# Exposure to better-performing peers: consequences and mechanisms

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**Abstract**

The existing literature on peer effects in education indicates that the impact of better-performing peers varies across different ability groups, manifesting both positive and negative directions. However, the factors contributing to the negative turns in these effects remain inadequately understood. This study employs a comprehensive approach to deepen our understanding of these mechanisms. Firstly, it explores the influence of peer performance on a broader spectrum of outcomes, including short-term cognitive and non-cognitive abilities, as well as long-term educational achievement into adulthood. Secondly, the study rigorously tests the three most suspected channels within a unified institutional and empirical framework. Utilizing a representative sample of American high school students, a within-school, cross-cohort analysis reveals that exposure to high-achieving peers negatively impacts cognitive abilities, self-discipline, and the likelihood of college graduation. These adverse effects seem to stem from performance competition, fostering the development of negative beliefs about one's abilities relative to peers. The results highlight the pivotal role of self-perception in shaping the direction of peer effects. To illustrate this, I propose a novel network game, incorporating the concept of self-perception. The theoretical predictions of the model are versatile and provide a foundational framework for a broader range of empirical results, diverging from the assumption of unconditionally positive peer effects.

**JEL classification**: I23, J13, J24,
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# 1 Introduction

In the realm of educational policy, a persistent question looms: should students be grouped by ability (tracking) or educated together in inclusive classrooms? This long-standing debate has motivated the vast majority of studies on peer effects in education over the last twenty years. While research underscores that peer ability impacts various groups differently and can yield both positive and negative consequences (see Cools and Patacchini, 2021; Sacerdote, 2011, 2014, for reviews), the understanding of the underlying mechanisms driving these effects and the factors influencing their positive or negative trajectories is still limited (de Gendre Alexandra and Salamanca, 2020).

The literature has identified three potential channels through which peer effects operate. Firstly, peers indirectly influence academic outcomes by affecting the learning environment and teacher practices (Duflo, Dupas, and Kremer, 2011; Lavy, Paserman, and Schlosser, 2012). Secondly, students directly learn from each other through knowledge spillovers, or by observing and emulating each others' behaviors (Bursztyn, Egorov, and Jensen, 2019; Bursztyn and Jensen, 2015; Wu, Zhang, and Wang, 2020). In psychology this process is also known as social learning. Thirdly, students engage in social comparison by comparing their performance and abilities, which in turn, shapes their self-perceptions (who they think they are) and aspirations (who they aim to be).[1] However, the limited simultaneous testing of multiple channels leaves uncertainties about the existence and identity of the dominant mechanism.

This study addresses precisely this gap by taking a comprehensive approach. Firstly, I consider a broader set of outcomes, including both cognitive and socio-emotional abilities in the short run,[2] as well as education attainment in adulthood.[3] Secondly, I investigate all three potential channels within the same institutional and empirical setting. Leveraging cross-cohort, within-school variation in a representative sample of American high school students, the findings reveal that exposure to better performing peers negatively impacts various outcomes. Comparing students with identical school performance from two different cohorts of the same school, those exposed to a higher-performing cohort exhibit, on average, a reduced likelihood of college graduation, lower verbal skills, and diminished self-discipline. The mechanism analysis point to social comparison as the primary driver of these adverse effects, revealing that exposure to better-performing peers negatively influences self-perception of abilities and future aspirations.

These findings underscore the pivotal role of self-perception in determining the direction of peer effects on individual outcomes. I substantiate this assertion by proposing a novel theoretical framework of peer effects that incorporates the concept of self-perception. This framework demonstrates how using self-perception as a 'switcher,' turning the presence of more engaged peers into either a bonus or a penalty, effectively explains a broader range of empirical findings. This includes studies that challenge the common assumption that better peers should inherently

[1] See Buechel, Mechtenberg, and Petersen (2018); Carneiro et al. (2022); Denning, Murphy, and Weinhardt (2021); Elsner and Isphording (2017); Elsner, Isphording, and Zölitz (2021) for recent evidence.

[2] The concept of *cognitive abilities* encompasses what psychologists typically call fluid intelligence—the ability to use logical reasoning to solve new problems—and crystallized intelligence—acquired/memorized knowledge (Cattell, 1971). In contrast, socioemotional (or noncognitive) abilities describe relatively stable patterns of thoughts about oneself, feelings and behaviors in given circumstances (Almlund et al., 2011; Borghans et al., 2008). Economists often also refer to the latter as personality traits.

