Effort and dynamics of educational inequality: Evidence from a laboratory study among primary school children

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Abstract

If opportunities were equal, effort would be the main driver of individual success. However, in real life, people do not start the “race of life” with the same endowments. Thus, the study of Inequality of Opportunity in the tradition of John Roemer is dedicated to measuring the share of achievements that is determined by effort – viewed as the only “legitimate” source that is under individual control – versus by circumstances – that is, the “illegitimate” sources of achievement beyond by the individual’s influence. However, effort is often measured either merely as the residual that is left after controlling for a vector of circumstances (such as socioeconomic background, race or gender) or with imperfect proxies such as self-reported psychological traits or attitudes towards learning.

The aim of the paper is twofold: First, it intends to assess the importance of “real effort” for determining academic performance in contrast to circumstances. Using an accurate measure of cognitive effort, measured in the lab, we can compare its impact on school grades in Math and Spanish with the effect of having highly educated parents or high IQ. Second, the paper explores the role of teachers’ perception of student effort in their academic grades. We expect that the perception of the teachers will be very relevant for academic performance. Furthermore, we argue that although teachers’ perception of student effort is not the most accurate measure of effort, it might be an important mediator between cognitive effort and academic grades.

Data stems from a lab experiment carried out with 380 5th grade students from primary schools in the metropolitan area of Madrid, Spain, during the school year 2019/2020. The schools were randomly selected from a sample stratified by neighborhood income quartile and type of school. All the students carried out three real-effort tasks adopted from economics and psychology (i.e. the Simon, AX and Slider tasks), covering different executive functions. This multidimensional measure of cognitive effort ensures a comprehensive approach to effort that minimizes the influence of ability. We also gathered information on various “circumstances” of the students – such as parental education, gender and IQ (Raven’s Progressive Matrices).

Provisional results indicate that effort exerts a sizeable influence on student grades, similar to IQ in the magnitude of its predictive power. Nevertheless, the association between teachers’ perception of student effort and school grades is significantly larger, comparable with the effect of having parents with tertiary education. Furthermore, we find evidence that teachers’ perception of student effort is an important mediator between cognitive effort and school grades, although, interestingly, the magnitude varies depending on the subject.

1. Introduction

Out of all determinants of educational attainment, effort is often the one on which teachers and parents put more emphasis (Geven et al., 2018). Assuming that students have full agency over it, it is seen as a teachable lesson that students can improve their school grades by exerting more effort at school and studying at home. Nevertheless, it is one of the least researched determinants of learning. Effort is an intuitive yet elusive phenomenon, and due to the difficulties of measuring effort, we do not fully understand its role in the process of educational attainment (Radl and Miller, 2021). A prominent strand of the literature addresses the influence of non-cognitive skills on future life outcomes and on the intergenerational transmission of inequality (Farkas, 2003; Heckman et al., 2006; Kröger et al forthcoming). Several of those "non-cognitive" characteristics that tap into certain aspects of effort, have been shown to be good predictors of future educational attainment. By the same token, traits like conscientiousness, self-control or grit contribute to the transmission of educational inequality (Duckworth et al., 2007; Shanahan et al., 2014; Hsin and Xie, 2017). However, the empirical correlation between these so-called non-cognitive skills and actual cognitive effort is not very high (Apascaritei et al., 2021).

The objective of this paper is four-fold: our first aim is to examine the association between students' cognitive effort and school grades. Using an innovative and objective measure of cognitive effort with strong claims to validity and collected in the lab, we can test its impact on school grades in math and Spanish and compare it with the effects of socioeconomic background or IQ. The most direct way in which effort should affect grades is through engagement-based learning gains. However, an indirect way in which effort could improve grades is by appearing as hardworking in the eyes of teachers, the gatekeepers of the education system. Thus, the second aim of the paper is to study the impact of teacher-perceived effort on school grades. Academic achievement measured with standardized tests only accounts for 63 percentage points of school grades (Südkamp et al., 2012). Hence, it is apparent that teachers also take other factors into account for determining school grades. As teacher perceptions come into play here, it is interesting to investigate the impact of teachers' effort evaluations for educational attainment (Randall and Engelhard, 2010). Furthermore, it is insightful to compare the magnitude of the effect of teacher-perceived effort with a strong measure of cognitive effort to scrutinize potential discrepancies.

The third aim consists in investigating the potential moderation of parental background on the effect of effort on educational achievement. Specifically, we test two sociological theories that might explain the potential contribution of effort to the transmission of educational inequality: compensatory advantage and cultural reproduction. The first one posits that high socioeconomic status (SES) families are able to compensate for an emerging disadvantage during children's educational career (Bernardi, 2012). In this vein, we argue that parents with high education are able to identify the lack of effort exerted by their children in educational activities and help them compensate for that deficiency. In order to preserve their offspring's good grades, affluent parents can activate different resources such as private tutoring or spending more time at home with homework. Thus, the impact of low cognitive effort on school grades should be less severe for high SES students than for their disadvantaged peers. Cultural reproduction theory was postulated by Bourdieu and Passeron (1990) and it states that individuals from high SES families inherit cultural resources that help them to get advantage in life. In this context, Dumais (2005) and Jæger (2011) show that cultural capital influences teacher's judgment of student's academic ability and effort. We hypothesize that due to the different amounts of cultural capital inherited by children, teachers are not able to equally judge students with low effort but from different SES backgrounds. Teachers could perceive habitual behaviors and attitudes derived from cultural capital as relevant for school grades, resulting in less penalization for high SES students for their low effort when being graded.

Finally, the last objective is to explore the impact of the COVID-19 pandemic on the educational process. Thanks to the timing of the data collection we are able to examine whether the pandemic has exacerbated the effect of social origin on educational outcomes by splitting the sample after and before COVID. Most research shows that the learning gap between low and high SES students has widened due to school closures and homeschooling (Engzell et al., 2021; Betthäuser et al., 2022). Thus, our fourth hypothesis is that a year after the school closure in Spain the gap in school grades between low and high SES students has increased as consequence of the learning gap enlarged during the pandemic. Furthermore, since effort and self-discipline were crucial while learning from home as teacher supervision largely disappeared, we also hypothesize that the gap in school grades between low and high effort students has widened.

To better understand differential benefits of effort, we propose a novel research design based on data collected in "field-in-the-lab" experiments carried out in the metropolitan area of Madrid, Spain. The experiments were designed for fifth grade students from a representative sample of primary schools (public, private and charter schools). In total, our study comprises 698 students participating in the experiments in the lab, where they carried out different real-effort tasks, an IQ test and a survey. The three real-effort tasks stem from cognitive psychology and behavioral economics. The rationale for having three tasks is to tap into different executive functions (Diamond, 2013) with the objective of measuring cognitive effort net of ability. Hence, having different tasks overcomes limitations in previous research, by allowing us to calculate a more comprehensive and complete measure of cognitive effort that does not rely only on one particular dimension of cognitive effort. The measure of teacher-perceived effort of the student is provided by the teacher in an interview. The parental and child surveys provide us with the socioeconomic information needed as well as with the school grades in math and language.

We find that, as expected, our measure of cognitive effort is positively associated with better school grades, both in math and Spanish. Similarly, teacher-perceived effort of the student is also positively associated with better grades. However, the magnitude of the effect of teacher-perceived effort is significantly larger than for the effect of cognitive effort. Furthermore, we do not find evidence of compensatory advantage in either language or math grades. In other words, the effect of cognitive effort on grades is independent of parental background. Strikingly, the results for the interaction between parental education and teacher-perceived effort go in a different direction: for both math and Spanish grades the interaction is negative and significant. The grades of students with highly educated parents are shown to be less sensitive to effort than among their low SES counterparts. This finding reveals an underappreciated mechanism through which educational inequalities are perpetuated. Regarding the impact of the pandemic, we do not find evidence to support our hypotheses implying widening grade gaps. Instead, there seems to have been a trend towards the equalization in school grades, both by SES and by effort, although the findings are not conclusive.

The paper is structured in the following way: section 2 frames the investigation within the relevant literature on educational achievement and inequality. Moreover, it theorizes on the potential mechanisms behind heterogeneous effort payoffs. Section 3 presents the experimental setup behind the data collection and describes the methodological strategy that has been followed. Section 4 shows the main results and offers plausible interpretations. Finally, the last section summarizes the key takeaways and future challenges.

2. Theoretical framework

2.1. Effort and educational achievement

Effort is widely recognized as decisive driver of academic achievement. However, due to the difficulty of measuring effort, not much research on the topic had been conducted until recent decades. With the popularization of research on the determinants of children's future life outcomes, effort and similar concepts referred to as non-cognitive skills began to be more investigated (Heckman et al., 2006). The importance of non-cognitive skills for educational achievement was put forward in the seminal work of Bowles and Gintis (1976). In the last decades, thanks to the increasing interdisciplinarity, a lot of attention has been paid to this topic. Using insights from personality psychology, economists and sociologists have shown that a wide variety of non-cognitive skills are important predictors of educational attainment and other life outcomes (Heckman and Rubinstein, 2001; Heckman et al., 2006; Blanden et al., 2007; Carneiro et al., 2007; Smithers et al., 2018). Several of these papers use psychological scales that are closely related to effort. For example, Duckworth and Seligman (2005) and Duckworth et al. (2007) focus on self-discipline –the ability to control your own impulses- and grit -the perseverance and determination to achieve a goal-, to investigate their effect on school performance. Both studies find that these characteristics are positively related to academic performance. Similarly, Shanahan et al. (2014) emphasize the importance of conscientiousness, one of the Big Five personality traits, which characterizes hard-working and thorough individuals. They show that this skill is positively associated with school completion and higher educational outcomes. Hsin and Xie (2017), as part of their chosen set of non-cognitive skills, use self-control, another variable that taps in another aspect of effort. Accordingly, the ability of inhibiting certain adverse behaviors is also correlated with future academic achievement. However, one of the problems with personality scales is that they are self-reported and hence, we do not observe if the individuals actually behave as they say. For example, recent research has shown that the association between some of these subjective traits and the actual provision of cognitive effort is low or even inexistent (Duckworth and Kern, 2011; Apascaritei et al., 2021).

An alternative approach is to use indirect measures based on observed behavior. For example, Borghans and Schils (2012) developed a variable with PISA data, test effort, that consist in the persistence of performance throughout the 2-hour test. They show that this indirect measure of effort is correlated with other non-cognitive skills like conscientiousness and associated with future life outcomes such as life satisfaction and drinking behavior. Zamarro et al. (2019) show that test persistence explains between 32 and 38 of the variation in PISA scores across countries. Moreover, Borgonovi et al. (2020) as well as the first paper of this thesis find evidence that persistence is a strong predictor of future educational attainment. We expand the previous literature by using an innovative measure of cognitive effort with strong claims to validity, which observes actual behavior in the lab. Our first hypothesis is that there is a positive and significant association between cognitive effort and school grades in math and Spanish.

