Garen Avanesian[1] *and Ksenia Rozhkova*[2]

THE EFFECT OF NON-COGNITIVE SKILLS ON ACADEMIC PERFORMANCE: DOES IT VARY BY SOCIO-ECONOMIC STATUS?[3]

Academic achievement at school as a crucial determinant of further educational attainment is largely affected by family socio-economic status (SES). Non-cognitive skills may, at least partly, mediate this effect and serve as a promising aim for educational policy in leveling educational inequality. Based on OECD Survey for Social and Emotional Skills (OECD SESS), this paper uses multilevel modeling approach to explore the relationship between non-cognitive skills, SES, and academic achievement for schoolchildren from 7 countries. The results suggest that non-cognitive skills significantly reduce the effect of SES on achievement, although it depends on the differences in country-level socio-economic and cultural context. Task performance and open-mindedness are the most influential non-cognitive skills related to achievement, with the effect being most pronounced among low-SES children. Significant non-linear effects are also observed for collaboration and emotional regulation. Overall, our models reveal that while individual student differences account for most of the variance in academic performance, there is a non-trivial proportion of variance explained by non-cognitive skills, particularly among high achievers. This underlines the potential of targeted interventions aimed at developing these skills to foster academic excellence, especially within socio-economically diverse urban environments.

JEL Classification: I24, Z13, J24

Keywords: academic performance, school, SES, non-cognitive skills, personality

---

[1]Future Skills Research Lab, Southern Federal University, Rostov-on-Don, Russia; avanesian@sfedu.ru

[2]Laboratory for Labour Market Studies, Higher School of Economics, Moscow, Russia; krozhkova@hse.ru

[3]This Working Paper is an output of a research project implemented within NRU HSE's Annual Thematic Plan for Basic and Applied Research. Any opinions or claims contained in this Working Paper do not necessarily reflect the views of HSE. The research leading to these results has been carried out under the initiative "Supply and demand of youth skills: between education and labor market" estiablished between Higher School of Economics and Southern Federal University as part of the program of joint thematic labs for 2022-2024.

Introduction

Education serves as a key facilitator for social mobility. Academic performance at school may compensate for disadvantaged background, meaning that better marks at early stages of education lead to higher educational aspirations, higher achieved degrees, and result in better socio-economic outcomes. At the same time, academic performance may be significantly affected by socio-economic inequality. Almost one fifth of the variance in education is explained by family socio-economic status (SES) (Erikson, 2016). Children, whose parents (especially mother) have higher education, higher cultural capital, and better financial resources, generally study better (Ditton et al., 2018). Since later achievements build up on the earlier performance, initial academic disparities, which are already formed at kindergarten entry, increase with the progress of ones educational trajectory (Reardon & Portilla, 2016; Stumm, 2017). Children from higher SES-families demonstrate a steadier transition to higher education compared to their disadvantaged peers (Jackson, 2013), even when they have similar levels of skills (Gil-Hernández, 2021). A vicious circle arises as better performance contributes to social mobility, but it is hardly reachable for those with disadvantaged background.

Research concerning academic performance is usually centered on cognitive abilities. However, ignoring non-cognitive skills biases the estimates of the related returns to education (J. J. Heckman, 2000). Non-cognitive skills, also referred to as personality or socio-emotional skills in different fields of social sciences, have recently turned into a prominent instrument of educational research. There are several reasons for that. First, they are known to be linked to a wide array of adult outcomes from wages and employment to health and longevity (J. Heckman et al., 2006). Second, non-cognitive skills are affected by early social environment, socialization, and family, and, therefore, may serve as a transmission mechanism of inequality. For low-SES students, non-cognitive skills are especially predictive of educational attainment and may help in overcoming their disadvantaged background (Liu, 2020). Third, non-cognitive skills influence the process of human capital accumulation, supporting the development of cognitive abilities from early childhood ("skills beget skills") (Cunha & Heckman, 2007; Cunha & Heckman, 2008). Evidence suggests that non-cognitive skills explain as much as 21% in literacy development at early educational stages (Hindman et al., 2010). Finally, non-cognitive skills remain responsive to external influences until late adolescence, despite early initial development (J. Heckman & Kautz, 2013). Therefore, certain policies, aimed at developing positive non-cognitive skills, may be useful to reduce social inequality. In this paper, using a large sample of data collected from the OECD Survey in Social and Emotional Skills and applying multilevel modelling approach, we explore the relationship between non-cognitive skills and academic performance of schoolchildren, aged 10 and 15, in 7 countries across the world. Multilevel modelling allows us to simultaneously account for school and city effects, which may significantly influence differences in performance. We use a framework close to the traditional Big Five to measure non-cognitive skills. Finally, the richness of the dataset enables us to differentiate the results, based on the family SES of the surveyed children. There are several gaps in contemporary research literature in social sciences on the relationship between achievements and non-cognitive skills. First, although non-cognitive skills and SES have been separately shown to have strong effects on performance, little evidence combines these characteristics. Second, the existing evidence is mostly centered on high school or university students. For instance, openness and emotional stability from the Big Five are shown to be a strong predictor of pursuing higher education among adolescents (Lundberg, 2013). Less is known about earlier educational stages. Third, as most of the research on the topic was conducted in psychology and pedagogy, the results are usually based on small samples (see reviews by (De Raad & Schouwenburg, 1996; Poropat, 2009)) and lack a proper international comparative analysis.

The contribution of this paper is threefold. First, to our knowledge, this is the first cross-country study, exploring the effect of non-cognitive skills on academic performance. Using a large sample of data allows us to see whether the relationship between non-cognitive skills, SES, and academic performance shows a universal pattern across the world or can only be observed in certain socio-cultural contexts. Second, we shift the research focus from high school and university students to earlier educational stages and differentiate between two cohorts of schoolchildren: 10- and 15-year-olds, i.e., those attending primary and lower secondary school. Third, multilevel modeling accounts for unobserved effects, resulting in more robust and valid estimates. Our results suggest that family SES to a different extent affects academic achievement of schoolchildren in different countries. However, the inclusion of non-cognitive skills into the analysis notably reduces its contribution globally. Open-mindedness (category representing openness to experience) and task performance (conscientiousness) significantly reduce the probability of low academic performance and increase that of high performance, with a robust linear effect across all SES groups and a special importance for children from disadvantaged background. Unexpected negative effect is observed for emotional regulation, while nontrivial non-linear effects arise for collaboration (agreeableness). We conclude with the discussion of policy relevance of non-cognitive skills in the educational context.

Literature Review

Unlike other socio-economic results, where non-cognitive skills were incorporated only recently (e.g., labour market outcomes), the search for the association between personality and academic performance has a long- standing history (Kline & Gale, 1971). However, little agreement exists on which non-cognitive skills should be in the focus of research and policy. The most convenient and widespread approach is relying on well-developed psychological concepts such as the Big Five (McCrae & John, 1992). In this framework, personality can be described from the perspective of five orthogonal factors: conscientiousness (task performance), openness to experience (open-mindedness), extraversion (engaging with others), neuroticism (emotional regulation), and agreeableness (collaboration). By providing a critical review, De Raad & Schouwenburg (1996) contributed to the Big Five becoming widespread in educational context.

The most influential out of five is conscientiousness (Bratko et al., 2006; O'Connor & Paunonen, 2007; Poropat, 2009). Conscientiousness is positively correlated with student effort, self-regulation, and norm following (Zamarro et al., 2019), resulting in higher attendance rates (Chamorro-Premuzic & Furnham, 2003; Conard, 2006), consistently doing homework, and behaving well in a school setting (West et al., 2016). Conscientiousness is associated with better academic results across the whole educational cycle from elementary school (Richardson et al., 2012; Rosander & Bäckström, 2014) to tertiary education (De Raad & Schouwenburg, 1996). Irrespective of social background, non-cognitive skills measured before university entry are strong predictors of academic achievement, with high levels of conscientiousness compensating for poorer cognitive skills (Edwards et al., 2022; Gil-Hernández, 2021). In contrast, low levels of conscientiousness are shown to aggravate the negative effect of lower socio-economic background on academic achievement, at least in university students (Edwards et al., 2022).

Neuroticism, or lack of emotional stability, has as well proved to predict performance and to limit academic success (Chamorro-Premuzic & Furnham, 2003). The relationship appears to be non-linear: while emotionally stable students are more likely to employ effective learning styles (Komarraju et al., 2011), they also spend less time on homework (Lubbers et al., 2010). Therefore, the effect of neuroticism on academic performance may vary, depending not only on the level of education, but rather on the level of manifestation of the trait. Neuroticism is characterized by anxiety, which may lead to worse performance under pressure (e.g., in exam setting). Neuroticism and conscientiousness together predict exam marks above academic variables, accounting for 10 percent of the variance (Chamorro-Premuzic & Furnham, 2003). Mixed results exist for openness.

