common non-cognitive skills, positive figures in (*Motivat)* and in (*Anxtest*) denote relatively high levels of motivation and control of test anxiety, respectively. As can be seen in Table 2, the variability in these two variables is high between countries or regions, but it may be noted that in all countries and regions the average of anxiety is positive, showing that students report feeling nervous or anxious when they have to do a school test or homework, ranging from the lowest (0.07) in Korea to the highest (0.65) in Singapore.

Finally, high variability between countries or regions can be observed with respect to the general non-cognitive skills dealing with the students' ICT interest (*Intict*) and students' use of ICT as a topic in social interaction (*Soiaict*). Students in Japan report the lowest levels, similar to QCH only in ICT interest, following Korea, whereas the highest levels are in Singapore, together with Taipei only in the use of ICT as a topic in social interaction.

At school level, the indices come from the school principal questionnaire. In relation to school climate, negative figures show that the learning of students is not hindered by the teachers' behaviour (*Teachbeha*), as is the case in Korea, whereas positive figures indicate that teachers' behaviour hinders, to some extent, students' learning, such as in Macao and QCH. Student behaviour (*Stubeha*) also influences their learning in different ways depending on the country or region: relatively low in Japan or Singapore and highest in Korea and Taipei.

Other information from the school principals used in our models has to do with school ownership and human resources. The lowest student/teacher ratios (*Stchratio)* are in Japan and Singapore whereas the highest are observed in Korea and Taipei. Moreover, the school type (*Schtype*) shows a high variability in the ratio of private/public schools between the countries or regions.

To conclude with this brief descriptive analysis, Table 2 shows the mean values reported by the students about their perceptions on educational environment, such as the adaptation to the instruction of their teachers (*Adinst*), the interest and support given by their teachers (*Teachsup*), and the level of order and discipline in science classes (*Disclisci*). Except for Singapore, the students reported a high level of discipline in science classes, being the highest in Japan. However, the students in Singapore report the highest level of teacher's interest and support and, in turn, the students in Japan report the lowest level. Concerning the adaptation of instruction by teachers to the students' level, Japan has the lowest level and Singapore the highest.

3.2 Multilevel regression analysis

For each country or region, a model was selected that presented all the coefficients of the predictor variables statistically significant to at least 90% (p-value<0.1). Table 3 shows the coefficients of the independent variables of the multilevel regression for each country and indicates their level of statistical significance. We only present the final models, although intermediate results are available on demand.

[Table 3 near here]

The independent variables of the school level have a different behaviour depending on what they measure and the country or region of the research (Table 3). A bad school climate (*Stubeha*) has a negative impact on resilience in Hong Kong, Japan, Korea, and Singapore, while high values of the student/teacher ratio (*Stchratio*) have a positive impact on resilience in Hong Kong, Macao, Singapore, and Taipei. Attending a private school (*School Type*) has a positive effect on resilience.

With regard to the students' science-related non-cognitive skills, the enjoyment of science (*Joyscie*) and interest in science (*Intbrsci*) have a positive impact on the countries and regions analysed. With regards to common non-cognitive skills: the social interaction (*Soiaict*) of students is statistically significant and negative in all countries and regions analysed, the interest in ICT (*Intict*) is also significant but positive in all except Hong Kong, and motivation (*Motivat*) has a positive impact on a large number of countries and regions analysed. It is important to note that students' anxiety towards exams (*Anxtest*) has a negative influence on resilience.

[Table 4 near here]

Table 4 presents the odds ratio for resilience together with its 95% confidence interval for each of the selected variables. The odds ratios reported here compare the probability of being resilient for two groups of students. These two groups are identified by a one unit increase in the variable measuring the factor of interest. Odds ratios over one indicate that higher values of a particular factor are associated with a greater likelihood that a disadvantaged student will be resilient, while an odds ratio below one is suggestive of a negative relationship between that factor and resilience.

After analysing the school level, it is observed that one additional point in the index of bad school climate (*Stubeha*) reduces the probability of resilience in Japan by half and lowers it by 18 percentage points in Singapore and 31 and 39 in Hong Kong and Korea, respectively. High values of the student/teacher ratio (*Stchratio*) double the probability of student resilience in Singapore and multiplies this probability by 4.5 in the case of Hong Kong.

Analysing science-related non-cognitive skills, the enjoyment of science (*Joyscie*) by students increases the probability of being resilient in Japan by 32 percentage points and doubles this probability in Korea. Something similar occurs in the case of the variable that measures the interest in student sciences (*Intbrsci*); high values increase the probability of resilience by 26 percentage points in QCH and it reaches 77 in Japan.