H1a: Cognitive effort is associated with higher grades in math and Spanish

While objective measures of actualized individual effort are arguably superior to survey-based self-evaluations, subjective measures are very relevant when it comes to the perceptions of gatekeepers. Here, we focus on teacher-perceived effort of the students, an influential "eye of the beholder" measure that directly affects the grades of the students. As teachers who give out grades act as gatekeepers of educational trajectories, it is important to shed some light on the teachers' judgments when evaluating the students. A comprehensive meta-analysis performed by Südkamp et al. (2012) finds that the correlation between teachers' grades and student's performance on standardized achievement tests is on average 0.63. While this magnitude is considerable, it still leaves substantial room for the perception of the teacher to make a difference. Randall and Engelhard (2010) set up an experiment to investigate what teachers take into account when grading students. Subjects are provided with information about student's ability, effort, behavior and achievement. The authors find that in most cases grades are primarily based on achievement, however, non-achievement factors such as effort also help to determine the final grade. This coincides with the results of Bowers (2011), proving the multidimensional nature of teacher grading. Teachers tend to reward effort and classroom behavior, independently of current achievement, partly because they think that these factors will improve future academic achievement (Kelly, 2008). Nevertheless, the appropriateness of taking student's effort into account for the final grade is up to debate and complicated by the difficulty of observing it without bias (Linn, 2008). In turn, teachers' grading practices also engender an effect on students' achievement and effort (Bonesrønning, 2004; Krohn and O'Connor, 2005). Hence, the factors that influence achievement and grades but that cannot be assessed properly by the teachers merit particular attention.

In the previous literature, especially scholars in the education field have examined the role of teacher-perceived effort; for example, Siegle and Reis (1998) show that teachers tend to rate girls higher on effort than boys. Moreover, Meltzer et al. (2004) and Miller et al. (2017)

find that students' self-perceptions and teachers' self-efficacy are positively related to higher ratings in teacher perceived effort. Teacher evaluations of effort have been previously used also in sociology (Domina et al., 2011), economics (Asadullah et al., 2021) and psychology (Upadyaya and Eccles, 2015). Indeed, Asadullah et al. (2021) shows that teacher perceived effort is the main source of within-school variation in math and English performance in Bangladesh. Here, we want to test the association between teacher perceived effort and school grades in Spanish and math to explore the magnitude of the influence of this variable. Furthermore, our particular setting allows us to compare the impact of students' actual cognitive effort under different incentives with the effort perceived by their teachers. This not only addresses the accuracy of teachers' perceptions but also opens up the black box of the grading process. We expect teachers' perceptions of students' effort to be strongly predictive of school grades.

H1b: Teacher perceived effort of the student is associated with higher grades in math and Spanish.

2.2. Effort and mechanisms of educational inequality

Following Boudon's (1974) influential approach, the study of educational stratification has been heavily informed by the distinction between two different effects through which educational inequality is transmitted across generations: the primary effect is the influence of the family's class background on the academic performance of their children. On average, children with more favorable class background tend to perform better than kids with worse fortune at birth (Bowles and Gintis, 2002). The secondary effect captures how the respective class background affects the decision-making of children and their parents throughout their educational trajectory. Accordingly, class background shapes the propensity to advance within the educational system due to differential parental preferences and abilities to cover the economic costs of post-obligatory education, amongst other factors contributing to intergenerational inequality. In line with this approach, Breen and Goldthorpe (1997) developed a model to explain the differences in educational attainment by class origin through the process of decision making, taking into account benefits, costs and probability of success. Furthermore, in the last years an additional effect has been coined, the tertiary effect operating at the school level. Tertiary effects may arise when gatekeepers misjudge the capacity of students due to their socioeconomic background and that has a direct effect on the educational careers. The clearest case is teacher bias, where teachers tend to favor students with privileged backgrounds (Jæger and Møllegaard, 2017).

The role of non-cognitive skills in educational stratification was highlighted by Farkas (2003), and other researchers have since studied different aspects of this relationship. A handful of studies find that these skills are less directly transmitted across the generations than cognitive skills. This has led some researchers to conclude that the intergenerational transmission is not very influenced by the socioeconomic background of the family (Mayer et al., 2004; Loehlin, 2005; Duncan et al., 2005). In the same vein, Holtmann et al. (2021) show that most measures of non-cognitive skills do not mediate the intergenerational transmission of education, only educational aspirations are a relevant mediator in Germany. However, two papers find evidence in the opposite direction. Hsin and Xie (2017) report for the US that non-cognitive skills are a relevant mediator between parental SES and children's academic achievement. Furthermore, its impact increases over the life course because these skills are more sensitive to changes in socioeconomic background. Similarly, Mood et al. (2012) present evidence of a somehow weak mediation effect of socio-behavioral skills in Sweden.

Another strand of the literature explores the moderation effect of non-cognitive skills on the intergenerational transmission of educational inequality. There are two dynamics that might take place: the first one is the Matthew effect, which implies that individuals with advantaged social background get even more advantage from their skillset, i.e. there is a positive interaction between parental SES and the moderating skill variable. For example, Holtmann et al. (2021) find evidence of the Matthew effect for some non-cognitive skills such as pro-social behavior and agreeableness, which create higher returns for privileged children. Compensatory advantage is the other dynamic that can act as moderating effect.

Accordingly, socio-economically advantaged families are able to compensate for a 'setback' in the early stage of children's educational career (Bernardi, 2012). Similarly, Shanahan et al. (2014) and Damien et al. (2015) borrow the theory of "resource substitution" outlined by Ross and Mirowsky (2011) and postulate that personality traits might be more strongly associated with future life outcomes for poorer families. Thus, resource substitution leads to similar predictions as compensatory advantage. Most empirical evidence of compensatory advantage has focused on the advantage of students with richer background and poor grades into the transition to university (Bernardi, 2012; Bernardi and Boado, 2014; Bernardi and Triventi, 2020).

It has been less explored by previous research whether compensatory advantage also takes place through the primary effect, i.e. mediated by students' academic achievement. Bernardi (2014) and Bernardi and Grätz (2015) find that students that have been born later in the year with richer parents tend to perform better in school and are less likely to repeat a year. Liu (2019) shows evidence of compensatory advantage during childhood and early adolescence. The effect of parental SES on academic achievement increases when children have low non-cognitive skills. Thus, we are interested in examining whether highly educated parents are also able to identify the potential problems of their offspring when they exert low cognitive effort in school and compensate for them. Such targeted compensation could take place through two mechanisms, parental time investment and private tutoring. As Kalil et al. (2012) explain, highly educated mothers not only spend more time with their children in educational related activities, they also adapt better when the child needs it. Besides that, high SES parents display a slightly different parenting style; they tend to favor inductive reasoning and parenting consistency, leading to fewer behavioral problems and better cognitive outcomes (Cano, 2021). Furthermore, the SES gradient in the access to private tutoring prevents poorer students from benefiting from an important vehicle to enhance academic achievement (Park et al., 2011; Park et al., 2016). In sum, high SES parents have different tools at their disposal to help their children if they perceive that it is necessary. We hypothesize that high SES parents are able to identify when their children exert low effort and use their resources to compensate for this deficit.

H2: The effect of tertiary parental education on school grades is larger at low levels of cognitive effort.

As we have explained previously, the process of grading relies substantially on teachers' perceptions of the students, which are not fully accurate. However, teacher bias is not a random error. Teachers tend to be particularly inaccurate due to certain sociodemographic characteristics, particularly socioeconomic status and migrant background (Geven et al., 2018). Previous research shows empirical evidence, for example, Ready and Wright (2011) find that teachers perceive differently children's literacy skills due to ethnic, socioeconomic and gender characteristics, once ability is controlled for. Similarly, Triventi (2020) uses a comparison between standardized tests and teachers' grading in Italy to study discrimination against children of immigrant families. He finds that these children are graded less generously by teachers than natives with the same ability and that one of the most relevant factors is the socioeconomic status. In a recent experiment carried out in Germany, Wenz and Hoenig (2020) test whether there is evidence of discrimination in grading due to ethnicity or social class. The authors do not find bias in grading, but they find teachers' expectations of future performance to be more favorable to high SES children. This is in line with the results of Tobisch and Dresel (2017) that show that teachers tend to overestimate achievement expectations from students with high socioeconomic status. Moreover, inaccurate expectations have an important impact on the educational trajectories of students (Salazar et al., 2020). The clearest instances are track recommendations; in some countries students are separated into different educational tracks after primary school. The selection depends significantly on the perception of the teacher since they recommend to the parents the presumed best fit for the student – sometimes the recommendation is binding. Multiple studies have found that teachers recommend more frequently academic tracks to students from higher SES background, even though they have the same skills as their less privileged counterparts (Boone and Van Houtte, 2013; Timmermans et al., 2015; Timmermans et al., 2018; Gil-Hernández, 2021). Therefore, teacher perceptions and expectations have an effect on future educational attainment of the student (Wang et al., 2018) and contribute to the intergenerational transmission of educational inequalities, mediating between parental background and student' performance (De Boer et al.; 2010).

The reasons behind these dynamics are, however, not yet fully clear. Teachers, as everybody, might be explicitly or implicitly biased when assessing the merits of the students. Due to certain socio-demographic characteristics they might get the impression that some individuals are more intelligent or work harder than others (Geven et al., 2018). One of the explanations for the influence of socioeconomic background on the perception of the teachers builds on the insights from the "cultural reproduction" theory postulated by Bourdieu and Passeron (1990), in which children from richer families inherit cultural resources that help them to get ahead in life. As Jæger and Breen (2016) explain, students with cultural capital might impress teachers, who might confuse habitus with academic proficiency or effort. For example, Jæger (2011) and Jæger and Møllegaard (2017) show that cultural capital leads to higher academic achievement and biases the teacher's judgment of student's academic ability. Moreover, cultural capital also influences teachers' evaluation of effort (Dumais, 2005). Although the particular theoretical mechanism is not spelled out in detailed, it is likely that high SES individuals signal their position through specific behaviors, preferences and attitudes (Lamont & Lareau, 1988). Boone and Van Houtte (2013) argue that those traits that are taken into account favorably by the teachers for grading are more frequent among high SES students, leading to transmission of inequality.

Against this backdrop, this study examines the interplay between teacher-perceived effort of the student and socioeconomic background. We argue that teachers do not judge all children that exert low effort equally because at the same time they also value other dimensions of school engagement, such as disciplined behavior or appropriate interaction with the teacher, where students from high SES have an inherent advantage. Therefore, we expect that higher SES students will be less penalized by the teacher for low levels of effort than their disadvantaged peers.

H3: The effect of tertiary parental education on math and Spanish grades is higher at low levels of teacher-perceived effort.

The COVID-19 pandemic has caused a huge disruption on the educational process (Hanushek and Woessmann, 2020). Many countries closed the schools during several months to halt the spread of the virus. Classes were taught online and students had to spend many hours in front of the screen. In that context, the supervision of teacher was implausible so the parents had to support their children during that time. Even though few months have passed since then, already a few studies have appeared analyzing the impact of the pandemic on student learning. Most of them find evidence of a learning loss equivalent to the period of time in which the schools were closed; moreover, this deficit persists over time (Engzell et al., 2020; Betthäuser et al., 2022). However, the loss has not been homogeneous for all students. Low SES students may be particularly affected by the lack of support during that time because their parents did not have the time or the capacity to help them with school work. Therefore, the learning gap between students from lower social background and their more privileged counterparts was widely seen as growing even more. For example, Agostinelli et al. (2022) show that less-advantage students suffered a loss of 0.4 standard deviations (SD), whereas privileged students did not lose anything. Similarly, Engzell et al. (2020) find up to a 0.6 SD gap between low and high SES students in learning. In the country examined here, Spain, the schools were fully closed during almost four months, from March until the summer of 2020. Therefore, we expect that the learning gap due to the pandemic shock will be persistent throughout the next years and that it will be translated into school grades. Our hypothesis is that after school closures due to COVID, the gap in school grades due to parental background has increased.