[3] The scope of considering a wider range of outcomes is to gain a more comprehensive picture of the relevant dimensions that are affected by peer performance.

exert positive externalities on others (see for example Booij, Leuven, and Oosterbeek, 2017; Carrell, Sacerdote, and West, 2013; Feld and Zölitz, 2017).

My results are robust to a large number of controls, including individual covariates, peer covariates, the within-school fraction of missing observations, within-school performance dispersion, and school-specific time trends. Further, validity tests show that the effects are not driven by exclusion bias (Caeyers and Fafchamps, 2020), sample selection, students' strategic course selection, multiple hypothesis testing (Kling, Liebman, and Katz, 2007), or measurement error (Ammermueller and Pischke, 2009; Balestra, Eugster, and Puljic, 2021; Feld and Zölitz, 2017).

To investigate the mechanisms at play, I employ the same empirical strategy from the main analysis to examine whether peer performance affects individuals' perception of the learning environment and individuals' perception of their academic abilities. Additionally, to verify whether the negative impact is attributed to the observation and imitation of specific behaviors exhibited by higher-achieving peers, I employ an instrumental variable (IV) approach. Namely, I instrument one's own behavior with the equivalent peer behavior in the previous period and consider only outcomes realized thereafter. The underlying premise is that if students observe and imitate one another, individual and peer behavior should be strongly, positively related, but peer behavior should not directly affect later outcomes.

Taken together, the three sets of results consistently point towards performance competition as the overarching driver. In the first stage of the IV analysis, for instance, it is observed that students tend to exert greater effort towards the end of the school year when exposed to a higher fraction of hardworking peers at the beginning of the school year. This suggests a tendency among students to emulate each other's study behaviors. However, despite the imprecise estimates, the second stage indicates that this heightened effort may not necessarily translate into improved outcomes. It appears that greater effort improves school performance but does not enhance knowledge. This phenomenon can be attributed to the prevalence of performance-oriented goals in competitive environments (Ames and Ames, 1984). While performance-oriented goals have been linked to better overall performance (Cagiltay, Ozcelik, and Ozcelik, 2015; Lam et al., 2004), they may not necessarily result in deeper learning (Chen, Law, and Huang, 2019). In psychology, it is also well-documented that competition accentuates one's relative abilities, potentially influencing students' self-assessment based on their position in the competition (Ames and Ames, 1981). Consistent with this evidence, the findings indicate that students exposed to a better-performing cohort are, on average, more likely to perceive themselves as having below-average abilities and express less confidence in enrolling in college. Additionally, they are more inclined to report lower levels of happiness in school and feel less aligned with their peers.

The present study contributes to the literature on peer effects in education in three major ways. Firstly, it expands upon the limited research on the mechanisms behind peer effects by simultaneously testing the three most supposed channels under the same institutional setting. Previous studies were often constrained to focus on a single channel due to data limitations (Booij, Leuven, and Oosterbeek, 2017; Bursztyn et al., 2014; Carrell, Sacerdote, and West, 2013; Duflo, Dupas, and Kremer, 2011; Feld and Zölitz, 2017; Golsteyn, Non, and Zölitz, 2021; Lavy and Schlosser, 2011).

Secondly, this study enriches the theoretical literature on peer effects by offering novel insights for theoretical modeling and introducing a new model that incorporates these insights. Recent applied work (including this study) has challenged a fundamental assumption in theoretical work on peer effects, which posits that peer effects are exclusively positive (Calvó–Armengol, Patacchini, and Zenou, 2009; Liu, Patacchini, and Zenou, 2014; Ushchev and Zenou, 2020). My findings suggest that this assumption likely holds for behaviors, that is own study effort proportionally increases in peer effort. However, an increase in effort not necessarily result in a proportional increase in other outcomes, such as college graduation or knowledge accumulation. The reason is that outcomes are influenced not only by abilities and effort but also by beliefs, which can act as either boosters or obstacles. Through a slight modification of the local-average model and the introduction of the notion of self-perception, this study demonstrates that allowing self-perception to determine the direction of the peer effect enables a more comprehensive explanation of empirical findings that may initially appear contradictory.