Openness to experience is positively related to intelligence, stronger than any other personality trait (Borghans et al., 2008), especially at higher stages of education (Poropat, 2014). However, its correlation with achievements is more pronounced for high-ability adolescents (Heaven & Ciarrochi, 2012). On one hand, openness increases the probability of higher education enrollment for adolescents with disadvantaged backgrounds (Lundberg, 2013) and may be associated with deeper knowledge of subjects. On the other hand, Individuals low in openness may be more practical in choosing their learning strategies, leading to better academic results (Chamorro-Premuzic & Furnham, 2003). The remaining Big Five categories (extraversion and agreeableness) usually show little to no association, except for primary education (Poropat, 2014).

The economic gaps in non-cognitive skills are well documented in economic literature (Attanasio et al., 2020; Elkins & Schurer, 2020; J. J. Heckman & Mosso, 2014). The evidence affirms that the disadvantage of the poorest tends to increase over time (Fletcher & Wolfe, 2016). One of the reasons refers to the difference in children's upbringing, associated with parental SES (Reardon & Portilla, 2016). (Orel et al., 2018) showed that the development of both cognitive and non-cognitive skills among Russian first-graders is associated with such family characteristics as mother's education, parental involvement, and number of books at home as a proxy for cultural capital. Non-cognitive measures are more predictive of academic achievements for low-SES students (Liu, 2020). Although low-SES individuals demonstrate substantially lower levels of non-cognitive skills measured by the Big Five, they enjoy higher returns to these skills (Shanahan et al., 2014). Moreover, socio-economic status is more related to non-cognitive skills, not cognitive abilities (Marks, 2016). Existing evidence points out at developing growth mindset, self-efficacy, and grit as measures of non-cognitive skills is positively associated with academic achievement, especially for children coming from low-SES families (Avanesian et al., 2022).

Different Big Five categories may be linked to different subjects (Rosander & Bäckström, 2014). Evidence suggests that personality traits may be more relevant for the explanation of mathematics grades and the overall GPA rather than languages (Smrtnik Vitulić & Zupančič, 2012). Conscientiousness is more important for Math and Science scores (Heaven & Ciarrochi, 2012). Self-efficacy and education aspirations, which are also correlated with conscientiousness, predict academic performance in mathematics, based on data from PISA and TIMSS (Lee & Stankov, 2018). Openness appears to be the only Big Five category, significantly associated with verbal SAT score (Noftle & Robins, 2007). Limited studies of non-cognitive skills and achievement exist for countries other than the US and EU. A positive correlation with conscientiousness and openness among high school students (Mishkevich, 2021), however, only 135 respondents were present in the sample. Similarly, on a sample of 176 respondents, introversion, agreeableness, neuroticism, and openness appear to be significant contributors to academic achievement of university students in Russia (Nye et al., 2013).

A problem, arising with the measurement of personality traits in a survey setting, is reference bias which is a tendency to respond to questionnaires in a socially acceptable way. For instance, being more conscientious (hard-working, aim-oriented etc.) and emotionally stable is more socially acceptable. Therefore, item response for some of the Big Five categories, including conscientiousness and neuroticism, may be unlikely to capture extremes (Morris et al., 2021). Self-reports overstate at the bottom and top of the distribution of non-cognitive skills (Edwards et al., 2022). Other-rated traits (e.g., parents, teachers, peers) may show more valid and consistent results (Feng et al., 2022; Poropat, 2014). Another issue is possible reversed causality. For example, schooling intensity decreases emotional stability (Dahmann & Anger, 2018; Korthals et al., 2021)but increases openness for students with lower SES (Dahmann & Anger, 2018). Therefore, methodological approaches should address the issue of causality.

Methodology

The study uses the data from the OECD Survey on Social and Emotional Skills (SSES) carried out in 10 cities across 9 countries in 2019. The covered cities include Ottawa (Canada), Houston (USA), Bogota and Manizales (both located in Colombia), Helsinki (Finland), Moscow (Russia), Istanbul (Turkey), Daegu (South Korea), Sintra (Portugal), and Suzhou (China). This novel survey program aimed to fill a sizable gap that has been present with regards to the data on non-cognitive skills and factors associated with their acquisition at home, school, and peer environment. Acknowledging that while considerable data are available when it comes to the development of cognitive competences, the survey assessed non-cognitive skills of 10- and 15-year-olds by triangulating the information collected from students themselves, as well as their parents and teachers. As data from Sintra did not reach response rate, and data from Ottawa did not include information on academic performance, they were dropped from the current study (OECD, 2021b). In this study, we use the self-reported measures of non-cognitive skills, i.e., the data come from the student questionnaires. To reflect a skill-based approach to the well-known Big Five Inventory, the survey proposed the following taxonomy to measure non-cognitive skills: open-mindedness (similar to openness), task performance (reflecting conscientiousness), engagement with others (or extraversion), collaboration (or agreeableness), and emotional regulation (the opposite for neuroticism) (OECD, 2021a). These broad skills, in turn, are broken down into 3 facets that represent various sub-dimensions

Table 1: Sample Summary

City	1. Younger	2. Older	Female	Male	N_Schools	Total_Obs
Bogota	2,709	2,833	2,812	2,730	145	5,542
Daegu	1,555	3,184	2,381	2,358	104	4,739
Helsinki	715	1,477	1,114	1,078	65	2,192
Houston	3,053	2,929	3,115	2,867	102	5,982
Istanbul	2,591	2,996	3,059	2,528	101	5,587
Manizales	3,135	3,412	3,360	3,187	85	6,547
Moscow	3,244	3,372	3,231	3,385	78	6,616
Suzhou	3,591	3,598	3,391	3,798	122	7,189
Total	20,593	23,801	22,463	21,931	802	44,394

Source: Calculations of the authors based on the OECD SSES 2019 data.

of the revised BFI. The detailed description of the framework, as well as validity and reliability of the items adopted to measure the suggested skills are presented in OECD (2021b). Given that the original dataset provides the raw scores for the sub-dimensions, we aggregated them into five skills by taking arithmetic means of 3 facets that constitute each of them. As our research aimed to produce comparative analysis, we standardized the aggregated scores of non-cognitive skills to the sample average across all 8 cities. Despite substantial coverage of schools in each participating city and a balanced sample that aimed to recruit approximately equal numbers of students from both age cohorts and by sex, the data suffers from missingness and non-response in some key variables of the study. In addition to five non-cognitive skills, these variables referred to academic performance in reading/language and mathematics, index of socio-economic status (a composite indicator produced by the OECD based on education and occupation of both parents, as well as household possessions), and migration background. Sample summary after dropping all missing values is presented in Table 1.

The primary purpose of the study is to estimate the effect that non-cognitive skills have on academic performance. Grades in reading and language, as well as in mathematics, served as dependent variables of the analysis. Since the grades were fixed on the ordinal scale and grading system differs from country to country, for the plausibility of interpretation we binarized these variables, with 1 referring to the schoolchildren that represent top 25% performers in both subjects, and 0 otherwise. This approach enabled interpretation of the estimated effects of non-cognitive skills on high academic performance on the probability scale, with calculated coefficients representing a probability change of high or performance due to the increase of a skill on 1 standard deviation. As the students were nested within schools, and the data were collected by cities, the verification model needed to account for the hierarchical nature of the data. Furthermore, a number of unobserved city and school factors beyond the scope of this study affect academic performance, which implies that students enrolled in the same schools within respective cities are not independent from each other in terms of their grades, and, as a consequence, variance in the outcome variables is non-random. In addition, we wanted to estimate the degree to which the effect of non-cognitive skills on academic performance varies across SES groups, implying that children from the poorest families could substantially differ from the richest ones in both non-cognitive skills and their chances to demonstrate high academic performance.

To address the outlined challenges, we adopted a three-level multilevel modeling approach. We calculated two regression models to estimate the probability of the belonging to the top 25% of performers in reading and language, and mathematics. The fixed part of the regression included such controls as sex, age cohort, a binary categorical variable with the values representing the younger (10-year-olds enrolled at primary school) and older (15-year-olds enrolled in lower secondary school) groups, SES group, and migration background. To account for the hierarchical nature of the data, the models incorporated a random intercept term with fixed means for the school id within each city. The same term was applied to control for the potential non-independence of the observations due to age. The main regression for the study has the following equation:

$$\begin{aligned}\text{Grades: Top 25\%}_{ij} = \beta_0 + &\beta_1 \times \text{Sex} + \beta_2 \times \text{Migration Background} + \\ &\beta_3 \times \text{Open Mindedness} + \beta_4 \times \text{Task Performance} + \\ &\beta_5 \times \text{Engaging with Others} + \beta_6 \times \text{Collaboration} + \\ &\beta_7 \times \text{Emotional Regulation} + \\ &u_{0ij} + u_{1ij} + u_{2ij} + \epsilon_{ij},\end{aligned} \tag{1}$$

where:

$Grades: Top25\%_{ij}$ is the academic achievement score for student i in school j.
β_0 is the intercept.
β_1 to β_7 are the fixed effect coefficients for Sex, Immigrant background, and the Big Five personality traits (Open-Mindedness, Task Performance, Engaging with Others, Collaboration, Emotional Regulation).
u_{0ij} represents the random intercept for each City and School ID.
u_{1ij} represents the random intercept for each Cohort of age (10- and 15-year olds).
u_{2ij} represents the random slopes for the Big Five personality traits within each City and SES Group.

