The prize for hard work: effort, educational attainment and the transmission of social inequality

by

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Abstract

The meritocratic paradigm, predominant in our society, consists of the idea that success in life is determined by the combination of ability and effort. However, individuals only have agency over effort, a concept that has remained understudied in comparison to its importance for equality of opportunity. Bridging interdisciplinary literature from sociology, economics and psychology, this thesis seeks to expand the knowledge on the relevance of effort for educational processes and the transmission of social inequality. To expand the knowledge on effort, two measures of actual exerted effort are employed. The first reflects test effort, measured with the PISA test. The second is an experimental measure of cognitive effort stemming from real-effort tasks. These measures are used in different contexts (Australia, Spain and cross-country) to analyze the impact of effort on short and long-run educational outcomes. Furthermore, the thesis tests mechanisms based on sociological theories through which effort could contribute to the reproduction of social inequality. The results demonstrate that effort is indeed a crucial determinant of educational attainment. The magnitude of the impact is comparable to the effect of cognitive skills. Nevertheless, effort also contributes to the transmission of social advantage. The specific mechanisms and the implications for the conception of meritocracy and equality of opportunity are discussed.

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Chapter 1

Introduction

Children hear since a very young age that they should try hard to achieve their goals because effort is crucial if they want to succeed in life. The statement rests on two assumptions: effort is a very important predictor of future life outcomes, and individuals have full agency to decide to exert it. Indeed, liberal societies have embraced the equality of opportunities paradigm, which posits that every person has the same chances of succeeding in life, independently of ascriptive characteristics (Swift, 2005). Under this normative ideal, socioeconomic status is only determined by choices, effort and ability (we will come back to the role of ability in the next section). Thus, inequality in outcomes due to those factors can be regarded as fair (Roemer, 1998). This notion began to develop around the mid-twentieth century with the coming of the post-industrial society. As economic development increased its dependence on knowledge, education gained importance (Bell, 1976). Therefore, according to the functionalist theory, to satisfy the increasing demand for high-skilled workers, the states expanded the educational system to cover the entire population. The underlying intention was to improve the educational level of the whole population to maximize the potential of individuals from poorer backgrounds that in other conditions would not have been educated. In this context, education functions as a bridge between family and society, socializing individuals into the values of individualism, competition and achievement (Parsons, 1951). The new type of society required a new form of social stratification with education at the core of the postindustrial system. Hence, educational attainment became the main determinant of socioeconomic status to incentivize the acquisition of skills. The condition was that all individuals would have the same opportunities of getting an education. It would only depend on their intelligence and effort to achieve the desired level (Blau and Duncan, 1967). This paradigm of society became known as meritocracy. Ironically, the term was coined by Michael Young (1958) in a dystopian novel as a criticism of such system. However, nowadays it has become widely accepted as the ideal normative framework.

But is not the same to regard meritocracy as the ideal paradigm as actually having a meritocratic society. A lot of research in the last decades has investigated the intergenerational transmission of inequality, particularly in sociology. Scholars analyze the relationship between classes or occupations in different generations, analyzing which factors contribute to the persistence of social inequality. Indeed, they find that educational attainment is the major determinant factor of class mobility (Erikson and Goldthorpe, 2002). Nevertheless, there is also a lot of evidence showing that family background exerts a strong impact on educational attainment through several channels such as economic resources, social networks or cultural assets (Breen and Jonsson, 2005). Moreover, education does not come close to cancelling existing inequality; more direct redistribution from the state is required to guarantee equality of opportunities (Solga, 2014). Back to the initial premise, substantial research has investigated the importance of intelligence for educational attainment and its role in the transmission of educational inequality (Bowles and Gintis, 2002; Heckman et al., 2006). However, the same cannot be said about effort.

Bridging literature from economics, psychology and sociology, this thesis seeks to investigate the role of effort as a determinant of educational attainment and as a potential channel of social inequality. One of the main challenges of research on effort is its inherent abstraction as a concept. Everybody has a clear intuition of what it is, but there is no universally established definition. This derives from the difficulty when trying to measure it. Here, I frame effort within the literature of non-cognitive skills –or personality traits as psychologists prefer to say- because several of those, such as conscientiousness, locus of control or grit, are closely related to effort. These concepts are usually measured by self-reported questionnaires, which can be problematic (Apascaritei et al., 2021). Therefore, I focus on cognitive effort, which can be defined as the “mobilization of mental resources to fulfill a task” (Radl and Miller, 2021: p.). For operationalization, I use two recently developed direct measures of effort. The thesis contributes to the existing literature by studying its impact on educational attainment in the short and long run. Furthermore, it examines potential mechanisms proposed by sociological theories through which effort might contribute to the reproduction of educational inequality. Specifically, it tests its role as a mediator between parental socioeconomic status and educational attainment and as a moderator in inequality processes. In summary, the thesis analyzes the extent to which the meritocratic ideal is accomplished in contemporaneous societies by studying the impact of its core element, effort, on educational attainment and on inequality.

In the next sections of the Introduction, I present the philosophical and theoretical framework of the thesis. First, I explain why effort is often considered the most legitimate source of inequality according to different theories of distributive justice. Then, I summarize the literature on skill formation and the importance of non-cognitive skills close to effort on educational outcomes, discussing the challenges of their measurement and potential alternatives. I also review the literature on educational inequality, departing from the classic sociological theories and arriving at the role of effort in the mechanisms that contribute to the intergenerational transmission of inequality. Finally, I give an overview of the rest of the thesis, providing a brief summary of the following chapters.

1. Theories of distributive justice and equality of opportunity

Most contemporary theories of distributive justice derive, in one way or another, from the Lockean conception of natural rights.[1] John Locke (1690) established that every person has a set of equal natural rights that are independent of the cultural or political context. According to his conception, each person has the right to do whatever she chooses excluding those actions that harm or violate other person's rights. Furthermore, each person is the rightful owner of herself and of the property acquired legitimately. This conception of property rights allows the exclusion of others from the use and control of own property. However, we have to differentiate between owning our bodies and owning external resources. Each individual owns her own body from the beginning, but to legitimately acquire external resources requires more conditions. Locke proposes that any individual has the right to claim any material resource that is previously

[1] Except for strict egalitarians and doctrines that reject self-ownership.

unowned if doing so leaves enough and as good for others. Consequently, individuals rightfully deserve the products and benefits from working the material resources owned on property. This implies a strong conception of self-ownership, and the interpretation of this Lockean Proviso is central to the development of different theories of distributive justice.

Robert Nozick is the most prominent interpreter of Lockean self-ownership from the libertarian right-wing perspective. Nozick (1974) takes a step forward the Lockean Proviso, applying it to contemporary developed countries. He argues that what is relevant for the just acquisition of material resources is not whether enough materials have been left for others, but whether others are worse off in terms of welfare due to the action. Therefore, Nozick puts the weight of distributive justice on the compensation of other individuals for the appropriation of resources. Compensation might take place in different ways such as providing a service or a good for a certain price. He argues that this proviso is already satisfied in free-market economies. In his conception, the legitimacy of a distribution comes from the procedure through which it has been reached, i.e. a historical principle of justice. According to Nozick, it is possible that luck determines what individuals own –e.g. when parents transfer their goods to their offspring-, but that does not invalidate the individual's entitlement if the proviso is satisfied.

Views from the left-wing adopt the Lockean body self-ownership and combine it with a more egalitarian view of private property. For example, in Marx, even though he did not develop a theory of justice, his theories derive from a strong conception of self-ownership. He argues that according to his theory of exploitation, workers are compensated less than the benefit from the products of their labor. Capitalists benefit themselves from the appropriation of workers' labor. In the higher phase of communism, individuals will be rewarded "from each according to his ability, to each according to his needs", implying that each individual will have the right to satisfy his needs to the same extent that contributes to society.

More contemporary views have taken an egalitarian perspective that wonders which are the legitimate sources of outcome inequalities. Prominently, John Rawls is the author of the most influential theory of distributive justice. In his seminal book "A Theory of

Justice" he argues that the social and natural lotteries –i.e. the socioeconomic and biological characteristics that each individual is born with- are a product of mere luck and, thus, the outcomes arising from them should be justified. In order to extract the justice principles that induce this theory, he proposes a thought experiment called "The Original Position" in which all the citizens have to agree on which principles of justice should prevail in society. To avoid self-interest, individuals are placed behind a veil of ignorance, meaning that they do not know the characteristics they are born with, such as race, gender or class. Rawls (1971) derives from this experiment his two principles of justice as fairness that should inspire the institutional framework: The first principle acknowledges a basic set of liberties for every person. The second principle states that social and economic inequalities have to satisfy two conditions. Condition A is that all job positions should be open under fair equality of opportunity, implying that ascriptive characteristics such as gender or race cannot influence the outcome. Condition B –also called the difference principle- declares that socioeconomic inequalities are only allowed if they benefit the least-advantaged persons. The principles follow a hierarchical order, so one cannot sacrifice basic liberties to enhance equality of opportunity or level up the less-advantaged individuals.

The difference principle has received some criticism from *luck egalitarians* as they consider that it is not enough to compensate for the potential impact of bad luck. Dworkin (1981) distinguishes between "ambitions" and "endowments", being the former the choices that individuals make and their consequences, and the latter are the results of brute luck in the social and natural lottery. He agrees with Rawls that outcome inequality should not be determined by endowments, only by ambitions, but deems the *difference principle* as insufficient to address the impact of bad luck on outcomes. He argues that those less fortunate in the social and biological lottery should be compensated to equalize their opportunities. Furthermore, the resulting outcome distribution should be completely determined by people's choices, in contrast to the *difference principle*. Inequalities arising due to choices are the only fair inequalities, therefore, questioning the legitimacy of differences in cognitive skills as a source of inequality.

Rawls (1999) implies that social institutions should eliminate inequality of opportunities stemming from differences in the socioeconomic background since luck in the social lottery is the ultimate cause of them. However, as Anderson (1999) and other *luck egalitarians* point out, differences in talent are also due to luck in the natural lottery but, according to Rawls, are a fair source of inequality, which is contradictory. Luck egalitarians' conception of equality of opportunity is modeled in detail by John Roemer (1998). He designs a model in which socioeconomic outcomes are determined by two sets of variables, *circumstances* and *efforts*. The former are all the variables that are out of the control of the individual, such as class background, gender, race or innate skills – resembling Dworkin's endowments. The latter are the variables that are in the individual's hand and for which one is responsible. Taking that into account, inequality of outcomes can be decomposed into two, *inequality of opportunities*, which consists of differences in circumstances, and *inequality of efforts*, attributed to differences in choices and actions. According to luck egalitarians, only *inequality of efforts* should be a legitimate source of inequality of outcomes. However, Roemer's (1998) view is more radical. According to him, individuals should only be accountable for their level of effort relative to the average level of effort associated with their set of circumstances. This suggests that effort could be conditioned by circumstances.

Independently on which theory of distributive justice is preferred, effort always plays a central role as a legitimate source of inequality, as it is assumed that it is a strong determinant of socioeconomic outcomes and depends entirely on individual's free will to exert it.

2. Skill formation and non-cognitive skills

2.1. Skill formation

Social science research has shown extensively that education is the main mediating factor for life outcomes and social mobility (Ishida, Miller and Ridge, 1995; Marshall, Swift and Roberts, 1997; Erikson and Goldthorpe, 2002). Many researchers have developed models to explain the process of educational attainment. Human Capital Theory, one of the earliest theories, views education as an investment decision (Becker, 1964; Becker and Tomes, 1979). Higher levels of education result in higher productivity, which would lead to higher returns in the labor market in form of wages. According to this model, investment in education is subject to credit constraints and the role of ability is not clear. Another early competing explanation is the signaling theory, which proposes that education is a mere reflection of innate ability (Stiglitz, 1975). Schools only translate the ability into levels of educational achievement that act as a signal in the labor market.

More contemporaneous models derive mainly from the skill acquisition model developed by Cunha and Heckman (2007) and Cunha et al., (2010). They draw from research in disciplines such as psychology and neuroscience to establish a multi-stage model that explains skill formation throughout the life course. Skills are multifaceted, ranging from cognitive to non-cognitive skills –called personality traits in psychology- such as motivation and self-control (Cunha and Heckman, 2007). The production function of the model establishes that the skills acquired in the second stage are a function of innate skills and parental investments made during the first stage. This dynamic process is repeated throughout the life cycle.

The process of skill acquisition has three main properties: self-productivity, cross-productivity and dynamic complementarity (Cunha et al., 2006). Self-productivity implies that having more developed skills at an early stage boost acquiring more skills in later stages. For example, being able to do basic math operations at an early age will facilitate learning more complex operations in the future. Skills beget (more of the same) skills. This property suggests that skill gaps at an early age grow over time if there are no further interventions. Cross-productivity suggests that the increase of one skill also fosters other skills, i.e. skills beget other skills. Finally, dynamic complementarity means that investments made during the early stages enhance the productivity of later investments –i.e. the effect is non-linear (Heckman, 2007). Therefore, all these properties have to be taken into account when disentangling the dynamics of skill formation.

The stage at which cognitive and non-cognitive skills are formed varies between the two. While cognitive skills are very malleable at a very early age during childhood and stabilize at the beginning of adolescence, non-cognitive skills develop a bit later, throughout childhood and adolescence, after this, changes are very modest in both

(Cunha et al., 2010; Cobb-Clark and Schurer, 2012; Hsin and Xie, 2017).[2] Thus, one of the most important implications is the importance of early stages, which is why scholars in this literature insist on the relevance of early-childhood interventions to narrow skill gaps and foster future talent (Heckman and Mosso, 2014; Cebolla-Boado et al., 2016).

2.2. Non-cognitive skills and educational attainment

Skills are usually divided between cognitive and non-cognitive, as explained in the previous section. Cognitive skills, i.e. intelligence, have been present in human capital theories since the beginning (Becker, 1964; Stiglitz, 1975). Its effect on future life outcomes is very straightforward: individuals with higher IQ (the classic measure of cognitive skills) have important rewards in terms of wages and other life outcomes (Hanushek et al., 2015). However, there are other skills that are also relevant for those outcomes and cannot be measured with IQ tests. Thus, the concept of non-cognitive skills emerged in opposition to cognitive skills, due to the need to label certain neglected traits that are relevant for life outcomes. Bowles and Gintis (1976) were among the first scholars in proposing that non-cognitive skills such as motivation and perseverance play a very important role in determining life outcomes. Building on research in psychology on personality traits, a lot of attention has been paid to this topic in economics and sociology since the beginning of the new millennium (Heckman, 2000; Heckman and Rubinstein, 2001; Farkas, 2003).

Many studies have shown the predictive power of non-cognitive skills for different spheres of life outcomes such as education, labor market or health (Heckman et al., 2006; Carneiro et al., 2007; Almlund et al., 2011; Heckman and Kautz, 2012). Furthermore, there is evidence of the rising returns of non-cognitive skills in recent years (Deming, 2017; Edin et al., 2017). Focusing on the effect to non-cognitive skills on educational attainment, there is ample evidence of the positive impact of a wide variety of non-cognitive skills in different contexts. For example, Duncan et al. (2007) analyze six studies that use different longitudinal data sets and find that attention skills are a significant predictor of academic achievement. However, other socioemotional skills are

[2] The stability of non-cognitive skills is not entirely settled. For example, Kautz et al. (2014) perform an intervention and find that non-cognitive skills are responsive even during adulthood.

not. On the other hand, Duncan and Magnuson (2011) find that in the US several skills such as self-regulation, behavioral problems, emotional regulation and motivation positively predict school completion. Smithers et al. (2018) carry out a large meta-analysis taking into account experimental studies on the effect of non-cognitive skills on educational achievement. They find a positive effect of non-cognitive skills on academic achievement. The magnitude of the effect is 0.2-0.4 Standard Deviation for most studies. However, the effect is very heterogeneous due to the vast array of non-cognitive skills used. In the case of some skills, the effect is null or even negative.

As we have seen, the term "non-cognitive skills" comprises a wide range of concepts very different between them. Here, we are going to focus on those non-cognitive skills conceptually close to effort. The first one is *conscientiousness*, a factor that belongs to the Big Five personality traits, a very common measure of non-cognitive skills developed by psychologists (Costa and McCrae, 1992). Conscientiousness is defined as "the tendency to be organized, responsible, and hardworking".[3] Several studies have shown that it is the Big Five trait that best predicts educational attainment (Almlund et al. 2011, Shanahan et al, 2014). Poporat (2009) conducts a meta-analysis of the Big Five personality traits as predictors of school grades in primary, secondary and tertiary education. They find that, not only is conscientiousness the best predictor among the Big Five, it is increasingly important throughout the educational career, reaching its peak during college. Remarkably, in that stage, conscientiousness is an even better predictor of school grades than intelligence. This is not the only study arguing that conscientiousness is as important or even more than intelligence for educational outcomes. Almlund et al. (2011) also show that conscientiousness is as influential as intelligence when predicting years of schooling. In another meta-analysis, Richardson et al. (2012) confirms the importance of conscientiousness on educational outcomes and argues that its impact could be mediated through effort regulation. This concept is understood as motivation and persistence when facing difficult work (Pintrich, 2004). The correlation between both concepts is significantly large (around 0.5), and the

[3] By the American Psychology Association Dictionary.

authors argue that effort regulation could be an aspect of conscientiousness (Richardson et al., 2012).

Locus of control (LOC) is another non-cognitive skill close to effort that has been widely used in economics (Heckman et al., 2006; Borghans et al., 2008; Cobb-Clark and Tan, 2011).[4] It refers to the individual's belief that life outcomes depend on his own action –internal LOC- versus the perception that those outcomes are out of his hands –external LOC. A number of studies find that individuals with more internal LOC are more likely to graduate from high school even after controlling for cognitive skills (Coleman and DeLeire, 2003; Cebi, 2007; Baron and Cobb-Clark, 2010). Moreover, it has been shown that the positive impact of internal LOC on wages is mainly mediated by the increasing probability of getting higher education (Piatek and Pinger, 2016). There are many other non-cognitive skills that reflect some aspects of effort and are positively related to educational outcomes. For example, Duckworth et al. (2010) and Hsin and Xie (2017) find that self-control, the ability to inhibit certain behavior, predicts school grades and future educational attainment. Similarly, Duckworth and Seligman (2005) and Duckworth et al. (2007) using two other skills, self-discipline and grit, also show their positive impact on academic performance and school completion. Finally, Zhou et al. (2010) test the impact of effortful control, defined as the efficiency of executive attention, including the ability to inhibit a dominant response, on academic achievement. They find that effortful control positively predicts future Grade Point Average (GPA), even after controlling for initial GPA.

2.3. Measurement challenges and alternatives

The distinction between cognitive and non-cognitive skills is not as straightforward as it seems. Many of the traits considered non-cognitive are not even skills and some are related to cognitive processes (Borghans et al., 2008). Executive function comprises a set of top-down cognitive processes needed to control certain behaviors (Diamond, 2013). There are at least three executive functions: inhibitory control, working memory and cognitive flexibility. Inhibitory control refers to the capacity to control one's

[4] Scale created by Rotter (1966).

attention, behavior and ignore external stimuli to do what is required (Diamond, 2013). This is really similar to some constructs classified as non-cognitive skills such as self-control and effortful control. The fact that some non-cognitive skills actually reflect cognitive processes does not impede distinguishing them from intelligence. This is because fluid intelligence is closely related to working memory, a different executive function (Heitz et al., 2005). Both processes, although complementary, are separated in the brain and thus, we are able to differentiate them (Garon et al., 2008). Indeed, there is evidence showing that children with ADHD, that have problems with inhibitory control, are not different from other children regarding IQ - as a measure of fluid intelligence (Schuck and Crinella, 2005). Nevertheless, although theoretically intelligence and non-cognitive skills come from different executive functions, we are constrained in measuring them directly. We have to rely on cognitive tests and scale self-reports to measure them, and the problem is that non-cognitive skills influence the performance on IQ tests and the other way around (Kyllonen and Kell, 2018). Recent research shows that the association between cognitive skills and non-cognitive skills is not very large (Rammstedt et al., 2018). Openness has the highest correlation with fluid intelligence, 0.15, and the correlation with the other Big-Five trait conscientiousness is even negative, -0.17. Nevertheless, this negative association is challenged by other studies (Murray et al., 2014).

Another potential problem of measuring non-cognitive skills with self-reported scales is that they also capture contextual effects such as the conditions in which the individuals complete the questionnaire or whether they are incentivized. The effect of the conditions is relatively large, ranging from 0.05 to 0.11 Standard Deviations (Chen et al., 2020). Furthermore, the respondents might be subject to potential biases such as "social desirability bias" or "reference bias" (Duckworth and Yeager, 2015). One alternative is to rely on others to rate the individual, but this also has its own problems. First, it is very likely that even close persons like parents or teachers do not have complete information on the subject. Second, they are also subject to potential biases related to an individual's characteristics -such as gender or age- or their relationship with him. Conelly and Ones (2010) find that the correlation between self-reported non-cognitive skills and others' rating of the same skills is not very high, ranging from 0.29 to 0.41.

A new strand of research has focused on the measurement of non-cognitive skills in a different way. As we cannot be certain that the individual's response in the self-reported questionnaire would be translated into actions, it might be a good idea to measure what they actually do. Applied economists have used response patterns in standardized tests and surveys to measure non-cognitive skills because they reflect how individuals behave (Borghans et al., 2016). For example, Borghans and Schils (2012) use the PISA test to measure the persistence of the students. The test lasts 2 hours and the order of the questions is random so they can observe that there is a steady decline of performance throughout the test as students get tired or distracted. They show that the individual measure of test effort is correlated with conscientiousness and predicts life outcomes such as life satisfaction and drinking behavior. Zamarro et al. (2019) also use two other variables that reflect the effort that students exert in answering the PISA survey. The first one is the item non-response rate, i.e. when students skip the question or answered "I don't know". The second is careless answering patterns, which takes place when students inconsistently answer questions that are very similar and deal with the same topic in a different way. They find that these measures of effort explain an important part of the variance in PISA results across countries, between 32 and 38 percentage points. Moreover, Hitt et al. (2016) show that item response rate positively predicts educational attainment and labor market outcomes. Another similar variable derived from standardized tests is response time effort, assuming that when individuals spend more time answering one question it is because they are exerting more effort. Indeed, Silm et al. (2020) perform a literature review of the studies using that variable a as predictor of performance and find that the average correlation between the two is .72, which is strikingly high, especially if we compare it with the correlation between self-reported effort and performance, 0.33. However, these measurements are not exempt from criticism. The main one is that they are taken on low-stakes exams such as PISA. Thus, individuals might not exert their maximum effort because the result does not reward them directly. Gneezy et al. (2019) find that the PISA score gap between the US and China disappears when introducing extrinsic incentives for the students to perform.

Another alternative stems from the behavioral revolution in economics. Researchers measure behavior and preferences in a controlled environment and subjecting the individuals to different incentives and conditions. In this vein, recent research has compared self-reported non-cognitive skills usually related to effort such as conscientiousness and locus of control with an experimental measure of cognitive effort. Cognitive effort is measured in the lab under controlled conditions and using different real-effort tasks. The authors show that the correlations between the self-reported and the experimental measures are low or even inexistent (Apascaritei et al., 2021). The artificial conditions of the lab are one of the most common criticisms of this line of research, questioning the external validity of the results. Nevertheless, it is a promising avenue for future research because it helps us to better measure and understand these fuzzy skills.

3. Intergenerational transmission of educational inequality

The intergenerational transmission of inequality is a key research theme in the social sciences, especially in sociology. Social fluidity has great importance for assessing the degree of equality of opportunity that is realized in society and for studying the mechanisms that allow the transmission of advantage (Bowles and Gintis, 2002; Erikson and Goldthorpe, 2002). A lot of emphases has been put on education as one of the major determinants of social mobility. There is abundant evidence showing that it is mainly through educational attainment that parental socioeconomic background finds its way to express itself in the offspring's life outcomes (Breen and Jonsson, 2005). Therefore, the study of educational stratification has become central to understand how inequality is transmitted through generations (Jackson et al., 2005). There are several channels that transmit the advantage, such as social networks, cultural assets or cognitive advantage.