Third, this article provides a more comprehensive understanding of peer effects in education, by also exploring the impact of peer performance on noncognitive abilities and future outcomes. While most of the literature has focused on academic achievement measured as either standardized test scores (Fruehwirth Cooley, 2014; Hoxby and Weingarth, 2005; Lavy, Silva, and Weinhardt, 2012)[4] or GPA (Carrell, Sacerdote, and West, 2013; Feld and Zölitz, 2017; Sacerdote, 2002),[5] ewer studies have explored noncognitive abilities (Neidell and Waldfogel, 2010; Wu, Zhang, and Wang, 2023) and adult attainments as outcomes (Balestra, Eugster, and Liebert, 2022; Bietenbeck, 2020; Bifulco, Fletcher, and Ross, 2011; Carrell, Hoekstra, and Kuka, 2018; Cools and Fernaández, 2022; Olivetti, Patacchini, and Zenou, 2020).

Lastly, contributes to the literature on ordinal rank by presenting the flip side of the effects of relative performance. While existing literature demonstrates how being the big fish in the pond has persistent positive effects on motivation (Buechel, Mechtenberg, and Petersen, 2018), self-confidence (Murphy and Weinhardt, 2020), Elsner and Isphording (2017); Elsner, Isphording, and Zölitz (2021), educational choices (Delaney and Devereux, 2021), and attainments (Bertoni and Nisticò, 2023; Carneiro et al., 2022; Denning, Murphy, and Weinhardt, 2021; Elsner and Isphording, 2017; Elsner, Isphording, and Zölitz, 2021), this study uncovers how being a regular fish in the pond can negatively impact self-perception, motivation, aspirations, and eventually decrease the likelihood of success later in life.

The rest of the paper is structured as follows. Section 2 comprehensively reviews the evidence on potential mechanisms underlying peer effects. This review lays the foundation for the mechanism analysis presented in Section 5 and motivates the empirical analysis described in Section 3, the results of which are presented in Section 4. Section 6 presents the model and Section7 concludes.

## 2 Peer effects in education: Their potential sources

Peer composition can affect a student's academic achievement and abilities through at least three channels. One of the most widely discussed channels supposedly works through the *learning environment*: group composition affects the whole learning environment, which, in turn, affects

[4]See also Antecol, Eren, and Ozbeklik (2016); Balestra, Eugster, and Liebert (2022); Eren (2017); Hanushek et al. (2003); Kristoffersen et al. (2015); Neidell and Waldfogel (2010); Vigdor and Nechyba (2007).

[5]See also Burke and Sass (2013); Carrell, Fullerton, and West (2009); Foster (2006); Griffith and Rask (2014); Lavy, Paserman, and Schlosser (2012); Lyle (2007); Stinebrickner and Stinebrickner (2006); Zimmerman (2003).

individual outcomes. For example, high-ability students may promote a better functioning of classrooms (Booij, Leuven, and Oosterbeek, 2017; Feld and Zölitz, 2017) by favoring a more stimulating learning environment more through their active participation and questions, while low-ability students may disrupt the classroom by misbehaving or diverting teachers' attention to meet their specific needs (Imberman, Kugler, and Sacerdote, 2012; Lavy, Paserman, and Schlosser, 2012; Lazear, 2001). Alternatively, teachers may adjust their behavior and the teaching material to better match the classroom composition (Duflo, Dupas, and Kremer, 2011).

More recent studies suggest that peer effects might arise from *social learning*. This process can occur in a more direct way through knowledge spillovers (Wu, Zhang, and Wang, 2020) or observation-imitation of others' behavior (Bursztyn, Egorov, and Jensen, 2019; Xu, Zhang, and Zhou, forthcoming). Alternatively, it can occur indirectly through the recognition of rewards and punishments—also known as social norms—associated with specific behaviors (Bandura, 1977). Bursztyn and Jensen (2015), for example, show that when study effort is punished and observable by everybody in the group (public), students' performance worsens. Conversely, if effort is rewarded and public, students' performance improves because effort is associated with high abilities.[6] Bursztyn, Egorov, and Jensen (2019) also show that the observability of actions and abilities is a crucial prerequisite for peer effects to manifest through social pressure.[7] This prerequisite, in fact, also motivates the choice of the peer measure considered in the present study.