ϵ_{ij} is the residual error term.

Finally, to highlight the heterogeneous effect across different levels of socio-economic ladder, we incorporated random slope terms of non-cognitive skills by the SES groups in each of the participating cities. In other words, the slopes of non-cognitive skills varied by the interaction term between the city and SES percentile groups. The adopted framework allows for outlining the policy implications that target the most vulnerable, accounting for the national differences in education systems and country-level contexts. The study zooms in on the schoolchildren from economically disadvantaged families, thus also emphasizing an equity-based perspective on human capital acquisition. The econometric analysis was carried out in R, with the help of the lme4 package (Bates et al., 2015), an open-source tool for fitting multilevel models.

Results

Socio-Economic Disparity in Academic Performance

The polarization of academic performance along socio-economic lines presents a challenge for educational equity and policy. Table 2 delineates the proportion of students demonstrating high academic achievement in core subjects such as reading, language, and mathematics, contrasting the bottom 40% against the top 10% of students classified by family SES. Based on this, we calculate wealth parity ratios (WPR), a critical measure to indicate equity of learning outcomes, which puts the value for disadvantaged group in the numerator, and that of the advantaged one in denominator. A WPR value approaching 1 suggests a balanced distribution of quality learning across socio-economic strata, with students from the lowest and highest SES backgrounds being equally represented amongst top performers. Oppositely, WPR values significantly below 1 highlight a disparity to the detriment of students from less affluent backgrounds.

In our analysis, WPR reveals a consistent trend of underrepresentation of high achievers among the bottom 40% of SES across all cities examined (Table 2). For instance, in Moscow, the share of high achievers from the bottom 40% is 9% compared to 16% from the top 10%, yielding to the most equitable distribution of quality learning amongst socio-economic groups, with WPR of 0.540. This suggests that the chances of high academic achievement for the bottom 40% are less that 50% reduced than that of their top 10% counterparts. However, cities like Helsinki, Manizales, and Houston, demonstrate way more substantial patterns of disparity, with odds of high academic achievement amongst children from the poorest families being more than 70% reduced. These findings underscore the persistent influence of socio-economic status on educational achievement.

Table 2: Socio-Economic Disparities in High Academic Achievement

City	Bottom 40%	Top 10%	WPR
Bogota	11.443	21.903	0.522
Daegu	12.976	26.766	0.485
Helsinki	8.288	32.675	0.254
Houston	8.337	32.249	0.259
Istanbul	18.424	56.423	0.327
Manizales	9.204	34.908	0.264
Moscow	8.667	16.105	0.538
Suzhou	13.833	33.650	0.411

Source: Calculations of the authors based on the OECD SSES 2019 data.

Cities exhibit diverse profiles of academic excellence and struggle, with wealth-based disparities manifesting both the highest and lowest echelons of performance. The WPR serves as a stark reminder of the pervasive inequities that characterize educational systems and the importance of socio-economic considerations in crafting policy interventions.

Can Non-Cognitive Skills Increase the Equity for the Poorest?

Recognizing the potential of non-cognitive skills (NCS) to bridge the performance gap, this analysis probes deeper into the influence of these skills on academic outcomes. To examine whether NCS can attenuate the socio-economic inequities in academic performance, we juxtapose two multilevel regression models, a baseline model that predicts belonging to the top 25% of best achievers controlling for sex, migration background, and SES group. The baseline model also incorporates random intercept with fixed means by age cohort, three-level random term by schools and cities, and random slope of SES effect by city. The advanced model has the same equation, but also accounts for 5 non-cognitive skills in the fixed part of the equation. The outputs of both regression models are summarized in Table 3.

Table 3: Multilevel regressions on probability of high achievement, before and after accounting for non-cognitive skills

	Model without NCS			Model with NCS		
Characteristic	**Beta**	**95% CI[1]**	**p-value**	**Beta**	**95% CI[1]**	**p-value**
(Intercept)	0.28	-0.05, 0.61	0.094	0.27	-0.41, 0.94	0.4

[1]CI = Confidence Interval

Table 3: Multilevel regressions on probability of high achievement, before and after accounting for non-cognitive skills

	Model without NCS			Model with NCS		
Characteristic	**Beta**	**95% CI[1]**	**p-value**	**Beta**	**95% CI[1]**	**p-value**
Sex						
Female	—	—		—	—	
Male	-0.05	-0.05, -0.04	<0.001	-0.04	-0.05, -0.04	<0.001
SES Group						
Top 10%	—	—		—	—	
Bottom 40%	-0.12	-0.45, 0.20	0.3	-0.11	-0.22, 0.01	0.063
Middle 50%	-0.08	-0.37, 0.22	0.5	-0.07	-0.17, 0.04	0.2
Migration Background						
0	—	—		—	—	
1	0.00	-0.01, 0.01	0.9	0.00	-0.01, 0.01	>0.9
No. Obs.	44,394			44,394		
Open Mindedness				0.03	0.02, 0.03	<0.001
Task Performance				0.04	0.04, 0.05	<0.001
Engaging with Others				0.01	0.00, 0.01	0.020
Collaboration				-0.02	-0.02, -0.01	<0.001
Emotional Regulation				-0.01	-0.02, -0.01	<0.001

[1] CI = Confidence Interval

In examining the effects of non-cognitive skills on academic performance, two nested multilevel models were compared using a likelihood ratio test. The base model, which included only socio-demographic controls (Model 1), was compared to an extended model incorporating non-cognitive skill measures (Model 2). The test revealed a significant difference between the models ($\chi^2(5) = 829.13, p < .001$), indicating that non-cognitive skills contribute meaningfully to the explanation of academic performance variations among students beyond the effects of socio-economic status alone.

In the base model without non-cognitive skills, the effect of being in the bottom 40% by SES on the probability of high academic performance is clearly pronounced across all cities (Figure 1). This model confirms the results of the WPR analysis, reflecting the socio-economic disparities in educational achievement. However, the introduction of non-cognitive skills into the model results in a notable reduction in the SES effect size. Almost all cities exhibit a reduction in SES effect size with the inclusion of non-cognitive skills, but this reduction is not uniform. Average fixed effect of being a child from the poorest 40% of household on high academic achievement increases from -12.5% to -10.7%. Further, the change is observed across all the cities of the study. However, in the cities like Istanbul or Houston, where disadvantage of bottom 40% by SES in comparison to top 10% is highly pronounced, the reduction in the effect size of socio-economic status is smaller than in other cities, indicating that while non-cognitive skills play a role in academic outcomes, they do not fully counterbalance the effects of socio-economic disparities. The disparity between the models is most striking in cities like Daegu, Manizales, and Suzhou, where the incorporation of non-cognitive skills shifts the SES impact on low performance by more than 2 percentage points.

How Strong Are the Effects of Non-Cognitive Skills on Academic Performance?

For students categorized within the high academic achievement bracket (top 25% in each city), the model indicated significant effect for the intercept, meaning that for an average student in the sample there is difference in the baseline probability of being a high achiever. The model identified statistically significant effect of sex, with males less likely to be high achievers. Migration background had no significant effect on high academic achievement.

Finally, when it comes to the non-cognitive skills, open mindedness and task performance positively affect high achievement. As such, increase in task performance on 1 standard deviation would result in increasing the probability of high achievement by 4%. Open mindedness, another critical skill for academic performance, with one increase in its standard deviation results in the increased likelihood of high achievement by 3%.