Drawing from Boudon (1974)'s influential approach we can distinguish two different effects through which social inequality is transmitted between generations through education. The primary effect is the advantage on academic achievement that individuals from high socioeconomic status (SES) families enjoy. Children from families with more socioeconomic resources tend to perform notably better than their less-fortuned counterparts (Erikson and Goldthorpe, 2002). The secondary effect refers to the influence of SES background on choices over children's educational careers. Children with high SES parents are more likely to advance to higher levels of the educational trajectory than less-advantaged children even after controlling for academic achievement (Jackson et al., 2007). This might be due to different preferences, attitudes towards risk and ability to cover the economic costs of upper education (Breen and Goldthorpe, 1997). Furthermore, a recent strand of research has identified a tertiary effect, consisting in how the misjudgments of teachers due to students' socioeconomic characteristics might benefit high SES students in their educational trajectories (Jæger and Møllegaard, 2017; Gil-Hernández, 2021). For example, teachers tend to confuse cultural habits with academic ability (Jæger, 2011).

3.1. Theories of social stratification

There are several sociological theories that explain the transmission of educational inequality through generations. However, each theory posits its own mechanism of functioning. One of the most prominent theories is the Cultural Reproduction Theory outlined by Bourdieu and Passeron (1977) which explains how social stratification is transmitted through generations. They argue that high SES families possess a certain level of cultural capital that signals their high status on the socioeconomic ladder. This is transmitted effortlessly to the offspring, helping them to reproduce their privileged socioeconomic status. One of the problems of this theory is that it lacks clarity. It does not delimit what cultural capital is and how the specific mechanisms that transmit cultural capital work. Lamont and Laureau (1988) define cultural capital as "high-status cultural signals (attitudes, preferences, formal knowledge, behaviors, goods and credentials) used for social and cultural exclusion". Following that definition, Jæger and Breen (2016) differentiate three states of cultural capital: embodied (attitudes, knowledge and preferences), material resources (books, art, music) and institutionalized (educational credentials). What is clear is that, for Bourdieu, education is the key pillar in the mechanism of social reproduction because it is where cultural capital is transformed into educational advantage. There are two views on how cultural capital impacts educational attainment. Bourdieu (2006) suggests that cultural capital works as a signaling device. Teachers might confuse cultural capital with ability, good attitude towards school or effort, translating that into better grades (Jæger and Breen, 2016). The other interpretation posits that cultural capital enhances skills such as creativity or reading comprehension that help children in the educational context (Kingston, 2001; Sullivan, 2001).

The evidence on the interpretations is somehow mixed. Some studies find that teachers' judgment is biased by cultural capital, confusing it with academic ability or effort, and benefiting those from higher SES families (Dumais, 2005; Jæger and Møllegaard, 2017). On the other hand, a couple of studies show that cultural capital does not influence teachers' evaluations of skills. However, skills fostered by cultural capital such as reading interest have a positive impact on education (Jæger, 2011; Breinholt and Jæger; 2020). Somehow in between, Mikus et al. (2020) explain that both channels –skill formation and signaling- are at work. Using reading behavior and consumption of beaux-arts as proxies of cultural capital, they find that the previous measure is positively associated with standardized test scores and the latter measure has also a positive correlation with school grades, net of skill.

According to the Wisconsin model, another classical theory, social influence shapes the way in which individuals think about educational opportunities (Sewell et al., 1969). At the core of the model are educational expectations, which are developed through social relationships with significant others, such as parents, friends, and teachers.[5] Thus, individuals that come from highly educated families, usually also attend schools where the SES is higher than on average, and that environment will strengthen their belief that the standard is to get tertiary education. On the other hand, less-advantaged individuals will grow up in a very different environment, where few or no significant others have higher education. Therefore, their conception of higher education will be that it is very difficult to achieve and the possibilities are low. There are two different mechanisms through which individuals' expectations are influenced by others (Sewell et al., 1970): The first one is adoption: it refers to the influence that parents, teachers and other hierarchical figures have on children who tend to adopt the expectations that these role figures have about their educational career. The second is imitation, which corresponds to the influence of friends and peers, i.e. other equals, on children's educational expectations. If they perceive that most classmates intend to attend college, it is very likely that they'll have the same objective. There is recent empirical evidence of both mechanisms, adoption (Bozick et al., 2010) and imitation (Raabe and Wölfer, 2019).

[5] Educational expectations and aspirations are used interchangeably in this literature. See, for example, Bozick et al. (2010), Domina et al. (2011) or Zimmerman et al. (2020).

Furthermore, educational expectations are quite stable over time and do not really update with new school information, especially for high SES children (Gabay-Egozi et al., 2009; Andrew and Hauser, 2011).[6] Then, higher educational expectations will be translated into achieving higher educational attainment, as a self-fulfilling prophecy (Haller and Portes, 1973; Messersmith and Schulenberg, 2008). There are two mechanisms through which expectations can impact future educational attainment. First, it might have a direct impact on educational achievement, for example, through effort. As individuals expect to attend higher education, they exert more effort in school activities to accomplish their expectations (Domina et al., 2011). Second, by choice during the transition to higher education.

During the last decades, Rational Choice Theory has gained a lot of traction in many fields of sociology (Hedström and Stern, 2008) and one of these fields has been educational stratification. Breen and Golthorpe (1997), using the rational action perspective, develop a model that explains educational differences (Erikson and Jonsson, 1996). They argue that individuals and their families (largely) act rationally when choosing future educational trajectories. Individuals calculate the potential costs and benefits of each option, weighing the probabilities of the outcomes and acting accordingly. In Boudon's terms, the secondary effect outweighs the importance of the primary effect. The key mechanism in this theory is relative risk aversion, which posits that the main goal of individuals is to avoid downward mobility. Thus, children from highly educated families will be more ambitious than less-fortunate children in pursuing higher education to achieve at least the same level of education as their parents. Furthermore, children and families from less-advantaged backgrounds tend to perceive higher financial costs from attending higher education and find lower probabilities of success. Numerous studies have found empirical evidence for this theory. Indeed, children from low SES families think that they have lower probability of succeeding and that higher education is more costly than high SES children (Tolsma et al 2010; Schindler and Lörz, 2012). Furthermore, these perceptions are good predictors of

[6] This is challenged by the Bayesian learning theory (Morgan, 2005). This approach argues that educational expectations are formed by a rational calculation of probabilities taking into account performance in school and they update when new information appears. There is also evidence of deprivation of expectations in difficult contexts, such as economic crises (Salazar et al., 2020).

enrollment in higher education (Daniel and Watermann, 2018). Holm et al. (2019) find that students who receive a positive signal about their academic ability are more likely to enroll and complete college than those who do not receive it. Interestingly, the effect of the signal is stronger for low SES students, although only for enrollment, not completion. However, the importance of the secondary effect for class differentials in educational attainment is still up to debate. For example, Jackson et al. (2007) show that the secondary effect accounts for between one quarter and half of the educational inequality.

3.2. Transmission through non-cognitive skills

The relevance of non-cognitive skills for educational stratification was highlighted by Farkas (2003). Thanks to the recent attention to the importance of non-cognitive skills on future life outcomes, many researchers have focused on its role in the intergenerational transmission of inequality (Blanden et al., 2007). However, it was already when Bowles and Gintis (1976) made the case for the importance of non-cognitive skills that they warned about the potential transmission between parents and children. They argued that through parenting behavior they could transmit non-cognitive skills to their children. Indeed, Zumbuehl et al. (2021) find that those parents that are more involved in the upbringing of their children are more similar in terms of non-cognitive skills. However, other mechanisms such as socioeconomic resources, genetic inheritance and role-modeling also play a role in the transmission (Duncan et al., 2005). Recent studies show that the correlations between parents and children are not very high. For example, Loehlin (2005), using the Big Five personality traits as measures of non-cognitive skills in the US, shows that correlations range from 0.09 to 0.17. Similarly, Anger (2012) finds that in Germany the correlations between parents and children range between 0.12 and 0.24 during adolescence and between 0.19 and 0.24 during adulthood. This suggests that non-cognitive skills continue to develop during adolescence and they do not stabilize until early adulthood. In this context, Grönqvist et al. (2017) using Swedish register data find significantly larger intergenerational correlations of non-cognitive skills, around 0.42. They argue that it is because they correct for measurement error that they obtain such a significant magnitude.

Other researchers have studied the influence of SES parental background on the development of non-cognitive skills as a potential channel of the transmission of advantage. In a previous section, we have seen that there is plenty of evidence of the importance of non-cognitive skills for future life outcomes. Hence, if parental SES favors the development of those skills, they would constitute a mediator between social origins and life outcomes. Blanden et al. (2007) observe a positive correlation between parental income in the UK and non-cognitive skills, particularly with internal LOC. Similarly, Anger (2012) also suggests that there are differences by SES in some non-cognitive skills such as LOC and the Big Five personality traits in Germany. However, the differences are not statistically significant. For the same country, Kaiser (2017) obtains that focus, an important facet of conscientiousness, is strongly influenced by mother education. For Mexico, Campos-Vazquez (2018) reports that belonging to a high SES family is positively associated with having a more internal LOC and lower risk aversion. Overall, there seems to be consensus on the positive impact of SES on non-cognitive skills, although the magnitude of the effect is not very clear.

Nevertheless, to confirm the role of non-cognitive skills as a mediator between SES parental background and children's educational attainment it is necessary to test both links at the same time with structural equations. Mood et al. (2012) do so by employing Swedish registry data to test the mediation. They find that non-cognitive skills do indeed mediate between SES and educational attainment. However, the effect is somehow weak in comparison with cognitive skills, which are the main mediating factor. Kaiser and Diewald (2014) use German data to test the potential mediation of children's conscientiousness between parental education and school grades. They show that focus, a facet of conscientiousness, accounts for around 20% of the total effect of parental education on math and German grades. Also in the German context, Holtmann et al. (2021) test the potential mediation of a wide range of non-cognitive skills. However, they find that none of those skills are significant mediators, only educational aspirations are. Another study carried out by Hsin and Xie (2017) in the US reports a significant mediating effect of non-cognitive skills between SES and educational achievement. The magnitude is not very large but it grows with age, reaching the maximum in adolescence, around 13% of the total effect. Therefore, there is mixed evidence about the mediating role of non-cognitive skills in the intergenerational transmission of education, ranging from non-significance to a noticeable, although not large, effect.

Another way through which SES can contribute to the transmission of educational inequality is moderation. This refers to when SES influences the impact of some covariate, non-cognitive skills in this case, on educational attainment. We can differentiate between two potential mechanisms contributing to the transmission: First, compensatory advantage posits that high SES parents compensate for the potential problems that their children might have at the early stage of their educational trajectory thanks to their socioeconomic resources (Bernardi, 2012). Thus, they will be less penalized by certain obstacles than less-advantaged children. Second, the Matthew effect states that children from SES families benefit more from having the same level of skills as other children, accumulating the advantage (Damian et al., 2015). In the context of non-cognitive skills, there is mixed evidence of both mechanisms. For example, Shanahan et al. (2014) find evidence of resource substitution- an alternative explanation to compensatory advantage for observing the same dynamic- in certain non-cognitive skills when predicting educational attainment. Similarly, Damian et al. (2015) also report the same finding, but when they control by cognitive skills only conscientiousness appears to be mediated by SES as a compensatory advantage. In the same vein, Liu (2019) finds evidence of the same mechanism for educational achievement in the US. Finally, both Gil-Hernández (2021) and Holtmann et al. (2021) show for the German context that compensatory advantage is at play. However, they use different outcomes, the former study the transition to secondary education and the latter educational attainment. Furthermore, Holtmann et al. (2021) also find that for certain non-cognitive skills such as prosocial behavior and agreeableness the Matthew effect is the predominant mechanism. Overall, compensatory advantage seems to be the main moderating mechanism between SES and educational attainment as it has been shown in different contexts.

3.3. Institutional framework

In individual-level models that explain educational stratification, the macro-level –i.e. institutions and educational policies- also shapes the opportunities that individuals enjoy (Breen and Jonsson, 2005). Academic outcomes and educational choices made by students and their families interact with the particular environmental conditions that they experience such as the educational policies in place, the structure of the educational system or the quality of the neighborhood' school. Indeed, a significant part of the cross-country variation in educational inequality is explained by the differences in the educational context (Pfeffer, 2008). Since educational spending is one of the largest components of government budgets, a lot of attention has been brought to the efficiency of the amount spent. This is particularly relevant due to the inconclusive debate about the impact of increasing educational spending on educational outcomes (Hanushek, 2003). Nevertheless, in the last years, several studies have appeared arguing about the importance of having well-funded schools for academic outcomes (Lafortune et al., 2018). In some countries such as US, schools are funded with local taxes, so poorer areas had worse-funded schools. Looking at reforms that increase school spending, they find that it improves wages, increases college enrolment and years of education completed (Jackson et al., 2015; Hyman, 2017). Larger school spending had a positive impact on school quality by improving teacher-student ratios and increasing teacher salaries (Frediksson et al., 2013; Jackson et al., 2015). Furthermore, more resources benefit particularly students from low SES families, improving their educational and economic outcomes, besides lowering their probabilities of incarceration (Johnson and Jackson, 2019).

But the impact of the environment is not limited to school quality. Neighborhood effects are very complex and matter a lot for life outcomes (Chetty and Hendren, 2018). In contexts where economic inequality is high, that is translated into increasing educational inequality by a feedback loop consisting in more residential segregation as high SES parents want to raise their children in better neighborhoods (Fogli and Guerrieri; 2019). One of the reasons why they move to better neighborhoods is to shape their children's peer group (Agostinelli et al., 2020). Peer effects have been found to exert a significant impact on students' academic outcomes, although the magnitude is still up to debate (Sacerdote, 2011; Paloyo, 2020). Generally, having peers from higher SES background and high achievers have a positive impact on academic achievement (Ammermueller and Pischke, 2009; Burke and Sass, 2013). Moreover, low-achieving students are the most benefited from the positive influence of high-achieving peers (Schneeweis and Winter-Ebmer, 2007; Rangvid, 2008).

There are many parameters that depend on the organization of the educational system that influence the calculations and educational choices of families. The perceived costs of attending, the probabilities of succeeding, and the age at which certain decisions have to be taken differ significantly from one country to another. One of the institutional characteristics that have received more attention in research is educational tracking (or ability grouping), and specifically the age at which students are placed in different educational tracks (Van de Werfhorst and Mijs, 2010). A significant amount of studies find that having tracking at an early age increases inequality of educational opportunity because the effect of family background on educational attainment increases significantly (Schütz et al., 2008; Horn, 2009; Heisig et al., 2020). When tracking placement takes place at a younger age the influence of parents is larger, especially if the teacher's recommendation is not binding, because, irrespective of achievement, highly educated parents usually choose that their children attend the academic track (Checchi and Flabbi; 2007). Furthermore, there is also evidence that those students that are at the margin but end up in academic tracks achieve a higher educational degree and a better wage than those going to lower tracks (Borghans et al., 2019). However, some studies argue that although early tracking worsens equality of opportunity it improves equality of outcomes (Brunello and Checchi, 2007; Bol and Van de Werfhorst, 2013). They find that in countries with early tracking the allocation of individuals in the labor market is improved thanks to their vocational training, which translates into higher wages (Österman, 2018).

Different institutional characteristics can interact creating a new effect. For example, Bol et al. (2014) explain that the influence of socioeconomic background on educational achievement in early-tracking countries is attenuated if the country performs central examinations. They argue that central examinations test accountability, hence, schools are incentivized to allocate students to objective indicators and to invest in low-tracked students. Regarding grade repetition, Salza (2022) finds that early-tracking exacerbates the already existing SES gradient in repeating probabilities. He explains that the differences by SES in grade repetition probabilities are even higher in academic tracks.

4. Overview of the chapters

In this section, I will provide a summary of the following chapters contained in this thesis. In Chapter 2, I examine the role of effort as a determinant of educational attainment. To do so, I use a proxy of effort that was recently developed to measure effort exerted in the PISA test. This contrast with the approach of non-cognitive skills proxies, such as conscientiousness of locus of control, that are measured by self-reports. Thus, the first aim is to study the impact of exerted effort on future educational attainment. Furthermore, the chapter also investigates the role of effort in the transmission of educational inequality. As outlined above, two sociological theories posit different mechanisms through which inequality could be transmitted by the mediation of effort. The Cultural Reproduction Theory (CRT) claims that children from high SES families inherit cultural resources, behaviors and attitudes that help them in future life outcomes, and attitudes towards effort could be one of those. Therefore, the second objective is to test the mediation of effort between parental SES and educational attainment. The Wisconsin status attainment model states that the central pillar for educational attainment is educational expectations. Those children from high SES families adopt high expectations from their parents and social environment, which leads them to achieve the expectations. The last objective is to study whether effort mediates between educational expectations and educational attainment. I use the Longitudinal Surveys of Australian Youth (LSAY), an Australian longitudinal database that follows the individuals who participate in the PISA test 2003 during the next 10 years. The results provide evidence of the positive impact that test effort has on the completion of tertiary education 10 years later. Furthermore, it seems that effort does mediate between educational expectations and educational attainment, but not between parental SES and educational attainment. This suggests that effort contributes to the transmission of inequality through the mechanism outlined by the Wisconsin model.

Chapter 3 addresses the effect of social influence on effort in a cross-country study. More specifically, I use peer effects as a proxy of social influence in school since it has been shown that it is an important determinant of educational attainment. In this chapter, I propose that effort might be one of the channels through which peer effects influence educational attainment. The mechanism stems from the Wisconsin model, which states that individuals tend to imitate the educational expectations of their school peers. Therefore, if an individual has peers with high parental SES, he/she will develop higher expectations, and thus, exert higher effort in educational activities to accomplish the expectations. To test the mechanism, I analyze the influence of having high SES peers in school on effort. Furthermore, I study the potential asymmetry of the effect and the impact of peer heterogeneity. Finally, I explore the peer effects in different educational tracks. As in Chapter 2, I use the variable of test effort constructed with PISA 2012. The results provide support to the suggested mechanism. The impact of having high SES peers on test effort is significant and the magnitude is quite large in comparison with other covariates. Moreover, the impact is homogeneous throughout the distribution of effort. Peer heterogeneity in school affects negatively effort, but the magnitude is very small. The results also show that the importance of peer effects is similar for students in comprehensive tracks and vocational tracks, but the effect disappears for students in the academic track.

Chapter 4 studies again the importance of effort for educational attainment. In contrast to Chapter 2, this paper uses a novel and objective measure of cognitive effort that derives from an experiment with primary students that perform three different real-effort tasks. The new measure is very comprehensive because it taps into different executive functions and has strong claims of validity. Additionally, another measure of effort is used for comparison, namely teacher-perceived effort. This measure is significantly more subjective but very important for the educational achievement of students since teachers also grade them. Hence, I analyze the impact of these two different measures of effort on school grades. Furthermore, I keep the focus on the potential role of effort as a contributor to the transmission of inequalities. Here, I study two potential mechanisms: compensatory advantage and teacher bias. Compensatory advantage states that high SES families might compensate for potential setbacks that their children suffer during childhood. I propose that students from high SES families that exert low effort could be compensated by their parental resources such as having more help while doing homework or hiring private tutors. Therefore, high SES students would be less penalized on school grades by the low level of effort than their poorer counterparts. The second mechanism derives from CRT and the literature that finds teachers to be biased when they judge the students due to their socioeconomic characteristics. Hence, it is possible that teachers penalize less-advantaged students more than richer students when they perceive low effort. This might be due to unconscious bias or because they consider other characteristics derived from the SES as relevant for grades. The results show a strong and positive effect of both cognitive and teacher-perceived effort on school grades. In the case of cognitive effort, its magnitude is similar to or even larger than the effect of cognitive skills, considered one of the key determinants of academic achievement. The effect of teacher-perceived effort is even larger, between two and three-fold the size of cognitive skills. This suggests that teachers are also influenced by other factors when they judge the effort exerted by students. Regarding the mechanisms that could moderate the effect of effort, the findings do not provide evidence for the existence of compensatory advantage with cognitive effort. Indeed, its effect is independent of parental SES. However, the interaction between parental SES and teacher-perceived effort is significant and negative as expected. Low SES students are more penalized than their richer counterparts on school grades when teachers perceive that they exert low effort.

Finally, in the conclusion I summarize all the relevant results of the thesis, putting them in context. Furthermore, I discuss the potential implications of the findings for the theoretical debate about equality of opportunities and the understanding of the intergenerational transmission of inequality. Limitations and future avenues of research are also addressed.

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Chapter 2
Strive to succeed? The role of persistence in the process of educational attainment

1. Introduction

Effort is often viewed as one of the main pillars of a meritocratic society. In this context, Michael Young coined the term meritocracy, meaning a system in which socioeconomic status is determined by the sum of intelligence and effort.[7] The concept of meritocracy is the idealistic basis of Western society, although we know that in reality, social mobility is also shaped by inequality (Bowles and Gintis, 2002). Hence, in the original conception of meritocracy, it is argued that the inequality that arises from differences in intelligence and/or effort is fair, assuming that intelligence and effort depend only on the individual. For example, in the debates surrounding the existing meritocracy in the UK between Saunders (1995, 1997) and Breen and Goldthorpe (1999, 2002), the authors argue about the extent to which social mobility is explained by those two variables relative to the influence of parental background. However, we do not know much about effort and its determinants since little research has been conducted on the topic, partly because of the difficulty in measuring it.

This paper examines the role of effort in the process of educational attainment over the life course. Constituting a black box that is not yet fully understood, the transmission of social inequality has always been a main topic in sociology (Breen and Jonsson, 2005). Therefore, this paper attempts to shed light on the mechanisms through which effort impacts future educational attainment and the extent to which effort might constitute a factor that tends to perpetuate social inequality across generations. To explore this previously neglected research gap, I investigate the potential socioeconomic gradient of effort and its impact on education, since educational attainment is considered the main

[7] The term was coined in the book “The Rise of Meritocracy” published in 1958.

mediating factor in class mobility by many scholars (Ishida et al., 1995; Marshall et al., 1997; Erikson and Goldthorpe, 2002). Hence, if the socioeconomic background of children plays a role in the effort they exert, as some sociological theories suggest (Bourdieu and Passeron, 1977), this might constitute one of the channels through which social inequality is transmitted across generations (Radl and Miller, 2021).

The Wisconsin status attainment model developed by Sewell, Haller and Portes (1969) provides an explanation for the determination of educational attainment. In this seminal model, the main explanatory factor is the student's educational expectations since they are shaped by parental socioeconomic backgrounds and social relationships. In this context, effort acts as the mediator between educational expectations and educational attainment, as higher expectations should incentivize children to put more effort into education-related activities and thus achieve better grades. Hence, I analyze the importance of effort as a predictor of tertiary education. Furthermore, I test whether effort transmits educational inequality due to (a) parental education and (b) educational expectations.

Despite the difficulties in measuring non-cognitive skills (called personality traits in psychology), in recent years, numerous scholars have shown their importance in predicting future life outcomes such as educational attainment or occupation (Heckman et al., 2006; Blanden et al., 2007; Roberts et al., 2007)). Some of these self-reported traits, such as *locus of control* (LoC) or *conscientiousness,* are similar to some aspects of effort but do not constitute a complete measure of it since they rely on self-reporting, and there might be differences between saying and doing (Apascaritei et al., 2021).[8]

Here, I use an alternative measure of effort, directly observed while being exerted during the Programme for International Student Assessment (PISA) test, a program carried out by the OECD. Borghans et al. (2016) show that exams capture both cognitive and non-cognitive skills. The measure that I use, originally developed by Borghans and Schils (2012), is based on decreases in performance throughout the test, which are

[8] Locus of Control and Conscientiousness are psychological constructs. LoC is the perception of control over the outcomes during your life course created by Rotter (1966). Conscientiousness is one of the Big Five personality traits. It reflects self-discipline and diligence.

observable in most test results. They show that this measurement is related to some non-cognitive skills such as LoC and to future life outcomes. Furthermore, this measure of declining effort has also been shown to account for a significant part of the variation across countries in PISA test scores (Debeer et al., 2014; Zamarro et al., 2019). Following Azzolini et al. (2019), I argue that the measure that I use reflects one key aspect of effort: persistence. For example, keeping up a certain level of effort is crucial for studying or performing well on exams. Hence, this measure of effort exerted while individuals complete the PISA test allows us to analyze the impact of this key element.