H4a: After COVID the gap in school grades between low and high SES students has widened.

During the homeschooling period, self-discipline and effort were especially crucial for learning because in absence of teacher supervision - and with parents mostly overburdened with work and care duties - the children themselves had to decide whether to attend online classes or not, and how much homework to do. Thus, we also expect that those children that tend to exert high effort would be more focused on assignments and learning, whereas on the other side, those who tend to exert low effort would pay particularly little attention. The consequence would be that the gap in learning between low and high effort children would also increase due to homeschooling and persist over time. Therefore, the last hypothesis posits that the gap in school grades between low and high effort has become larger after COVID.

H4b: After COVID the gap in school grades between low and high effort students has widened.

3. Data and methods

Data stems from a lab experiment carried out with 698 5th grade students from primary schools in the metropolitan area of Madrid, Spain, during the school year 2019/2020 and 2021/2022. The schools were randomly selected from a sample stratified by neighborhood income quartile and type of school (public, private and charter). All the students carried out three real-effort tasks (adopted from behavioral economics and cognitive psychology), selected to engage different executive functions. This multidimensional approach yields a comprehensive measure of cognitive effort that minimizes the influence of ability.

The first task is the "Slider Task", a well-known task in experimental economics that focuses on goal maintenance (Gill & Prowse, 2012). The second task is the "Simon Task", a cognitive psychology task focused on inhibition and attention (Cespón, Galdo-Álvarez & Díaz, 2016). The third task is the "AX-Continuous Performance Task", another psychological task that measures cognitive control (Gonthier, McNamara, Chow, Conway, & Braver, 2016).[1]

[1] The order of the tasks varies across classes to avoid an order effect.

Table 1. Experimental setup

Task	Duration
Instructions + Leisure task	1 round each game of 1.5 min
Task 1	
Intrinsic condition	2 rounds of 2 min
Extrinsic condition	2 rounds of 2 min
Task 2	
Extrinsic condition	2 rounds of 2 min
Task 3	
Extrinsic condition	2 rounds of 2 min
Tournament condition	2 rounds of 2 min

Source: own elaboration

Table 1 gives the rundown of the experimental sessions. At the beginning of the experiment, basic instructions were given to the students. During the experiment, the students carried out the tasks under different conditions. The first one was the intrinsic condition, where the participants did not receive any reward for doing the task. Afterwards, in the extrinsically condition students received points for each correct trial. They were informed that they could convert the points that they earned throughout the tasks into toys at the end of the day.[2] Finally, the last condition was the tournament, where besides still getting points for correct responses, the students were competing with their classmates for being the best in the class. As announced at the start of the tournament, the three best-performing students got a diploma as extra reward, indicating their podium position. A "leisure task" was offered for students, as an option for not doing the tasks and playing a computer game during that period of time. The purpose was to introduce an opportunity cost for doing the tasks, which makes the setup resemble real life situations more closely, where distractions from learning or working are omnipresent.

[2] The students do not know which toys will be available until the end of the experiments.

Table 2. Task engagement by condition

% of rounds in which students play games	Intrinsic condition			Piece-rate condition		
	% of Low SES	% of High SES	% of Total	% of Low SES	% of High SES	% of Total
0	17.5	25.1	21.9	92.5	93.5	93.1
1-50	51.7	45.8	48.3	7.5	6.5	6.9
51-100	30.8	29.1	29.8	0	0	0
Total	100	100	100	100	100	100

Source: own elaboration

Table 2 displays the proportion of students choosing the leisure task over the real-effort task. We can observe stark differences across conditions in the number of rounds in which the students choose to play games instead of doing the task. During the intrinsic condition, 21.9% of the sample carried out the tasks in all the rounds, 48.3 % in less than half and 29.8% played games more than half of the rounds. However, during the piece-rate condition over 90% of the students carried out the tasks in all the rounds, and only 6.9% played games at some point. Importantly, there are no significant differences in task engagement by parental SES. This means that students from different social classes were equally motivated by the piece-rate payoff, avoiding potential heterogeneity in the response to the extrinsic condition that might otherwise lead to biased results.

To construct the measure of cognitive effort we use the standardized average performance throughout the three tasks. As the main measure we only use the tasks performed with the extrinsic condition since it most closely resembles the educational context.[3] As previously mentioned, we also employ an alternative measure of effort, the teacher-perceived effort of the student. This was gathered in a survey administered to the teacher, who rated his/her

[3] We carry out a robustness check using a variable of cognitive effort constructed with all the conditions in Table 5. The results are substantively similar to the results with our main measure.

perception of the effort disposition of each student in the class on a scale from 1 to 10. This measure is standardized by class to allow comparability across teachers.

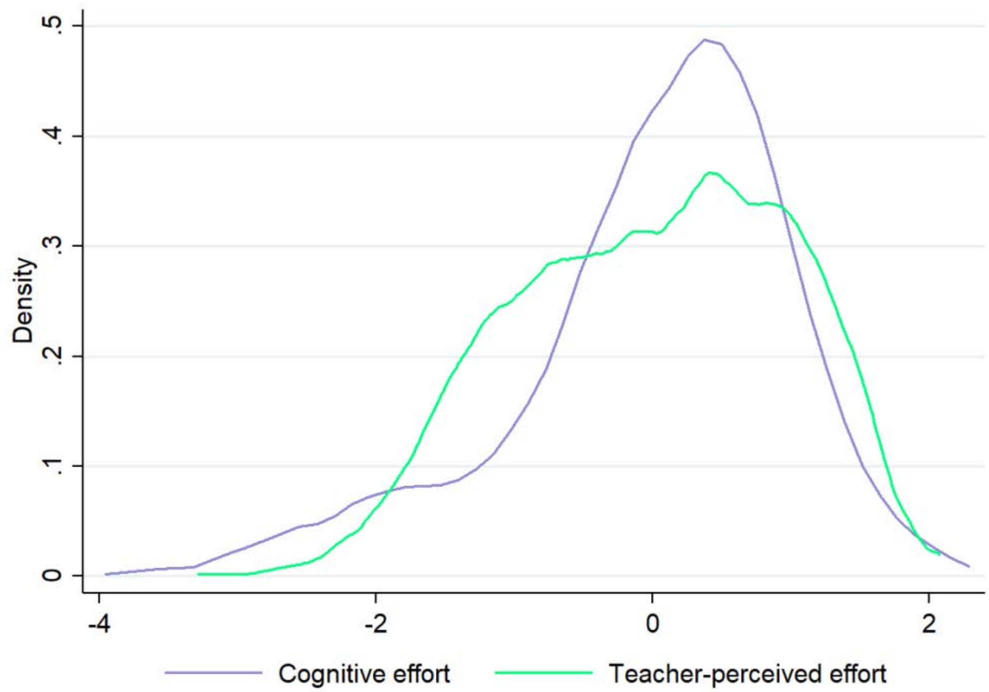

Figure 1. Kernel density distribution of teacher-perceived effort and cognitive effort

Figure 1 shows the distribution of the two effort measures. Both have a longer tail on the left, particularly cognitive effort, which is also somewhat more concentrated in the central values. Looking at Figure 2 we can observe that the correlation between both measures of effort is not very high. The R2 stands at 0.206, which is noticeable but not a large as we would have expected. The low correlation might be due to the differences and difficulties by the teachers in assessing effort.

The main dependent variables are the students' grades in Spanish and math in the last official school report cards. This information was provided by the parents on a 5-point scale, where 1 is Insufficient (1-4), 2 is Sufficient (5), 3 is Good (6), 4 is Noteworthy (7-8) and 5 is Excellent (9-10). To ease its interpretation the measure is normalized from 0 to 1 by school class because teachers tend to grade on a curve (Piopiunik and Schlotter, 2012).[4] To ensure that any residual influence of skills on effort is not skewing the results, we control for cognitive ability in all models. Cognitive skills are measured by fluid intelligence using Raven's progressive matrices test (Raven, Court & Raven, 1996). Children had 5 minutes to complete as many matrices as possible. The total number of correct matrices is then standardized to make effect sizes comparable. The students' gender is also observed. The socioeconomic background of the students is measured with parental education. We construct a dummy variable that is 1 for those students with at least one parent with tertiary education and 0 otherwise.[5] Migration background is also taken into account with a dummy variable that indicates whether the mother/father that filled the survey was not born in Spain. Moreover, we also control for difficulties of some children with a dummy variable that captures when the student has repeated one course or more and another dummy for children that have been diagnosed with Attention-deficit/hyperactivity disorder (ADHD). We also control by the task order and by regular use of computers (which is relevant for the slider task).

[4] In Appendix C we run robustness checks for the main models using grades normalized by the whole sample.

[5] As robustness check we use the International Socio-Economic Index as an alternative measure of parental socioeconomic background. See Appendix for details.

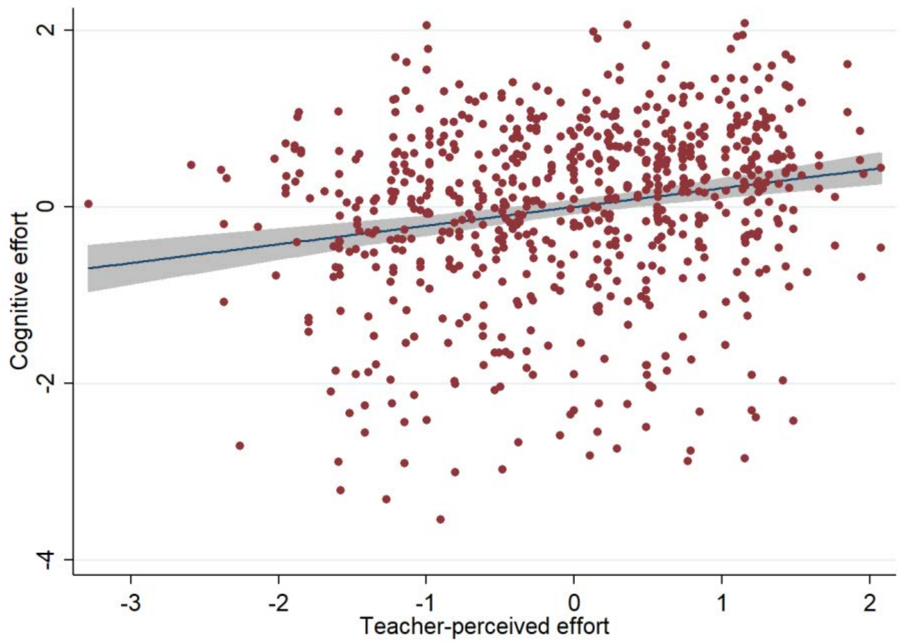

Figure 2. Correlation between teacher-perceived effort and cognitive effort

Table 3. Descriptive statistics

Variable	*Obs.*	*Mean/ proportion*	*Std. Dev.*	*Min.*	*Max.*
Grade in Spanish	698	.658	. 296	0	1
Grade in math	698	.665	.302	0	1
Cognitive effort	698	.0	1.00	-3.544	2.078
Teacher perceived effort	698	.0	0.97	-3.284	2.07
Cognitive skills	698	.0	1.00	-3.06	3.1
Parental tertiary education	698	.575	-	0	1
Male	698	.481	-	0	1
Age in months	698	126.02	5.41	118	163
Migrant parent	698	.227	-	0	1
Repeated course	698	.093	-	0	1
ADHD diagnosed	698	.0401	-	0	1
Language problems diagnosed	698	.025	-	0	1
Quartile	698	2.44	1.1	1	4