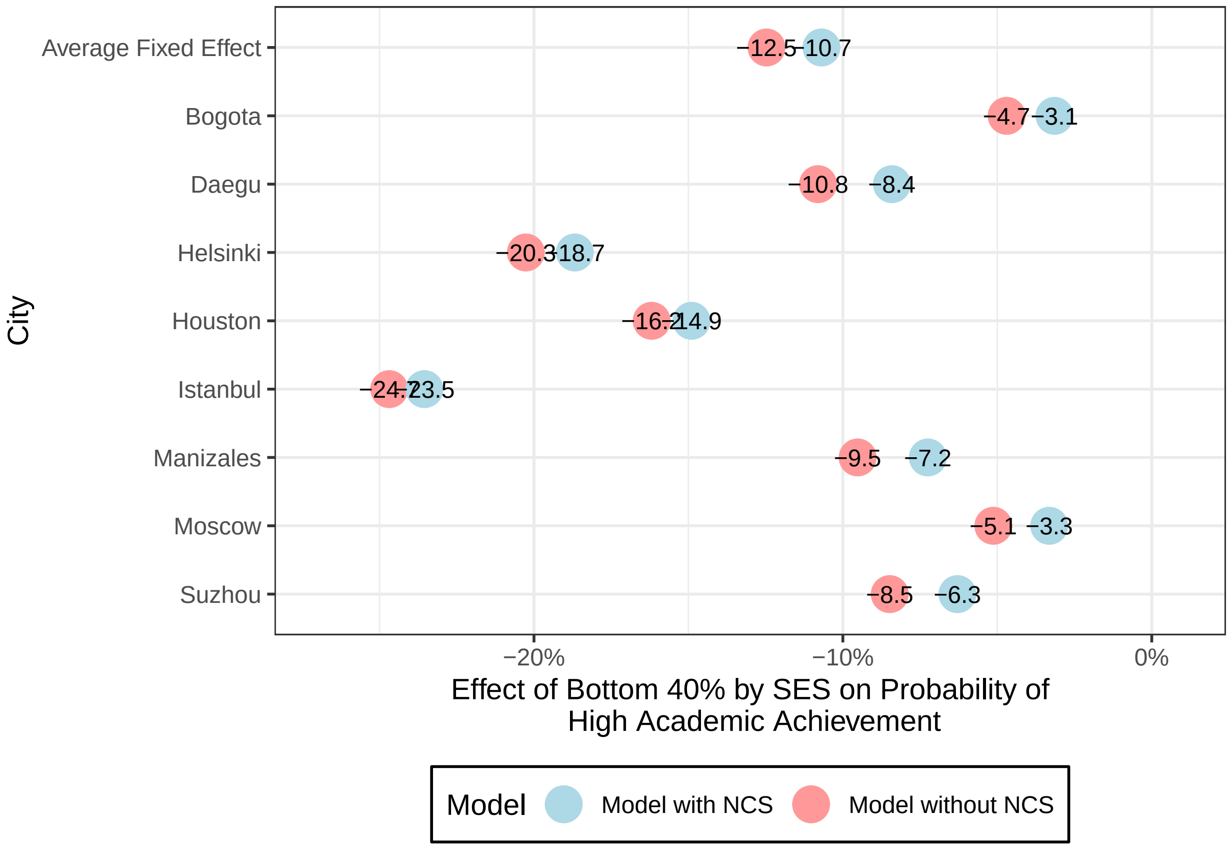

Figure 1: Comparison of the effect of SES (Bottom 40%) on Academic Achievement, multilevel models before and after accounting for non-cognitive skills

Emotional regulation and collaboration also show statistically significant effects on academic achievement, though their direction appears to be somewhat counter-intuitive. As such, they negatively affect the probability of high performance. As an example, increase on 1 standard deviation in collaboration would decrease the likelihood of high achievement by 2%, whereas in emotional regulation on 1%. An analysis carried out further in this paper aims to unpack more the reasons behind this observed pattern. Finally, engaging with others does not have a statistically significant effect on academic performance. The results of the fixed effect part of the multilevel model are presented in Table 4.

Table 4: Multilevel regressions of probability of high achievement with random slopes of non-cognitive skills

Characteristic	**Beta**	**95% CI**[1]	**p-value**
(Intercept)	0.20	0.09, 0.32	0.015
Sex			

[1] CI = Confidence Interval

Table 4: Multilevel regressions of probability of high achievement with random slopes of non-cognitive skills

Characteristic	Beta	95% CI[1]	p-value
Female	—	—	
Male	-0.04	-0.05, -0.04	<0.001
Migration Background			
0	—	—	
1	0.00	-0.01, 0.01	0.8
Open Mindedness	0.03	0.02, 0.03	<0.001
Task Performance	0.04	0.04, 0.05	<0.001
Engaging with Others	0.01	0.00, 0.01	0.11
Collaboration	-0.02	-0.03, -0.01	<0.001
Emotional Regulation	-0.01	-0.02, -0.01	<0.001
No. Obs.	44,394		

[1] CI = Confidence Interval

It is also important to consider the variance partitioning coefficients from the calculated multilevel model. Examining the variance contributions by model predictors refers to one of the key advantages of the multilevel model framework, as it allows to identify the areas where most of the variability persists. As such, for high performers, the random intercept attributable to the school ID nested within the city accounted for 16.5%, suggesting that the between-school and city differences in high achievement are substantially pronounced. The results emphasize that school-level factors refer to the major contributors of variation in academic performance. Additionally, within-age differences (we have two age cohorts, namely, 10- and 15-year-olds) account for 1% of variation in non-cognitive skills.

When examining the random slopes associated with the interaction of city and socio-economic status group on non-cognitive skills, we observed variability in the impact of these skills on academic outcomes. First of all, despite the effect sizes of non-cognitive skills are quite notable, altogether, five characteristics have a very little explanatory power in terms of heterogeneity observed in high achievement. However, this should not be misinterpreted. Even though non-cognitive skills may not vary widely across the sample (hence the low variance explained), where they do vary, they make a significant difference. Notably, the additional variance component due to the random slope of the intercept across cities and SES groups accounted for 2.7% for high performers, pointing to the existing heterogeneity in the baseline achievement levels across different SES groups within cities. The residual variance, representing within-student variability not explained by the model, accounted for 79% for high performers, underscoring a consistent level of individual differences in academic performance. The results are presented in Table 5.

Effect	Group	Term	VPC	Explained Variance (%)
Random Intercept	City * School ID	sd (Intercept)	0.148	16.481
Random Slope	City * SES Group	sd Emotional Regulation	0.009	0.061
Random Slope	City * SES Group	sd Collaboration	0.013	0.127
Random Slope	City * SES Group	sd Engaging with Others	0.014	0.147
Random Slope	City * SES Group	sd Task Performance	0.012	0.108
Random Slope	City * SES Group	sd Open Mindedness	0.007	0.037
Random Slope	City * SES Group	sd (Intercept)	0.060	2.709
Random Intercept	City	sd (Intercept)	0.005	0.019
Random Intercept	Cohort	sd (Intercept)	0.042	1.327
Random	Residual	sd Observation	0.324	78.984

Source: Calculations of the authors based on the OECD SSES 2019 data.

Effect of Non-Cognitive Skills on the Academic Achievement of the Poorest and Its Robustness Across Socio-Economic Contexts

In assessing the impact of non-cognitive skills on high academic achievement within socioeconomically disadvantaged groups, our multilevel modeling revealed nuanced city-specific patterns. The analysis, focusing on students in the bottom 40% of the SES gradient, highlighted the significant role of task performance and open-mindedness as predictors of academic success (Figure 2). Task performance, with positive slopes ranging from 3.5% to 5.1%, emerged as a robust facilitator of high achievement, aligning with existing literature that underscores its importance in educational outcomes (Dumfart & Neubauer, 2016). Open-mindedness similarly exhibited positive associations, suggesting that cognitive flexibility may enhance academic resilience, a finding supported by most existing studies (Poropat, 2014).

However, the random slopes for emotional regulation and collaboration presented a complex landscape. Both skills were consistently associated with lower probabilities of high achievement—a result that stands in contrast to conventional educational theories that typically associate collaborative skills and emotional control with positive academic performance. Specifically regarding emotional regulation, the observed effect may arise due to the multidirectional impact of the facets. In The Big Five framework, while anxiety facet of neuroticism is found to be positively associated with academic motivation, depression and vulnerability demonstrate an opposite effect (Apostolov & Geldenhuys, 2022). These counterintuitive findings may also point to the potential nonlinearity in the effects of these traits, as has been suggested by recent inquiries into the intricate dynamics of social skills in academic contexts (ref).

The substantial dataset of 44,394 individual observations lends robustness to these insights, suggesting the findings may be generalizable across similar urban educational settings. Future research could further elucidate the mechanisms at play, potentially guiding the design of targeted interventions that consider the rich tapestry of individual and environmental factors influencing student achievement.

How Equitable Are Returns to Non-Cognitive Skills?

While the previous analysis indeed affirms that investing into development of non-cognitive skills, especially task performance and open mindedness, produces substantial returns to academic performance and can be used to facilitate human capital gains, it is still unclear which socio-economic group would benefit the most from these investments. In order to address this issue, we visually explore the regression model on high performance, plotting the predicted probabilities of the skills with the most profound and positive effect. The charts on Figure 3 illustrate the predicted probabilities of high academic achievement for students across three SES groups (Bottom 40%, Middle 50%, and Top 10%) as a function of two non-cognitive skills: Task Performance and Open Mindedness. The slopes represent the relationship between each skill and high achievement within each SES group, disaggregated by city.