The emerging strand of literature on the effects of ordinal ranks suggests that peer effects may also arise from *social comparison*—the psychological process of self-evaluation that people employ to assess the value of their own opinions, accomplishments, and abilities (Festinger, 1954). The competitive and evaluation-driven nature of education inevitably leads to constant comparisons with one's peers, as well as constant self-evaluation (Ames and Ames, 1984; Johnson and Johnson, 2009). Hence, students care about their relative performance and ability peer effects are at least partly driven by comparisons in performance (Cicala, Spenkuch, and Fryer, 2018; Tincani, 2014, 2017). Recent findings suggest that a students' relative performance has substantial effects on their motivation (Buechel, Mechtenberg, and Petersen, 2018), assessment of their abilities (Murphy and Weinhardt, 2020), future aspirations Elsner and Isphording (2017); Elsner, Isphording, and Zölitz (2021), and attainments (Bertoni and Nisticò, 2023; Carneiro et al., 2022; Denning, Murphy, and Weinhardt, 2021; Elsner and Isphording, 2017; Elsner, Isphording, and Zölitz, 2021).[8]

Some studies have also proposed assortative matching (Carrell, Sacerdote, and West, 2013; Wu, Zhang, and Wang, 2023) or family involvement (Cooley Fruehwirth, 2017; Xu, Zhang, and Zhou, forthcoming) as alternative mechanisms of peer effects in education. However, neither of these aspects is a stand-alone mechanism, as they can both result in any of the three channels outlined above. Parents might decide to invest differently in their children through household investments (Ammermueller and Pischke, 2009), shadow education (Guo and Qu, 2022), direct involvement in school (Cooley Fruehwirth, 2017), or by affecting their child's selection of friends (Agostinelli et al., 2020), but any of these actions would eventually result in a spillover effect that manifests through either social comparison (Paffenholz, 2023), direct learning from each other (Wu, Zhang,

[6]This is in line with findings by Fryer Jr. and Torelli (2010) and Austen-Smith and Fryer (2005) showing how social norms about study effort change by race, which contributes to widening the racial gap.

[7](see Agranov et al., 2022; Bandiera, Barankay, and Rasul, 2010; Bursztyn et al., 2014; Han, Hirshleifer, and Walden, 2019; Jackson and Breugmann, 2009; Lieber and Skimmyhorn, 2018; Mas and Moretti, 2009; Neffke, 2019; Sorense, 2006).

[8]Further affected outcomes include educational choices (Delaney and Devereux, 2021) and the likelihood of adopting risky behaviors (Elsner and Isphording, 2018).

and Wang, 2020), or an impact on the learning environment (e.g. teacher's practices).

Furthermore, the proposed channels do not replace the mechanisms listed by Sacerdote (2011),[9] or de Gendre Alexandra and Salamanca (2020),[10] but rather include and summarize them.

## 3 Empirical design and data

The following section presents the empirical design and the data. The first part presents the data and its institutional background, while the second part outlines the empirical strategy and presents various test results affirming its validity.

### 3.1 Data

The current study uses data drawn from the National Longitudinal Survey of Adolescent Health (Add Health), a nationally representative sample of American adolescents that was designed to study the impact of the social environment on students' behavior and health during adolescence throughout adulthood. Figure 1 provides a timeline of the data collection. The study began in September 1994 with an in-school survey that was completed by more than 90,000 students from 132 different high schools.[11] The questionnaire was completed during class hours between September 1994 and April 1995. Approximately 20,000 students were then selected for a series of follow-ups conducted at interviewees' houses. The first in-home follow-up (Wave I) was conducted between April and December 1995, the second (Wave II) was conducted between April and September 1996, the third (Wave III) was conducted between July 2001 and April 2002, and the fourth (Wave IV) was conducted between April 2008 and 2009. During Wave III were also collected the official transcripts from the high schools that the participants last attended.[12] This supplemental data collection is better known as the Adolescent Health and Academic Achievement (AHAA) study and includes detailed measures of school performance and course details, such as the difficulty level or the value in terms of credits.[13]

The analysis sample is obtained by selecting all individuals with a valid identification number who completed both the in-school questionnaire and the first in-home interview ($N = 15,350$). Among these, only students who completed the in-school questionnaire between September and November 1994 are kept. In doing so, information from the in-school questionnaire and the first in-home interview can be treated as information from two distinct periods, namely, the beginning and end of the 1994/95 school year. Furthermore, to guarantee a certain homogeneity among the students, only students from grades 9 through 12 are regarded. To ensure the pertinence of

[9]The "bad apple", "focus", and "boutique/tracking" models, for instance, are specific examples of peer effects operating through the learning environment. The "shining light" and "rainbow" models are, instead, examples of peer effects working through social learning, while the "invidious comparison" model is a specific type of social comparison.