We use a hierarchical two-level linear probability model in order to account for the heterogeneity between school classes, where the students are nested. A random intercept accounts for the differences in academic grades among school classes. Furthermore, following standard estimation procedures we also use a random slope for the predictor variable of interest, effort (Snijders and Bosker, 2011).

$$G_{ij} = (\beta_0 + \mu_{0j}) + (\beta_1 + \mu_{1j})E_{ij} + \beta_2 X_2 + \varepsilon_{ij} \qquad (1)$$

Where G_{ij} is the academic grade of student i in the school class j. β_0 is the general intercept across all the clusters and μ_{0j} is the random term that allows for variation around the intercept for each school class. β_1 is the general slope of effort, whereas μ_{1j} is the random term of the slope that confers some noise at the class-level. β_2 is the slope of the vector of covariates, X_2, and ε_{ij} is the error term.

4. Results

First, it is informative to take a look at the correlations between the variables of interest. In Table 4 all bivariate correlations are displayed, and some of them are surprising. For example, the variable that has the highest correlation with both math and Spanish grades is teacher-perceived effort, significantly higher than cognitive skills, cognitive effort or parental education. This suggests that teachers' effort perceptions are crucial for grading, and pick up other things beside effort. Furthermore, the correlations between both variables of effort with cognitive skills are very similar, around 0.3. The magnitude is notable, and higher than the correlation between cognitive effort and teacher-perceived effort. Finally, parental education has a similarly moderate correlation with both measures of effort.

Table 4. Pearson correlation matrix

	Math grades	Spanish grades	Cognitiv e effort	Teacher-perceived effort	Cognitive skills	Parental education
Math grades	1					
Spanish grades	0.6877*	1				
Cognitive effort	0.3589*	0.3178*	1			
Teacher-perceive effort	0.5378*	0.5547*	0.2066*	1		
Cognitive skills	0.3799*	0.3200*	0.3058*	0.3020*	1	
Parental education	0.2490*	0.2322*	0.2085*	0.1890*	0.1881*	1

* $p<0.05$

The next tables focus on the hypotheses to be tested. Model 1 in Table 5 shows the results for the first research question: the impact of effort on school grades. Cognitive effort is a highly significant predictor and positively associated with grades in both Spanish and math, thus providing support for the hypothesis H1a. The magnitude of the estimated coefficients is striking: in Model 1, the effect of an increase in one SD of cognitive effort amounts to 6.9 percentage points better math grades, which is not far from the 7.7 percent effect of cognitive skills. Furthermore, in the case of Spanish grades, the similarity of the effects of cognitive skills and effort is even more surprising. Cognitive effort has an impact of around 6.5% on Spanish grades, slightly higher than the effect of cognitive skills. Having a parent with tertiary education is also significantly and positively associated with school grades. Remarkably, and in contrast with effort and intelligence, the social origin effect is larger for Spanish than for Math, 7.6 versus 9.2 percentage points. Most remaining covariates show up as expected. Having repeated one or more courses in primary school is significantly and very negatively associated with grades. Female students have significantly better grades than male students in Spanish, but in math there is no gender difference. Surprisingly migration status is not a significant predictor of grades, although this might be because we only have information on the country of birth of the parent who filled in the survey.

Table 5. Hierarchical regression with cognitive effort as the main independent variable

	Model 1		Model 2	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0773***	0.0606***	0.0775***	0.0610***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)
Cognitive effort	0.0693***	0.0652***	0.0755***	0.0720***
	(0.0104)	(0.0116)	(0.0149)	(0.0163)
Parental education	0.0766***	0.0929***	0.0763***	0.0929***
	(0.0227)	(0.0227)	(0.0227)	(0.0227)
Parental education *Cognitive effort			-0.0114	-0.0126
			(0.0197)	(0.0205)
Male	0.0186	-0.0563**	0.0189	-0.0560**
	(0.0197)	(0.0196)	(0.0197)	(0.0196)
Age in months	-0.00318	-0.00345	-0.00313	-0.00340
	(0.00222)	(0.00221)	(0.00222)	(0.00222)
Migrant background	-0.00248	-0.0351	-0.00218	-0.0352
	(0.0246)	(0.0248)	(0.0246)	(0.0248)
Repeated course	-0.271***	-0.219***	-0.271***	-0.219***
	(0.0427)	(0.0428)	(0.0428)	(0.0428)
ADHD diagnosed	-0.148**	-0.201***	-0.146**	-0.199***
	(0.0510)	(0.0509)	(0.0511)	(0.0511)
Language problems diagnosed	0.0962	0.00903	0.0944	0.00668
	(0.0637)	(0.0634)	(0.0638)	(0.0636)
Constant	1.070***	1.107***	1.065***	1.102***
	(0.282)	(0.282)	(0.282)	(0.282)
Observations	698	698	698	698
Number of groups	34	34	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

In Model 2 we test the second hypothesis using the interaction term between effort and parental education. The interplay between cognitive effort and tertiary parental education is not significant in any of the cases. For better illustration, the marginal effects of cognitive effort by parental education are shown in Figure 3. In both Spanish and math grades the impact of cognitive effort seems to be independent of parental education. This contradicts our hypothesis of compensatory advantage of higher SES children.

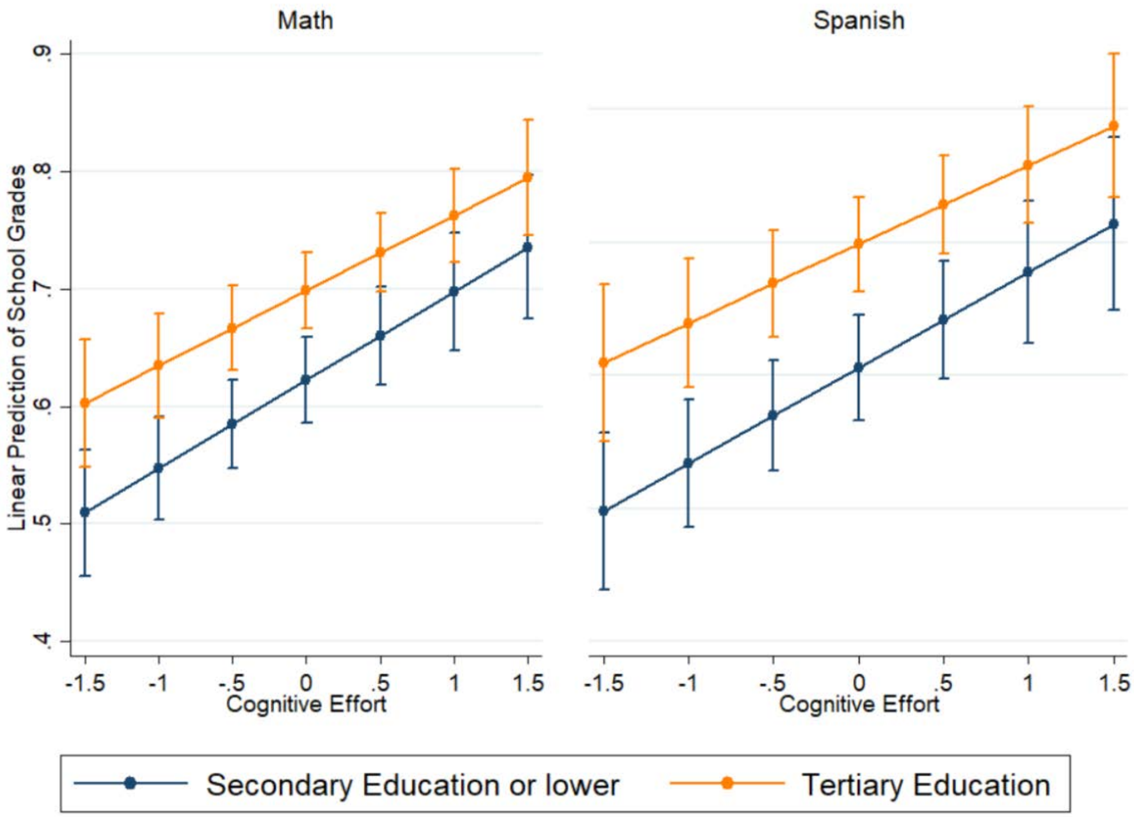

Figure 3. Linear prediction of school grades by tertiary parental education and cognitive effort

In Table 6 instead of students' real effort exhibited in laboratory tasks we use teacher-perceived effort of the students to test our hypotheses related to teacher bias. In Model 3 the association between teachers' perception of effort and school grades turns out to be statistically significant and the magnitude is remarkably large. In fact, the effect size is around twice that of students' displayed effort for math and Spanish. Furthermore, it is also substantially larger than the effect of cognitive skills, more than twice the magnitude. The effect of tertiary parental education is positive, although it is only significant for Spanish, with a notably smaller magnitude than in the previous table. These results seem to suggest that the teacher-perceived effort comprises much more than just effort. Indeed, our findings indicate that teachers might not be able to properly differentiate between skill and pure effort. In any case, the results support the Hypothesis 1b in that teacher-perceived effort is a very strong predictor of school grades.

Table 6. Hierarchical regression with teacher-perceived effort as the main independent variable

	Model 3		Model 4	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0604***	0.0417***	0.0609***	0.0420***
	(0.00937)	(0.00929)	(0.00936)	(0.00928)
Teacher-perceived effort	0.133***	0.135***	0.154***	0.158***
	(0.0102)	(0.0110)	(0.0144)	(0.0151)
Parental education	0.0381	0.0465*	0.0364	0.0449*
	(0.0210)	(0.0208)	(0.0210)	(0.0208)
Parental education *Teacher-perceived effort			-0.0375*	-0.0398*
			(0.0185)	(0.0189)
Male	0.0824***	0.00293	0.0810***	0.00257
	(0.0176)	(0.0175)	(0.0176)	(0.0174)
Age in months	-0.00245	-0.00281	-0.00228	-0.00265
	(0.00202)	(0.00200)	(0.00202)	(0.00200)
Migrant background	0.00963	-0.0183	0.00775	-0.0203
	(0.0225)	(0.0223)	(0.0224)	(0.0223)
Repeated course	-0.214***	-0.164***	-0.207***	-0.154***
	(0.0395)	(0.0394)	(0.0396)	(0.0395)
ADHD diagnosed	-0.152**	-0.198***	-0.158***	-0.208***
	(0.0466)	(0.0463)	(0.0465)	(0.0463)
Language problems diagnosed	0.0333	-0.0571	0.0303	-0.0596
	(0.0582)	(0.0576)	(0.0581)	(0.0575)
Constant	0.930***	0.982***	0.913***	0.966***
	(0.256)	(0.254)	(0.256)	(0.254)
Observations	698	698	698	698
Number of groups	34	34	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

In Model 4 we test our third hypothesis, i.e. that low SES students are more harshly penalized than their high SES peers when teachers perceive that they exert low effort. The interaction between teachers' perception of student effort and parental education turns out to be negative and statistically significant for Spanish and math. This means that having parents with tertiary education buffers the negative impact of the teacher perceiving low effort on school grades, supporting our hypothesis 3. In Figure 4, it can be observed that the pattern is very similar for both Spanish and math, although the buffering is slightly stronger in the former case. These findings underpin the arguments about teacher bias derived from cultural reproduction theory.