As indicated by Figure 3, higher levels of both task performance and open mindedness consis-

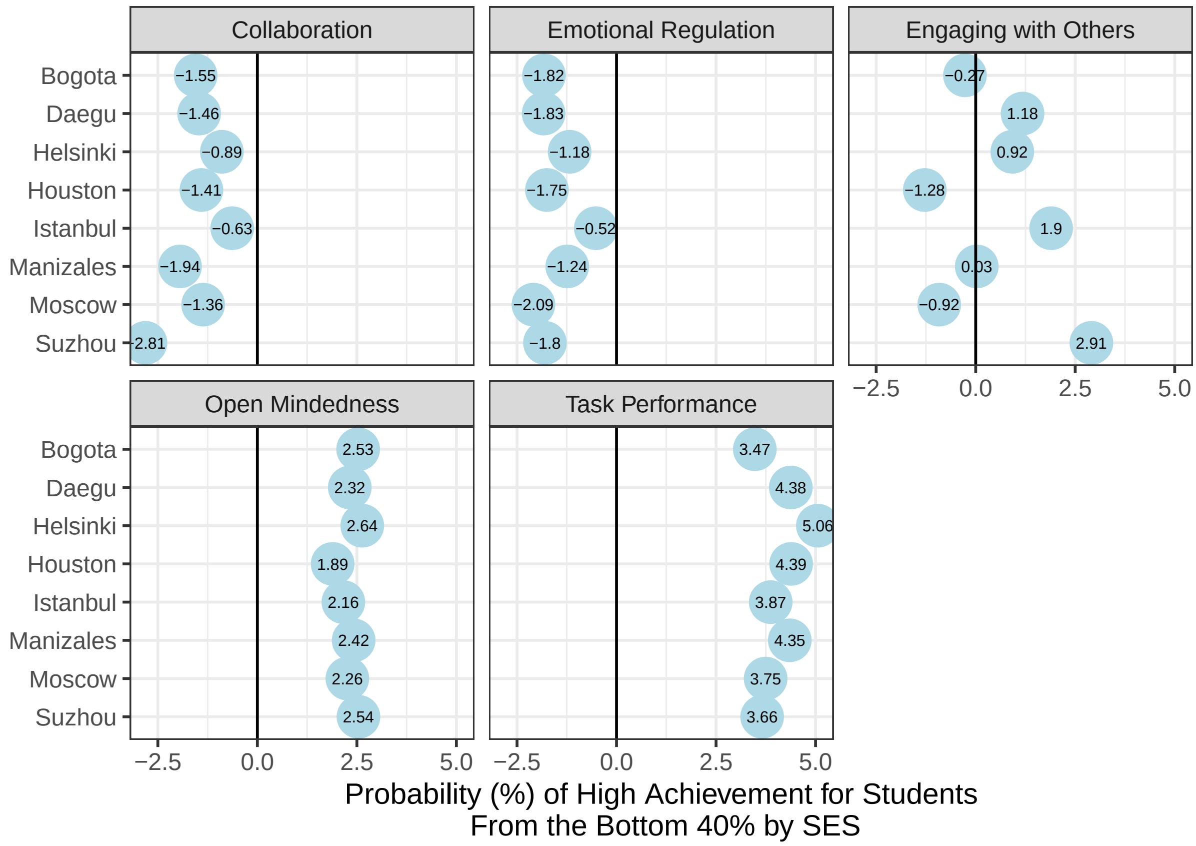

Figure 2: Predicted Probability (Regression Coefficients) of Effect of Non-Cognitive Skills on High Academic Achievement of Students from the Bottom 40% by SES

tently correlate with a higher probability of high academic achievement across all cities and SES groups. However, visual inspection of the skill slopes across SES groups and cities suggests that the slopes are rather parallel, with the observed differences arising due to the intercepts. In other words, the advantage of children from the top 10% richest households in the ways task performance and open-mindedness affect their academic achievement is due to a higher baseline probability of the wealthier students to be at the top of distribution in learning outcomes. These differences at the intercept could be due to various unobserved factors such as differences in prior educational opportunities for children from the wealthier families, disparities in parental education and social capital of families, opportunities to maintain basic needs of the everyday life, such as health and nutrition, etc. If richer kids always seem to have better outcomes regardless of non-cognitive skills (as reflected by task performance and open mindedness slopes), the benefits of these skills are not distributed equally across SES groups. While non-cognitive skills are necessary for academic success, they are not sufficient; the advantages conferred by high SES (such as those listed above) might amplify the effects of these skills.

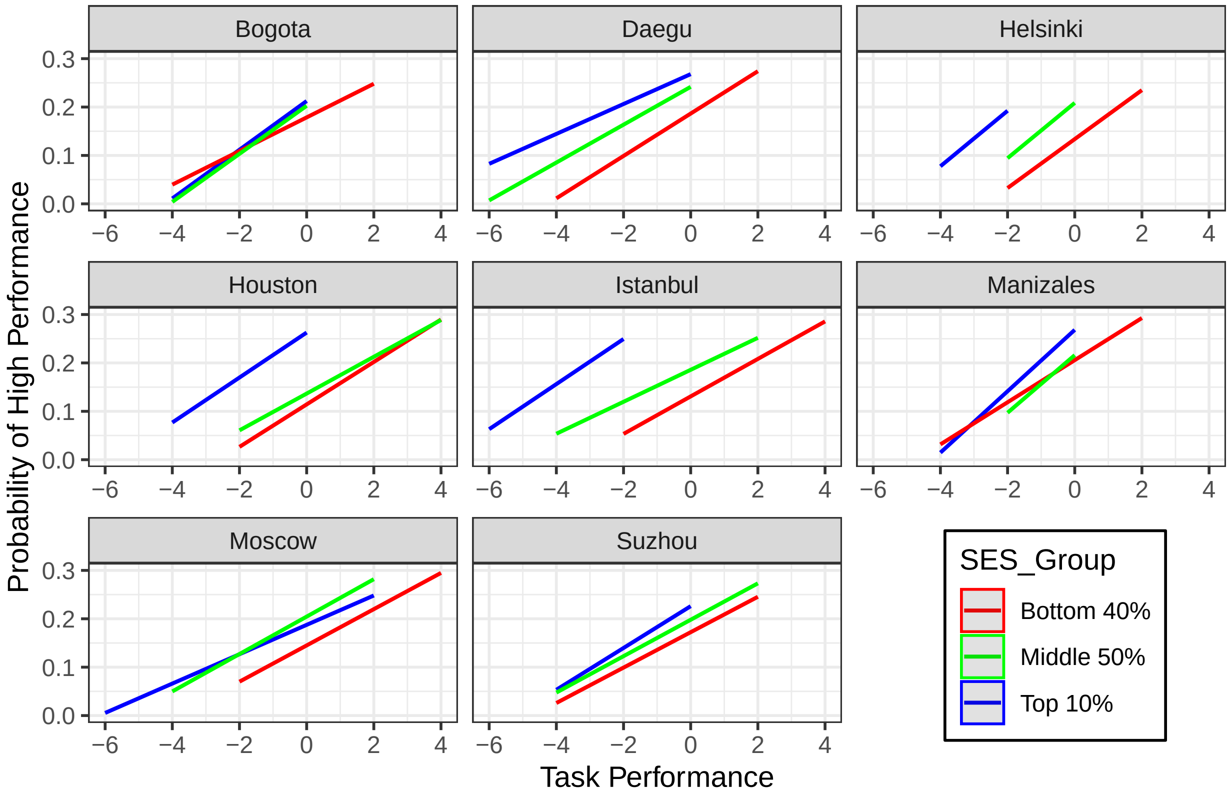

Figure 3: Predicted Probabilities of Task Performance on High Academic Achievement, by SES and City