In the case of common non-cognitive skills, the probability of being resilient is reduced by a minimum of 16 percentage points (Japan) to a maximum of 43 (Macao) when studying the social interaction of students (*Soiaict*). However, when the interest in ICT (*Intict*) is taken into account, the probability of being resilient is increased by between 20 and 70 (Singapore and QCH) percentage points. High values in the motivation index (*Motivat*) translate to a variation of between 25 and 57 additional percentage points on the probability of resilience. Previously, the negative impact caused by anxiety towards tests (*Anxtest*) on the condition of resilience was indicated; this is reflected in countries or regions such as Singapore, whose students who have high anxiety values are 17 percentage points less likely to be resilient, and which reaches 37 points less in QCH.

The rest of the variables have a disparate impact from some countries or regions to others (Table 4).

4. Discussion

We have seen that there are important differences on the level of non-cognitive skills within countries and regions. Regarding those skills closely related with science, all the countries and regions have in common a negative level of self-efficacy on science. This self-efficacy (measured by *Scieff*) is used to describe students' belief that they can, with their actions, achieve a particular goal. These negative values mean that the Asia region's level is below that of the OECD average, thus the students underestimate their talents. Alternatively, they believe that science is so difficult that they would not be able to accomplish their goal. It is important to change this perception of science as this science self-efficacy is a powerful incentive to act or to persevere in the face of difficulties.

The influence of non-cognitive skills on resilience has been clearly demonstrated through the model estimated. In every educational system except for the four Chinese provinces (QCH) and Taipei the enjoyment of science (*Joyscie*) has a positive influence on resilience. The other two aspects related to motivation for learning science (interest in broad science topics, *Intbrsci,* and instrumental motivation for learning science, *Intscie*) follow an interesting pattern. For the broad interest in science topics, the effect, when it is relevant (all the countries and regions but Korea and Singapore), is positive, meaning that the chances of being an academic resilient student increase when the student has a genuine interest on the topic. By contrast, when the student has an instrumental motivation for learning science (he or she is interested on science because it is useful for his or her career plans), the influence is negative.

On the group of common (generic) non-cognitive skills, we would like to put the focus on the impact of the ICT on resilience. The index *Soiaict* measures the degree to which ICT (information communication technology) is a part of the daily social life of the students, an index informed by question such as “I like to share information about digital devices with my friends” or “I like to meet friends and play computer and video games with them”. In all the studied countries and regions, the effect of this socialization through ICT on resilience is both significant and negative. Actually, it is the only factor that all countries and regions have in common. But fortunately, to promote resilience the authorities do not have to go against the grain on ICT. As the relation between *Intict*, a measure of the student’s ICT interest shows, with positive coefficients for all the countries and regions but Hong Kong, the resilient students are interested on ICT but, we can conclude, they prefer not to use technology in their daily interactions with their friends.

The results of this study should be evaluated in light of some limitations, which should be addressed in future research. First, and given the nature of PISA studies, some student variables that may influence resilience were not available such as personality profiles and family involvement[3] . Another limitation is that this study used a design that did not allow us to examine progression over time, which would have been extremely interesting. We do not know whether our results for science would be generalizable to other areas of academic performance such as reading comprehension or mathematics. We do not know

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[3] As a robustness check, we used the information of parental interest on science, available only for Korea. The results were comparable and the model passes the test. That questionnaire was optional for the countries. The results are available on demand.

which of the findings in the East and South-East Asian zone could be significative in other parts of the world. These could be potentially interesting directions for future research to pursue.

Declaration of interest statement

None.

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Figure 1: Classification of the variables included in our analysis

Student level	Demographics	*Gender*	Science-related non-cognitive skills	*Joyscie*
		Repeat		*Scieeff*
	Student’s perception	*Adinst*		*Intbrsci*
		Disclisc		*Instscie*
		Teachsup	Common non-cognitive skills	*Anxtest*
				Motivat
				Soiaict
				Intict
School level	School characteristics	*School type*	School climate	*Stubeha*
		Stchratio		*Teachbeha*

Table 1. Description of the independent variables.

	Name	Description	Type	Min	Max	Mean	Sd
	FIRST LEVEL: STUDENTS						
Students' personal issues	***Sex***	Gender	categorical	0	1		
	Repeat	Grade repetition	categorical	0	1		
Students' percepction	***Adinst***	Adaptation of the instruction to the students needs and knowledge	index	-1.966	2.047	-0.037	0.892
	Teachsup	Teacher support in a science classes of students choice	index	-2.720	1.448	0.017	0.869
	Disclisc	Disciplinary climate in science classes	index	-2.416	1.884	0.294	0.882
Science related non-cognitive skills	***Scieeff***	Science self-efficacy	index	-3.757	3.278	-0.367	1.175
	Joyscie	Enjoyment of science	index	-2.115	2.164	0.031	0.956
	Intbrsci	Interest in broad science topics	index	-2.547	2.730	-0.015	0.938
	Instscie	Instrumental motivation for learning science	index	-1.930	1.736	0.217	0.828
Common non-cognitive skills	***Motivat***	Achiving motivation	index	-3.088	1.854	-0.173	0.894
	Anxtest	Anxiety before taking a text	index	-2.505	2.549	0.315	0.940
	Sociact	Students' ICT as a topic in Social Interaction	index	-2.136	2.428	-0.095	0.892
	Intict	Students' ICT interest	index	-2.988	2.680	-0.210	0.954
	SECOND LEVEL: SCHOOLS						
School nature	***Schooltype***	Public or private school	categorical	0.000	1.000		
	Stchratio	Students/teacher ratio	continuous	1	100	13.088	7.802
	Teachbeha	Teacher behaviour hindering learning	index	-2.118	4.259	0.140	1.187