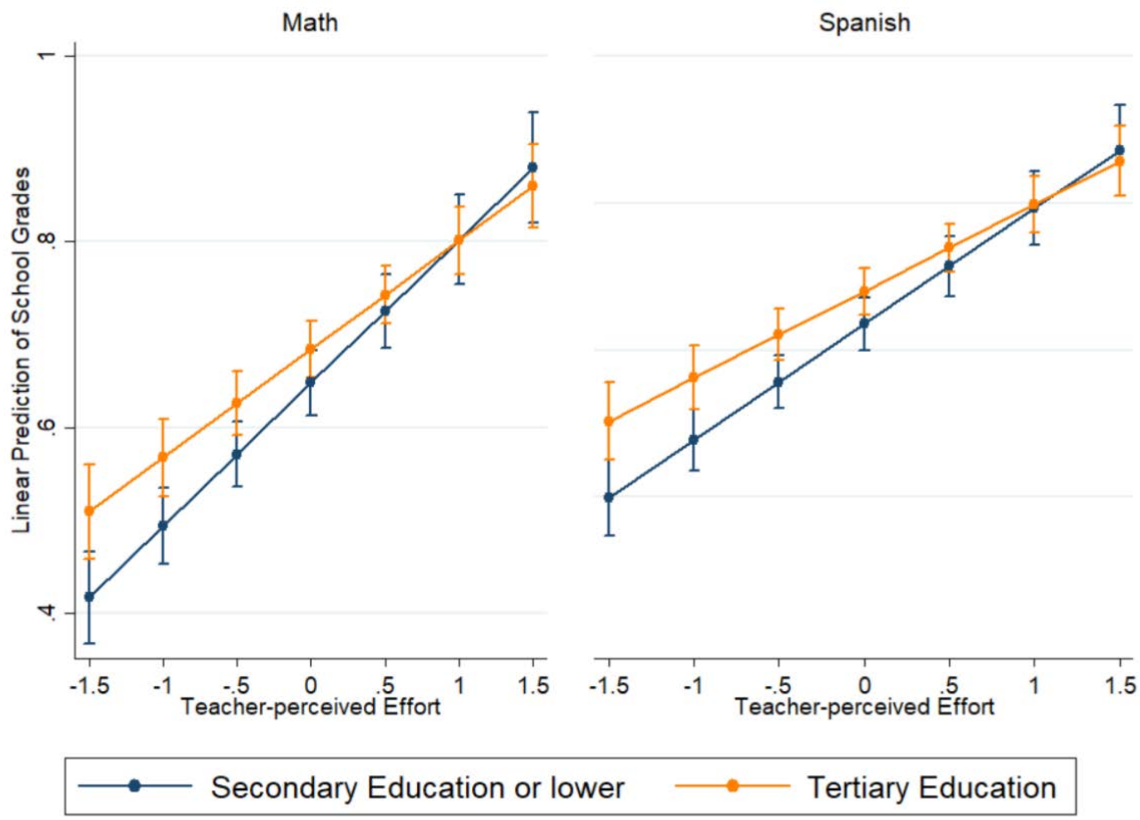

Figure 4. Linear prediction of school grades by tertiary parental education and teacher-perceived effort

4.1 The impact of COVID-19

Initially we were going to carry out all experiments during the school year 2019/2020. However, the pandemic appeared and we had to postpone about half of the experiments.

The rest of the experiments were carried out as soon as it was possible again during the school year 2021/2022. Coincidentally, this results in a close to 50/50 split of the sample before and after the pandemic hit. Specifically, we have valid data for 365 students before COVID and 333 afterwards. The average school grades in math and Spanish are quite similar (just 0.04 points higher in the sample after COVID), and the SD is almost the same. However, they are not well balanced in terms of socioeconomic characteristics. In Table 7 we can observe that the share of parents with tertiary education is 24 percentage points higher in the sample after COVID. These differences should be taken into account when interpreting the following analyses and the results should be taken with due caution.

Table 7. Sample differences

	Before COVID	**After COVID**
Number of Observations	365	333
Math Grades	.646	0.685
Spanish Grades	.639	0.678
Average IQ	-.094	.103
Average Cognitive Effort	-.103	.113
Share of parents with Tertiary Ed.(%)	46	70
Repeated Course (%)	12.5	5.9
Migrant Background (%)	24.8	20.9
Average Neighborhood Income Quartile	1.95	2.97

To explore the impact of the pandemic we introduce a dummy for those experiments that were carried out in the school year 2021/22. We test our hypotheses that the gap in school grades has widened between low and high SES children and between high and low effort children. To do so, we introduce in the model a triple interaction of the dummy after COVID with cognitive effort and parental education. The results are displayed in Table 8. Most notably, the triple interaction is positive and significant for both math and Spanish. This is better understood by looking at the Figures 5 and 6. We observe for both math and Spanish that before COVID, there seems to be a compensatory advantage: at the lower part of the effort distribution children from highly educated parents get better grades than their less-privileged peers –although the interaction is only significant for math. Nevertheless, after COVID, the pattern is completely different. The slope of cognitive effort for children with low-educated parents is flatter and the slope for children with high-educated parents is steeper. There is therefore no evidence of an increase in the school grades gap between low and high SES children. Rather, the results suggest that high SES children that exert high effort are better off but those high SES children with low effort are worse off. What seems clear is that the school grades of low SES children after COVID have become less dependent on cognitive effort than before.

Table 8. Hierarchical regression with cognitive effort as main independent variable

	Math	Spanish
Cognitive skills	0.0807***	0.0638***
	(0.0103)	(0.0103)
Cognitive effort	0.103***	0.0893***
	(0.0181)	(0.0205)
Parental education	0.0936***	0.122***
	(0.0283)	(0.0284)
Parental education * Cognitive effort	-0.0643*	-0.0535
	(0.0268)	(0.0285)
After COVID	-0.0215	0.0392
	(0.0409)	(0.0457)
After COVID *Cognitive effort	-0.0802**	-0.0500
	(0.0302)	(0.0335)
After COVID * Parental education	-0.0497	-0.0770
	(0.0459)	(0.0461)
After COVID * Parental education* Cognitive effort	0.125**	0.0902*
	(0.0400)	(0.0422)
Controls	Y	Y
Observations	698	698
Number of groups	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

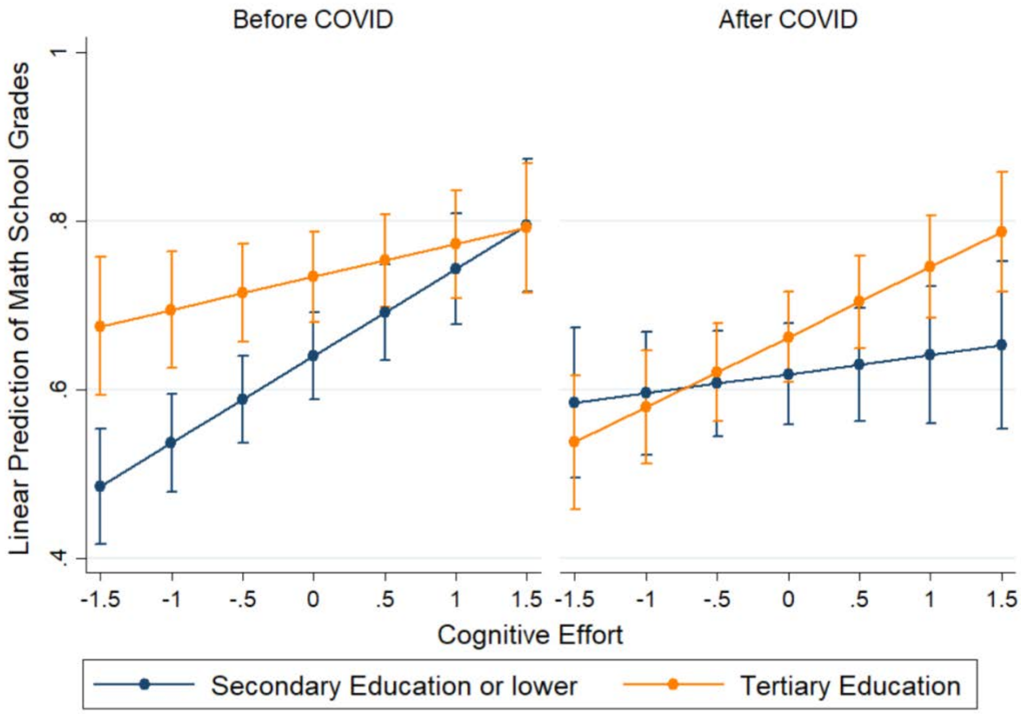

Figure 5. Linear prediction of math grades before and after COVID by cognitive effort

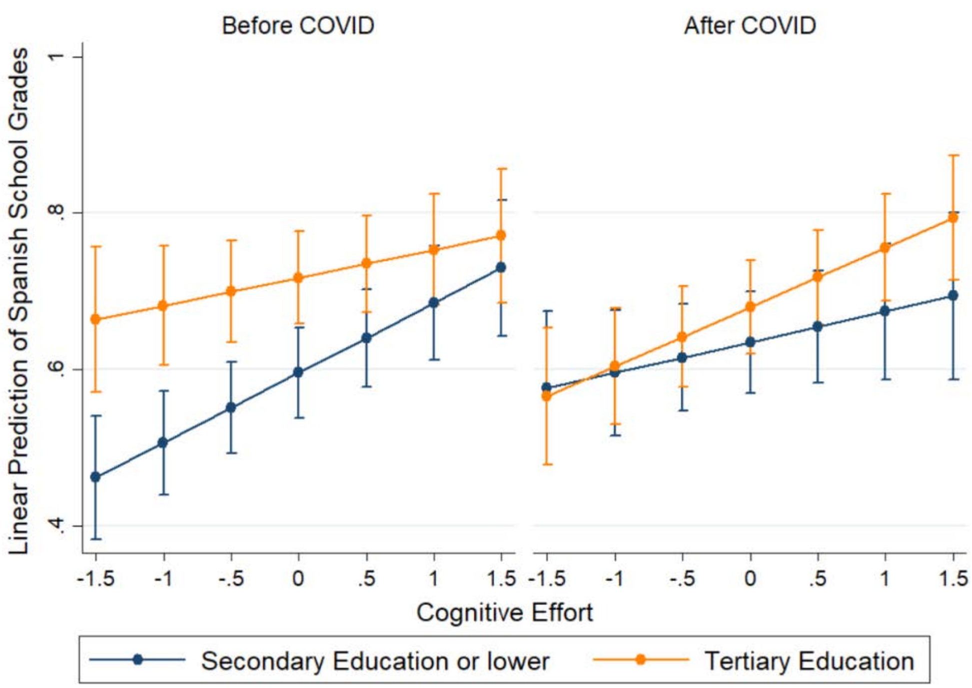

Figure 6. Linear prediction of Spanish grades before and after COVID by cognitive effort