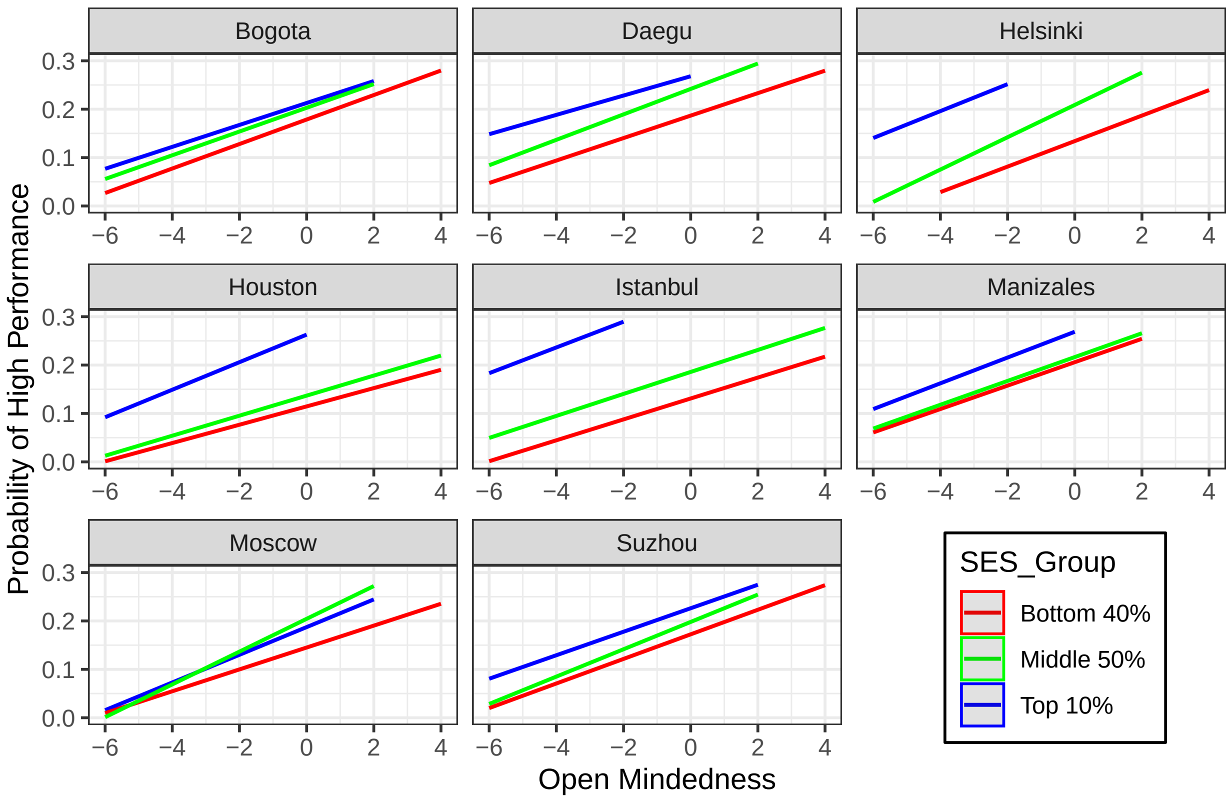

Figure 4: Predicted Probabilities of Open Mindedness on High Academic Achievement, by SES and City

Non-Linearity of Emotional Regulation and Collaboration

At the final stage of our analysis, we are coming back to the effects of emotional regulation and collaboration. We are testing the hypothesis that these skills could present a nonlinear relationship with academic performance and carry out an additional regression model that adopts quadratic terms for these two variables. While the results for emotional stability do not change, patterns identified in the relationship of collaboration and academic achievement across SES groups and cities present a compelling case.

Figures 4 and 5 visualizes the non-linear relationship between collaboration and the probability of high academic achievement for students across three SES groups in various cities. The non-linearity is depicted by the curvature in the plotted lines for each SES group within each city, indicating that the effect of collaboration on high achievement varies at different levels of collaboration skill.

Across the cities, the relationship between collaboration and high academic achievement shows a pronounced non-linear pattern, particularly in Bogota, Daegu, Helsinki, and Istanbul, where the probability of high performance initially increases with collaboration but begins to decrease beyond a certain point. This inverted U-shaped curve suggests that moderate levels of collaboration are most conducive to high academic achievement, while both lower and higher levels are less so. The peak of the curve represents the optimal point of collaboration that maximizes the probability of being a high achiever. In contrast, cities like Suzhou exhibit a different trend, with a consistent decline in the probability of high performance as collaboration increases, highlighting the variability of collaboration's impact on academic success across different cultural and educational contexts.

The non-linear trends are particularly interesting when analyzed across SES groups: for the Top 10% SES group, the benefits of collaboration are more pronounced at moderate levels but decline after a certain threshold. The Middle 50% SES group displays a similar but less pronounced non-linear trend, suggesting that the balance of collaboration for optimal academic outcomes also applies to this group but with a wider range of effective collaboration levels. For the Bottom 40% SES group, the increase in high performance probability is less steep, and the decline starts at lower levels of collaboration compared to the other SES groups. This could suggest that students from lower SES backgrounds may have a narrower range of beneficial collaboration or that other factors, such as access to resources or support systems, may limit the positive effects of collaboration on their academic outcomes.

The observed patterns raise critical questions about the role of collaboration in academic success and its potential interaction with students' socio-economic backgrounds. While previous models suggested a straightforward negative effect of emotional regulation on high achievement, the intricate non-linear relationship revealed for collaboration indicates that the impact of such non-cognitive skills on academic performance is multifaceted and contingent upon the level of skill exhibited.

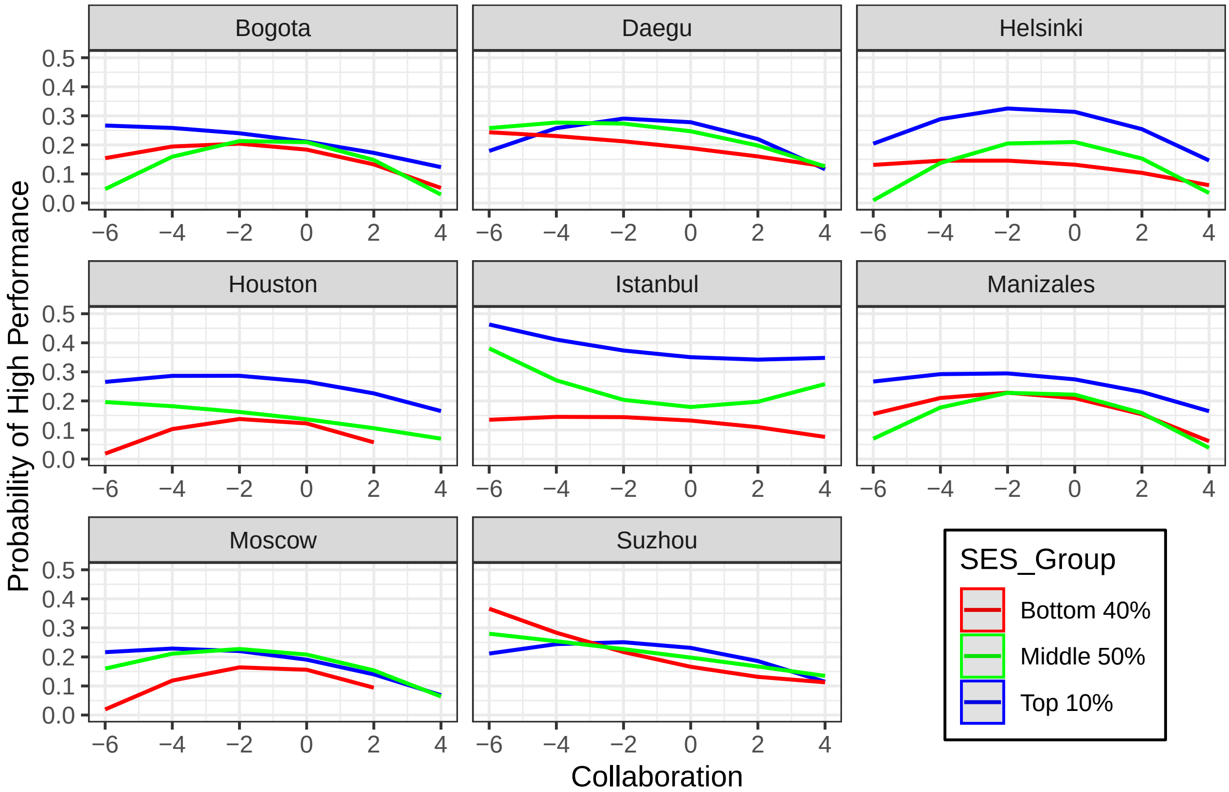

Figure 5: Predicted Probability of Collaboration (Non-Linear Trend) on High Academic Achievement, by SES and City

Research Limitations

Although our methodological approach allows us to account for different unobserved effects associated with school and social status, it still has several limitations. The first limitation is a natural consequence of survey data. A problem, usually arising with the measurement of personality traits in a survey setting, is reference bias which is a tendency to respond to questionnaires in a socially acceptable way. For instance, being more conscientious (hard-working, aim-oriented etc.) and emotionally stable is more socially acceptable. Therefore, item response for some of the Big Five categories, including conscientiousness and neuroticism, may be unlikely to capture extremes (Morris et al., 2021). Self-reports overstate at the bottom and top of the distribution of non-cognitive skills (Edwards et al., 2022). Another issue is possible reversed causality. For example, schooling intensity decreases emotional stability (Dahmann & Anger, 2018; Korthals et al., 2021), but increases openness for students with lower SES (Dahmann & Anger, 2018) Finally, we do not control for cognitive abilities in our analysis due to lack of proper measurements in the dataset.