I use the Longitudinal Surveys of Australian Youth (LSAY), an Australian longitudinal dataset that follows the participants of the 2003 PISA test for the next 10 years. This allows for tracking individuals beginning when they were 15 years old and observing how variables such as effort, educational expectations and parental education at that age have influenced their educational outcomes years later. I find that the measure of effort I use has a positive and significant association with the probability of having obtained a tertiary degree ten years later. I also observe that parental education and students' own educational expectations have significant and strong positive effects on student effort, especially the latter. However, the effect of effort as a mediator between parental education and future educational attainment is not significant. In contrast, I find that effort mediates educational expectations and the probability of having completed tertiary education in the future.

The paper is structured as follows. Section 2 summarizes the relevant literature on the determinants of future life outcomes, the determinants of the transmission of educational inequality and the Wisconsin model of educational attainment. Section 3 provides details about the LSAY dataset, explains the construction of the effort measure and presents the methodological strategy. Section 4 explains the results and discusses the implications for the tested hypothesis. Finally, the last section provides a summary of the conclusions.

2. Literature and hypothesis

2.1. Later life outcomes

Over the last few years, an important strand of literature has emerged, both in economics and to a lesser extent in sociology, which explores the importance of cognitive and non-cognitive skills for life outcomes. There is robust empirical evidence showing that both cognitive and non-cognitive skills have a significant influence on educational attainment and future employment (Bowles et al., 2001; Heckman et al., 2006; Blanden et al., 2007, Carneiro et al., 2007).

The impact of cognitive skills is more straightforward and has been more widely studied than that of non-cognitive skills (Boissiere et al., 1985; Farkas and Vicknair, 1996). One of the reasons is that the use of IQ as a measure of cognitive skills is highly standardized and available in many surveys. Another reason is that the channel through which cognitive skills have a positive impact on future life outcomes is more intuitive. A higher IQ improves educational attainment, which enhances the probability of getting a better job in the future.

Research on non-cognitive skills such as effort, leadership, and extraversion has shown that they might also positively influence educational attainment (Groves, 2005; DiPrete and Jennings, 2012). However, the effect of these traits is more difficult to measure since there is no standardized way to do so. Most research concerning non-cognitive skills uses psychological measures as a proxy. For example, Heckman et al. (2006) and Hall and Farkas (2011) use self-esteem and the locus of control; Borghans et al. (2008) use risk preferences, motivation and the Big Five personality traits; Hsin and Xie (2017) use the Social Ratings Scale. In the previous articles, a higher level of conscientiousness and a more internal LoC (the concepts closest to effort) are associated with a higher level of educational attainment in the future. However, these proxies capture very different aspects of human personality, as for instance, some aspects measured by conscientiousness differ from those captured by the locus of control. Hence, the channels through which these non-cognitive skills influence future life outcomes are not sufficiently well understood. To make a clear case, I focus on one selected non-cognitive skill, namely, effort. Furthermore, it is interesting to use a directly observable measure because differences between self-reports and actually what people do might exist, as Apascaritei et al. (2021) show.

Borghans and Schils (2012), using a directly observable measure, show that it is positively associated with future life outcomes in the Netherlands. Therefore, I test the relevance of this measure in other settings. My hypothesis is that this measure positively predicts the completion of tertiary education ten years later.

H1: Student effort predicts the probability of completing tertiary education in the long run.

2.2. Effort and social stratification

Already decades ago, prominent sociologists such as Boudon (1974) and Bourdieu and Passeron (1977) argued that since parents play a key role in the socialization of their children, they shape the development of their non-cognitive skills and expectations on the basis of their socioeconomic status (SES). The theory states that parents from higher SES backgrounds take advantage of their social and cultural capital to foster the positive aspects of personality that will help their offspring be successful in life. Thus, the distribution of non-cognitive skills would not be normally distributed within the population.

As mentioned in the previous section, some non-cognitive skills have a positive influence on future life outcomes. If parents with a high SES manage to influence the non-cognitive skills of their offspring, as Farkas (2003) argues, those variables might play an important role in the stratification process. For example, Gil-Hernández (2021) shows that the returns to non-cognitive skills are higher among high SES parents. Some studies find that non-cognitive skills are not equally distributed across social classes (Hsin and Xie, 2017). However, other existing studies claim these skills to be less directly transmittable than cognitive skills and that the transmission is not influenced by the socioeconomic background of the family (Loehlin, 2005; Duncan et al., 2005). However, the level of intergenerational transmission found varies by the non-cognitive skill and the country analyzed (e.g., Anger (2012) shows that transmission is stronger in Germany than in the US). Moreover, Holtmann et al. (2021) find that, in the context of Germany, personality traits do not mediate the association between parents' and children's educational attainment. Overall, the literature is not entirely conclusive about the effect of parental SES on the development of the non-cognitive skills of their offspring.

Hence, following Bourdieu and Passeron (1977), I aim to test whether effort, a variable that so far has been assumed to be solely individually determined, plays a role in the process of inequality transmission. My hypothesis is that children of parents with higher education tend to exert more effort in education-related activities due to their socialization. At the same time, higher effort enhances their chances of completing tertiary education in the future.

H2: Student effort is a mediator between parental education and future educational attainment.

Students' educational expectations are one of the main predictors of future educational attainment. Students with higher educational expectations are more likely to obtain a bachelor's degree in the future than those with lower expectations (Messersmith and Schulenberg, 2008; Ou and Reynolds, 2008). Furthermore, during the last 20 years, there has been a sharp increase in educational expectations among students (Goyette, 2008), although some research shows that negative economic scenarios depress educational expectations (Salazar et al., 2019). The wide expansion of education that has taken place during the end of the 20th century has caused a decrease in the influence of parental background on educational expectations because tertiary education is becoming the norm.[9]

A long-standing model in sociology views educational expectations as the "strategic center" of a social psychological model of educational attainment, also known as the Wisconsin status attainment model (Haller and Portes, 1973). This model posits that social inequality is transmitted across generations through the educational expectations

[9] Rosenbaum (2001) argues that unrealistic educational expectations lead to negative effects in educational attainment. Students who try but fail to get a bachelor's degree (especially students with lower grades) might end up without any other educational degree after high school. Instead, they could have gone for a vocational training degree, which would have been more suitable for their characteristics. Hence, they end up with neither of the two degrees, which penalizes them in the future labor market (Rosenbaum, 2011).

of the children, since the social environment in which they are raised shapes these expectations. Children build themselves an idea of their future educational prospects through interactions with their parents and family at home and with friends and teachers at school. Thus, children who were born into families with a high SES and who have many relatives with a high level of education most likely have friends from similar families. Therefore, those children are more likely to develop higher expectations about their own future education. On the other hand, children who were born in lower SES families are surrounded by fewer people with a high level of education, so it is less likely that they will develop higher educational expectations. Later, the higher expectations of the children are translated into increased educational attainment through higher levels of motivation and effort (Spenner and Featherman, 1978).

Nevertheless, an opposite view is that of Bayesian learning theory, which states that individuals adapt their expectations continuously as they gather new information concerning their academic performance (Morgan, 2005). According to Morgan (1998), educational expectations are not illusions or parental wishes but rational calculations of the costs and benefits of further education. Hence, he argues that expectations are not so stable over students' educational career because individuals adapt their educational expectations to the grades they obtain during the school period. Thus, the early influence of the socioeconomic environment is not as strong. However, some studies show that students do not truly update their expectations on the basis of new information about their performance and that expectations are quite persistent over time (Gabay-Egozi et al., 2009; Andrew and Hauser, 2011). Bozick et al. (2010) find that the expectations of children with higher SES and/or higher grades are more stable than those of other children during elementary school. Furthermore, the study argues that more stable expectations are stronger predictors of future college enrollment than volatile expectations. Alexander et al. (2008) and Johnson and Reynolds (2013) obtain the same result for young students during the transition from adolescence to adulthood.

However, although the connection between educational expectations and educational attainment is well established, the channels through which educational expectations operate are less clear and are worth studying. Effort is one of the channels that is mentioned as a potential mediator in the foundational articles of the Wisconsin model.

Spenner and Featherman (1978) argue that students with higher educational expectations exert more effort during the school day to obtain better grades and to be more likely to reach college. Domina et al. (2011), using different proxies for effort, find that students in the US with higher educational expectations exert higher levels of effort.[10]

Following the Wisconsin model, I propose testing whether effort is a mediator between educational expectations and educational attainment. It is also interesting to measure the extent to which the influence of educational expectations on educational attainment is explained by effort. The hypothesis is that higher educational expectations lead to higher effort, which in turn leads to higher educational attainment in the future.

H3: Student effort is a mediator between educational expectations and future educational attainment.

3. Data and methods

3.1. Data and measurement

The Longitudinal Surveys of Australian Youth (LSAY) is an Australian longitudinal study that follows the cohort that takes part in the country's PISA study over a period of ten years. The study is managed by the National Centre for Vocational Educational Research and focuses on the transition of young students from high school to further education and finally to their first jobs. For this paper, I use the cohort that participated in the 2003 PISA test. Hence, the LSAY data cover the period from 2003 to 2013, ending when the individuals are approximately 25 years old. I assume that at that point, most of the individuals have already completed their education. There are 10,370 individuals in the sample at the beginning of the study. However, due to attrition, the sample decreases to 3,741 individuals in the last round. Hence, I use the sampling weights recommended by the LSAY documentation.

[10] Domina et al. (2011) use three different measures of effort. The first measure is the teacher's rating of each student's regular behavior and attention. The second is the student's self-report about how many hours per week they spend on homework. The third is the student's self-report about how frequently they attend school with textbooks, pencils and homework completed.

Initially, the individuals in the sample were selected to participate in PISA, a study conducted and published by the OECD in most developed countries that focuses on the evaluation of the education system in each country. Therefore, 15-year-old students' performance is assessed in mathematics, science, reading and problem solving. In the 2003 PISA test, each individual had to fill in the booklet to which he or she was randomly assigned. Each booklet has four clusters, and the participants have two hours in total to answer all questions. Each cluster comprises a set of questions, and in total, there are 13 different clusters that are arranged in different positions to form 13 different booklets. The position of the clusters differs between the various booklets, which are randomly assigned to students. In 2003, the PISA test was focused on math, so seven out of 13 clusters were math clusters. The rest of the test consisted of two clusters from each of the other fields: the sciences, reading and problem solving.

Previous studies, such as Borghans and Schils (2012) or Debeer et al. (2014), have found that in the PISA tests, there is a steady decline in performance throughout the test. The authors take advantage of the random allocation of booklets to students, which results in the same cluster being administered in a different position within the test to different students. Hence, the difficulty throughout the test is constant on average. This ensures that the difficulty of the clusters is not the driver of the observed decline. The same decreasing trend can be observed in the Australian data. As illustrated in Figure 1, there are differences in the average number of correct answers between clusters in different positions. All these differences are significant according to a t-test for paired samples. The mean of the correct answers at the beginning of the test, in Position 1, is 66.2%, and at the end, in Position 4, it is 60%; hence, there is an almost 10% decrease in relative terms.

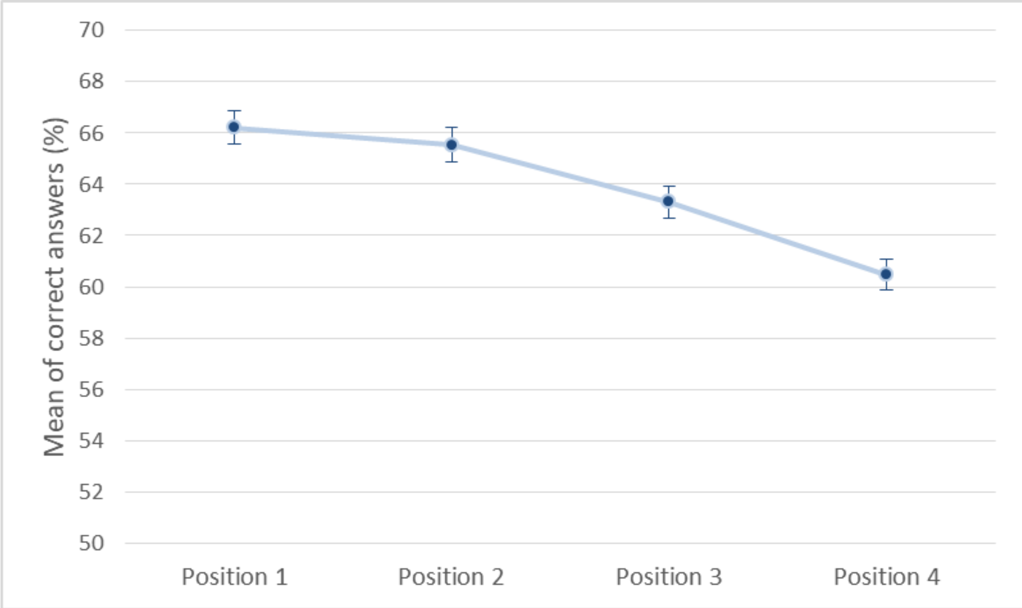

Figure 1. Average correct answers per cluster

Following the idea of Zamarro et al. (2019) and Borgonovi and Biecek (2016), I construct the measure for the decline in performance throughout the PISA test for each individual. Hence, for this measure, I calculate the difference in average correct answers between each cluster and the cluster in the first position.[11] Then, I calculate the average of the differences since not all individuals reach the last cluster. It is important to highlight that for calculating the average correct answers, I only consider the questions that were answered. Furthermore, some questions were designed in such a way that students could obtain partial credit. On those occasions, I gave them half a point. Thus, the equation for the effort measure is:

$$E_i = \frac{\sum_n (C_{ji} - C_{1i})}{n-1}$$

where n is the number of clusters reached by the individual i and C is the average number of correct answers for the cluster in position j. After calculating the variable, I adjust it by the booklet number. This is necessary, as the difficulty of the booklets might be somewhat heterogeneous despite the booklets having been designed to have the

[11] To avoid spurious correlations, we construct an alternative effort variable using only the difference between the first and the last cluster, which is closer to Zamarro et al.'s (2019) measure. We use that measure for robustness tests in Appendix B.

same level of difficulty. I also adjust by the percentage of correct answers in the cluster in position 1 since due to the methodology employed to calculate the effort variable, there is a threshold effect. This effect emerges as individuals with a higher rate of correct answers have a smaller margin within which to improve their performance, whereas individuals with lower rates have a smaller margin to worsen their performance and can only improve. Thus, the correlation between performance in cluster 1 and the effort variable is quite high (approximately -0.5) when it should not be. The correlation disappears after adjusting effort for performance in cluster 1. To ease the interpretation of the results, I standardize the variable after making this adjustment.

This effort variable requires making certain assumptions and has some limitations. The variable taps into one of the two aspects of cognitive effort, namely, persistence, the other being intensity. Persistence constitutes the ability to maintain performance over an extended period of time. The PISA test is a suitable setting since it lasts two hours and therefore resembles a regular exam in school or a period of study time. However, it is not possible to observe the other important aspect of effort, which is intensity. I cannot know the intensity of the effort exerted at the beginning of the test and I cannot make any assumptions on intensity since is a low-stakes exam. This means that my estimate of the impact of effort is a lower bound since the estimation does not fully capture the entire effect of effort.

Hence, as Gneezy et al. (2019) point out, the measure of effort in the PISA test only reflects intrinsic motivation since PISA is a low-stakes assessment. Moreover, cultural differences between countries (Asian countries tend to place more emphasis on effort and diligence) might explain part of the differences in results. Gneezy et al. (2019) conducted an experiment in the US and in Shanghai (China) with different schools where the students had to take some of the PISA test questions. Some students were allocated to the control group, where they had no extrinsic incentives for correctly completing the questions, and the rest of the students were placed in the treatment group, where the students received a monetary reward for each correct answer. They show that in the US, the difference in test performance between groups relying on intrinsic motivation and those relying on extrinsic motivation was quite large; meanwhile, in China, the difference in performance did not exist. This shows that intrinsic motivation varies across countries and cultures. However, studies such as Segal (2012) (for the US) and Borghans and Schils (2012) (for the Netherlands and the UK) indicate that motivation in low-stakes assessments is positively related to non-cognitive skills (especially conscientiousness) and future life outcomes, such as years of education, wages and employment.

3.2. Variables

As Heckman et al. (2006) argue, both cognitive skills and non-cognitive skills play a relevant role when predicting future life outcomes. Following Borghans and Schils (2012), I use accuracy in the first cluster as a proxy for cognitive skills. I assume that at the very beginning of the test, student performance mostly depends on cognitive skills. As Borghans and Schils (2012) show, performance at the beginning of the test is very closely correlated with IQ, the most common measure of cognitive skills. Furthermore, I again control for the booklet number to avoid having certain booklets drive the results. I also standardize this variable to allow for a straightforward interpretation of the results. To further control for the student's previous experience with mathematics, I use a dummy variable that indicates whether the student passed his or her last math exam or not.

To measure parental socioeconomic backgrounds, I follow Goyette (2008) and use a dummy variable that takes on the value one if any of the parents have obtained a tertiary education.[12] This measure is used because parental education better reflects the educational context of the family than a SES index. Furthermore, in countries such as Australia, the main difference lies between individuals with and without a tertiary education because very few people have less than a secondary education. Following the same reasoning, I construct a variable to measure the educational attainment of the individuals in 2013, consisting of a dummy for having completed tertiary education. In the sample, approximately 70% of the students declare that they expect to obtain a tertiary education. This division emerges as the most relevant for the research. Hence, I

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[12] It is referred to tertiary education as obtaining a certificate level of 5A, 5B or 6 according to ISCED 1997.

construct a dummy variable for expecting to complete a tertiary education as the variable for expectations.

Table 1. Descriptive statistics

	Count	Mean	SD	Min	Max
Tertiary education in 2013	3485	.624	.484	0	1
Parental tertiary education	3485	.637	.480	0	1
Effort	3485	0	1	-3.60	3.06
Cognitive skills	3485	0	1	-3.41	1.91
Expectations for tertiary education	3485	.811	.391	0	1
Passed last math exam	3485	.887	.316	0	1
Female	3485	.505	.500	0	1
Family Structure	3485				
Single-parent family	537	0.154		0	1
Nuclear family	2688	0.771		0	1
Mixed family	260	0.075		0	1
Region of parents' birth	3485				
Australia	2763	0.792		0	1
Anglo-Saxon countries	205	0.058		0	1
Europe	101	0.029		0	1
Latin America	15	0.004		0	1
Middle East and Africa	108	0.031		0	1
Southeast Asia	220	0.063		0	1
Central and East Asia	73	0.020		0	1
Kindergarten	3485				
No	193	0.055		0	1
Yes, one year or less	1651	0.473		0	1
Yes, more than one year	1641	0.470		0	1
Speak foreign language at home	3485	.0748	.263	0	1

I control for a standard set of individual covariates such as age, gender, household structure and whether the individual went to kindergarten, all measured in 2003, since these have been shown to have an impact on education. I also control for the migration status of the parents if both parents were not originally from Australia. Specifically, I control for the country-region where they were born if it is different than Australia. We can observe the descriptive statistics of the main covariates in Table 1. In the sample, 62.4% of the individuals had completed a tertiary education by 2013. This number is very similar to the share of families in which any of the parents have a tertiary education, which is 63.7%. This indicates that Australia is a developed country that had already undergone the educational expansion some decades ago. Furthermore, the share of individuals who expect to complete a tertiary education is remarkably high: 81.1%. It is interesting to note that there is almost a 20% gap between tertiary expectations and the actual completion of tertiary education.

The share of individuals with any parents born in Australia is 79.2%. The second most important region represented in this sample is Southeast Asia (6.3%), closely followed by other Anglo-Saxon countries (5.8%). The remaining regions are less represented in the sample. Most of the individuals live in nuclear families, 77.1%, and almost all of them went to kindergarten (only 4.5% did not). The sample is also very balanced in gender, with 50.5% of the individuals being female. Effort and cognitive skills have been standardized; thus, the mean is approximately 0, and the standard deviation is approximately 1.

3.3. Methods

Considering the structure of the dataset and the variables of interest that are observed in Figure 2, I use multilevel models (MLM) to account for the heterogeneity in the upper levels of observation. In this sample, the individuals are nested within schools since for the PISA test, schools are selected to participate. Hence, I allow for the random intercept to vary at the school level, avoiding potential biases when dealing with this type of data.

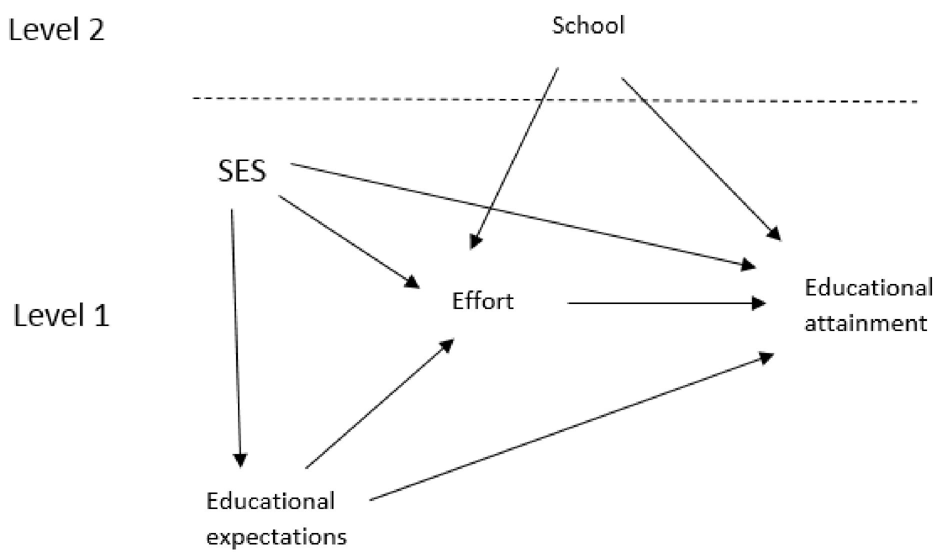

Figure 2. General framework

To test the first hypothesis (H1), I use the linear probability model given in Equation 1.[13] The dependent variable is a dummy that indicates whether individual *i* in the school in which he or she is nested, *j*, has completed a tertiary education in 2013 (D_i). Then, I also use as independent variables the set of covariates (X_i) explained in the previous section. My main independent variable in Equation 1 is the effort variable calculated from the PISA test in 2003.

$$D_{ij} = \alpha_{00} + \alpha_{1j} S_{1j} + \varepsilon_{0j} + \beta_2 X_i + \mu_i \qquad (1)$$

In line with the hierarchical approach, in Equation 1, in addition to having the general intercept α_{00}, there is a random intercept that controls for the particularities of each school α_{1j}. For the second and third hypotheses (H2 and H3), different methods are used to test for mediation in the clustered data. The most straightforward approach uses multilevel models (MLM), such as the previous model. However, recent literature (Zhang et al., 2009) has shown that the MLM might have potential biases leading to conflated

[13] Further robustness checks with logit models are shown Table B.1. in Appendix B.

estimates. Preacher et al. (2011) present empirical evidence that multilevel structural equation modeling (MSEM) overcomes those problems and outperforms MLM in terms of confidence intervals and potential biases. Hence, as the authors suggest, I use MSEM to test whether effort mediates the relationship between parental education and educational attainment (H2) and whether effort mediates the relationship between educational expectations and educational attainment (H3). Thus, the second equation of the MSEM is Equation 2, which is very similar to Equation 1. I change only the dependent variable, which is now effort (E_{ij}). The rest of the covariates are the same.

$$E_{ij} = \alpha_{00} + \alpha_{1j}S_{1j} + \varepsilon_{0j} + \beta_2 X_i + \mu_i \qquad (2)$$

One important assumption when using structural equation modeling is that the potential omitted variables that determine one dependent variable are not correlated with other potential omitted variables that determine the other dependent variable. In this case, that implies that effort is not determined by unobservable covariates that are correlated with other unobservable covariates that determine future educational attainment. If this assumption holds, it is possible to calculate the direct and indirect effects of covariates on future educational attainment.