Table 9. Hierarchical regression with teacher-perceived effort as main independent variable

	Math	Spanish
Cognitive skills	0.0618***	0.0438***
	(0.00940)	(0.00930)
Teacher-perceived effort	0.168***	0.181***
	(0.0184)	(0.0184)
Parental education	0.0494	0.0619*
	(0.0264)	(0.0261)
Parental education * Teacher-perceived effort	-0.0542*	-0.0524*
	(0.0255)	(0.0253)
After COVID	-0.0172	0.0288
	(0.0387)	(0.0410)
After COVID * Teacher-perceived effort	-0.0369	-0.0610*
	(0.0294)	(0.0292)
After COVID * Parental education	-0.0340	-0.0411
	(0.0428)	(0.0425)
After COVID * Parental education* Teacher-perceived effort	0.0419	0.0391
	(0.0379)	(0.0376)
Controls	Y	Y
Observations	698	698
Number of groups	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Now we turn to Table 9, which includes the same model but including teacher-perceived effort instead of cognitive effort. Here, the previous results barely change when differentiating between before and after COVID. We only find the interaction between teacher-perceived effort and after COVID to be significant and negative in Spanish grades. The rest of the interactions with after COVID are not statistically significant. Furthermore, we can observe that in both cases the two-way interaction between parental education and teacher-perceived effort is still significant and negative. Looking at Figures 7 and 8, the only observable difference before and after COVID is that at the lower part of the effort distribution the gap between high and low SES children decreases after the pandemic, possibly reflecting a small movement towards equalization. Overall, the results regarding the impact of COVID do not support our hypotheses of widening gaps in school grades due to SES or effort differences. This can be striking since previous literature has found mostly evidence of growing inequalities. However, there is a key difference between learning and grades. As previous literature shows, grading has a multifaceted nature, and teachers take into account more things than just achievement (Bowers, 2011).

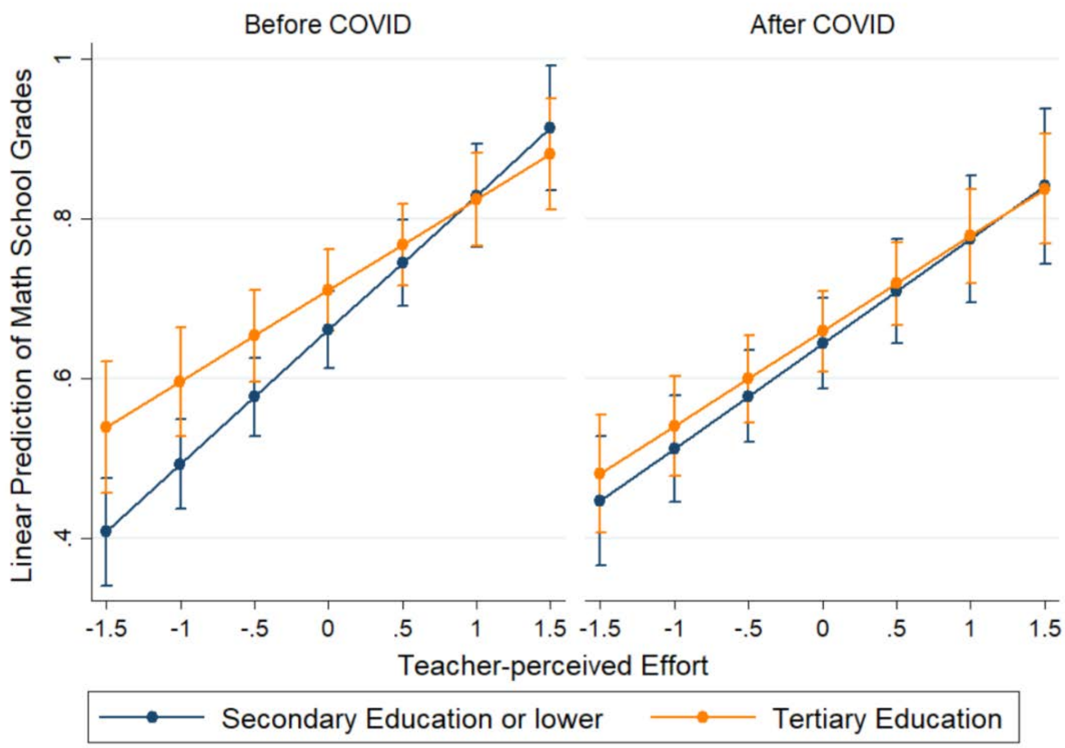

Figure 7. Linear prediction of math grades before and after COVID by teacher-perceived effort

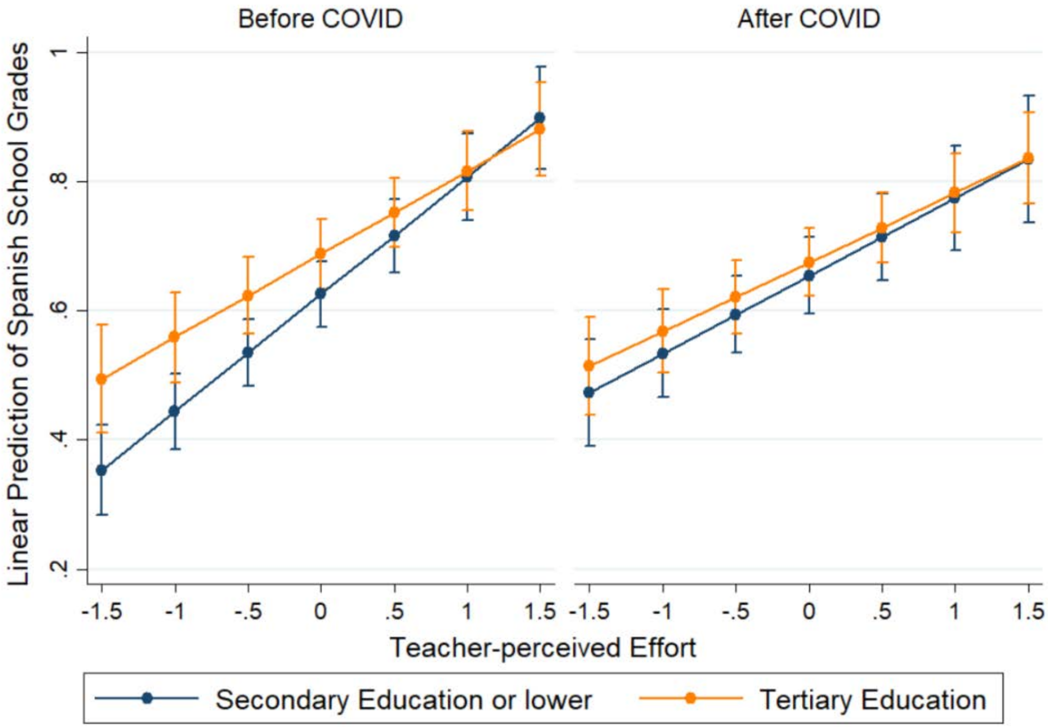

Figure 8. Linear prediction of Spanish grades before and after COVID by teacher-perceived effort

5. Conclusions

This paper investigates the impact of effort on school grades and on the transmission of educational inequalities. It is a topic that has been understudied in comparison to its importance mainly due to the difficulty of measuring effort accurately. We use a novel measure based on real-effort tasks developed in cognitive psychology and behavioral economics to analyze its effect on school grades. We also study the impact on school grades of an alternative measure, teacher-perceived effort, since teachers are important educational gatekeepers whose perceptions matter significantly for students to advance through the educational ladder. Moreover, we test the potential contribution of effort to the intergenerational transmission of educational inequality by analyzing whether the impact of effort on grades is heterogeneous across social origins, as two prominent sociological theories predict. Finally, the timing of our data collection made it possible to explore the impact of COVID on the previous dynamics because our sample got randomly split in half by the pandemic.

As we expected, we find resounding evidence of the positive impact of both cognitive and teacher-perceived effort on math and Spanish grades. However, it is important to pay attention to the magnitudes. The effect of cognitive effort on educational achievement is fairly large. An increase of one SD has the same effect as one SD increase of cognitive skills and slightly lower than the effect of having parents with tertiary education. When we consider teacher-perceived effort instead, the results are very different. The effect size of teacher-perceived effort on school grades is more than twice the effect size of cognitive skills. Interestingly, the effect of having parents with tertiary education decreases notably, and in the model of math grades, even becomes non-significant. This suggests that teacher-perceived effort by no means only captures effort. Indeed, teachers appear to mistake cognitive skills or higher class habitus for effort, as previous literature suggested (Jæger and Møllegaard, 2017). Nevertheless, the exact mechanism of how teacher perceptions are formed is not clear yet and remains a worthy avenue for further research.

When we turn to investigating the role of effort in the intergenerational transmission of advantage, the empirical evidence supports one of our hypotheses and rejects the other. On the one hand, we expected that, according to the compensatory advantage theory, children from high SES families that exert low cognitive effort would be less penalized than their poorer peers. Nevertheless, the evidence shows that the effect of cognitive effort is independent of social background, rejecting our hypothesis. This suggests that highly educated parents are not able to counter-act when their children exert low effort. On the other hand, we do find evidence of high SES children getting better school grades than their less-advantaged peers when both have low teacher-perceived effort. As previous literature shows, grading is a multi-faceted process that also takes into account pedagogical elements (Südkamp et al., 2012). Teachers might consider that certain attitudes and behaviors that are frequent in affluent families –i.e. habitus according to the cultural reproduction theory-are legitimately relevant for school grades, for instance because they believe those to predict educational performance in post-mandatory stages (Boone and Van Houtte, 2013). Therefore, they could be more benevolent with lazy high SES children because they either deem their habitus as worthy of consideration or are unconsciously biased.

The evidence of the role of the COVID-19 pandemic is mixed. In the models with cognitive effort, the patterns after and before COVID are very different. There are clear signs of compensatory advantage in the partial sample before COVID both in math and Spanish grades. However, afterwards, the picture changes completely. The overall magnitude of the cognitive effort effect on grades decreases, especially for low-SES children. Therefore, the results contradict the hypothesis of a widening grades gap in SES and effort. When we use teacher-perceived effort the results before and after the onset of the pandemic are more similar. Before COVID we observe the same SES gap as in the model of the full period at the lower part of the effort distribution that favors children from highly educated families. After COVID the gap is closed, with the effect of teacher-perceived effort on grades becoming independent of parental background. This again points to a slight equalizing effect. Nevertheless, the results should be taken with caution because the samples were not balanced, making our findings difficult to ascertain. While they are interesting first pieces of evidence on a swiftly moving field, more research is needed to establish clear conclusions.