Principals' perception	***Stubeha***	Student behaviour hindering learning	index	-2.387	3.891	-0.337	1.399

Note: descriptive statistics for the whole sample: minimum (Min), maximum (Max), sample mean (Mean) and standard deviation (Sd) for the numerical variables.

Table 2. Descriptive statistics per country: Sample size of students and schools, percentages of resilient students, males, students who have repeated at least a grade, and means for the rest of the variables included in the analysis.

	HKG	JPN	KOR	MAC	QCH	SGP	TAP
FIRST LEVEL: STUDENTS							
Sample size	764	1.434	1.153	977	1.501	1.340	1.573
% Resilient	69%	50%	44%	67%	55%	52%	48%
%Male Q1	53%	49%	51%	54%	53%	54%	51%
% Repeat	24%	-----	4%	45%	29%	6%	1%
Adinst	0.01	-0.36	-0.08	-0.12	-0.04	0.33	0.03
Teachsup	-0.01	-0.20	-0.10	-0.08	0.11	0.22	0.03
Dsiclisc	0.32	0.73	0.56	0.14	0.17	-0.04	0.12
Science related non-cognitive skills							
Scieff	-0.16	-0.72	-0.30	-0.25	-0.27	-0.22	-0.14
Joysci	0.38	-0.52	-0.08	0.18	0.20	0.43	-0.25
Intbrsci	0.32	-0.24	0.56	0.04	0.37	0.19	-0.15
Intscie	0.36	-0.17	-0.05	0.23	0.52	0.49	0.18
Common non-cognitive skills							
Motivat	0.14	-0.67	-0.10	-0.66	-0.00	0.33	-0.25
Anxtest	0.26	0.21	0.07	0.42	0.26	0.65	0.37
Sociact	0.04	-0.63	-0.54	0.13	-0.06	0.19	0.20
Intict	-0.01	-0.61	-0.46	0.12	-0.64	0.43	-0.02
SECOND LEVEL: SCHOOLS							
Sample size	114	182	154	38	207	158	196
Schtype	8%	74%	68%	5%	91%	97%	71%
Stchratio	0.01	-0.23	0.17	-0.07	-0.03	-0.18	0.20
Teachbeha	0.32	0.30	-0.51	0.71	0.81	0.07	0.06
Stubeha	-0.73	-0.55	-0.25	0.06	0.27	-0.56	-0.64

Note: ISO codes: JPN: Japan; KOR: Korea; HKG: Hong Kong (China); MAC: Macao (China); SGP: Singapore; TAP: Taipei. OECD code: QCH: refers to the four PISA-participating Chinese provinces: Beijing, Shanghai, Jiangsu, and Guangdong.

Table 3. Final selected resilient model for each country or region.