The MSEM is composed of Equations 1 and 2, where Equation 1 is the outcome model and Equation 2 is the mediation model. Hence, I use the same model, only changing the main independent variable, to calculate the direct and indirect effect of parental education (H2) and educational expectations (H3) on future educational attainment as mediated by effort. Following Preacher and Hayes (2004), I use bootstrapped standard error to avoid potential biases that arise from assuming asymmetry in the confidence intervals associated with normal standard errors.

4. Results

Before presenting the results, it is important to further examine the relationship between effort and other important covariates, such as parental tertiary education and educational expectations. Figure 3 shows the differences in effort between such categories. Regarding parental tertiary education, we can see that those individuals with a parent who has a tertiary education have an effort of 0.1 on average on the standardized measure, in contrast to those who do not have such a parent and who have an average effort of -0.15. Remember that the overall mean is 0, so the difference is significant but not very stark. This finding is in line with the results of Balart and Cabrales (2014) when they use the ESCS index[14] as a predictor of persistence for students in Spain.

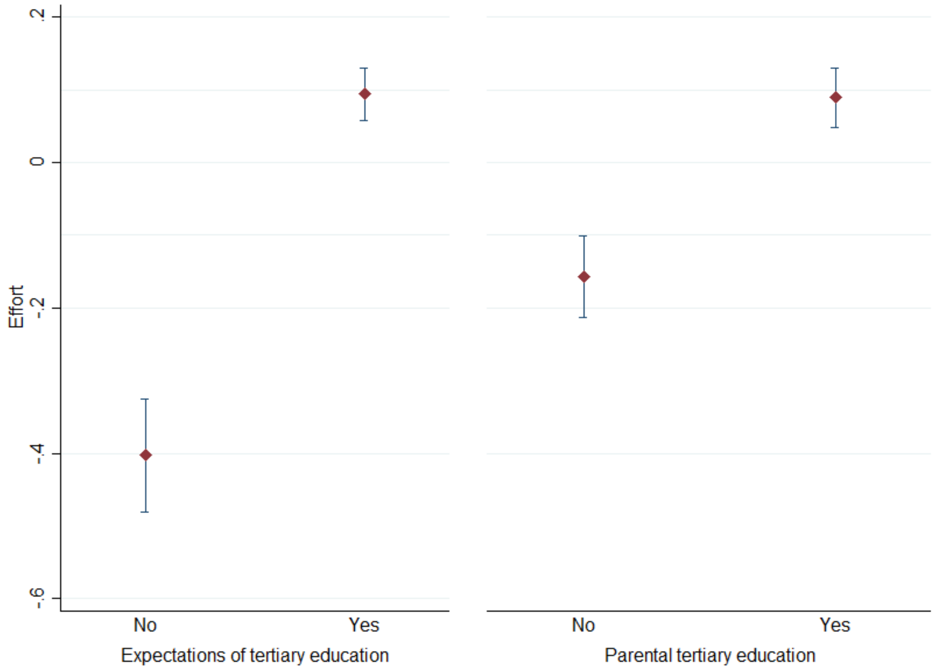

Figure 3. Effort by educational expectations and parental education

For educational expectations, the difference is larger. Having expectations of completing tertiary education is related to having 0.5 SD more effort than if you do not have such expectations (from -0.4 to +0.1). That difference is twice as large as the difference in effort based on parental education. This result resembles similar results obtained by Domina et al. (2011) for students in the US, using different measures of effort to find that educational expectations are the largest predictor of effort.[15]

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[14] The ESCS is an index of economic, social and cultural status created by the OECD with the PISA data. This index is created for the parental background of the students that participate in PISA.

[15] Another important variable that influences effort is country/region of origin of the parents. Previous literature such as Borghans and Schils (2012), Borgonovi and Biecek (2016) and Zamarro et al. (2019) show that individuals from East Asian countries tend to be more persistent than individuals from other

The results are presented in the following tables. The first hypothesis (H1), that effort is positively associated with future tertiary educational attainment, is tested in Table 2. In specification 1, I use only the basic control variables parental tertiary education, cognitive skills, gender and educational expectations. Here, I find that effort has a very significant and positive correlation with future tertiary education. However, the magnitude is also important. I find that a one standard deviation increase in effort results in an increase of 4.24% in the probability of obtaining a tertiary education. This is almost half of the size of the effect of having parents with a tertiary education. It is a significant magnitude when taking into account the fact that parental education is one of the main predictors of offspring education (Erikson and Goldthorpe, 2002). For the rest of the covariates, I find few surprises. Most covariates have the associations predicted by the previous literature. Educational expectation is the variable with the largest impact on tertiary education. This is in line with the literature previously discussed (Messersmith and Schulenberg, 2008; Ou and Reynolds, 2008). Other covariates, such as parental education and cognitive skills, which have been shown to have a positive effect on educational attainment, also have a significant and positive association in this model. Moreover, being female is one of the most important predictors of future tertiary education, in line with the latest research.[16]

In specification 2, I add additional control variables such as the result of the last math exam, family structure, kindergarten attendance or the country/region of parents' birth. Nevertheless, the previous results are robust, and the significance and magnitude of the effect of effort remain unchanged as well as those of the other covariates, which exhibit minimum changes. In specification 3, I test whether there is a significant interaction effect between effort and parental tertiary education, and I find no significant effect.

regions. Gneezy et al. (2019) find that students in China are more intrinsically motivated than US students. Figure A.1 of Appendix A shows the different levels of effort by country/region.

[16] Figure A.2 of Appendix A also indicates a slight nonlinear effect of effort. However, this nonlinearity is only significant at the 10% level.

Table 2. Multilevel linear probability model for tertiary education in 2013

	(1)	(2)	(3)
Effort	0.0424***	0.0432***	0.0411**
	(0.0110)	(0.0108)	(0.0142)
Parental tertiary education	0.113***	0.113***	0.114***
	(0.0199)	(0.0195)	(0.0195)
Parental tertiary education*Effort			0.00388
			(0.0180)
Cognitive skills	0.0839***	0.0838***	0.0838***
	(0.0120)	(0.0117)	(0.0117)
Female	0.113***	0.124***	0.124***
	(0.0226)	(0.0213)	(0.0213)
Expectations for tertiary education	0.272***	0.250***	0.250***
	(0.0261)	(0.0255)	(0.0254)
Passed last math exam		0.0549+	0.0548+
		(0.0290)	(0.0290)
Family Structure: (Ref. nuclear family)		.	.
		(.)	(.)
Single-parent family		-0.115***	-0.115***
		(0.0253)	(0.0254)
Mixed family		-0.0683+	-0.0681+
		(0.0354)	(0.0354)
Kindergarten (Ref. Yes, more than one year)		.	.
		(.)	(.)
No		0.0612	0.0612
		(0.0446)	(0.0446)
Yes, one year or less		-0.0184	-0.0183
		(0.0201)	(0.0201)
Speak foreign language at home		0.0360	0.0362
		(0.0468)	(0.0468)
Region of parents' birth (Ref. Australia)		.	.
		(.)	(.)
Anglo-Saxon countries		0.00501	0.00512
		(0.0390)	(0.0391)
Europe		0.111+	0.111+
		(0.0603)	(0.0603)
Latin America		-0.0898	-0.0884
		(0.147)	(0.147)
Middle East and Africa		0.214***	0.214***
		(0.0546)	(0.0546)
South East Asia		0.196***	0.195***
		(0.0497)	(0.0494)
East Asia		0.261***	0.262***
		(0.0595)	(0.0596)
Observations	3,485	3,485	3,485
Number of groups	312	312	312

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Level 1 is the students and level 2 is the school cluster. Fixed effects for month and year of birth are included.

This result seems to confirm the first hypothesis, in line with the previous literature, meaning that effort is an important predictor of educational attainment in the future. Furthermore, it appears that the effect of effort is not influenced by parental education. Regarding the next hypothesis, I test whether effort is a mediator between parental tertiary education and having completed a tertiary education ten years later. I use an MSEM to calculate the indirect effect of effort. In Table 3, we can observe the results for H2.[17] I find the indirect effect of parental tertiary education through effort to be insignificant, in contrast with the direct effect, which is highly significant. This suggests that although parental tertiary education has a direct effect on the tertiary education of the child ten years later, that influence is not transmitted through effort. This result is line with the evidence shown by Holtmann et al. (2021) for Germany. However, we have to take into account that some of the other covariates that appear as controls may be partially determined by parental education, such as cognitive skills, results on previous exams or educational expectations.

Table 3: Mediation of parental education and future educational attainment by effort

	MSEM (4)
Parental tertiary education	
Total effect on student's education	0.127*** (0.019)
Direct effect on student's education	0.119*** (0.02)
Indirect effect through effort on student's education	0.0071 (0.004)
% of total effect mediated by Effort	5.6

Bootstrapped standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Level 1 is the students; level 2 is the school cluster. The effects are calculated with the MSEM. I compute the bootstrap using 1000 repetitions to calculate the standard errors of the indirect effect.

This implies that if any of those covariates have an effect on both effort and future educational attainment, they could constitute another channel through which parental education affects future educational attainment. However, as we see in Equation 2 of

[17] We can observe the results of the full model in Table A.1 of Appendix A.

Table A.1, only educational expectations have a positive and significant association with effort. Hence, I use the same MSEM as before to test whether effort is a mediator between expectations for completing a tertiary education and having completed a tertiary education ten years later (H3). The only difference is that now, instead of parental education, I use the child's educational expectations. We can observe the results of the mediation analysis in Table 4.

Table 4: Mediation of educational expectations and educational attainment by effort

	MSEM (5)
Expectations of tertiary education	
Total effect on student's education	0.269***
	(0.026)
Direct effect on student's education	0.2484***
	(0.026)
Indirect effect through effort on student's education	0.0213*
	(0.010)
% of total effect mediated by Effort	7.8

Bootstrapped standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Level 1 is the students; level 2 is the school cluster. The effects are calculated with the MSEM. I compute the bootstrap using 1000 repetitions to calculate the standard errors of the indirect effect.

The indirect effect of educational expectations through effort is significant and positive. Mediation through effort accounts for 7.8% of the total effect of expectations on the probability of going to university 10 years later. This finding confirms the H3 and is consistent with the mechanism outlined in the Wisconsin Model of educational attainment. Hence, educational expectations shape the level of effort exerted in the educational context, which has an effect on educational attainment years later.

5. Conclusions

This paper examines the role of effort in the process of educational stratification. In particular, it explores the mechanisms through which effort might transmit social inequality across generations. I use a measure of effort originally created by Borghans and Schils (2012), which is directly observed while students complete the PISA test. This measure is based on decreases in performance over the course of the test. I use the

LSAY, an Australian longitudinal database that allows me to follow the evolution of the students who took the PISA test in 2003 through 2013.

This study has three key results. First, I test the impact of effort at age 15 on educational attainment 10 years later. The result is significant, and the size of the impact is noteworthy. A one standard deviation increase in effort has an effect equivalent to half of the impact of having parents with a tertiary education. This is in line with the research on non-cognitive skills (Heckman et al. 2006) and with what Borghans and Schils (2012) show with a similar measure for future life outcomes. Second, I analyze whether effort is a mediator between parental education and future educational attainment, as suggested by some sociological theories (Bourdieu and Passeron, 1977). I find that the indirect effect of parental education through effort is not significant. However, we have acknowledge that other controls used in the model might also be influenced by parental education, for example, educational expectations, which, according to the Wisconsin Model, are the main pillar of the process of educational stratification. This is because parents with a higher SES raise their children in an environment in which having a tertiary education is the norm. Those children will have higher expectations of completing a tertiary education than children from poorer backgrounds. Thus, I test whether effort is one of the channels through which educational expectations are transformed into higher educational attainment in the future. The third key finding is a significant and positive effect supporting this hypothesis. In line with the Wisconsin Model, effort seems to be one of the channels through which educational inequality is transmitted across generations. This also yields support to the results of Domina et al. (2011) on the positive effect of educational expectations on effort in school, suggesting that it is indeed one of the channels through which expectations have a positive effect on educational attainment (Messersmith and Schulenberg, 2008; Ou and Reynolds, 2008).

In terms of the scope of these findings, it is important to consider the limitations of this study when interpreting the results due to the inherent characteristics of the effort variable. As effort is measured when students are taking the PISA test, it cannot be assumed that the intensity (i.e., the level of effort) is maximized since the PISA is a low-stakes test. The results show that the country of origin of the students matters when there is only intrinsic motivation. For example, students with East Asian backgrounds tend to perform better than average. However, as Gneezy et al. (2019) shows, adding extrinsic incentives make that difference almost disappear. Due to this particularity, it is reasonable to think that these results are a lower bound estimation of the full effect of effort. I would expect that a measure of effort in a situation with extrinsic incentives and/or that also captures initial intensity would account for a larger part of the effect, leaving this question open for future research. Moreover, these results are valid for Australia, and their external validity has to be taken with caution due to the particularities of the country.

The results hold in the robustness checks. Test effort is shown to be a significantly important determinant of tertiary education. The evidence suggests that the effect of test effort is homogenous across parental education and that the impact of parental education on children's future education is not channeled through effort. Furthermore, children's educational expectations are the variable that seems to have the highest influence on future educational attainment. The results show that effort is one of the mediators between educational expectations and future completion of a tertiary education. However, in the robustness checks, the mediation is only significant at the 10% level. This implies that this effect is not very strong. The expansion in tertiary education during the last decades in Western countries (Goyette, 2008) has boosted the educational expectations of young students. In the sample, almost 80% of the students declare that they expect to complete a tertiary education in the future. This suggests that if expectations are rising, their effect through effort might be weakening, and therefore, there is less room for expectations to remain one of the sources of educational inequality. However, Rosenbaum (2001, 2011) argues that unrealistic expectations have negative effects on educational attainment and future labor market outcomes due to discouragement, which might potentially offset the positive effect of rising expectations. Therefore, more research is needed to explore the new dynamics between rising educational expectations and educational attainment. In particular, it would be interesting to investigate the potential effects of disappointed educational expectations on effort due to demotivation and its impact on educational inequality. These questions remain possible avenues for future research.

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7. Appendix

Appendix A. Further information

Table A.1. Full results of MSEM

Dependent variable:	(1) Tertiary education 2013	(2) Effort
Effort	0.0587***	
	(0.0167)	
Parental tertiary education	0.120***	0.122*
	(0.0200)	(0.0536)
Expectations of tertiary education	0.254***	0.426***
	(0.0272)	(0.0563)
Cognitive skills	0.105***	
	(0.0140)	
Female	0.124***	-0.0188
	(0.0211)	(0.0445)
Passed last math exam	0.0580*	0.0938
	(0.0293)	(0.0706)
Family Structure: (Ref. nuclear family)	.	.
	(.)	(.)
Single parent family	-0.117***	-0.0538
	(0.0250)	(0.0543)
Mixed family	-0.0923*	-0.108
	(0.0402)	(0.0747)
Other	-0.000986	-0.219
	(0.0772)	(0.173)
Kindergarten (Ref. Yes, more than one year)	.	.
	(.)	(.)
No	0.0321	-0.0799
	(0.0465)	(0.123)
Yes, one year or less	-0.0274	-0.0165
	(0.0202)	(0.0458)
Speak foreign language at home	0.0325	-0.209+
	(0.0478)	(0.111)
Region of parents' birth (Ref. Australia)	.	.
	(.)	(.)
Anglo-Saxon countries	0.0103	0.0245
	(0.0389)	(0.0852)
Europe	0.134*	-0.0954
	(0.0597)	(0.118)
Latin America	-0.0686	-0.386
	(0.143)	(0.450)
Middle East and Africa	0.237***	-0.262*
	(0.0584)	(0.116)
South East Asia	0.222***	0.0388

	(0.0483)	(0.117)
East Asia	0.287***	0.556***
	(0.0569)	(0.134)
Year of birth: 1987	.	.
	(.)	(.)
1988	-0.0129	0.0988
	(0.0462)	(0.101)
Observations	3,498	3,4985
Number of groups	312	312

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 Level 1 is the students; level 2 is the school cluster. Fixed effects for month of birth.

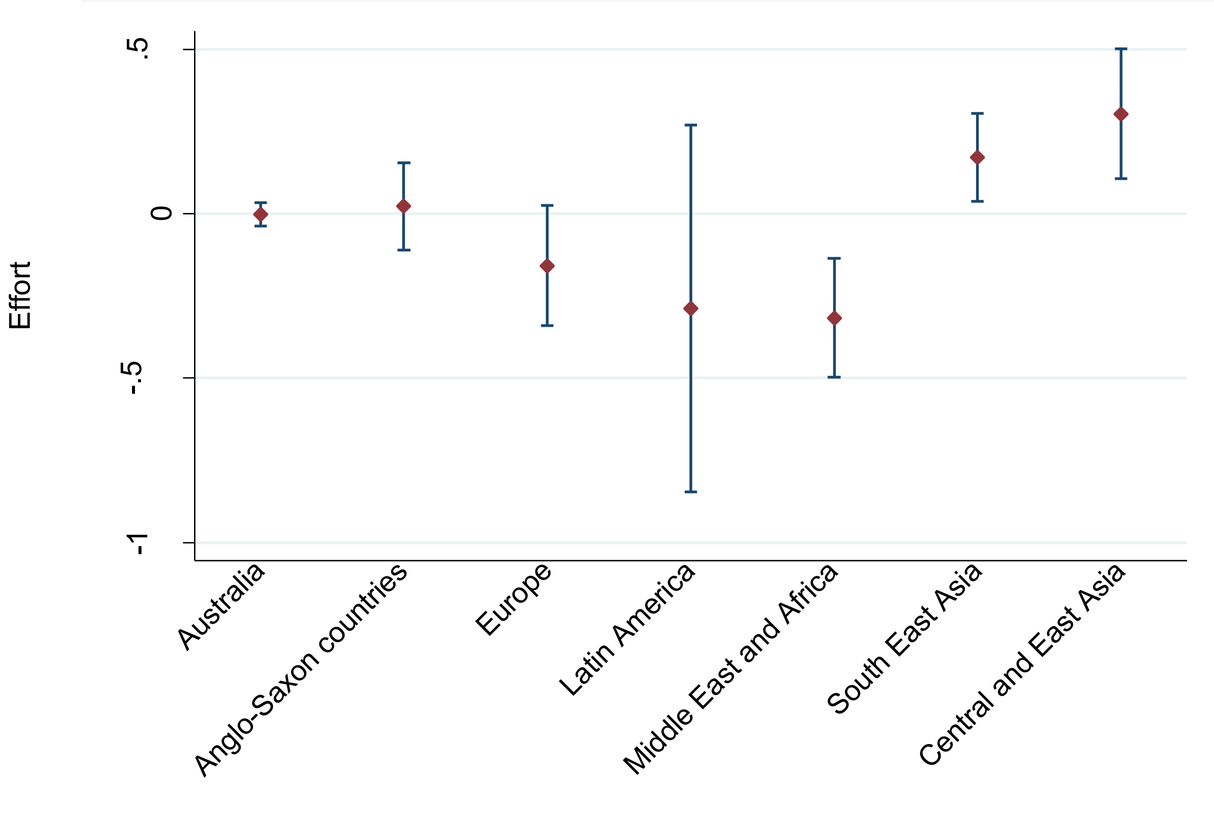

Figure A. 1. Effort by country region of the parents

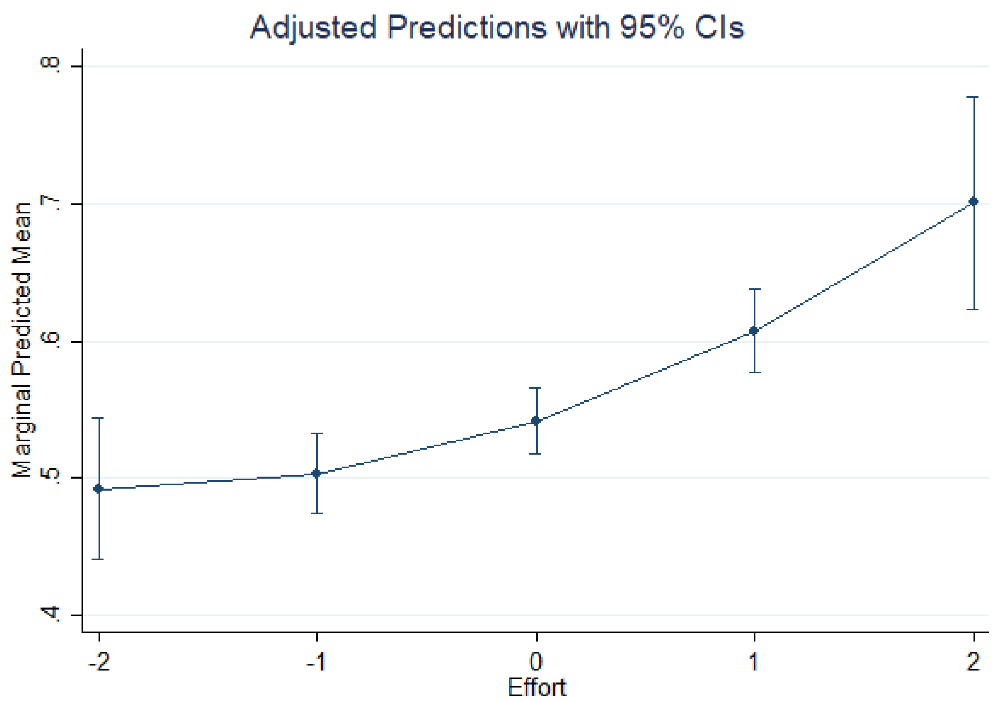

Figure A. 2. Marginal effect of effort on tertiary education

Appendix B. Robustness checks

Table B.1. Logit model of tertiary education in 2013

	(1)	(2)	(3)
Effort	0.231***	0.253***	0.257**
	(0.0614)	(0.0637)	(0.0848)
Parental tertiary education	0.598***	0.637***	0.635***
	(0.106)	(0.109)	(0.109)
Parental tertiary education*Effort			-0.00694
			(0.106)
Cognitive skills	0.452***	0.481***	0.481***
	(0.0680)	(0.0702)	(0.0704)
Female	0.626***	0.744***	0.744***
	(0.125)	(0.124)	(0.124)
Expectations of tertiary education	1.364***	1.290***	1.290***
	(0.140)	(0.141)	(0.141)
Passed last math exam		0.355*	0.355*
		(0.173)	(0.173)
Family Structure: (Ref. nuclear family)		.	.
		(.)	(.)
Single parent family		-0.671***	-0.671***
		(0.143)	(0.144)
Mixed family		-0.369+	-0.369+
		(0.193)	(0.193)
Kindergarten (Ref. Yes, more than one year)		.	.
		(.)	(.)
No		0.431	0.431
		(0.293)	(0.293)
Yes, one year or less		-0.0999	-0.0999
		(0.117)	(0.117)
Speak foreign language at home		0.194	0.193
		(0.330)	(0.330)
Region of parents' birth (Ref. Australia)		.	.
		(.)	(.)
Anglo-Saxon countries		0.0206	0.0204
		(0.209)	(0.209)
Europe		0.664+	0.664+
		(0.373)	(0.372)
Latin America		-0.400	-0.402
		(0.778)	(0.782)
Middle East and Africa		1.330***	1.331***
		(0.378)	(0.380)
South East Asia		1.332***	1.332***
		(0.385)	(0.384)
East Asia		2.527***	2.526***
		(0.715)	(0.715)
Observations	3,485	3,485	3,485
Number of groups	312	312	312

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 Level 1 is the students and level 2 is the school cluster. Fixed effects for month and year of birth.

I use an alternative measure of effort as robustness check. This measure follows the same steps as the original one, only the equation changes. Hence, the new equation to calculate the measure is the following one:

$$E_i = (C_{ni} - C_{1i})$$

The new measure is the slope of the decrease in performance between the last and the first cluster. As before, I standardize the variable in order to ease the interpretation. In the following tables I use this alternative measure as robustness check of the original models.

It can be observed than in most models the results hold. Only in the Table B.4 the result differs slightly from the original result. Here the indirect effect of effort is significant only at the 10% level instead of the original 5%. Further implications are explained in the Conclusions section.