Several robustness checks are performed in the appendix. For example, we construct an alternative measure of cognitive effort using the results from all the conditions, intrinsic, extrinsic and tournament motivation. The results are quite similar; the effect of this alternative effort variable is even larger than the preferred variable (only based on extrinsically motivated effort). We also employ an alternative measure of parental socioeconomic background, the ISEI. We obtain that its impact on grades is significant and positive, as was parental education. However, we do not find an interaction with teacher-perceived effort. This may suggest that parental education is more relevant for teacher perceptions than economic resources, broadly in line with CRT. Overall, the results hold across most robustness checks. Our experimental variable of cognitive effort shows its importance for educational achievement and its effect is independent of social background, which is good news for equality of opportunity. But the same cannot be said about teacher-perceived effort. The results suggest that, when grading, teachers are influenced by traits that favor privileged children. Therefore, two potential avenues of future research depart from here. First, it would be important for the equality of opportunity framework to investigate whether effort is really equally distributed across the population or whether there is a social background gradient. Second, the relationship between the real effort exerted and the effort perceived by others merits to be studied in greater depth because the perception of gatekeepers may be at least as important as the effort actually exerted. Hence, the indirect effect of effort on grades, as it is mediated by teacher perceptions, may be even more pertinent than its direct effect on learning.

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7. Appendix

A. Robustness checks

We perform a robustness check using an alternative measure of cognitive effort. Instead of calculating cognitive effort only with the results from the extrinsic condition, we construct a new measure using also the intrinsic and tournament condition. In Table A.1 we can observe that the results are quite similar. The magnitude of the effect on grades is a bit larger than with the main measure in all the cases, and larger than the effect of cognitive skills. When it comes to the interaction with parental education the effect is not significant in both cases as in the main results.

Table A.1. Alternative cognitive effort as predictor of school grades

	Model 1		Model 2	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0739***	0.0610***	0.0742***	0.0612***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)
Cognitive effort	0.100***	0.0907***	0.109***	0.0964***
	(0.0139)	(0.0152)	(0.0202)	(0.0215)
Parental education	0.0805***	0.0979***	0.0803***	0.0980***
	(0.0231)	(0.0232)	(0.0231)	(0.0232)
Parental education *Cognitive effort			-0.0162	-0.0103
			(0.0263)	(0.0272)
Male	0.0150	-0.0569**	0.0154	-0.0566**
	(0.0200)	(0.0200)	(0.0200)	(0.0200)
Age in months	-0.00350	-0.00339	-0.00347	-0.00338
	(0.00241)	(0.00242)	(0.00242)	(0.00242)
Migrant background	-0.00285	-0.0316	-0.00284	-0.0317
	(0.0252)	(0.0254)	(0.0252)	(0.0254)
Repeated course	-0.283***	-0.235***	-0.282***	-0.234***
	(0.0440)	(0.0442)	(0.0441)	(0.0443)
ADHD diagnosed	-0.162**	-0.207***	-0.160**	-0.206***
	(0.0516)	(0.0517)	(0.0517)	(0.0518)
Language problems diagnosed	0.109	0.0367	0.108	0.0356
	(0.0657)	(0.0658)	(0.0658)	(0.0659)
Constant	1.116***	1.098***	1.114***	1.097***
	(0.307)	(0.308)	(0.307)	(0.308)
Observations	669	669	669	669
Number of groups	33	33	33	33

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located

As an additional robustness check, we want to check whether the strong effect of teacher-perceived effort is driven by the cases in which the school grades and teacher-perceived effort were given by the same teacher. This only happens in the experiments carried out after the Christmas break, after the first trimester, because before that the survey captured the school grades from the previous academic year and in Spain most school classes change teacher from 4th to 5th grade. In our case, four classes out of 34 came after Christmas, which corresponds to 84 students, or 12% of the sample. Thus, we construct the dummy variable Post-break to identify those students.

Table A.2. Teacher-perceived effort as predictor of school grades

	Model A3		Model A4	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0599***	0.0412***	0.0605***	0.0416***
	(0.00938)	(0.00930)	(0.00936)	(0.00929)
Teacher-perceived effort	0.135***	0.135***	0.156***	0.158***
	(0.0109)	(0.0118)	(0.0147)	(0.0154)
Parental education	0.0390+	0.0478*	0.0373+	0.0462*
	(0.0210)	(0.0208)	(0.0210)	(0.0208)
Parental education *Teacher-perceived effort			-0.0377*	-0.0409*
			(0.0187)	(0.0190)
Post-break	-0.0230	-0.0246	-0.0247	-0.0268
	(0.0507)	(0.0539)	(0.0512)	(0.0531)
Post-break * Teacher-perceived effort	-0.0164	-0.000711	-0.0110	0.00530
	(0.0293)	(0.0321)	(0.0281)	(0.0308)
Male	0.0826***	0.00342	0.0812***	0.00313
	(0.0177)	(0.0175)	(0.0176)	(0.0175)
Migrant background	0.0103	-0.0189	0.00818	-0.0214
	(0.0226)	(0.0224)	(0.0226)	(0.0224)
Repeated course	-0.239***	-0.191***	-0.229***	-0.179***
	(0.0342)	(0.0342)	(0.0345)	(0.0345)
ADHD diagnosed	-0.149**	-0.195***	-0.156***	-0.206***
	(0.0467)	(0.0464)	(0.0467)	(0.0465)
Language problems diagnosed	0.0339	-0.0553	0.0309	-0.0577
	(0.0582)	(0.0577)	(0.0581)	(0.0576)
Constant	0.623***	0.630***	0.628***	0.634***
	(0.0329)	(0.0346)	(0.0332)	(0.0342)
Observations	698	698	698	698
Number of groups	34	34	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

We do not find any evidence of the results being driven by those cases as Table A.2 shows. The results are almost identical to those in Table 6. Furthermore, the new variable Post-breakt is not a predictor of school grades, and more importantly, does not moderate the effect of teacher-perceived effort in any case.

Furthermore, we consider the International Socio-Economic Index (ISEI) as an alternative measure of socioeconomic background. This measure is based on the occupation of the parents. Thus, we substitute the parental education variable from the preferred specifications by this alternative measure of household background.

Table A.3. Cognitive effort and ISEI as predictors of school grades

	Model A5		Model A6	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0798***	0.0647***	0.0792***	0.0645***
	(0.0102)	(0.0104)	(0.0103)	(0.0104)
Cognitive effort	0.0731***	0.0691***	0.0438+	0.0584*
	(0.0107)	(0.0113)	(0.0266)	(0.0278)
ISEI	0.00194**	0.00197**	0.00186**	0.00194**
	(0.000665)	(0.000675)	(0.000668)	(0.000679)
ISEI * Cognitive effort			0.000660	0.000241
			(0.000548)	(0.000571)
Male	0.0255	-0.0539**	0.0247	-0.0541**
	(0.0197)	(0.0199)	(0.0197)	(0.0199)
Age in months	-0.00282	-0.00337	-0.00286	-0.00339
	(0.00221)	(0.00224)	(0.00221)	(0.00224)
Migrant background	0.00359	-0.0314	0.000644	-0.0326
	(0.0252)	(0.0256)	(0.0253)	(0.0258)
Repeated course	-0.297***	-0.235***	-0.297***	-0.235***
	(0.0435)	(0.0441)	(0.0435)	(0.0441)
ADHD diagnosed	-0.155**	-0.211***	-0.158**	-0.212***
	(0.0518)	(0.0524)	(0.0518)	(0.0525)
Language problems diagnosed	0.107+	0.00182	0.109+	0.00269
	(0.0614)	(0.0621)	(0.0615)	(0.0622)
Constant	0.974***	1.056***	0.980***	1.058***
	(0.283)	(0.287)	(0.283)	(0.287)
Observations	686	686	686	686
Number of groups	34	34	34	34

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table A.4. Teacher-perceived effort and ISEI as predictors of school grades

	Model A7		Model A8	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0612***	0.0427***	0.0612***	0.0426***
	(0.00946)	(0.00945)	(0.00946)	(0.00944)
Teacher-perceived effort	0.132***	0.137***	0.150***	0.172***
	(0.00989)	(0.0112)	(0.0260)	(0.0274)
ISEI	0.00142*	0.00134*	0.00147*	0.00141*
	(0.000611)	(0.000611)	(0.000613)	(0.000613)
ISEI * Teacher-perceived effort			-0.000389	-0.000739
			(0.000517)	(0.000541)
Male	0.0860***	0.00262	0.0850***	0.00168
	(0.0177)	(0.0176)	(0.0177)	(0.0176)
Age in months	-0.00208	-0.00274	-0.00203	-0.00263
	(0.00202)	(0.00201)	(0.00202)	(0.00201)
Migrant background	0.0154	-0.0158	0.0162	-0.0145
	(0.0231)	(0.0231)	(0.0231)	(0.0231)
Repeated course	-0.242***	-0.174***	-0.240***	-0.170***
	(0.0402)	(0.0405)	(0.0405)	(0.0406)
ADHD diagnosed	-0.149**	-0.199***	-0.149**	-0.203***
	(0.0475)	(0.0475)	(0.0475)	(0.0475)
Language problems diagnosed	0.0474	-0.0633	0.0461	-0.0654
	(0.0565)	(0.0562)	(0.0565)	(0.0563)
Constant	0.840**	0.938***	0.831**	0.922***
	(0.258)	(0.258)	(0.259)	(0.258)
Observations	686	686	686	686
Number of groups	34	34	34	34

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

We find in Table A.3 and A.4 that ISEI is a good predictor of school grades. It is significantly associated with math and Spanish grades in all specifications. However, do not find an interaction between ISEI and teacher-perceived effort as in the specification using parental education.