Discussion

The pursuit of educational equity remains a paramount challenge in the face of persistent socio-economic disparities. Children from poorer households systematically demonstrate worse academic performance, being significantly less presented among top achievers. Recognizing the potential of non-cognitive skills to bridge the performance gap, this analysis probes deeper into the influence of these skills on academic outcomes.

First, our results suggest that non-cognitive skills are indeed linked to academic performance. In the modified Big Five framework, our analysis identified significant effects of task performance and open-mindedness on academic performance, with robust findings for the increase in the probability of high achievement. Task performance (or conscientiousness in traditional Big Five) reflects diligence, attention to details, and self-discipline, which are positively related to individual productivity and the choice of appropriate study style, leading to better academic outcomes (Poropat, 2014). Moreover, this trait has been systematically shown to be associated with better socio-economic decisions and outcomes in all life areas from attainment and degree completion (Mendez & Zamarro, 2017) to higher wages and employment (Brunello & Schlotter, 2011), longevity (Savelyev & Tan, 2019), and lower probability of crime activity (J. Heckman et al., 2006). Another critical non-cognitive skill for academic performance is open mindedness (similar to openness to experience). Our analysis shows that openness demonstrates rather stable effects on achievement for students along the whole SES distribution, with the effect being a little less pronounced in comparison to task performance. Open minded students tend to gain more profound knowledge in their study areas, which may result in better academic performance (McCrae & Costa, 1997). Emotional regulation and collaboration showed nontrivial effects negatively affecting the probability of high achievement but did not obtain high effect sizes. This result is different from those previously discussed in the literature, since agreeableness is not usually associated with any academic outcomes above primary school (Poropat, 2014). The effect of engaging with others (or extraversion) was not statistically significant. We suppose that this skill may be more relevant for contexts other than academic - for instance, labor market.

Second, we find that most of non-cognitive skills, including influential task performance and open mindedness, demonstrate stable associations with academic performance irrespective of the country in question. The only exception is the skill of collaboration, which demonstrates a significant, yet different non-linear trend in the relation with high academic achievement. Given the complexity of these relationships, further research is warranted to explore the underlying mechanisms driving the non-linear effects of collaboration and to determine how educational policies can be tailored to harness the benefits of collaboration for all students, particularly those from lower SES backgrounds.

Third, we do not find support for the hypothesis that non-cognitive skills are more valuable for a particular SES group. For instance, previous research, conducted on high school students and university entrants suggests that openness is especially relevant for the explanation of achievement for those with disadvantaged background (Lundberg, 2013). We do not find empirical support for the critical importance of openness for students from poorer households. In contrast, high SES students seem to benefit more from having better non-cognitive skills. Although non-cognitive skills are necessary for academic success, children with the similar levels of task performance and open-mindedness have higher chances of becoming high achievers if they come from a more favorable socio-economic background. Therefore, promoting the development of only non-cognitive skills in targeted interventions is not enough. Further research is needed to explore the mechanisms behind the observed disparities and to identify strategies that can promote equity in the returns of non-cognitive skill development.

Finally, we argue that the most influential non-cognitive skills can be fostered through targeted educational policies, especially during early stages of education. Since a significant part the model variance can be attributed to the heterogeneity within schools, school-level interventions on non-cognitive skill development within the established curricula may be very effective to promote academic success. However, the results observed for collaboration underscore the importance of a more nuanced approach. Educational strategies and interventions designed to enhance collaboration must consider the appropriate intensity and context to ensure that they are effectively supporting academic success. Same conclusion is applicable to emotional regulation. Although this skill has been shown to positively influence academic scores acquired in a high-stakes environment (e.g., during exams), in a less competitive setting to achieve consistent performance, high emotional regulation may have detrimental effects. In simple terms, one should care to be academically successful. The exploration of non-linearity in these relationships, as well as an investigation into moderating variables, may yield insights into the multifaceted nature of skill development and its consequences on learning.

Conclusions

This paper discusses educational inequality through the prism of non-cognitive skills on a large sample of schoolchildren from 7 countries. Using multilevel modeling approach, which allows controlling for fixed cohort, school, and country effects, we explore the impact of a modified Big Five personality framework, consisting of task performance, open mindedness, engaging with others, collaboration, and emotional regulation, on the probability of entering top 25% of academic performance distribution among middle and high schoolers. The results confirm that children from the poorest households systematically lag behind in academic performance and tend to be underrepresented amongst top performers. This can have substantial implications on their human capital gains in a long term, as well as reproduction of poverty patterns and lack of access to channels of social mobility.

Incorporating educational policies to enhance productive non-cognitive skills has been repeatedly discussed as a potential mechanism of reducing socio-economic gap in academic performance. Our results suggest that non-cognitive skills are indeed very predictive of achievement, although the magnitude of the effect varies by cultural and socio-economic context of the country. The most influential positive non-cognitive skills are task performance and open-mindedness, while emotional regulation has a negative effect on academic achievement. A non-trivial non-linear effect is observed for collaboration, suggesting that both low and high manifestation of collaboration skills may be detrimental for academic success.

Although non-cognitive skills indeed significantly reduce the effect of SES on the probability of high achievement among schoolchildren, they are not enough to close the achievement gap between the richest and the poorest. High SES students with similar levels of skills are more likely to become high achievers compared to low SES students due to the disparity of educational opportunities and other unobserved background factors. Therefore, performing targeted interventions, promoting productive non-cognitive skills, may be important but not sufficient to close the achievement gap.

References

Apostolov, N., & Geldenhuys, M. (2022). The role of neuroticism and conscientious facets in academic motivation. *Brain and Behavior*, *12*(8). https://doi.org/10.1002/brb3.2673

Attanasio, O., Blundell, R., Conti, G., & Mason, G. (2020). Inequality in socio-emotional skills: A cross-cohort comparison. *Journal of Public Economics*, *191*, 104171.

Avanesian, G., Borovskaya, M., Ryzhova, V., Kirik, V., Egorova, V., & Bermous, A. (2022). Can we improve learning outcomes of schoolchildren from the poorest families by investing into their non-cognitive skills? Causal analysis using propensity score matching. *Voprosy Obrazovaniya / Educational Studies Moscow*, *1*, 13–53. https://doi.org/10.17323/1814-9545-2022-1-13-53

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Borghans, L., Duckworth, A. L., Heckman, J. J., & Weel, B. ter. (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources*, *43*(4), 972–1059. https://doi.org/10.3368/jhr.43.4.972

Bratko, D., Chamorro-Premuzic, T., & Saks, Z. (2006). Personality and school performance: Incremental validity of self- and peer-ratings over intelligence. *Personality and Individual Differences*, *41*(1), 131–142. https://doi.org/10.1016/j.paid.2005.12.015

Brunello, G., & Schlotter, M. (2011). Non-Cognitive Skills and Personality Traits: Labour Market Relevance and Their Development in Education & Training Systems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1858066

Chamorro-Premuzic, T., & Furnham, A. (2003). Personality predicts academic performance: Evidence from two longitudinal university samples. *Journal of Research in Personality*, *37*(4), 319–338. https://doi.org/10.1016/s0092-6566(02)00578-0

Conard, M. A. (2006). Aptitude is not enough: How personality and behavior predict academic performance. *Journal of Research in Personality*, *40*(3), 339–346. https://doi.org/10.1016/j.jrp.2004.10.003

Cunha, F., & Heckman, J. (2007). *The technology of skill formation*. https://doi.org/10.3386/w12840

Cunha, F., & Heckman, J. J. (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Journal of Human Resources*, *43*(4), 738–782. https://doi.org/10.1353/jhr.2008.0019

Dahmann, S. C., & Anger, S. (2018). *Cross-fertilizing gains or crowding out? Schooling intensity and noncognitive skills*. No. 2018-065.

De Raad, B., & Schouwenburg, H. C. (1996). Personality in learning and education: a review. *European Journal of Personality*, *10*(5), 303–336. https://doi.org/10.1002/(sici)1099-0984(199612)10:5%3C303::aid-per262%3E3.0.co;2-2

Ditton, H., Bayer, M., & Wohlkinger, F. (2018). Structural and motivational mechanisms of academic achievement: a mediation model of social-background effects on academic achievement. *The British Journal of Sociology*, *70*(4), 1276–1296. https://doi.org/10.1111/1468-4446.12506

Dumfart, B., & Neubauer, A. C. (2016). Conscientiousness Is the Most Powerful Noncognitive Predictor of School Achievement in Adolescents. *Journal of Individual Differences*, *37*(1), 8–15. https://doi.org/10.1027/1614-0001/a000182

Edwards, R., Gibson, R., Harmon, C., & Schurer, S. (2022). First-in-their-family students at university: Can non-cognitive skills compensate for social origin? *Economics of Education Review*, *91*, 102318. https://doi.org/10.1016/j.econedurev.2022.102318

Elkins, R., & Schurer, S. (2020). Exploring the role of parental engagement in non-cognitive skill development over the lifecourse. *Journal of Population Economics*, *33*(3), 957–1004.