Table B.2. Linear probability model of tertiary education in 2013

	(1)	(2)	(3)
Effort	0.0426***	0.0420***	0.0459***
	(0.0101)	(0.00969)	(0.0132)
Parental tertiary education	0.113***	0.113***	0.112***
	(0.0201)	(0.0196)	(0.0196)
Parental tertiary education*Effort			-0.00722
			(0.0168)
Cognitive skills	0.0839***	0.0835***	0.0837***
	(0.0121)	(0.0117)	(0.0117)
Female	0.112***	0.124***	0.124***
	(0.0226)	(0.0214)	(0.0214)
Expectations of tertiary education	0.275***	0.254***	0.254***
	(0.0262)	(0.0256)	(0.0257)
Passed last math exam		0.0544+	0.0542+
		(0.0288)	(0.0288)
Family Structure: (Ref. nuclear family)		.	.
		(.)	(.)
Single parent family		-0.115***	-0.115***
		(0.0253)	(0.0253)
Mixed family		-0.0713*	-0.0715*
		(0.0355)	(0.0354)
Kindergarten (Ref. Yes, more than one year)		.	.
		(.)	(.)
No		0.0645	0.0643
		(0.0445)	(0.0445)
Yes, one year or less		-0.0181	-0.0181
		(0.0200)	(0.0200)
Speak foreign language at home		0.0317	0.0313
		(0.0461)	(0.0461)
Region of parents' birth (Ref. Australia)		.	.
		(.)	(.)
Anglo-Saxon countries		0.00221	0.00243
		(0.0387)	(0.0387)
Europe		0.113+	0.113+

		(0.0611)	(0.0611)
Latin America		-0.0878	-0.0900
		(0.148)	(0.149)
Middle East and Africa		0.208***	0.209***
		(0.0544)	(0.0544)
South East Asia		0.193***	0.194***
		(0.0489)	(0.0489)
East Asia		0.263***	0.263***
		(0.0595)	(0.0595)
Observations	3,485	3,485	3,485
Number of groups	312	312	312

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 Level 1 is the students; level 2 is the school cluster. Fixed effects for month and year of birth.

Table B.3. Mediation between parental tertiary education and educational attainment through effort

	Model 3 (3)
Parental tertiary education	
Total effect on student's education	0.125***
	(0.02)
Direct effect on student's education	0.12***
	(0.02)
Indirect effect through effort on student's education	0.005
	(0.003)
% of total effect mediated by	
Effort	4

Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 Level 1 is the students; level 2 is the schools cluster. The effects are calculated with the MSEM. I compute a bootstrap of 1000 repetitions to calculate the standard errors of the indirect effect.

Table B.4. Mediation between educational expectations and educational attainment through effort

	Model 3
	(3)
Expectations of tertiary education	
Total effect on student's education	0.278***
	(0.026)
Direct effect on student's education	0.262***
	(0.026)
Indirect effect through effort on student's education	0.016+
	(0.009)
% of total effect mediated by	
Effort	5.9

Bootstrap standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1 Level 1 is the students; level 2 is the schools cluster. The effects are calculated with the MSEM. I compute a bootstrap of 1000 repetitions to calculate the standard errors of the indirect effect.

Chapter 3

The virtue of peer pressure: The impact of social influence on effort

1. Introduction

Peer effects in education have received a great amount of attention over the last 20 years (Sacerdote, 2011). The role social influence plays is also an attractive topic for policy-makers with the prospect of improving overall performance at low expense, just by reorganizing students into different classes. However, research on this topic is not straightforward due to numerous methodological challenges and inconsistent previous results (Angrist, 2014). There have been different approaches to understand peer effects. Some studies have focused on the impact of peer academic outcomes on students' achievement, finding positive results both in the short run and in the long run (Hanushek et al., 2003; Patacchini et al., 2017). Other studies have investigated the effect of peer socioeconomic background. For example, Schneeweis and Winter-Ebmer (2007) and Ammermueller and Pischke (2009) show that being in a school with a larger presence of parents with high socioeconomic status has positive effects on students' reading achievement. A few recent studies have tried to shed some light on the causal mechanisms of peer effects, but there is still a lot of uncertainty (Duflo et al., 2011; Feld and Zölitz, 2017; Borgen et al., 2022).

Bridging literature from economics and sociology, this paper investigates whether social influence impacts educational outcomes through one specific mechanism, effort. Concretely, I want to study the effect on effort of having school peers with high socioeconomic background. I base the theoretical mechanism on the Wisconsin status attainment model developed by Sewell et al. (1969). The core of the model is students' educational expectations that are shaped by parental socioeconomic backgrounds and social relationships. According to the model, one of the mechanisms through which social relations influence an individual's expectations is imitation. Students tend to imitate the educational expectations of friends and classmates (Sewell et al., 1970). At the same time, higher expectations are translated into higher effort in educational activities (Domina et al., 2011). When channeled into greater effort, high expectations can propel academic achievement. In this vein, I show in Chapter 2 that effort acts as a mediator between educational expectations and educational attainment. Therefore, my first hypothesis is that, due to imitation, advantaged peer socioeconomic background has a positive impact on test effort. However, as previous literature suggests, peer effects tend to be heterogeneous among students (Schneeweis and Winter-Ebmer, 2007; Sacerdote, 2011). Low-achievers tend to benefit more from being in class with high-achievers and peers with privileged background. Correspondingly, it is also expected that students who exert low effort would benefit more from a change to schools with higher peer socioeconomic background than those students with high effort because the margin of improvement is larger when initial effort is low. Thus, the second hypothesis is that the effect of higher peer socioeconomic background on effort is non-linear and benefits more those students at the lower end than those at the higher end of the effort distribution.

Another factor of social influence that affects educational outcomes is peer heterogeneity. Most studies find that having very heterogeneous peers affects student grades negatively (Sacerdote, 2011; Raitano and Vona, 2013). Duflo et al. (2011) explain that one of the reasons is that it is more difficult for the teachers to teach a very heterogeneous group of students with different needs. Then, if the students feel that the teacher does not pay attention to them they might disconnect from the subject and exert less effort in class. Hence, the third hypothesis is that peer heterogeneity has a negative effect on test effort.

Taking into account the importance of school class composition, it is important to investigate the features of the educational systems that shape the composition. I focus on educational tracking, which affects the way in which students are placed in different educational tracks at different ages to study different curriculums. Furthermore, tracking has been shown to have an important effect on educational equality and outcomes (OECD, 2020). This institutional feature is also very relevant for peer effects, because those students in early-tracking countries are grouped in more homogenous classes and the future educational prospects are fundamentally shaped by the track in which they have been placed. Usually early-tracking countries differentiate between the academic track, which grants access to tertiary education, and vocational track for students that want to pursue vocational education. Here, I analyze the impact of peer effects for students in each track. My fourth hypothesis is that peer effects have a positive impact for those students in the academic track, although the magnitude will be smaller than in the case of the vocational track. Since students in the academic track are positively selected and have higher skills and expectations, their room for improvement will be lower. The last hypothesis is that peer heterogeneity is only relevant in the comprehensive, because in the early-tracking systems the students are placed into the academic or vocational track according to their skill, resulting in very homogeneous classes.

In order to examine these issues, I use the Programme for International Student Assessment (PISA) 2012, an international test carried out by the OECD in which numerous countries participate. Borghans et al., (2008) show that these international tests do not measure only cognitive skills, but also non-cognitive skills. Following Borghans and Schills (2012), I construct a measure of test effort by exploiting the randomized allocation of questions within the test. Test effort is associated with non-cognitive measures such as conscientiousness (Borghans and Schills, 2012) or future higher education as shown in Chapter 2 of the thesis. Furthermore, as the main independent variable, I use the leave-out mean of peers with highly educated parents in the school (the mean of students that have parents with tertiary education but excluding the individual). A wide set of covariates is used to mitigate the methodological challenges which are explained in the data and methods section.

As a first result, I find that higher peer socioeconomic background is positively and significantly associated with test effort. Furthermore, the results suggest that the impact of peer socioeconomic status (SES) is quite homogeneous across most of the distribution, being only slightly weaker for those students at the top of the distribution of effort. The impact of peer heterogeneity is significant and negative; however, the magnitude is very small. When the analysis is separated by educational tracking, the effect of peer SES appears stronger in countries with comprehensive tracks and for those students in the vocational track, in line with the theoretical expectations. These results seem to support the idea that effort is one of the channels through which social influence is translated into educational achievement.

The paper is structured as follows. Section 2 summarizes the relevant literature on peer effects in education. It also explains the recent literature on the consequences of educational tracking for students' average performance and its relation with peer effects. Section 3 describes the database used in the paper and how the main dependent variables are calculated. Furthermore, it presents the methodological strategy followed in the paper. Section 4 provides the results of the study and discusses possible interpretations. The last section summarizes the key conclusions and suggests further avenues for future research.

2. Literature review and theoretical framework

2.1. Peer effects and social influence

Peer effects have emerged in the last decades as a promising field of research in education. From a policy perspective, the allure stems from the potential of improving educational outcomes simply by reorganizing students in different schools, which is very efficient in terms of cost-benefit considerations (Sacerdote, 2011). Peer effects refer to the impact that peer group composition - mainly in school classes though some studies look at the school level too - has on the academic outcomes of an individual student (Hanushek et al., 2003). Overall, there is a broad consensus on the positive impact of peer effects, both in the short run and in the long run, but there is still a lot of debate about the magnitude (Paloyo, 2020). Researchers have tried different experimental settings to identify peer effects. Some studies have used exogenous within-school variation to explore the peer effects in school classes on academic outcomes (Burke and Sass, 2008; Ammermueller and Pischke; 2009; Lavy and Schlosser, 2011). Other studies have taken advantage of longitudinal data and use lagged academic outcomes (Hanushek et al., 2003; Vigdor and Nechyba 2007) or even created a randomized experiment when conditions allowed it (Duflo et al., 2011; Carrell et al., 2013). To investigate peer effects in a global context, a number of studies have used databases that contain data on several countries, such as PISA or PIRLS (Schneeweis and

Winter-Ebmer, 2007; Ammermueller and Pischke, 2009; Raitano and Vona, 2013). They find that higher peer social background, as measure of peer effects, has a positive impact on test scores. The evidence of the positive impact of peer effects is overwhelming, however, the social-engineering of reorganizing students in classes to maximize it is not as easy as it seems. Carrell et al. (2013), in a randomized experiment in the US, created a treatment that was meant as an "optimally" designed peer group in order to maximize the effect. Yet, the authors actually find a negative impact of their treatment on academic scores. They speculate that this can be explained by changing dynamics of social interaction and a changing class composition that might lead to the creation of different subgroups.

Despite the important amount of research, peer effects are still a black box when it comes to the mechanisms through which they take place. A number of recent papers have tried to analyze these processes in different contexts. For example, Duflo et al. (2011), find in the course of a randomized experiment in Kenya, that the adjustment of teachers' behavior is an important mechanism that drives peer effects. With a class of high-performing pupils, teachers can teach better and with fewer interruptions. Booij et al. (2017) also find evidence of this trend in the Netherlands. Similarly, Lavy et al. (2012) show that in classes with higher share of low-ability students the level of disruption and violence increases sharply, making the work of the teacher more difficult and worsening the teacher-students relationship. Feld and Zölitz (2017) argue that another potential mechanism underlying peer effects is the improved group interaction thanks to high-achieving peers. They explain that working in groups and studying together has a benefit for all students, and in classes with better peers the benefit is greater because they learn more from each other. As an addition to these explanations, I propose that effort might be another mechanism. Through social influence, being in class with better-performing peers might boost the effort that the student exerts in the school, which afterwards results in better performance and grades.

Social influence is the key mechanism through which educational inequality is transmitted according to the Wisconsin status attainment model (Sewell et al., 1969). This model establishes that individuals shape their beliefs about their educational opportunities and expectations through their social relationships with significant others, the core group of persons that includes the parents, teachers, friends and classmates. Therefore, an individual that grows up in an environment where most people have tertiary education will be expected to also achieve higher education. The opposite will occur for individuals that are born in low SES families. There are two mechanisms through which social influence shapes the development of individual's expectations: adoption and imitation (Sewell et al., 1970). The first one refers to the influence that older authority figures such as parents and teachers have on the student. Their opinions and expectations exert an important impact on the development of the children's educational expectations, contributing to the social reproduction of inequality (Bozick et al., 2010). The second mechanism, imitation, corresponds to the influence that same-aged peers such as friends or classmates have on the individual. Since students tend to imitate their friends when it comes to choices and preferences (Fletcher, 2012; Rosenqvist, 2018), having friends with higher educational expectations will also encourage the individual to aim higher in his educational future. Recent evidence of the positive impact of peer educational expectations on the individual's educational expectations has been shown by Raabe and Wölfer (2019) and by Zimmermann (2020). I argue that this is a key mechanism through which peer effects have a positive impact on academic achievement, detailed in Figure 1.

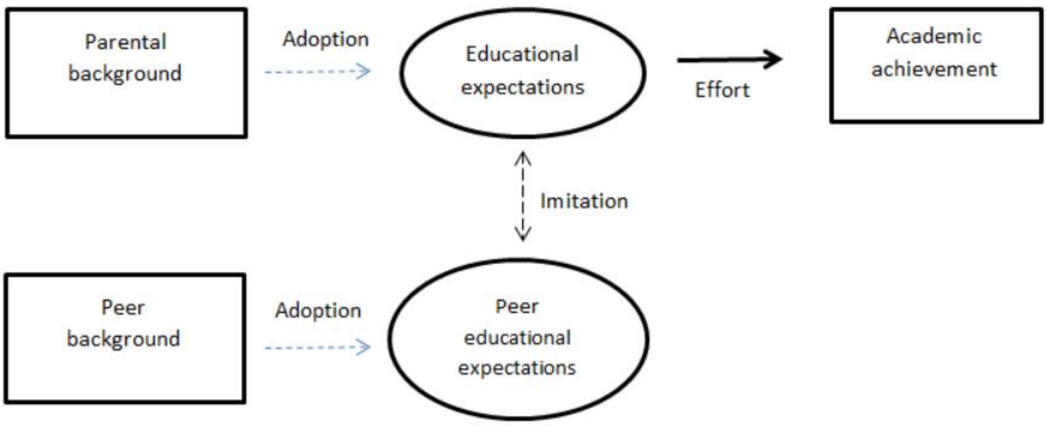

Figure 1. Stylized model of social influence adapted from Wisconsin Model

More specifically, peers with higher SES background will likely adopt the high educational expectations that their parents have for them. Hence, individuals in classes with mostly high SES background peers are more likely to develop high educational expectations through imitation. Then, as Domina et al. (2011) show, the rise of educational expectations will make the student exert more effort in educational activities in order to accomplish the expectations. Ultimately, higher effort will result in higher academic achievement. In Chapter 2, I find evidence of test effort being a very good predictor of future educational attainment. Hence, this third chapter tests whether test effort is a channel through which peer effects have an impact on individuals' academic achievement. The first hypothesis is that advantaged peer social background will have a positive effect on test effort.

H1: Advantaged peer social background has a positive impact on test effort.

However, there are some studies in the literature of peer effects pointing out that the impact is non-linear across the student distribution (Sacerdote, 2001; Winston and Zimmerman, 2007). Rangvid (2008) shows for Denmark that students in the low part of the achievement distribution are benefitting more from peer effects than students at the top. Similarly, Schneeweis and Winter-Ebmer (2007) find that in Austria low-achieving students also improve more in test scores when they have "good" peers around because, in line with the notion of a learning curve, there remains more to learn when the starting level is low. Applying this intuition to the peer-effort mechanism a similar result could be expected. Students at the top of the effort distribution have less margin of improvement since they already exert very high effort. However, those students at the bottom could be more benefited from acquiring higher educational expectations through peer imitation because they have more room for improvement. The second hypothesis states that peer effects are less beneficial to those students and the top and more beneficial to those at the bottom of the distribution.

H2: The positive effect of advantaged peer social background on test effort decreases with the initial level of effort.

Since classroom interactions are complex, another variable that should be taken into account when analyzing student interaction is peer heterogeneity. Several studies have analyzed the impact on academic outcomes of being in a class where the peers are very different between them, either in terms of parental social background or academic achievements. Hoxby and Weingarth (2005) and Vigdor and Nechyba (2007) analyze specific cases in the US and find contradictory results: while the former study shows a negative impact, the latter suggest a positive impact of peer heterogeneity. However, other studies have used databases that comprise more countries. For example, Fertig (2003) using PISA data finds a very negative impact of peer heterogeneity, measured as dispersion in test scores, on an individual's test scores. In the same vein, Raitano and Vona (2013), use a subsequent PISA cohort and report similar results, a negative impact of dispersion of peer social background on test scores. As Fertig (2003) argues, having more homogeneous classes facilitates the task of the teacher, because most of the students will have a similar level of capacities. On the other hand, if the class is very heterogeneous, the teacher will face a difficult situation because the students will require a different rhythm and a focus on different aspects of the lesson. As already mentioned, Duflo et al. (2011) show evidence of the positive impact of homogeneous classes on achievement due to the adjustment of teacher's behavior. In heterogeneous classrooms, it is likely that those students who do not have the attention of the teacher will disconnect from the class and exert less effort on those activities. Therefore, my third hypothesis is that peer heterogeneity has a negative effect on test effort.

H3: Peer heterogeneity has a negative impact on test effort

2.2. Educational tracking and peer effects

There are different characteristics in educational systems that explain social stratification processes in education (Kerckhoff, 2001). Here, following the importance of school composition laid out in the peer effects literature, I focus on educational tracking, which consists in the ability-based placement of students in different educational tracks when they reach a certain age. There is a lot of heterogeneity between countries when it comes to the design of tracking systems in schooling (OECD, 2020). On the one hand, there are countries, especially in Central Europe, that place their students at a very early age –between 10 and 12 years - in different tracks. These tracks differ in terms of the post-secondary education to which they give access to. On the other hand, most Anglo-Saxon and Nordic countries have only one comprehensive track until age 16 when students' educational path is decided. Nevertheless, there are multiple designs of tracking systems combining age of placement, number of tracks, length of tracks and other variables such as the vocational training system. In the second part of the 20th century, numerous countries carried out educational reforms seeking to increase the years of compulsory education, imposing a homogenous curriculum across the country and delaying the tracking of students (Meghir and Palme, 2005). These countries were mainly the Nordic countries and some Western countries such as United Kingdom or France. Moreover, at the end of the century, the former communist countries Poland and Rumania also carried out de-tracking reforms in order to improve the access to education for low SES individuals.

As the literature on peer effects shows, the composition of the school classes has an important effect of the educational outcomes of the student. Most students in early-tracking countries stay in the track where they have been allocated without a lot of agency to decide whether they want to change (Burger, 2021). Comparisons across countries show that early tracking increases inequality of opportunity in education because it reinforces the effect of parental background on educational attainment and future life outcomes (Brunello and Checchi, 2007; Pfeffer, 2008; Schütz et al., 2008; Horn, 2009; Lavrijsen and Nicaise; 2015). Van de Werfhorst (2018), in a study of the effect of the de-tracking reforms that several countries carried out in the last century, shows that the reforms greatly reduced socioeconomic inequalities, particularly for those at the bottom of the achievement distribution. Other scholars find evidence that early tracking also increases gender and ethnic inequalities (Scheeren et al., 2018; Alieva and Hildebrand, 2019). Nevertheless, while a large part of the literature points in the same direction, a couple of studies (Brunello and Checchi, 2007; Bol and Van de Werfhorst, 2013) show that there is a trade-off between decreasing equality of opportunities in education and allocation in the labor market. They explain that tracking, although it tends to reproduce inequalities, improves the allocation of the worse performing students due to the specialization in skills demanded by the labor market.

Proponents of early tracking argue that grouping students in classrooms by skills allows teachers to adapt the curricula and instruction to their level. The homogeneity at the class level supposedly helps most students since the pace of the course will be more adequate to their necessities, providing more difficult assignments to high skills students and easier to low level students –although there is contradictory evidence on this (Esser and Seuring, 2020; Heisig and Matthewes, 2021). Hence, nobody is left behind and every student receives more calibrated attention. Figlio and Page (2002) show for the US not only that low-skilled students are not harmed by tracking, they might even benefit from it. Duflo et al. (2011) also find evidence that tracking improves academic scores for students across the whole distribution in Kenya. In the German context, Dustmann et al. (2017) do not find evidence that attending a higher track leads to better future life outcomes in Germany. They argue that the flexibility of the German tracking system is crucial because it allows students to change the track at a later stage. Nevertheless, most research does not suggest such benevolent effects of tracking. Several studies in different countries such as the Netherlands, Germany, Poland or Rumania find negative effects of early tracking in student performance and future education (Van Elk et al., 2011; Malamud and Pop-Eleches, 2011; Piopiunik, 2014; Jakubowski et al., 2016; Borghans et al., 2019, Matthewes, 2021). Overall, cross-country studies such Hanushek and Wößmann (2006) and Lavrijsen and Nicaise (2015) suggest that early tracking is associated with lower average performance in international tests and higher dispersion in results. Van de Werfhorst and Mijs (2010) in a review of the previous literature conclude that early tracking has a negative impact on the average performance of students in international tests. Accordingly, inequality also increases, both as inequality of opportunity and as inequality of results.

Thus, due to the different peer composition of the classes in the vocational and the academic track, it is likely that the impact of peer socioeconomic background is different from the comprehensive track. Nevertheless, it relevant to study the importance of peer SES in those tracks because, as before, just by reallocating students within the same track but between schools could improve the average academic achievement. To test the effect, I will analyze the peer effects in each track separately. In the case of the students in the academic track, taking into account the positive selection of high skilled and ambitious students, the margin for raising their educational expectations is limited. In the vocational track, although the students receive a negative signaling of their skill, there are paths to pursue the academic track after finishing the vocational degree. For example, Buchholz and Schier (2015) show that in Germany, 27% of the students in the vocational track continue studying in higher tracks after finishing, especially those from advantaged families. Therefore, having peers with advantaged social background might increase the educational expectations and positively influence effort. Hence, I expect that the effect of peer SES will be positive in both cases, but significantly higher for the students placed in the vocational track than for those in the academic track.

H4: The effect of peer SES for students in the academic track is smaller than in the vocational track

The effect of peer heterogeneity on test effort is expected to be different across the tracks. In the comprehensive track I expect it to be negative as most literature argues. However, in the vocational and in the academic track I expect that the effect will not be significant. This is because the students in those tracks have been already selected by academic skill, resulting in very homogeneous classes. Hence, as academic skills are very homogeneous, I do not expect that heterogeneity in peer social background will be an important factor for the students in the academic and vocational tracks.

H5: The effect of peer heterogeneity is only relevant for students in the comprehensive system

3. Data and methods

3.1. Data and variables

The Programme for International Student Assessment (PISA) is a study conducted and published by the OECD that seeks to measure the educational achievement of students from different countries every three years. The students that take part in the test are on average 15.5 years old, which corresponds to attending tenth grade. The test assesses the students' capabilities on science, reading and math in order to provide a comparison between countries that also allows for the evaluation of different educational systems. I use the PISA edition of the year 2012, which focused on the field of math.[18] In my sample

[18] I use PISA 2012 because it contains a parental survey for a set of countries that allows me to perform a robustness check. Furthermore, PISA since 2018, TIMSS and PIRLS and use adaptive tests which does not allow to create the measure of test effort.

there are 203,870 students nested in 7,595 schools and 31 countries that have participated in the PISA study.[19]

The PISA test lasts 120 minutes and it is divided into two parts of 60 minutes each with a break in between. The exam provided to the students is called *booklet* and there are 13 different ones. Each booklet is divided into four clusters, two in the first half and other two in the second half. There are seven different clusters for math, three for science and three for reading. Each cluster contains around 20 questions. The allocation and position of the clusters in each booklet is randomly assigned. Furthermore, the assignment of booklets to the students is also random. This structure is essential for the construction of one of the main variables, namely test effort. Previous studies, such as Borghans and Schils (2012) or Zamarro et al. (2019), have found that in former PISA tests, there is a steady decline in the performance throughout the test. The slope is negative for all the countries, although the decline is more pronounced in some than in others. I find the same trend with the 2012 cohort, corroborating this fact. The difference in average performance between the first and the last cluster is around 14% in relative terms.