[10]The mechanisms reported in de Gendre Alexandra and Salamanca's Table 1 all belong to at least of the channels proposed in this paper. "Classroom atmosphere/interactions in the classroom", "classroom disruption", "teacher effort and engagement", and "parental investments" concern the peer impact on the learning environment. Direct learning from peers and effort provision are distinct types of social learning describing knowledge spillovers and observation-imitation patterns, respectively. However, the studies reported for "self-confidence/beliefs", "mental health", "preferences/personality traits", and "network formation/endogenous friendship ties" all presume a form of social comparison.

[11] Among the selected schools were public and nonpublic schools.

[12]Participants of Wave III were asked to sign a Transcript Release Form authorizing Add Health to collect information on their high-school transcripts. More than 90% of the respondents gave their consent ($N = 13,901$).

[13]See Riegle-Crumb et al. (2005) for more details on the AHAA data.

the identification strategy, first, I keep only schools where at least three grades are observed and all grades are in the same building are kept, second I select only grades where performance is observed for at least 20 students. After dropping all incomplete observations, the baseline sample counts 6,069 students from 58 distinct schools.[14]

**Outcomes.** The analysis focuses on different outcomes that are summarized in Table 1. Panel I reports cognitive and noncognitive skills at the end of the 1994/95 school year. These are derived using information from the in-home Wave I. Panel II reports noncognitive skills at the end of the 1995/96 school year, which are obtained from Wave II. Panel III reports outcomes in adulthood, which are all obtained combining information from Waves III and IV.

Cognitive abilities are measured through an adapted version of the Peabody Picture Vocabulary Test (PVT) score. The PVT is a common standardized test of development and cognition that psychologists typically use to measure verbal abilities, including listening and understanding of single-word vocabulary (see Stein and Lukasik, 2009). This test was conducted during both the first and the third in-home interviews; in both waves, it was standardized by age.

Indices of noncognitive skills—including self-esteem, emotional stability, and self-discipline—are computed as simple cross-item averages and standardized over the whole sample before selecting the sample.[15] For each skill, items are selected using exploratory factor analysis (EFA).[16] More precisely, I start by preselecting blocks of items based on validated psychological scales.[17] I then run EFA on the predefined blocks to select the items used to compute the ultimate indices.[18] I use the same procedure for all periods in which the information on noncognitive skills is used.

The third set of outcome variables consists of binary variables indicating whether the person graduated from high school, attended college, or graduated from college. The former is derived using high school transcripts from the AHAA data, whereas the other two are based on self-reported information obtained in Waves III and IV.

**Peer treatment.** The treatment of interest is peer performance, which is measured as the leave-own-out average GPA within a student's school cohort. GPAs are based on self-reported grades in math, science, and English, which are three courses that virtually all students have to take by the end of high school. However, to mitigate misreporting of grades I use school transcripts from AHAA data. This correction is only possible for students who signed their consent in Wave III, which amounts to approximately one-eighth of all students in grades 9 through 12. Alongside with peer performance, I also compute a number of other peer characteristics in a similar fashion, including their noncognitive abilities and behaviors.

**Summary statistics** Table 2 describes individual (Columns 1-3, Panels I-III), peer (Columns 4-6), and school characteristics (Panel IV). Individual time-variant and peer characteristics are obtained using information from the in-school questionnaire, while individual time-invariant information

[14] Table 13 of Appendix A provides an overview of the sample selection process.
[15] This is the reason why the mean and the standard deviation are not precisely zero and one, respectively.
[16] Note that EFA is based on a principal component analysis and the assessment of the Cronbach's alpha values.
[17] See Table 22 in the Appendix.
[18] See Appendix B.1 for more details on the selection process.