Appendix B. Other interactions

Table B.1. Cognitive effort interaction with gender

	Math	Spanish
Cognitive skills	0.0765***	0.0609***
	(0.0103)	(0.0103)
Cognitive effort	0.0793***	0.0620***
	(0.0143)	(0.0152)
Male	0.0189	-0.0563**
	(0.0197)	(0.0196)
Male * Cognitive effort	-0.0197	0.00670
	(0.0195)	(0.0197)
Parental education	0.0770***	0.0927***
	(0.0227)	(0.0227)
Age in months	-0.00305	-0.00347
	(0.00222)	(0.00222)
Migrant background	0.000137	-0.0359
	(0.0248)	(0.0249)
Repeated course	-0.275***	-0.218***
	(0.0429)	(0.0430)
ADHD diagnosed	-0.147**	-0.202***
	(0.0510)	(0.0510)
Language problems diagnosed	0.0954	0.00909
	(0.0636)	(0.0635)
Constant	1.055***	1.110***
	(0.282)	(0.282)
Observations	698	698
Number of groups	34	34

Standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table B.2. Teacher perceived effort interaction with gender

	Math	Spanish
Cognitive skills	0.0605***	0.0415***
	(0.00938)	(0.00929)
Teacher perceived effort	0.139***	0.126***
	(0.0135)	(0.0142)
Male	0.0826***	0.00236
	(0.0177)	(0.0175)
Male *Teacher perceived effort	-0.0112	0.0204
	(0.0182)	(0.0181)
Parental education	0.0375	0.0474*
	(0.0210)	(0.0208)
Age in months	-0.00238	-0.00294
	(0.00202)	(0.00200)
Migrant background	0.00990	-0.0187
	(0.0225)	(0.0223)
Repeated course	-0.218***	-0.157***
	(0.0400)	(0.0399)
ADHD diagnosed	-0.151**	-0.198***
	(0.0466)	(0.0463)
Language problems diagnosed	0.0351	-0.0608
	(0.0583)	(0.0576)
Constant	0.922***	0.998***
	(0.256)	(0.254)
Observations	698	698
Number of groups	34	34

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table B.3. Cognitive effort interaction with migrant background

	Math	Spanish
Cognitive skills	0.0773***	0.0606***
	(0.0103)	(0.0103)
Cognitive effort	0.0724***	0.0709***
	(0.0119)	(0.0129)
Migrant background	-0.00434	-0.0378
	(0.0249)	(0.0250)
Migrant background * Cognitive effort	-0.0115	-0.0215
	(0.0222)	(0.0230)
Parental education	0.0767***	0.0926***
	(0.0227)	(0.0227)
Male	0.0192	-0.0554**
	(0.0197)	(0.0197)
Age in months	-0.00315	-0.00338
	(0.00222)	(0.00222)
Repeated course	-0.269***	-0.216***
	(0.0430)	(0.0430)
ADHD diagnosed	-0.148**	-0.201***
	(0.0510)	(0.0509)
Language problems diagnosed	0.0946	0.00629
	(0.0637)	(0.0635)
Constant	1.066***	1.098***
	(0.282)	(0.282)
Observations	698	698
Number of groups	34	34

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table B.4. Teacher perceived effort interaction with migrant background

	Math	Spanish
Cognitive skills	0.0598***	0.0414***
	(0.00937)	(0.00930)
Teacher perceived effort	0.141***	0.140***
	(0.0117)	(0.0123)
Migrant background	0.00544	-0.0204
	(0.0226)	(0.0225)
Migrant background *Teacher perceived effort	-0.0317	-0.0165
	(0.0214)	(0.0216)
Parental education	0.0356	0.0456*
	(0.0210)	(0.0209)
Male	0.0833***	0.00326
	(0.0176)	(0.0175)
Age in months	-0.00245	-0.00281
	(0.00202)	(0.00200)
Repeated course	-0.215***	-0.165***
	(0.0395)	(0.0394)
ADHD diagnosed	-0.149**	-0.197***
	(0.0466)	(0.0463)
Language problems diagnosed	0.0382	-0.0544
	(0.0582)	(0.0577)
Constant	0.932***	0.983***
	(0.256)	(0.254)
Observations	698	698
Number of groups	34	34

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located

Appendix C. Grades normalized

Table C.1. Hierarchical regression with cognitive effort as the main independent variable

	Model 1		Model 2	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0619***	0.0454***	0.0622***	0.0456***
	(0.00887)	(0.00813)	(0.00889)	(0.00814)
Cognitive effort	0.0621***	0.0533***	0.0689***	0.0574***
	(0.00916)	(0.00872)	(0.0131)	(0.0123)
Parental education	0.0693***	0.0714***	0.0690***	0.0714***
	(0.0196)	(0.0180)	(0.0197)	(0.0180)
Parental education *Cognitive effort			-0.0124	-0.00752
			(0.0171)	(0.0159)
Male	0.00756	-0.0463**	0.00782	-0.0461**
	(0.0170)	(0.0156)	(0.0170)	(0.0156)
Age in months	-0.00246	-0.00267	-0.00240	-0.00264
	(0.00192)	(0.00176)	(0.00192)	(0.00176)
Migrant background	0.00363	-0.0230	0.00397	-0.0229
	(0.0213)	(0.0196)	(0.0213)	(0.0196)
Repeated course	-0.272***	-0.224***	-0.272***	-0.224***
	(0.0370)	(0.0339)	(0.0370)	(0.0339)
ADHD diagnosed	-0.129**	-0.122**	-0.127**	-0.121**
	(0.0441)	(0.0404)	(0.0442)	(0.0405)
Language problems diagnosed	0.105	0.0112	0.103	0.00988
	(0.0550)	(0.0503)	(0.0551)	(0.0504)
Constant	0.969***	1.053***	0.963***	1.050***
	(0.244)	(0.223)	(0.244)	(0.223)
Observations	698	698	698	698
Number of groups	34	34	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table C.2. Hierarchical regression with teacher-perceived effort as the main independent variable

	Model 3		Model 4	
	Math	Spanish	Math	Spanish
Cognitive skills	0.0476***	0.0317***	0.0481***	0.0321***
	(0.00810)	(0.00741)	(0.00808)	(0.00740)
Teacher-perceived effort	0.116***	0.106***	0.141***	0.124***
	(0.0103)	(0.00879)	(0.0133)	(0.0118)
Parental education	0.0334	0.0385*	0.0319	0.0374*
	(0.0181)	(0.0166)	(0.0181)	(0.0166)
Parental education *Teacher-perceived effort			-0.0452**	-0.0334*
			(0.0165)	(0.0149)
Male	0.0661***	0.00185	0.0637***	0.00146
	(0.0153)	(0.0140)	(0.0153)	(0.0139)
Age in months	-0.00177	-0.00221	-0.00166	-0.00207
	(0.00174)	(0.00159)	(0.00174)	(0.00159)
Migrant background	0.0145	-0.0115	0.0118	-0.0137
	(0.0195)	(0.0178)	(0.0194)	(0.0178)
Repeated course	-0.211***	-0.176***	-0.206***	-0.170***
	(0.0345)	(0.0314)	(0.0344)	(0.0314)
ADHD diagnosed	-0.139***	-0.121**	-0.145***	-0.129***
	(0.0405)	(0.0369)	(0.0404)	(0.0369)
Language problems diagnosed	0.0468	-0.0371	0.0451	-0.0397
	(0.0503)	(0.0460)	(0.0502)	(0.0459)
Constant	0.840***	0.958***	0.831***	0.945***
	(0.221)	(0.202)	(0.221)	(0.202)
Observations	698	698	698	698
Number of groups	34	34	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table C.3. Hierarchical regression with cognitive effort as main independent variable

	Math	Spanish
Cognitive skills	0.0652***	0.0475***
	(0.00887)	(0.00816)
Cognitive effort	0.0963***	0.0658***
	(0.0162)	(0.0152)
Parental education	0.0813***	0.0957***
	(0.0244)	(0.0225)
Parental education * Cognitive effort	-0.0623**	-0.0384
	(0.0236)	(0.0219)
After COVID	-0.0299	0.0134
	(0.0359)	(0.0331)
After COVID *Cognitive effort	-0.0791**	-0.0251
	(0.0268)	(0.0250)
After COVID * Parental education	-0.0342	-0.0657
	(0.0396)	(0.0365)
After COVID * Parental education* Cognitive effort	0.118***	0.0647*
	(0.0352)	(0.0326)
Controls	Y	Y
Observations	698	698
Number of groups	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Table C.4. Hierarchical regression with teacher-perceived effort as main independent variable

	Math	Spanish
Cognitive skills	0.0486***	0.0335***
	(0.00811)	(0.00743)
Teacher-perceived effort	0.155***	0.136***
	(0.0171)	(0.0145)
Parental education	0.0425	0.0529*
	(0.0228)	(0.0208)
Parental education * Teacher-perceived effort	-0.0637**	-0.0372
	(0.0225)	(0.0202)
After COVID	-0.0250	0.00800
	(0.0320)	(0.0299)
After COVID * Teacher-perceived effort	-0.0373	-0.0302
	(0.0271)	(0.0232)
After COVID * Parental education	-0.0267	-0.0413
	(0.0369)	(0.0338)
After COVID * Parental education* Teacher-perceived effort	0.0468	0.0132
	(0.0338)	(0.0299)
Controls	Y	Y
Observations	698	698
Number of groups	34	34

Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The controls include the type of school and the neighborhood income quartile in which the school is located.

Appendix D. Before and after COVID sample

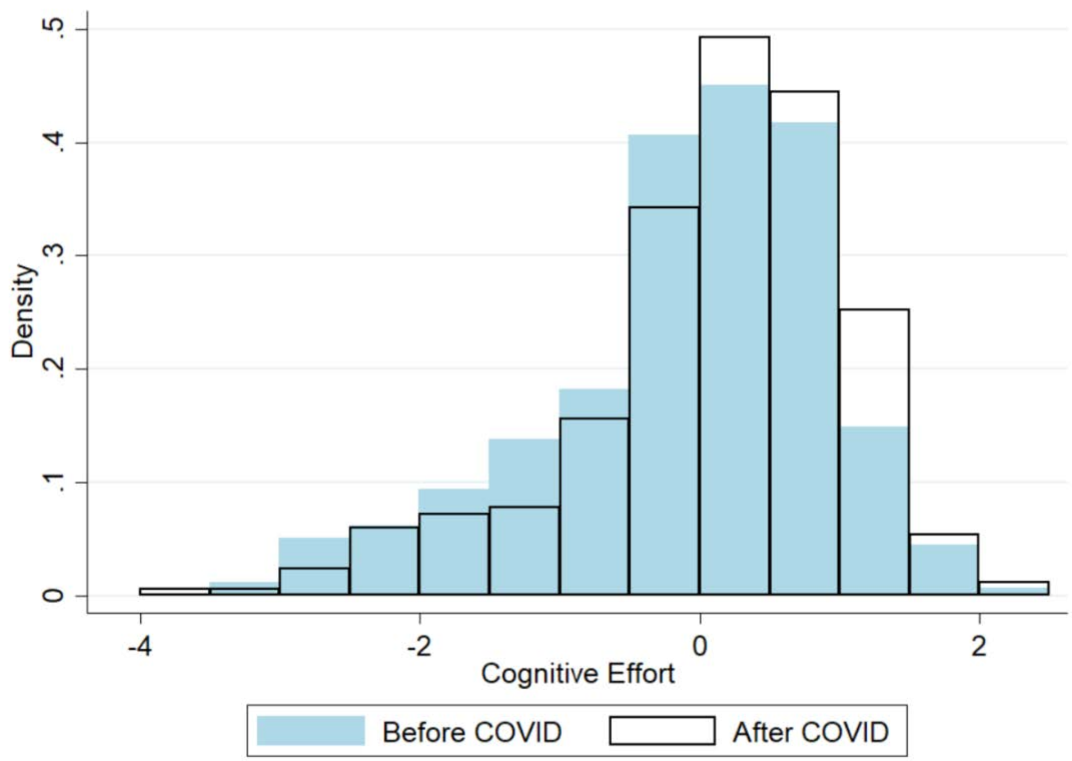

Figure D.1. Histogram of Cognitive effort before and after COVID