Hence, taking advantage of the random allocation of booklets and clusters that allows ruling out systematic differences in difficulty, I can construct a measure of test effort for each student based on the method designed by Borgonovi and Biecek (2016) and Zamarro et al. (2019), who followed the idea of Borghans and Schils (2012). I calculate the accumulated decline over the test adding the difference in average correct answers between each cluster and the first cluster. I only consider the answered questions, so if the student has not answered any questions in the fourth cluster, I exclude him or her. Afterwards, I divide the accumulated difference between the clusters reached. The equation is the following:

$$E_i = \frac{\sum_n (C_{ji} - C_{1i})}{n-1}$$

Test effort is denoted as E, the individual as i and the number of clusters reached as n and C is the average correct answers of the cluster j. Afterwards, I adjust the measure by

[19] Following Rangvid (2008) I restrict the sample to schools with at least 15 students participating in PISA.

the booklet that each individual has received to further control for the differences between booklets. In order to avoid ceiling and floor effects, I also control by the performance in the first cluster, since the correlation between raw test effort and average correct answers in Cluster 1 is negative. Then, I standardize the variable in order to have a mean of 0 and a standard deviation (SD) of 1.[20] In Figure 2, it can be observed that there is significant heterogeneity in test effort by country. At the top of the distribution is Hong Kong with almost 0.4 SD over the mean, followed by Germany, Belgium and South Korea. It is no surprise that the Asian countries appear at the top. As Gneezy et al. (2019) show that East Asian countries tend to perform better than Western countries when there is only intrinsic motivation.

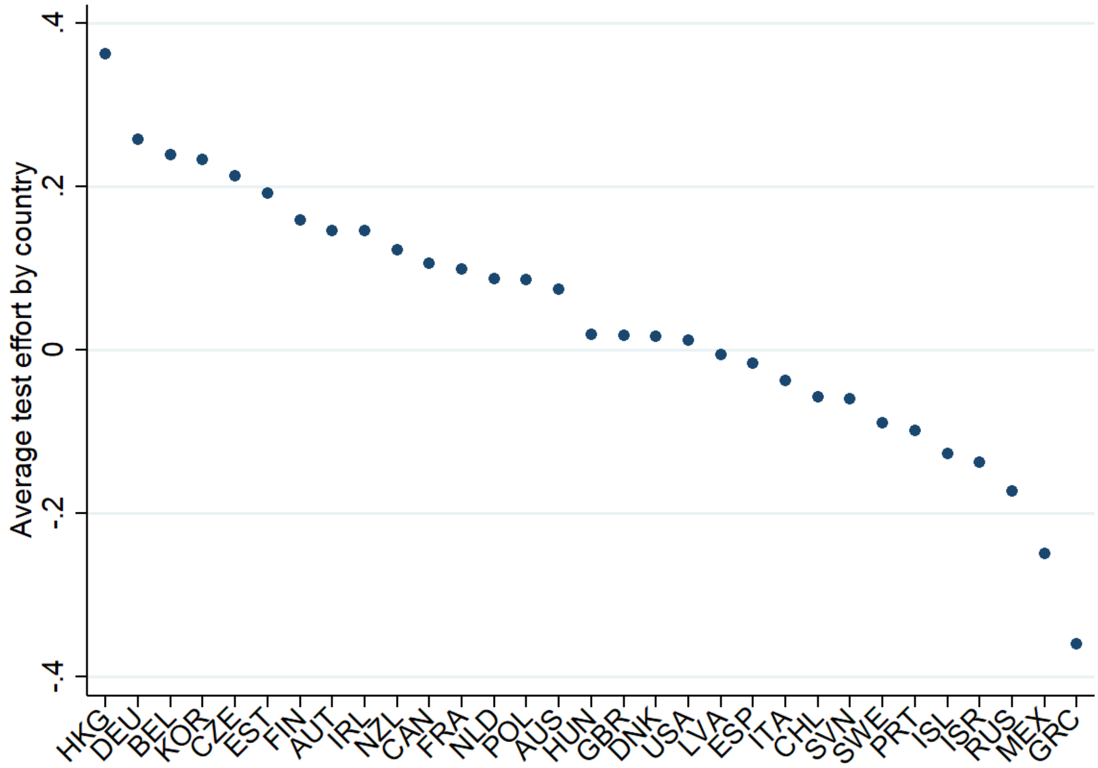

Figure 2. Test effort by country

The average peer level of socioeconomic background is considered the main peer effect because parental socioeconomic background is the main predictor of academic achievement (Ammermueller and Pischke, 2009). In this paper, I use the leave-out mean

[20] The distribution of test effort can be observed in the Figure A.1 of the Appendix.

of peers with highly educated parents, as the main independent variable. It is calculated as the share of school peers that have any parent with tertiary education, excluding the individual. This variable is also standardized with a mean of 0 and a SD of 1. Moreover, the SD of parents with tertiary education in the school is used as measure of peer heterogeneity. This variable is also standardized to ease the interpretation of the results.

Regarding the rest of the individual-level covariates, I use parental education as proxy of socio-economic background. More specifically, it is the highest level of education achieved by any of the parents. The measure is divided into three categories: basic education, upper secondary education and tertiary education.[21] Migration status is also taken into account as one independent variable with three different categories: native, first-generation migrant for those students that were born in another country and second-generation migrant for those that were born in the country but whose parents weren't. This pays heed to the fact that migration status is an important determinant of educational attainment and a source of inequality (Levels and Dronkers, 2008). Moreover, I also use students' gender and whether they have repeated an academic course as additional covariates. [22]

As for educational tracking, I classify the students into four categories depending on the educational track in which they are placed. The reference category is the *Comprehensive track*, for those students in countries without early tracking. The second category is *Vocational track*, for those students in early-tracking countries enrolled in Vocational Education and Training (VET) courses with the objective to acquire skills for the labor market but not for pursuing tertiary education. The third category is the *Academic* track, where students from early-tracking countries that want to continue to college are placed.[23]

[21] The classification corresponds to the following ISCED categories: Basic Education- ISCED 0, 1 and 2. Upper Secondary Education- ISCED 3 and 4. Tertiary Education- 5A, 5B and 6.

[22] The descriptive statistics of the variables are in the Table A.1 of the Appendix.

[23] In the Appendix Table A.2 the number of students in the sample appears, differentiated in each educational track by country. In a few countries with early tracking there is the possibility to continue in a track receiving general education without specializing in vocational or academic education, but the overall number of students attending that track is very small and I dropped them.

Differences across educational tracks in test effort can be observed in the box plots displayed in Figure 3. On the one hand, it comes as no surprise that those students in the academic track have on average the highest test effort, 0.2 SD over the mean. However, it is difficult to tell whether it is because usually the high achievers –who also tend to exert more effort- are placed in the academic track of due to the positive impact of the track placement. On the other hand, we find that those students in the vocational track exert on average the lowest effort, 0.1 SD bellow the mean. As before, we cannot distinguish between the selectivity of the group and the potential negative impact on students' educational prospects of being tracked there.

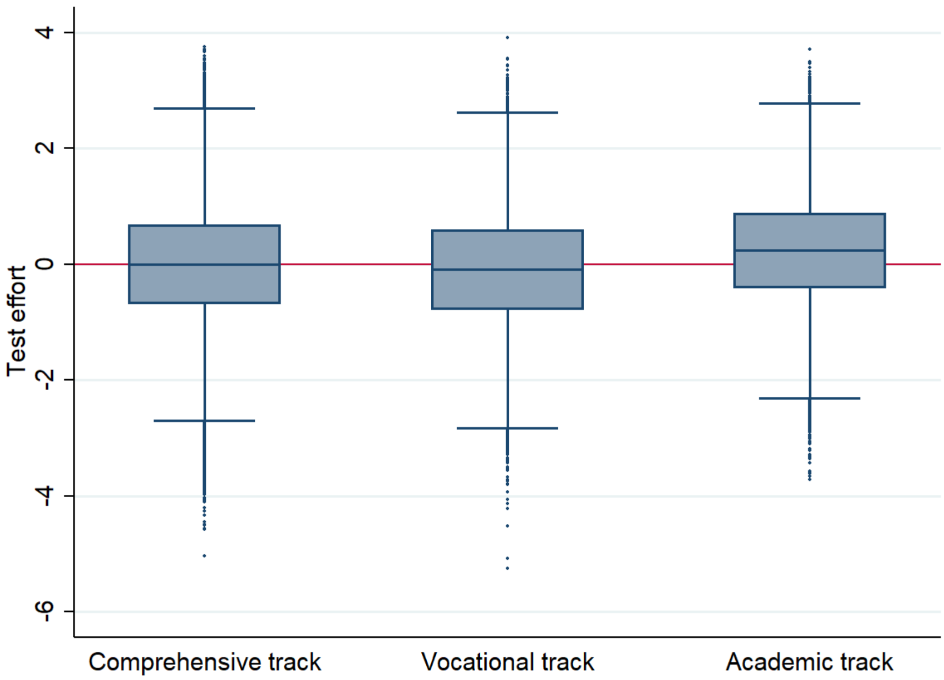

Figure 3. Test effort distributions by educational track

3.2. Methodology

The peer effects literature in education has identified two main challenges that require attention (Sacerdote, 2011). The first one is the reflexivity problem, i.e. when the outcome variable of the individual is affected by the peer variable but also the other way around. For example, this is relevant when the objective is to study the impact of peers' grades on an individual's grades. However, in this case it is not a problem as the main independent variable is the leave-out mean of peers with highly educated parents, which can by no means be influenced by the individual's test effort. The second challenge is the potential selection bias, which implies that the students are not randomly nested in schools. The ideal solution is to have a sample of students randomly placed in schools (Feld and Zölitz, 2017) or a source of exogeneity. As one example, Ammermueller and Pischke (2009) use the within-school variation in class composition as instrument with PIRLS data. However, those options are unavailable for the PISA test. To deal with selection, I follow the strategy used by Raitano and Vona (2013), which relies on the wide set of school information provided by the dataset to mitigate the selectivity problem. Therefore, the assumption is that after controlling for the observable variables, there is no significant selection bias. Reassuringly, Ammermueller and Pischke (2009) show that the error that arises due to selection bias is rather small. Hence, I include the following set of covariates at the school level that are relevant for the selection of students into those schools: type of school (public or private), size of the municipality in which the school is placed, student-teacher ratio, quality of school educational resources, school autonomy, teacher morale, quality of physical infrastructure of the school, average class size in the school and the methods used by the school for selecting new students. Moreover, I include pseudo fixed-effects for schools, which are calculated by dividing the schools into five quintiles according to the average parental education of the school (Raitano and Vona; 2013).

To further control by school composition, I also include the leave-out mean of female and migrant students within the school because both variables have been shown to influence educational outcomes independently (Entorf and Lauk, 2008; Lavy and Schlosser, 2011). The equation of the linear-in-means specification is the following:

$$E_{isj} = \beta_0 + \beta_1 P_{isj} + \beta_2 \bar{P}_{sj-i} + \beta_3 X_{isj} + \beta_4 Z_{sj} + \delta_j + \varepsilon_{isj}$$

Where E_{isj} is the test effort of the individual i in the school s in the country j. β_0 is the general intercept. P_{isj} is the parental education of the individual and $\bar{P}_{sj-i}$ the leave-out mean of peers' parental education. X_{isj} is a vector of individual background covariates and Z_{sj} is the set of covariates at the school level. δ_j represents the country fixed-effects and ε_{isj} the error term. To test the heterogeneity of the effects, I use an unconditional quintile regression following the same specification.

4. Results

The first results are shown in Table 1. Model 1 and 2 display the results for the hypothesis 1a. As expected, in the first model there is a positive and statistically significant association between peer socioeconomic background and test effort. Furthermore, the magnitude of the effect is substantial, a one SD increase in the average peer parental education increases test effort by 18% of a SD. In Model 2, school pseudo-fixed effects and a wide set of school covariates are introduced to mitigate the potential selectivity problem. Nevertheless, the observed effect remains almost the same, 18.1% increase in test effort per SD in peer SES. Thus, these results confirm the hypothesis that higher peer socioeconomic background has a positive effect on test effort. The effect size seems quite large, especially if we compare it with the effect of having a parent with tertiary education, which is associated with an increase in test effort by 13.9% of a SD. Furthermore, the estimate of peer background might be biased downwards, because as, Micklewright et al. (2012) argue, in PISA only a random sample of the population of peers is observed for each individual and not the full population.[24] They calculate that the estimate of PISA scores might be biased downwards by about one third if we compare it with the full sample of peers, because the peer effect would be stronger when considering the whole class. This does not translate directly to our estimations, but the direction of the bias will be similar. Therefore, it is likely that the true unbiased estimate of peer effects is even larger. As for hypothesis 3, we can observe in Model 1 of Table 1 that the effect of peer heterogeneity is significant and negative. But it should be taken into account that the magnitude is quite small; an increase of one SD in heterogeneity has a negative effect of 1.4% of a SD on test effort in Model 1. In Model 2 the impact seems not significant. Therefore, the results do not show a clear take-away from the analysis of being in a heterogeneous school in terms of socioeconomic characteristics.

[24] The number of students in each school that participate in PISA is around 35.

Nevertheless, even in the first model the result does not suggest an important role of peer heterogeneity for student's effort.

Table 1. Linear-in-means model of peer socioeconomic background on test effort

	Model 1	Model 2
Peer SES background	0.180***	0.181***
	(0.00596)	(0.0172)
Peer SES heterogeneity	-0.0142**	-0.0126
	(0.00464)	(0.00681)
Highest parental education (Ref. Basic)	.	.
Secondary	0.0451***	0.0452***
	(0.0106)	(0.0106)
Tertiary	0.138***	0.139***
	(0.0104)	(0.0108)
Migrant status (Ref. Native)	.	.
Migrant Second-Generation	-0.0809***	-0.0825***
	(0.0131)	(0.0131)
Migrant First-Generation	-0.0819***	-0.0804***
	(0.0150)	(0.0150)
Grade Repetition	-0.333***	-0.325***
	(0.0103)	(0.0102)
Female	0.0269***	0.0260***
	(0.00598)	(0.00598)
Share of female peers	0.0242***	0.0196***
	(0.00420)	(0.00413)
Share of peers with migrant background	-0.00453	-0.00600
	(0.00477)	(0.00491)
Constant	0.0525**	-0.0285
	(0.0200)	(0.0466)
Country fixed-effects	X	X
School pseudo-fixed effects		X
School selection variables		X
Observations	203,870	203,870
R-squared	0.069	0.072

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

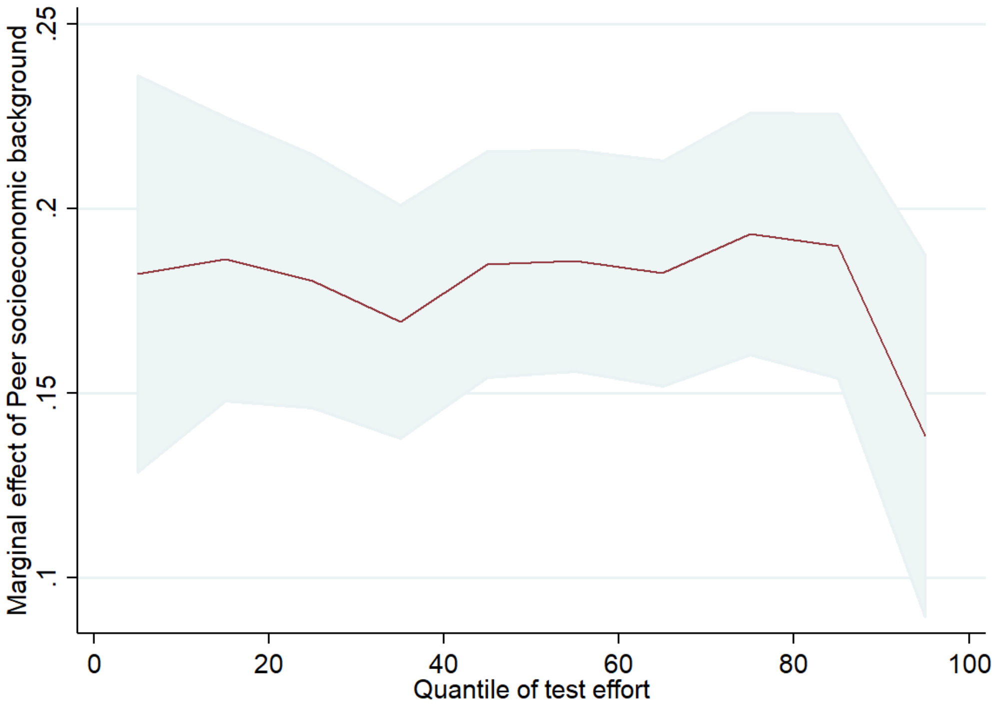

Figure 4. Marginal Effect of Peer SES by quantile of test effort

Hypothesis 2, regarding the non-linear impact of the peer background, is tested in Figure 4.[25] The graph displays very homogeneous results throughout the distribution. We only observe small dips at the top of the distribution, above the 90th quantile, where the effect appears smaller. Hence, the hypothesis of non-linearity cannot be confirmed, especially taking into account the stability of the effect throughout most of the distribution, which goes in the opposite direction as our theoretical expectations. Nevertheless, the dynamics at the top of the distribution do play out as expected. A slight decrease of peer benefits starts around the 90th quantile, although as before, the confidence intervals are quite wide and it is difficult to draw a firm conclusion.

[25] The table can be found in Table A.3 of the Appendix

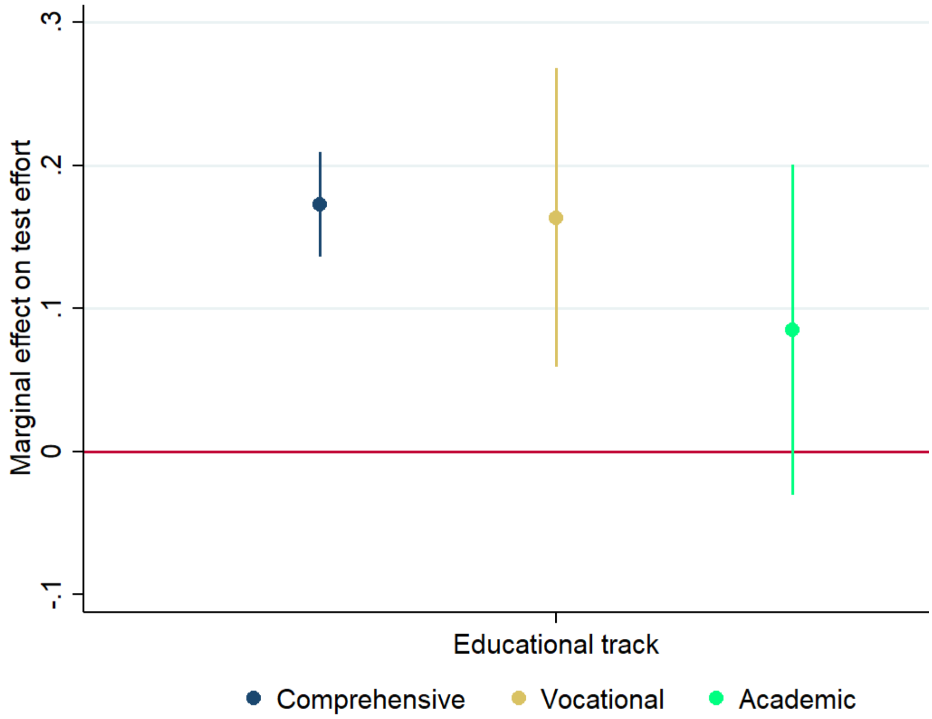

Figure 5. Marginal Effect of Peer SES by educational track

Afterwards, the differentiation by educational tracks is introduced. In Table 2 there is one regression for students in each track. In this way we can explore the different impact of peer background in the different tracks in greater detail. In the comprehensive track (where most countries are clustered) the results are quite similar to those in Table 1. Higher peer socioeconomic background has a strong and positive effect on test effort, 17.3% of a SD, and peer heterogeneity a small and negative effect. In the model of the vocational track we observe a slightly smaller effect of peer SES on test effort, around 16.4%, but it is not statistically different from the result of the comprehensive track, which goes in line with the hypothesis. Furthermore, the effect of peer heterogeneity is not significant. As for the academic track, the impact of peer background is 8.5% of a SD, clearly smaller than in the other tracks, and not statistically different from 0. Again, there is no significant impact of peer heterogeneity in the academic track either. This provides support for the hypothesis 4. Overall, the results seem to suggest that there is still room for maximizing test effort by reorganizing the composition of classes within the tracks.

Table 2. Linear-in-means model of peer socioeconomic background on test effort in different tracks

	Late-tracking countries	Early-tracking countries	
	Comprehensive track	Vocational track	Academic track
Peer SES background	0.173***	0.164**	0.0852
	(0.0187)	(0.0533)	(0.0589)
Peer SES heterogeneity	-0.0148*	-0.00300	0.00231
	(0.00729)	(0.0155)	(0.0310)
Highest parental education (Ref. Basic)			
Secondary	0.0331**	0.127***	0.0307
	(0.0119)	(0.0264)	(0.0391)
Tertiary	0.149***	0.111***	0.0647
	(0.0121)	(0.0281)	(0.0393)
Migrant status (Ref. Native)	.	.	.
Migrant Second-Generation	-0.0685***	-0.127***	-0.159**
	(0.0146)	(0.0377)	(0.0498)
Migrant First-Generation	-0.0667***	-0.146**	-0.190**
	(0.0163)	(0.0493)	(0.0607)
Grade Repetition	-0.334***	-0.248***	-0.203***
	(0.0122)	(0.0235)	(0.0286)
Female	0.0400***	-0.00232	-0.0667***
	(0.00677)	(0.0174)	(0.0175)
Share of female peers	0.0123*	0.0245*	-0.00351
	(0.00486)	(0.0100)	(0.0114)
Share of peers with migrant background	-0.00663	-0.0231	-0.0173
	(0.00527)	(0.0163)	(0.0226)
Constant	0.0744	-11.14**	-13.68***
	(0.0499)	(4.034)	(3.861)
Country fixed-effects	X	X	X
School pseudo-fixed effects	X	X	X
School variables	X	X	X
Observations	155,200	25,602	23,068
R-squared	0.068	0.102	0.068

Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05

4.1 Robustness check

To further check the robustness of the results and mitigate as much as possible the potential selection bias of students into schools, I take advantage of a subsample of nine countries that carried out an additional survey to the parents of the students that participated in PISA 2012.[26] This survey contains two questions that are related to the selection of the school by the parents. The first one asks the parents whether there are other schools in the area that compete with the school that the student attends. The second one asks the parents for their reasons to choose a school, giving several options to which they have to answer. For example, “the academic achievements of students in the school are high”, “the school has good reputation”, “the school is at short distance from home” or “the expenses are low”. Therefore, controlling for these school choice covariates should further mitigate the potential selectivity problem. To check how the additional covariates affect the robustness of the results, I replicate the results of the main specification, Model 2 in Table 1.

Table 3 shows the results of the robustness check. Model 3 replicates the main specification with the new sample and in Model 4 we add the school choice covariates. The magnitude of the effect of peer background decreases slightly after adding the additional controls, around 1.1 percentage points on the coefficient. Thus, the result seems to be quite robust and very similar to the specification with the full sample of countries. However, it is also worth noting that peer heterogeneity does not appear as a significant predictor here. This indicates that we should take caution when comparing these results with the full sample of countries.

[26] The countries that carried out the parental survey are Belgium, Chile, Germany, Hong Kong, Hungary, Italy, Mexico, Portugal and South Korea.