(e.g., gender, race, family education) is coded by combining information from Waves I-III.[19] Individual time-variant characteristics include given attitudes, behaviors, and beliefs about the future, such as partaking in extracurricular activities of various types (e.g., sports, foreign language, politics, arts).[20] skipping classes without a justification, partaking in risky behaviors,[21] and expecting to marry or to be killed by a certain age in early adulthood. In contrast, individual time-invariant characteristics include demographic characteristics (e.g., gender and race), an indicator of at least one grade repetition in the whole academic career, and a number of parental inputs, including indicators of low and high socioeconomic status (SES) such as whether at least one parent receives public assistance or is college-educated, the household size, an index of parental time investment and the degree of permissive parenting style (i.e., parents who let the child have freedom of choice).[22]

The baseline sample is composed of 52% female, 56% white, and 34% black or Hispanic students.[23] Minority groups are slightly overrepresented compared to the national statistics from 1994 (Snyder and Hoffman, 1994) because of the intentional oversampling that was applied while selecting the follow-up samples.[24]

A comparison of the individual and peer figures in Panel I indicates that the average student in the sample performs slightly worse than their peers and is slightly less emotionally stable, but more self-disciplined. The grade repetition rate is in line with the official statistics (see OECD, 2011).[25] Panel III further suggests that the sample is slightly more representative of students from better-off households. Compared to the US household statistics from 1994-95, the fraction of college-educated parents is by 7% higher, while the fraction of parents receiving public assistance is lower.[26]

Finally, Panel IV of Table 2 indicates that nearly all students are from large and mid-large public schools, which are mostly mixed-race and mainly located in urban or suburban areas. Compared to the national statistics, urban and suburban areas (72%) are slightly more represented in the selected sample, but the proportion of public schools (91%) and the average school size (512) are representative of the national statistics (Snyder and Hoffman, 1994).

### 3.2 Empirical design

The empirical strategy exploits within-school, cross-grade variation to identify the effect of peer performance; a common approach in the peer effect literature when dealing with observational data and non-randomly formed peer groups (see also Bifulco, Fletcher, and Ross, 2011; Carrell,

[19]This process mitigates potential measurement error in the covariates. As already shown by Garber and Klepper (1980); Griliches (1986), measurement error in the covariates can cause an attenuation bias in the estimates of other regressors if the latter ones correlate with the measurement error of the mismeasured variable.

[20]Students often reported being part of multiple clubs, which is why the fractions over different clubs do not sum up to 1.

[21]The risky behavior index is a cross-item average of information on cigarettes and alcohol consumption, as well as alcohol abuse. More details can be found in Appendix B.1.

[22]See Appendix B.1 for further details on indices of parental investment and permissive parenting style.

[23] The remaining 10% are either Asians, native Americans, or students of other ethnicities.

[24]The oversampling occurred after the in-school questionnaire. Hence, this has no impact on the peer variables and the estimates.

[25]OECD (2011) reported in 2009 that approximately 15% of American students repeated at least one grade by age 15.

[26] In 1994-95, only 23% of Americans held a bachelor's degree (Day and Curry, 1996; Snyder and Hoffman, 1994), and approximately 11.2% participated in the food stamp program (Stavrianos, 1997). The main suspects behind these discrepancies are attrition and misreporting.

Fullerton, and West, 2009; Hoxby, 2000; Lavy and Schlosser, 2011; Olivetti, Patacchini, and Zenou, 2020). The key idea is that even if parents select their children's high school, differences in the student composition across cohorts of the same school are as-good-as-random. The empirical model is a canonical linear-in-means model of following form:

$$y^j_{igs,T} = \beta_j GPA_{igs,t} + \gamma_j \overline{GPA}_{-igs,t} + \boldsymbol{\theta}_j X_{igs,t} + \boldsymbol{\rho}_j \overline{X}_{-igs,t} + \lambda_j W_{gs,t} + \alpha_g + \mu_s + \varepsilon_{igs,T}. \quad (1)$$

The dependent variable $y^j_{igs,T}$ is one of the multiple outcomes $j = 1, ..., J$ of individual $i$ in grade/-cohort $g$ of school $s$ at a given, future time $T > t = 1994$. Outcomes include cognitive abilities measured as the PVT score in spring 1995 as well as 2002, self-discipline, self-esteem, and emotional stability in spring 1995 and 1996, as well as a series of binary indicators for educational attainment in adulthood, including graduation from high school, college enrollment, and graduation from college (see Table 1).