Erikson, R. (2016). Is it enough to be bright? Parental background, cognitive ability and educational attainment. *European Societies*, *18*(2), 117–135. https://doi.org/10.1080/14616696.2016.1141306

Feng, S., Han, Y., Heckman, J. J., & Kautz, T. (2022). Comparing the reliability and predictive power of child, teacher, and guardian reports of noncognitive skills. *Proceedings of the National Academy of Sciences*, *119*(6). https://doi.org/10.1073/pnas.2113992119

Fletcher, J., & Wolfe, B. (2016). *The importance of family income in the formation and evolution of non-cognitive skills in childhood*. https://doi.org/10.3386/w22168

Gil-Hernández, C. J. (2021). The (Unequal) Interplay Between Cognitive and Noncognitive Skills in Early Educational Attainment. *American Behavioral Scientist*, *65*(11), 1577–1598. https://doi.org/10.1177/0002764221996764

Heaven, P. C. L., & Ciarrochi, J. (2012). When IQ is not everything: Intelligence, personality and academic performance at school. *Personality and Individual Differences*, *53*(4), 518–522. https://doi.org/10.1016/j.paid.2012.04.024

Heckman, J. J. (2000). Policies to foster human capital. *Research in Economics*, *54*(1), 3–56. https://doi.org/10.1006/reec.1999.0225

Heckman, J. J., & Mosso, S. (2014). The economics of human development and social mobility. *Annual Review of Economics*, *6*(1), 689–733.

Heckman, J., & Kautz, T. (2013). *Fostering and measuring skills: Interventions that improve character and cognition*. https://doi.org/10.3386/w19656

Heckman, J., Stixrud, J., & Urzua, S. (2006). *The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior*. https://doi.org/10.3386/w12006

Hindman, A. H., Skibbe, L. E., Miller, A., & Zimmerman, M. (2010). Ecological contexts and early learning: Contributions of child, family, and classroom factors during Head Start, to literacy and mathematics growth through first grade. *Early Childhood Research Quarterly*, *25*(2), 235–250. https://doi.org/10.1016/j.ecresq.2009.11.003

Jackson, M. (Ed.). (2013). *Determined to succeed?* Stanford University Press. https://doi.org/10.11126/stanford/9780804783026.001.0001

Kline, P., & Gale, A. (1971). EXTRAVERSION, NEUROTICISM AND PERFORMANCE IN A PSYCHOLOGY EXAMINATION. *British Journal of Educational Psychology*, *41*(1), 90–94. https://doi.org/10.1111/j.2044-8279.1971.tb00662.x

Komarraju, M., Karau, S. J., Schmeck, R. R., & Avdic, A. (2011). The Big Five personality traits, learning styles, and academic achievement. *Personality and Individual Differences*, *51*(4), 472–477. https://doi.org/10.1016/j.paid.2011.04.019

Korthals, R., Schils, T., & Borghans, L. (2021). Track placement and the development of cognitive and non-cognitive skills. *Education Economics*, *30*(5), 540–559. https://doi.org/10.1080/09645292.2021.2010277

Lee, J., & Stankov, L. (2018). Non-cognitive predictors of academic achievement: Evidence from TIMSS and PISA. *Learning and Individual Differences*, *65*, 50–64. https://doi.org/10.1016/j.lindif.2018.05.009

Liu, A. (2020). Non-Cognitive skills and the growing achievement Gap. *Research in Social Stratification and Mobility*, *69*, 100546. https://doi.org/10.1016/j.rssm.2020.100546

Lubbers, M. J., Van Der Werf, M. P. C., Kuyper, H., & Hendriks, A. A. J. (2010). Does homework behavior mediate the relation between personality and academic performance? *Learning and Individual Differences*, *20*(3), 203–208. https://doi.org/10.1016/j.lindif.2010.01.005

Lundberg, S. (2013). The College Type: Personality and Educational Inequality. *Journal of Labor Economics*, *31*(3), 421–441. https://doi.org/10.1086/671056

Marks, G. N. (2016). The relative effects of socio-economic, demographic, non-cognitive and cognitive influences on student achievement in Australia. *Learning and Individual Differences*, *49*, 1–10. https://doi.org/10.1016/j.lindif.2016.05.012

McCrae, R. R., & Costa, P. T. (1997). Personality trait structure as a human universal. *American Psychologist*, *52*(5), 509–516. https://doi.org/10.1037/0003-066x.52.5.509

McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

Mendez, I., & Zamarro, G. (2017). The intergenerational transmission of noncognitive skills and their effect on education and employment outcomes. *Journal of Population Economics*, *31*(2), 521–560. https://doi.org/10.1007/s00148-017-0661-0

Mishkevich, A. M. (2021). Relationship between personal characteristics and the academic performance of high school students. *Psychological-Educational Studies*, *13*(1), 101–116. https://doi.org/10.17759/psyedu.2021130107

Morris, T. T., Davey Smith, G., Berg, G. van den, & Davies, N. M. (2021). Consistency of noncognitive skills and their relation to educational outcomes in a UK cohort. *Translational Psychiatry*, *11*(1). https://doi.org/10.1038/s41398-021-01661-8

Noftle, E. E., & Robins, R. W. (2007). Personality predictors of academic outcomes: Big five correlates of GPA and SAT scores. *Journal of Personality and Social Psychology*, *93*(1), 116–130. https://doi.org/10.1037/0022-3514.93.1.116

Nye, J. V. C., Orel, E., & Kochergina, E. (2013). Big five personality traits and academic performance in russian universities. In *Higher School of Economics Research Paper No. WP BRP* (Vol. 10).

O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, *43*(5), 971–990. https://doi.org/10.1016/j.paid.2007.03.017

OECD. (2021a). *Beyond academic learning: First results from the survey of social and emotional skills*. OECD. https://doi.org/10.1787/92a11084-en

OECD. (2021b). *OECD survey on social and emotional skills technical report*. OECD. https://www.oecd.org/education/ceri/social-emotional-skills-study/sses-technical-report.pdf

Orel, E., Brun, I., Kardanova, E., & Antipkina, I. (2018). Developmental Patterns of Cognitive and Non-Cognitive Skills of Russian First-Graders. *International Journal of Early Childhood*, *50*(3), 297–314. https://doi.org/10.1007/s13158-018-0226-8

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.1037/a0014996

Poropat, A. E. (2014). Other-rated personality and academic performance: Evidence and implications. *Learning and Individual Differences*, *34*, 24–32. https://doi.org/10.1016/j.lindif.2014.05.013

Reardon, S. F., & Portilla, X. A. (2016). Recent Trends in Income, Racial, and Ethnic School Readiness Gaps at Kindergarten Entry. *AERA Open*, *2*(3), 233285841665734. https://doi.org/10.1177/2332858416657343

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. https://doi.org/10.1037/a0026838

Rosander, P., & Bäckström, M. (2014). Personality traits measured at baseline can predict academic performance in upper secondary school three years late. *Scandinavian Journal of Psychology*, *55*(6), 611–618. https://doi.org/10.1111/sjop.12165

Savelyev, P. A., & Tan, K. T. K. (2019). Socioemotional Skills, Education, and Health-Related

Outcomes of High-Ability Individuals. *American Journal of Health Economics*, *5*(2), 250–280. https://doi.org/10.1162/ajhe_a_00116

Shanahan, M. J., Bauldry, S., Roberts, B. W., Macmillan, R., & Russo, R. (2014). Personality and the Reproduction of Social Class. *Social Forces*, *93*(1), 209–240. https://doi.org/10.1093/sf/sou050

Smrtnik Vitulić, H., & Zupančič, M. (2012). Robust and specific personality traits as predictors of adolescents' final grades and GPA at the end of compulsory schooling. *European Journal of Psychology of Education*, *28*(4), 1181–1199. https://doi.org/10.1007/s10212-012-0161-2

Stumm, S. von. (2017). Socioeconomic status amplifies the achievement gap throughout compulsory education independent of intelligence. *Intelligence*, *60*, 57–62. https://doi.org/10.1016/j.intell.2016.11.006

West, M. R., Kraft, M. A., Finn, A. S., Martin, R. E., Duckworth, A. L., Gabrieli, C. F. O., & Gabrieli, J. D. E. (2016). Promise and Paradox. *Educational Evaluation and Policy Analysis*, *38*(1), 148–170. https://doi.org/10.3102/0162373715597298

Zamarro, G., Hitt, C., & Mendez, I. (2019). When Students Don't Care: Reexamining International Differences in Achievement and Student Effort. *Journal of Human Capital*, *13*(4), 519–552. https://doi.org/10.1086/705799