Table 3. Linear-in-means model of peer socioeconomic background on test effort

	Model 3	Model 4
Peer SES background	0.208***	0.197***
	(0.0290)	(0.0284)
Peer SES heterogeneity	-0.00619	-0.00978
	(0.0118)	(0.0115)
Highest parental education (Ref. Basic)	.	.
	(.)	(.)
Secondary	0.0373*	0.0259
	(0.0151)	(0.0150)
Tertiary	0.100***	0.0868***
	(0.0157)	(0.0156)
Migrant status (Ref. Native)	.	.
	(.)	(.)
Migrant Second-Generation	-0.0155	-0.0194
	(0.0304)	(0.0303)
Migrant First-Generation	0.0208	0.0191
	(0.0329)	(0.0327)
Grade Repetition	-0.310***	-0.299***
	(0.0174)	(0.0171)
Female	-0.0154	-0.0150
	(0.0106)	(0.0106)
Share of female peers	0.0274***	0.0266***
	(0.00772)	(0.00750)
Share of peers with migrant background	0.00650	0.00416
	(0.0133)	(0.0128)
Constant	0.0661	0.0495
	(0.0862)	(0.0975)
Country fixed-effects	X	X
School pseudo-fixed effects	X	X
School variables	X	X
School choice		X
Observations	72,204	72,204
R-squared	0.101	0.107

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

5. Discussion

This paper investigates the impact of higher peer socioeconomic background on test effort. Taking into account the importance of peer effects on educational attainment (Sacerdote, 2011), I examine whether effort acts as one of the channels of social influence. The theoretical mechanism derives from the Wisconsin status attainment model (Sewell et al., 1969), which postulates that class differentials in educational attainment can be explained by the process of socialization. Young students tend to imitate the educational expectations of friends and peers. Therefore, those students surrounded by peers with higher educational expectations will be more likely to develop high educational expectations, which then translate into higher effort in educational activities in order to accomplish these expectations. Using data from PISA 2012, a measure of test effort is created based on the methodology proposed by Borghans and Schills (2012). Furthermore, having data from 31 countries allows for comparing the peer effects in different educational systems.

The first contribution of this paper is to provide evidence that effort is indeed a key channel through which social influence impacts individuals' academic achievement as proposed in the Wisconsin model (Sewell et al., 1969). The results of this study show that having higher SES school peers has a very positive impact on test effort and the effect seems to be homogeneous throughout the effort distribution. The magnitude is even larger than the effect of parental education. This evidence contradicts the results provided by Feld and Zölitz (2017), who do not find effort to be one of the channels of peer effects. However, the proxy of effort that they use is the declared hours spent doing homework at home, which is a rougher measure than the exerted test effort. Therefore, we are confident that the results unveil a new mechanism at play. The impact of peer heterogeneity is quite ambiguous. Previous literature suggests that being in class with very heterogeneous peers has generally a negative influence on educational attainment (Sacerdote, 2011; Raitano and Vona, 2013). This paper finds that the impact of peer heterogeneity on test effort is very small and only significant in one of the specifications. The results seem to imply that peer heterogeneity is not a very relevant factor in students' effort.

The second contribution is to shed light on the impact of peer socioeconomic background on effort by educational track. The results show that the effect is somewhat heterogeneous across tracks. It is positive and significant larger for those students in comprehensive systems and in the vocational track, but not for those in the academic track. This goes in line with the hypothesis, because students in the academic track are positively selected in skill and their educational expectations are very high. Meanwhile, in the comprehensive systems and the vocational track there are more disparities in expectations (Van den Broeck, 2018). Thus, students can benefit from having peers from high SES backgrounds with high expectations. Regarding peer heterogeneity, different results appear. In the comprehensive track, the impact of peer heterogeneity is negative and significant, even controlling for all the school variables. However, in the case of the academic and vocational tracks, the estimate is insignificant. This is probably due to the fact that the students are already sorted by skill into those tracks, so there is a high degree of homogeneity within the tracks. Nevertheless, the magnitude of the impact is quite small in all cases. It appears that effort is not strongly affected by peer heterogeneity and it is highly dependent on the country tracking system. Overall, it looks like social influence has a greater effect in countries with comprehensive systems than in early-tracking countries. This can be explained due to the fact that early-tracking countries sort their students at a very early age into their educational tracks, which already shapes their destiny. In comprehensive countries, there is more room for external factors to come into play until tracking takes place. This does not imply that social background has a stronger effect in countries with comprehensive systems. On the contrary, most research points out that early-tracking systems tend to transmit more social inequality because the early sorting is strongly influenced by parental background (Brunello and Checchi, 2007; Van de Werfhorst, 2018). However, the results of this paper suggest that, in comprehensive systems, the social background also finds its ways to influence educational outcomes, for example, through effort.

The study has some limitations that are important to consider. First, when dealing with peer effects in the educational context it is paramount to consider potential selection bias. Usually, students are not randomly allocated in schools, so the characteristics of their peers might be correlated with other characteristics of the school. Hence, ideally, a source of exogeneity should be used to deal with this methodological problem (Ammermueller and Pischke, 2009). However, in the case of PISA, data this is not possible, and I rely on a wide set of covariates that comprises many characteristics of the school, similarly to Raitano and Vona (2013). Second, due to the inherent characteristics of the effort variable, some considerations have to be taken into account. The variable is measured during the PISA test, a low-stake exam for the students because it does not impact their grades. Thus, it cannot be assured that the students exert the same effort in the PISA test as in their school exams, where they are extrinsically motivated by their grades. Moreover, there is evidence that intrinsic motivation varies significantly by country. For example, Gneezy et al. (2019) show that East Asian countries tend to perform better than Western countries because their students tend to have more intrinsic motivation. However, when extrinsic incentives are added, US students performed as well as their Asian counterparts. These facts suggest that our estimate of the association between peer socioeconomic background and test effort is a lower bound since it is reasonable to expect that the association would be higher if effort could be measured in a situation where the students were extrinsically motivated.

The evidence here presented sheds some light on the black box that social influence still constitutes. Effort, a key determinant of educational attainment, is influenced by students' peer socioeconomic background, stressing the relevance of social influence in education. This might contribute to the transmission of intergenerational inequality because high SES parents tend to choose schools for their children according to their socioeconomic level. Nevertheless, a better understanding of peer effects also allows policymakers to improve educational outcomes effectively by rearranging students from one setting to another. More research is needed to be able to fully understand these dynamics and design effective policies, but it is a promising research field that can provide useful tools for mitigating educational inequality. This chapter contributes to it by showing that peer effects indeed partly consist of students affecting each other's effort.

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7. Appendix

Table A.1. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Test effort	203,870	0	1	-5.25	4.204
Peer SES background	203,870	0	1	-2.24	2.03
Peer SES heterogeneity	203,870	0	1	-4.94	0.84
Share of female peers	203,870	0	1	-2.81	2.73
Share of peers with migrant background	203,870	0	1	-0.67	5.9
Parental education					
Basic education	203,870	0.15		0	1
Secondary education	203,870	0.32		0	1
Tertiary education	203,870	0.52		0	1
Migration status					
Native	203,870	0.904		0	1
Migrant Second-Generation	203,870	0.049		0	1
Migrant First-Generation	203,870	0.047		0	1
Repeated course	203,870	0.111	0.315	0	1
Female	203,870	0.507	0.499	0	1
Easy booklet	203,870	0.15	0.36	0	1
School Autonomy	203,870	-0.09	0.926	-2.871	1.603
Class size	203,870	28.02	9.1	13	53
Quality of school resources	203,870	0.01	1.02	-3.59	1.976
Student-teacher ratio	203,870	15.3	18.6	0.632	1018
School type					
Private Independent	203,870	0.047		0	1
Private government-dependent	203,870	0.145		0	1
Public	203,870	0.792		0	1
Missing	203,870	0.014		0	1
School location					
Village	203,870	0.077		0	1
Small Town	203,870	0.205		0	1
Town	203,870	0.33		0	1
City	203,870	0.26		0	1
Large City	203,870	0.119		0	1

Invalid	203,870	0.0002		0	1
Missing	203,870	0.001		0	1
Academic records-Admission					
Never	203,870	0.413		0	1
Sometimes	203,870	0.202		0	1
Always	203,870	0.38		0	1
Missing	203,870	0.004		0	1
Feeder school- Admission					
Never	203,870	0.448		0	1
Sometimes	203,870	0.304		0	1
Always	203,870	0.21		0	1
Invalid	203,870	0.0001		0	1
Missing	203,870	0.005		0	1
Parents endorsement-Admission					
Never	203,870	0.635		0	1
Sometimes	203,870	0.182		0	1
Always	203,870	0.174		0	1
N/A	203,870	0.0001		0	1
Invalid	203,870	0.0003		0	1
Missing	203,870	0.007		0	1
Shortage of teaching staff	203,870	-0.75	0.98	-1.091	3.59
Teacher morale	203,870	-0.064	0.98	-3.97	1.445
Quality of school physical infrastructure	203,870	-0.038	1	-2.755	1.305

Table A.2. Classification of students by educational track in each country

	Late-tracking countries	Early-tracking countries	
Country	Comprehensive track	Academic track	Vocational track
Australia	9,516		
Austria		1,232	2,261
Belgium		1,512	2,254
Canada	16,165		
Chile	5,622		
Czech Republic		793	1,318
Denmark	4,954		
Germany		1,194	1,230
Estonia	3,945		
Finland	7,355		
France	3,348		
Great Britain	10,082		
Greece	4,192		
Hong Kong	4,269		
Hungary		1,855	2,247
Iceland	2,102		
Ireland	3,558		
Israel	3,397		
Italy		13,173	11,679
Korea, South	4,560		
Latvia	3,400		
Mexico	25,644		
Netherlands		1,497	1,752
New Zealand	3,006		
Poland	3,855		
Portugal	4,494		
Russia	4,112		
Slovenia		1,812	2,591
Spain	19,480		
Sweden	3,959		
USA	4,185		
Total	155,200	23,068	25,602

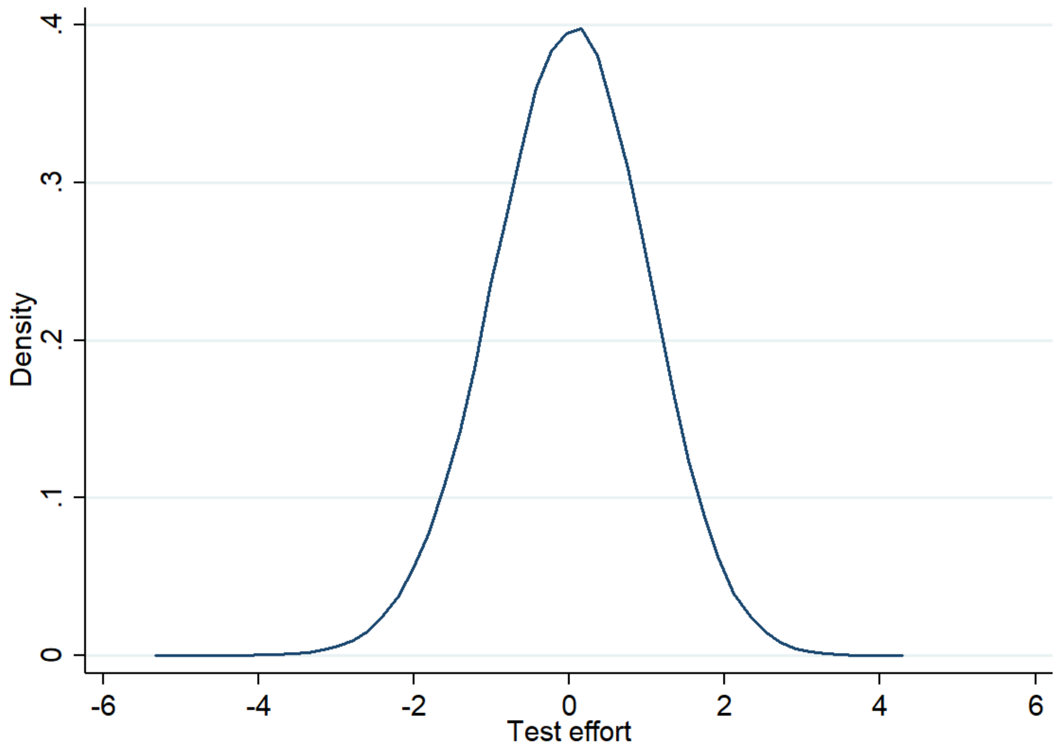

Figure A.1. Kernel density plot of test effort

Table A.3. Unconditional quantile regression of test effort

	10th	30th	50th	70th	90th
Peer SES background	0.190***	0.175***	0.187***	0.185***	0.181***
	(0.0228)	(0.0166)	(0.0155)	(0.0161)	(0.0204)
Peer SES heterogeneity	-0.0154	-0.00967	-0.0145*	-0.0109	-0.00306
	(0.00848)	(0.00622)	(0.00581)	(0.00612)	(0.00769)
Highest parental education (Ref. Basic)	.	.	.	.	
Secondary	0.0718***	0.0612***	0.0707***	0.0338**	0.00967
	(0.0215)	(0.0148)	(0.0130)	(0.0128)	(0.0155)
Tertiary	0.144***	0.161***	0.169***	0.139***	0.100***
	(0.0217)	(0.0149)	(0.0132)	(0.0131)	(0.0159)
Migrant status (Ref. Native)	.	.	.	.	
Migrant Second-Generation	-0.0855***	-0.0707***	-0.0813***	-0.0675***	-0.0773***
	(0.0252)	(0.0179)	(0.0166)	(0.0170)	(0.0211)
Migrant First-Generation	-0.101***	-0.0914***	-0.0885***	-0.0684***	-0.0505*
	(0.0280)	(0.0196)	(0.0178)	(0.0181)	(0.0224)
Grade Repetition	-0.342***	-0.368***	-0.356***	-0.315***	-0.231***
	(0.0218)	(0.0146)	(0.0125)	(0.0118)	(0.0137)
Female	0.0871***	0.0460***	0.0184*	-0.00640	-0.0257**
	(0.0110)	(0.00803)	(0.00753)	(0.00780)	(0.00985)
Share of female peers	0.0281***	0.0242***	0.0239***	0.0169***	0.00749
	(0.00499)	(0.00373)	(0.00355)	(0.00375)	(0.00486)
Share of peers with migrant background	-0.0143*	-0.0145**	-0.0115*	-0.00596	0.000483
	(0.00691)	(0.00493)	(0.00456)	(0.00464)	(0.00571)
Constant	-1.802***	-0.928***	-0.384***	0.261***	1.059***
	(0.0707)	(0.0518)	(0.0482)	(0.0499)	(0.0625)
Country fixed-effects	X	X	X	X	X
School pseudo-fixed effects	X	X	X	X	X
School variables	X	X	X	X	X
Observations	203,870	203,870	203,870	203,870	203,870
R-squared	0.026	0.048	0.055	0.045	0.021

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Chapter 4

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

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 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 fourth-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).[27]

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.[28] Finally, the last condition was the tournament,

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

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

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.

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.[29] 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 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.

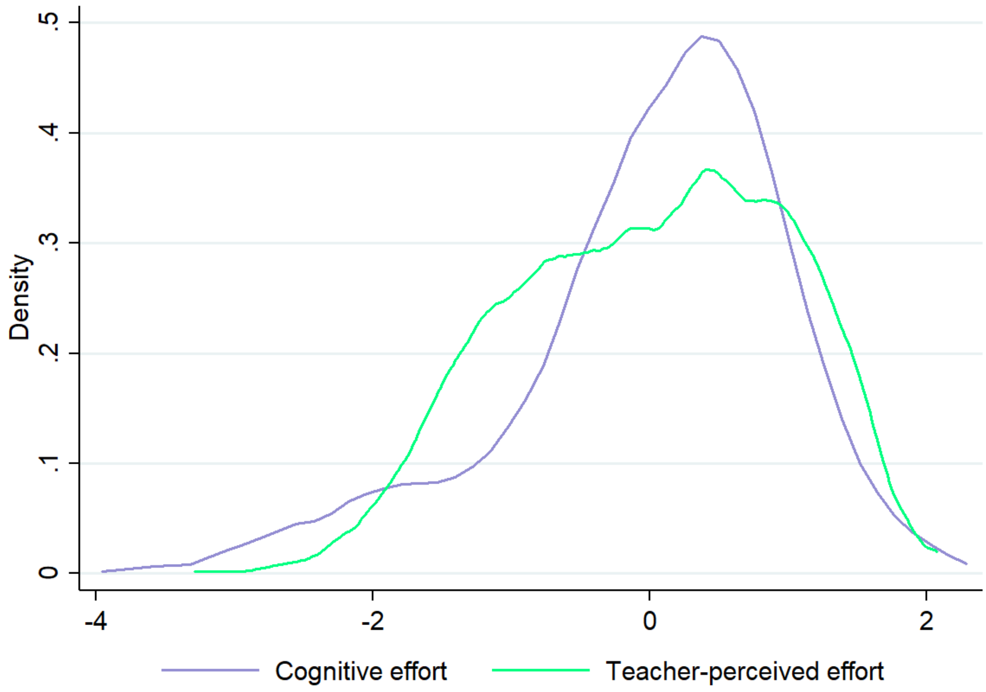

Figure 1. Kernel density distribution of teacher-perceived effort and cognitive effort

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.

[29] 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.

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).[30] 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.[31] 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).

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

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

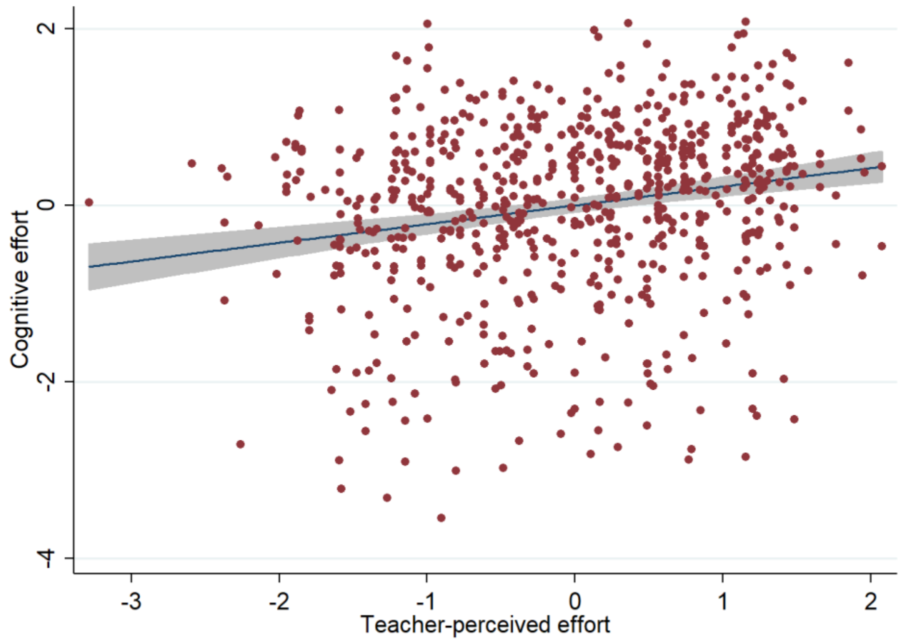

Figure 2. Correlation between teacher-perceived effort and cognitive effort

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	Cognitive 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.

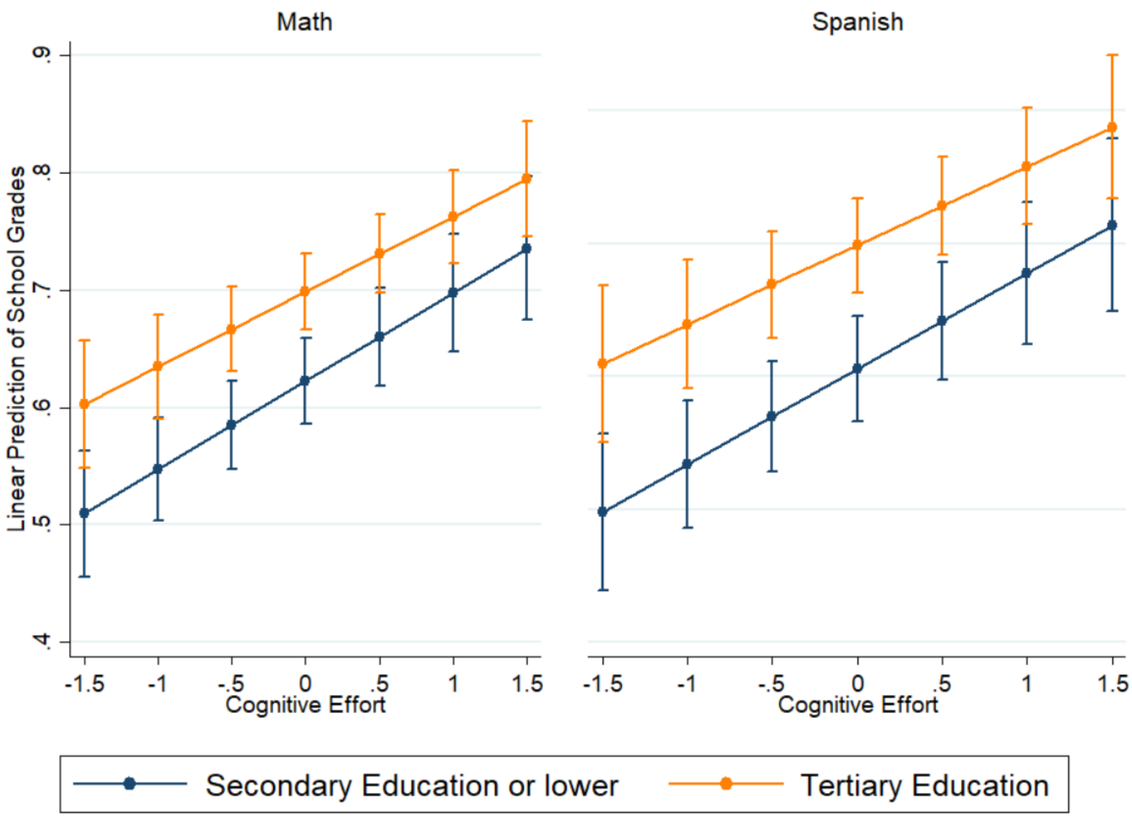

Figure 3. Linear prediction of school grades by tertiary parental education and cognitive effort

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.

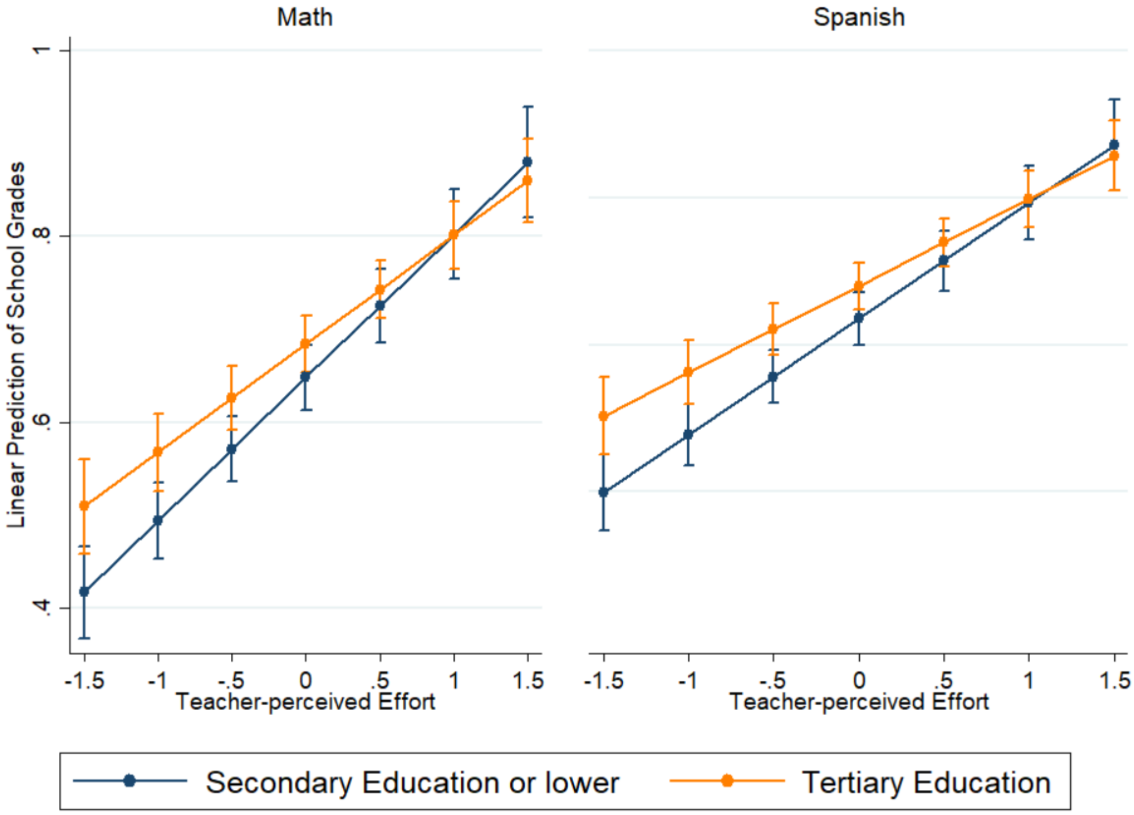

Figure 4. Linear prediction of school grades by tertiary parental education and teacher-perceived effort

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.