	HKG	JPN	KOR	MAC	QCH	SGP	TAP
FIRST LEVEL: STUDENTS							
Gender				0.605*** (0.219)		0.431*** (0.098)	
Repeat	-0.840*** (0.240)			-1.574*** (0.199)	-0.626*** (0.176)	-1.522*** (0.286)	
Adinst			-0.299** (0.116)			0.241*** (0.075)	-0.226** (0.101)
Teachsup	0.248* (0.130)	-0.365*** (0.089)					0.236** (0.104)
Disclisc		0.212** (0.089)		0.241** (0.102)	0.231** (0.089)	0.393*** (0.077)	
Science related non-cognitive skills							
Scieeff		0.108** (0.050)	0.228*** (0.063)			0.143** (0.072)	0.187** (0.083)
Joyscie	0.518*** (0.102)	0.280*** (0.089)	0.705*** (0.087)	0.379*** (0.087)		0.588*** (0.073)	
Intbrsci	0.303*** (0.088)	0.574*** (0.111)		0.316*** (0.094)	0.238** (0.113)		0.269** (0.109)
Instscie		-0.235** (0.101)	-0.253* (0.146)			-0.261*** (0.091)	-0.167* (0.099)
Common non-cognitive skills							
Motivat	0.227** (0.109)	0.234*** (0.065)			0.453*** (0.122)		0.451*** (0.088)
Anxtest	-0.262*** (0.095)				-0.450*** (0.115)	-0.183*** (0.068)	-0.198** (0.084)
Soiaict	-0.506*** (0.126)	-0.176** (0.086)	-0.196** (0.087)	-0.568*** (0.104)	-0.239** (0.105)	-0.520*** (0.078)	-0.319*** (0.104)
Intict		0.439*** (0.081)	0.229** (0.092)	0.462*** (0.127)	0.528*** (0.098)	0.188*** (0.072)	0.272*** (0.095)
SECOND LEVEL: SCHOOLS							
Intercept1							
Intercept2	0.726*** (0.175)	-0.860*** (0.208)	-0.267** (0.116)	1.013*** (0.227)	0.049 (0.358)		-1.146*** (0.303)
Stubeha	-0.372** (0.153)	-0.652*** (0.115)	-0.495*** (0.080)			-0.193** (0.088)	
Teachbeha		0.520*** (0.152)					
Stchratio	1.516* (0.856)			0.791*** (0.213)		0.695** (0.295)	1.020*** (0.339)
Schtype		1.043*** (0.215)			0.717 (0.334)		1.507*** (0.352)

Note: * p<0.1; ** p<0.05; *** p<0.01.

Table 4. Odds ratio for resilient together with its 95% confidence interval for each of the selected variables.

	HKG	JPN	KOR	MAC	QCH	SGP	TAP
FIRST LEVEL: STUDENTS							
Gender				1.831 (1.193; 2.812)		1.539 (1.271; 1.863)	
Repeat	0.432 (0.270; 0.691)			0.207 (0.140; 0.306)	0.535 (0.379; 0.755)	0.218 (0.125; 0.382)	
Adinst			0.742 (0.591; 0.930)			1.272 (1.097; 1.475)	0.798 (0.654; 0.973)
Teachsup	1.282 (0.993; 1.655)	0.694 (0.583; 0.827)					1.267 (1.033; 1.553)
Disclisc		1.237 (1.039; 1.473)		1.272 (1.042; 1.553)	1.259 (1.058; 1.499)	1.481 (1.275; 1.721)	
Science related non-cognitive skills							
Scieeff		1.114 (1.011; 1.228)	1.256 (1.110, 1.421)			1.154 (1.002; 1.329)	1.206 (1.026; 1.417)
Joyscie	1.679 (1.375; 2.051)	1.324 (1.111; 1.577)	2.023 (1.706; 2.400)	1.461 (1.232; 1.733)		1.801 (1.561; 2.079)	
Intbrsci	1.354 (1.139; 1.609)	1.776 (1.428; 2.208)		1.372 (1.141; 1.650)	1.268 (1.016; 1.583)		1.308 (1.056; 1.621)
Instscie		0.790 (0,648; 0.964)	0.777 (0.584; 1.033)			0.770 (0.645; 0.920)	0.846 (0.697; 1.026)
Generic non-cognitive skills							
Motivat	1.255 (1.015; 1.553)	1.264 (1.112; 1.436)			1.572 (1.239; 1.995)		1.570 (1.321; 1.867)
Anxtest	0.769 (0.639; 0.927)				0.637 (0.509; 0.798)	0.833 (0.729; 0.953)	0.820 (0.696; 0.967)
Soiact	0.603 (0.471; 0.772)	0.839 (0.709; 0.992)	0.822 (0.693, 0.974)	0.567 (0.462; 0.695)	0.788 (0.642; 0.967)	0.595 (0.510; 0.693)	0.723 (0.592; 0.892)
Intict		1.552 (1.325; 1.817)	1.257 (1.050; 1.504)	1.588 (1.239; 2.035)	1.695 (1.399; 2.055)	1.207 (1.048;1.391)	1.313 (1.091; 1.580)
SECOND LEVEL: SCHOOLS							
Intercept1							
Intercept2	2.066 (1.461; 2.922)	0.423 (0.281; 0.637)	0.766 (0.609; 0.963)	2.753 (1.740; 4.358)	1.050 (0.519; 2.124)		0.318 (0.175; 0.578)
Stubeha	0.690 (0.509; 0.934)	0.521 (0.415; 0.653)	0.610 (0.521; 0.714)			0.825 (0.694; 0.980)	
Teachbeha		1.683 (1.248; 2.269)					
Stchratio	4.554 (0.837; 24.778)			2.206 (1.433; 3.398)		2.005 (1.121; 3.586)	2.774 (2.256; 9.021)
Schtype		2.838 (1.856; 4.339)			2.045 (1.062; 3.954)		4.511 (2.256; 9.021)