The regressor of interest is $\overline{GPA}_{-igs,t}$, the peer performance measured as the leave-own-out average GPA within student $i$'s school cohort. I control for individual performance at the beginning of school year 94/95, $GPA_{igs,t}$, to compare students of the same school with similar performances but different performing peers. I also control for individual covariates $X_{igs,t}$, including self-discipline, self-esteem, and emotional stability at the beginning of the school year, gender, dummies for race or ethnicity (white, black, and Hispanic), grade repetition and partaking to extracurricular activities, dummies indicating whether at least one parent graduated from college or whether at least one parent perceives public assistance, the household size, the parenting style as well as parental investment, and binary indicators of expectations about the future, such as getting married by age 25, earning a middle-class income, or being killed by age 21. The scope of controlling for future expectations is to account for unobserved factors that might be more common in families with particular cultural backgrounds, low socio-economic statuses, and perhaps living in particularly dangerous neighborhoods.

Additionally, I control for peer covariates $\overline{X}_{-igs,t}$, including peer self-discipline, the fraction of peers who work hard, the fraction of peers who regularly skip class, and peer demographics, such as the fraction of female and black students, as well as the fraction of students with college-educated parents. The key idea behind the inclusion of these variables is to rule out the possibility that the effect of peer performance is driven by certain peer behaviors, such as discipline or that are typically found to be highly correlated with students' GPA (see e.g., Borghans et al., 2016).

The term $W_{sg,t}$ represents school-grade-specific controls, including the within-cohort dispersion of the GPAs, the fraction of missing GPAs within one's school grade. The inclusion of the within-cohort dispersion is motivated by the recent work of Tincani (2014) and Dijkstra et al. (2008) providing evidence that students care about relative performance, especially in more homogeneous groups. The fraction of missing GPAs, instead, is motivated by recent evidence showing that measurement error in the peer variable of interest can lead to substantial attenuation even when groups are randomly formed and balanced (Balestra, Eugster, and Puljic, 2021; Feld and Zölitz, 2017). The presence of students who do not report their GPAs causes mismeasurement in the peer average GPA. As long as the information is missing at random, the consequences of this information omission should be negligible. However, in my sample there are schools where the fraction of missing GPAs reaches 75%. Therefore, to address the potential problems that this might cause, I control for the fraction of students who did not report their grades in one's school grade.

The term $\mu_s$ represents school fixed effect, whereas $\alpha_g$ represents a full set of grade dummies controlling for unobserved factors that simultaneously affect one's own outcomes and the peer academic performance of a given cohort but not another (e.g., a nationwide policy that affects a single cohort). Remaining idiosyncratic determinants are summarized by the term $\varepsilon_{igs,T}$. I allow for arbitrary within-school correlation in the error term, by clustering the standard errors at the school level.

The coefficient of interest is $\gamma_j$, which measures the relationship between the peer performance and the various individual outcomes. The coefficient $\gamma_j$ can be interpreted as the difference between two students of the same school and different cohorts, with identical GPA and many other similar characteristics but differently performing peers. For $\gamma_j$ to have a causal interpretation, it means that conditional on being within the same school and keeping many other factors fixed, there is nothing left among the unobserved factors that simultaneously affects peer performance as well as one's outcomes. This assumption cannot be tested but considering Altonji, Elder, and Taber (2005)'s work, if changes in the estimate of interest are marginal after the inclusion of all the observables I control for, then a potential bias from unobservables can also be deemed highly unlikely. As I will show in the later section, results are robust to the sequential inclusion of all these controls.

### 3.3 Validity of the empirical design

The literature typically posits that variation in cohort composition within schools mainly arises from over-time, *natural* variation in the population.[27] This argument is pertinent in regard to predetermined attributes such as gender and race but does not necessarily hold true for academic performance, which may vary in a "nonnatural" (or nonrandom) way.