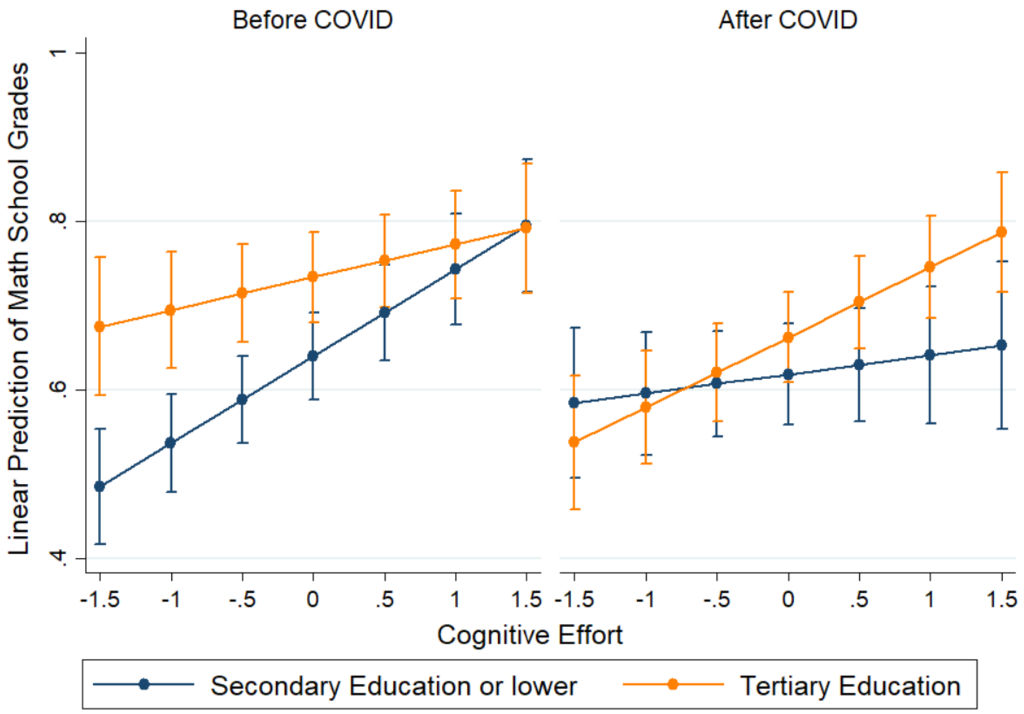

Figure 5. Linear prediction of math grades before and after COVID by cognitive effort

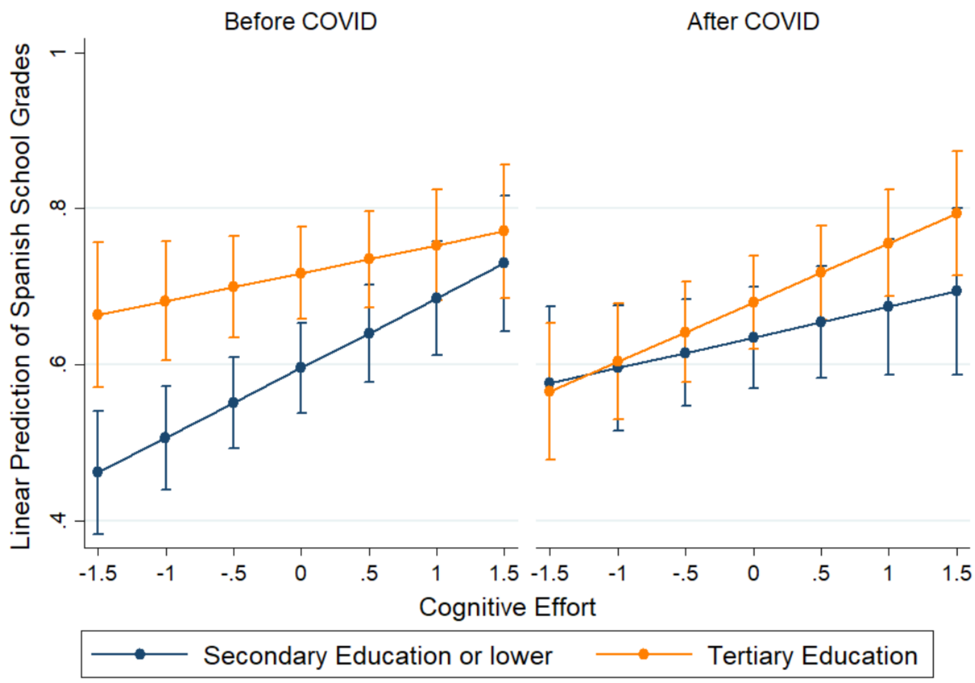

Figure 6. Linear prediction of Spanish grades before and after COVID by cognitive effort

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).

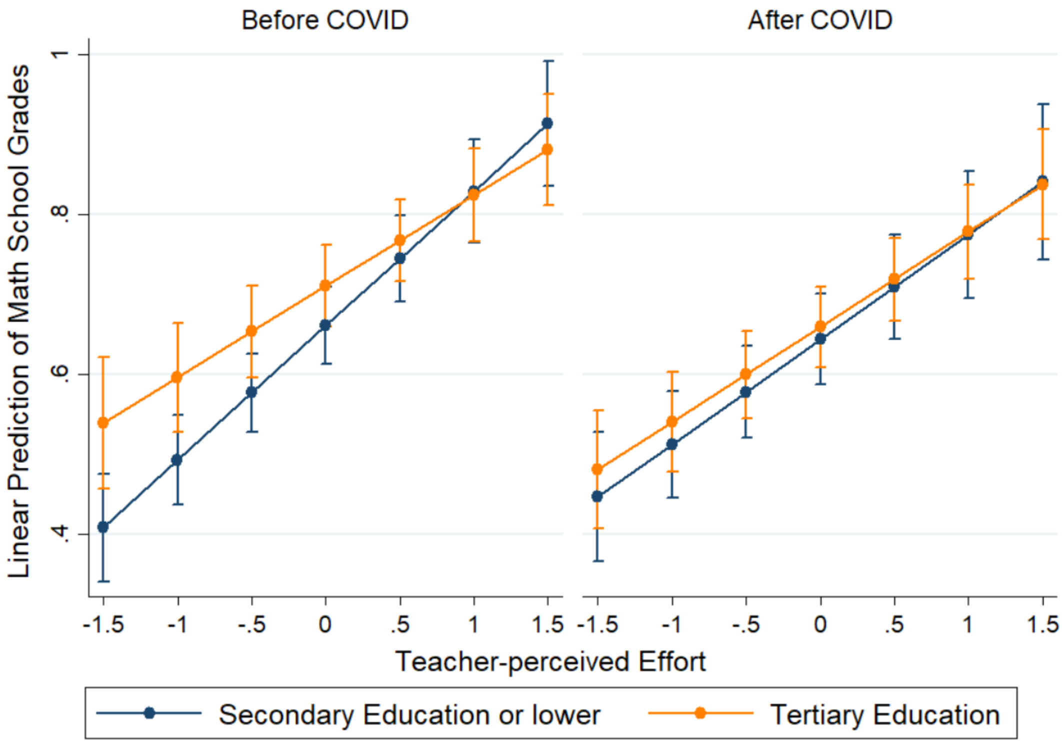

Figure 7. Linear prediction of math grades before and after COVID by teacher-perceived effort

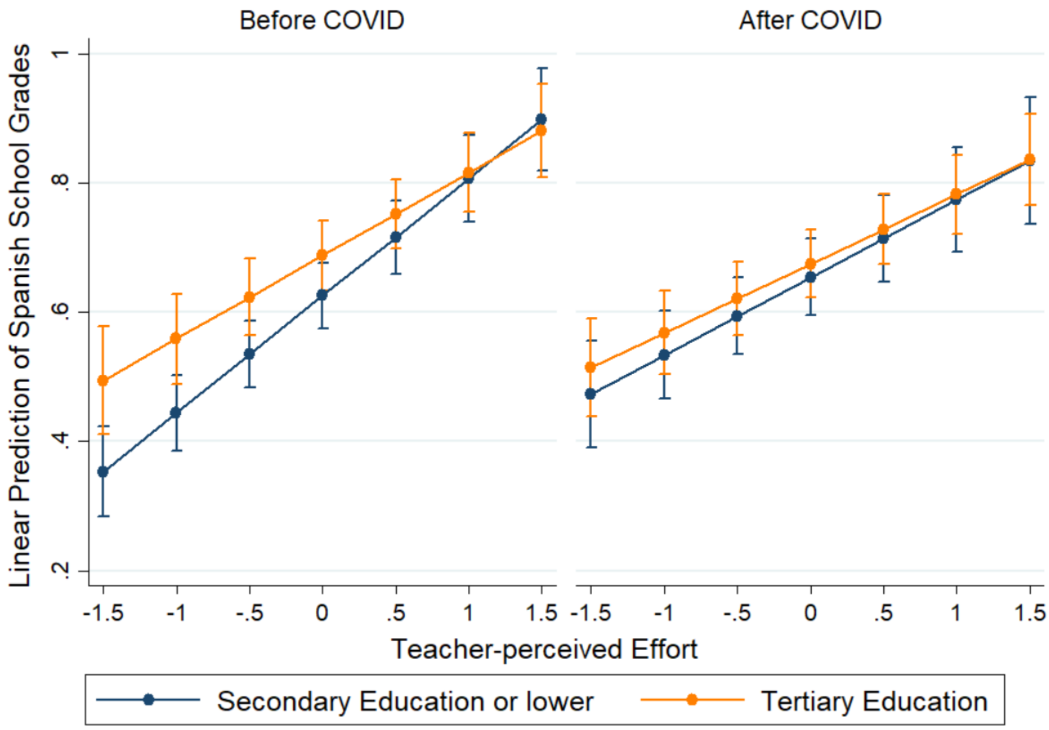

Figure 8. Linear prediction of Spanish grades before and after COVID by teacher-perceived effort

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

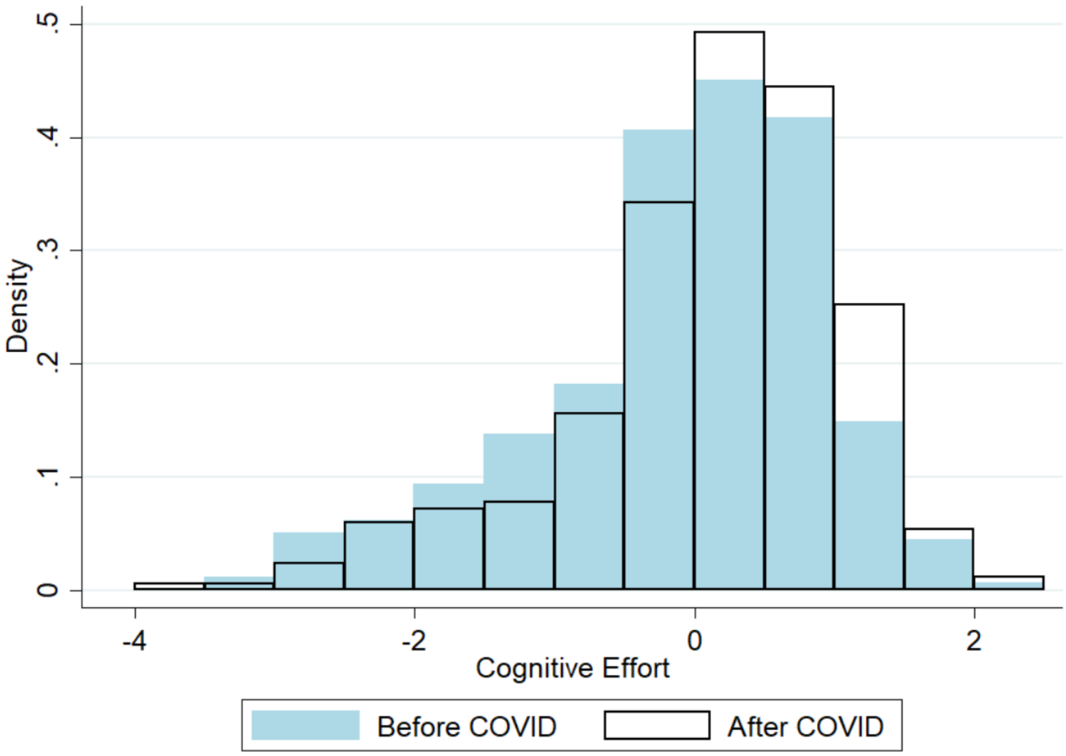

Figure D.1. Histogram of Cognitive effort before and after COVID

Chapter 5

Conclusions

1. Objectives and findings

This thesis deals with a crucial topic for equality of opportunity, the role of effort in the process of educational attainment. Effort is often assumed to be a main driver of life outcomes and social mobility. Furthermore, it is deemed the fairest source of inequality because individuals have full agency to exert it. However, these assumptions derived from the meritocratic narrative are not backed by evidence. In fact, we know little about the importance of effort for attainment. This topic has remained understudied in relation to its importance, probably largely due to the difficulties of measuring effort. This thesis seeks to contribute to the study of effort in different avenues. First, methodologically, by employing two measures of effort which are gathered by observing the actual effort exerted. The measures are the relative decline in performance throughout the PISA test, developed by Borghans and Schils (2012), and an experimental measure of cognitive effort based on real-effort tasks. This marks scientific progress because most literature that studies effort-adjacent concepts relies on self-reported non-cognitive skills. It has been shown that the correlation between those survey-based measures and experimental measures of cognitive effort is very low or inexistent (Apascaritei et al., 2021). Therefore, by employing objective measures of exerted effort we can establish a more reliable picture of the relevance of effort for educational attainment than previous scholarship.

The second contribution is empirical. In this regard, the objectives of this thesis are two-fold. First, I investigate the impact of effort on educational attainment. By comparing the magnitude of its effect with other important determinants such as cognitive skills or parental background relevant takeaways about the existence of equality of opportunity can be extracted. Second, I test the potential role of effort as a contributor to the transmission of social inequality. To do so, I analyze different mechanisms derived from the Cultural Reproduction Theory (CRT) and the Wisconsin model.

The results of the first paper indicate that test effort has a positive and significant effect on the probability of having completed tertiary education at age 25. Strikingly, the magnitude is substantial. The impact of an increase of an SD of test effort on the probability of tertiary education is half the effect of having parents with tertiary education. This result goes in line with the literature on non-cognitive skills (Almlund et al., 2011). Furthermore, when testing the mediating effect of effort between parental education and tertiary education no such mediation is found. It seems that parental education does not impact the probability of completing tertiary education through effort, as the CRT would suggest. However, there is evidence of the mediating effect of effort between educational expectations and future tertiary education. The mechanism proposed in the Wisconsin model seems to be in effect in the Australian context. This is in line with the findings of Domina et al. (2011) that educational expectations increase effort at school. Thus, the paper unveils a mechanism through which effort seems to contribute to the transmission of inequality.

The second paper shows evidence of the importance of peer effects as a proxy of social influence on effort. The results indicate that being in school with peers from high SES backgrounds increases test effort through educational expectations. This suggests that effort is one of the channels through which peer effects influence educational attainment. It is also worth highlighting the size of the peer effect, which is even larger than the effect of having highly educated parents. This goes against the results provided by Feld and Zölitz (2017), who do not find that effort acts as a channel of peer effects. However, their measure of effort is based on a self-reported measure of hours spent doing homework. This dubious operationalization can explain the divergence. Furthermore, the impact of peer background is homogeneous throughout the effort distribution. Regarding peer background heterogeneity, the result shows a negative effect on effort. This is in line with most literature that finds a negative effect of peer heterogeneity on test scores (Fertig, 2003, Raitano and Vona, 2013). Nevertheless, the magnitude of the effect is very modest, an order the magnitude smaller than the magnitude of peer background. Finally, the impact of peer background differs by educational track. In the comprehensive and vocational track, the impact is positive and significant, but for the academic track, peer background is not a significant predictor of test effort. This could be explained by the fact that those students attending the academic track are very positively selected in terms of academic skill and motivation and are surrounded by similar peers, even independently of their parental background.

In the third paper, the impact of effort on educational attainment is tested in the Spanish context. On this occasion two different measures of effort are used; an objective experimental measure of cognitive effort and the teacher-perceived effort of the student. The results provide new evidence of the positive impact of effort on school grades. The magnitude of the effect of cognitive effort is very important, similar to or even higher than the effect of cognitive skills. The magnitude is larger than the previous result in the first empirical paper, which we expected since the measure used here is more complete and the dependent variable is school grades. Turning to teacher-perceived effort, the size of the impact is even larger, being twice the size of cognitive skills. These results highlight the importance of effort for academic achievement. Furthermore, two moderating mechanisms of effort are also studied. First, the evidence suggests that there is no compensatory advantage for cognitive effort. It seems that highly educated parents do not effectively compensate for the low level of effort of their children. Rather, the effect of effort on school grades is independent of the parental background. Second, the results show a negative interaction between teacher-perceived effort and parental education on school grades. This implies that children from high SES families are less penalized in their school grades than their poorer peers when the teacher detects that they exert low effort.

2. Theoretical and policy implications

Overall, the results of this thesis yield more bad than good news for the equality of opportunity paradigm. On the positive side, results in Chapter 2 and 4 show that the impact of effort on educational attainment is significant and positive. Simply put, hardworking kids obtain better educational outcomes. The magnitude of this meritocratic effect is smaller in the first paper –although still substantial- probably because the measure of effort is partial and the variable of educational attainment takes place in the long run -having completed tertiary education ten years later. Thus, focusing on the third empirical paper, which employs arguably the most complete measurement of cognitive effort available thus far, we observe that its impact on academic achievement is very large, at the same level of cognitive skills, one of the established main predictors of achievement. It is also important to highlight that the impact of effort is independent of parental SES. Therefore, the thesis provides support for one of the basic assumptions of the meritocratic discourse. If children exert more effort they will get significantly better grades, independently of their socioeconomic background.

On the negative side, this thesis provides evidence of one mechanism through which effort contributes to the persistence of inequality through generations. Specifically, effort mediates between educational expectations and educational attainment. This is relevant because according to the Wisconsin model, individuals shape their educational expectations influenced by their parental background and the social environment in which they live. Thus, children from high SES families living in rich neighborhoods will develop very high educational expectations, and the opposite will happen for less-advantaged children. The finding of Holtmann et al. (2021) that educational aspirations are a strong mediator of intergenerational educational transmission is complemented by this result because it provides evidence of one particular mechanism, effort. Furthermore, another aspect that contributes to the persistence of inequality is related to the effort as perceived by the teacher. Our evidence indicates that students from less-privileged families are penalized more than their richer counterparts. This is another example of teachers being influenced by the socioeconomic characteristics of the students, which has been already shown by other studies (Jæger, 2011; Jæger and Møllegaard, 2017). Needless to say, this is particularly concerning because, at the end of the day, teachers are the gatekeepers of the educational process. Furthermore, we should keep in mind that although the effect of effort on educational attainment is quite large, it is similar to the effect of parental education.

The evidence presented in this thesis casts a grim shadow on the equality of opportunity paradigm. Even effort, which should be the main legitimate pillar of attainment, contributes to the intergenerational transmission of inequality. If we want to mitigate through policies its potential adverse effect on the persistence of inequality, we should pay attention to the particular mechanisms. Focusing on the students' expectations, the educational expansion of the last decades caused a sharp increase in educational expectations as aspiring to tertiary education is becoming the norm (Goyette, 2008). This decreases the influence that parental background has on educational expectations. Nevertheless, in western countries, there is still a gap in educational expectations due to family background (Li and Xie, 2020). Taking into account the importance of this determinant, again demonstrated in this thesis, policymakers could design programs to boost educational expectations for less-advantaged students. This could help the students at the lower end of the income distribution because it could increase the effort that they exert at school. A particularly beneficial intervention to reduce inequality is to improve both academic achievement and expectations because the impact of expectations is greater at high levels of academic achievement (Fishman, 2022). An example could be the GEAR UP program created by the U.S. Department of Education, which has as its first and second objectives to improve academic performance and increase educational expectations (Department of Education, 2020). Nevertheless, we should be careful when raising expectations because some studies warn about the potential negative impact of unrealistic educational expectations (Rosembaum, 2001; Rosembaum, 2011).

Another way to mitigate the persistence of inequality is to reduce the room for teacher bias. Some sociodemographic characteristics such as gender, race or social class tend to give wrong impressions to teachers (Geven et al., 2018). Furthermore, academic achievement accounts for around 63 percentage points of school grades (Südkamp et al., 2012). This implies that teachers take into account other factors that they perceive as important, including effort. For example, DiPrete and Jennings (2012) explain that teachers benefit students who conform better to school norms and other similar attitudes. Therefore, one option would be to create a guideline for teachers to make school grades only dependent on academic achievement, as Norway has done (Protivínský and Münich, 2018). However, the true potential to reduce inequality of this measure is not clear, there is need for more research.

3. Limitations and future research

The thesis also contains some limitations. First of all, although I have argued before that the measures of exerted effort used here are a step forward in the research about effort, they are not exempt from criticism. In particular, the decline of performance throughout the PISA test has two shortcomings. As the name of the variable indicates, it only reflects how stable the performance is throughout the test. Therefore, it accounts for persistence, one of the key elements of effort, but does not measure the initial intensity of effort. And this connects with the following problem, that the PISA test is a low-stake exam. Thus, some students might not be very motivated to exert a lot of effort because the test score does not affect their school grades. Furthermore, there are differences across countries in intrinsic motivation carrying out this type of exams. For example, Gneezy et al. (2019) find that in PISA, when there is only intrinsic motivation, East Asian countries perform better than the rest of the countries. However, when they add extrinsic incentives, students from the US perform almost as well as their East Asian peers. Therefore, it is likely that the results using this variable are a lower-bound estimate of the impact of effort. Regarding the experimental measure of cognitive effort, although we have included different motivations, an opportunity cost and various tasks tapping into diverse executive functions, it faces the common criticism of experimental measures that it might not be representative of what happens in a real setting. Recognizing that it is an imperfect measure of effort, we contend that the new measure contributes significantly to solidifying the knowledge about the role of effort in social dynamics. Methodological developments in this regard are crucial to understanding how effort works, and improving measurement remains an important avenue of future research.

Another caveat to keep in mind is that the first and third empirical papers use data from two particular countries, Australia and Spain. This implies that their specific characteristics can influence the results. For example, the share of individuals between the age of 25 and 34 years old that have completed tertiary education in 2013 in Australia is five percentage points higher than the OECD average and in Spain it is one percentage points higher than the average.[32] Therefore, the relationship between parental SES and educational attainment could be lower than in other countries where the educational expansion has not reached that far. Thus, these results would benefit

[32] Data from OECD: data.oecd.org

from being tested in other countries with different educational systems to study how stable they are.

The assessment of the meritocratic paradigm stemming from this thesis leaves a bittersweet taste. The relevance of effort for educational outcomes is out of the question. Its impact rivals in magnitude with cognitive skills. As promised, if you exert more effort, you will be more successful. Nevertheless, the evidence presented in the dissertation also puts into question one of the key assumptions of the narrative, that effort is the most legitimate determinant because it only depends on the willingness of the individual to exert it. As some differences in effort exertion are due to ascriptive characteristics, individuals could wonder whether it is fair that these differences are socially rewarded. To design a fairer society we should consider whether to put effort as the main factor that legitimates the social hierarchy is appropriate.

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