A number of reasons might cause nonrandom variation. One such reason is, for instance, grading on a curve (Calsamiglia and Loviglio, 2019). If the grading curve does not change over time, one runs into the problem of zero cross-cohort variation in the variable of interest (here peer performance). This problem is likely mitigated by the fact that American high school students self-select their courses, which means that if teachers use different grading curves across courses, zero variation is highly improbable. However, considering the nature of the main variable of interest—a LOO average of a cohort counting 300 students or more—it is plausible to expect a rather small variation.[28] This means that when adding school and grade fixed effects, all the existing variation could still be completely swept away.

Furthermore, the grading curve could also systematically change from grade to grade, resulting once again in nonexogenous variation. This would result in grade-to-grade, linear patterns in both the outcome and the peer performance within the individual schools that would need to be accounted for through school-specific time trends in equation (1).

Another reason for nonrandom variation in peer outcomes could be selection. Selection in a specific cohort could occur through parental pressure for children to remain in their current class or to be promoted to a higher class, or students could simply make strategic choices about subjects and their levels of difficulty. Either way, this would result in systematic correlations between the peer variable of interest and student predefined characteristics, such as race and family attributes—that

[27] See for instance Black, Devereux, and Salvanes (2013); Carrell, Hoekstra, and Kuka (2018); Hoxby (2000).

[28] The larger groups are, the larger the smoothing of the raw variation across students is when the group average is computed.

is, those attributes on which it is most likely to have segregation of some sort.

In what follows, I address these concerns by verifying that there is sufficient variation in peer performance testing that it does not follow school-specific time trends and that students' predetermined characteristics are not systematically correlated.

First, to verify that there is sufficient variation, I verify both the raw and residual variation. Table 3 presents the results of this exercise: Panel A shows the raw variation, Panel B shows the residual variation net of grade and school fixed effects, and Panel C shows the residual variation net of grade and school fixed effects and school-specific linear trends. As expected, the standard deviation of the raw variable is small. After removing school and grade fixed effects, approximately 67% of the raw variance is removed. If school-specific time trends are also added, 10% of the original variation is further lost. Although this might seem like a large loss of variation, it is in the range of those reported in other studies using similar data (see Bifulco, Fletcher, and Ross, 2011; Olivetti, Patacchini, and Zenou, 2020). [29].

Second, I verify whether school-specific linear trends are a potential source of concern by regressing both the outcomes and the peer performance on the continuous variable of grade conditional on school fixed effects.[30] The coefficient on grade conveys whether the various dependent variables evolve at a constant rate across grades of the same school.

Table 4 reports the above-described coefficients for the peer variable of interest (Column 1), the abilities in 1995 (Panel A) and 1996 (Panel B), and the future outcomes (Panel C). The variables following school-specific linear trends are the PVT scores (both in 1995 and in 2002), self-discipline in 1996, the probability of graduating from high school, and enrolling in and graduating from college. These are all measures in which one expects a linear evolution across cohorts. For instance, the older students are, the likelier it is that they graduated from both high school and college by the time of interviews in Wave III and IV. Similarly, self-discipline and cognitive abilities both increase with children's age (even if cognitive abilities are more contained after age 10). The presence of linear trends in some outcome variables is, however, not a real concern since the regressor of interest does not follow school-specific linear trends either (see Column (1) of Table 4).

To also visually prove that peer performance does not follow school-specific linear patterns, Figure 4 in Appendix A illustrates the evolution of peer GPA over grades for each of the 58 schools. For most schools, the pattern is flat or quadratic but virtually never linear.[31]

Third, to verify whether one's own and peer predefined characteristics are systematically correlated, I follow the examples by Sacerdote (2002) Guryan, Kroft, and Notowidigdo (2009) and regress the peer GPA on the predefined individual variables.[32] The idea is that systematic correlation between the target variable and the observables indicates potential selection into treatment based on those observable. Furthermore, the degree of systematic correlations with observables is a good indicator of systematic correlations with unobservables (Altonji, Elder, and Taber, 2005).

[29] Bifulco, Fletcher, and Ross (2011) report a 71% (78%) reduction when school and grade fixed effects (and time trends) are added, while Olivetti, Patacchini, and Zenou (2020) report a loss of approximately 64% (71%) of variation

[30] This test is very similar in spirit to the one proposed by Chetty et al. (2011) to check for balanced and random assignment across classrooms.

[31] Table 14 in Appendix A presents the results of a similar test with quadratic school-specific trends. These results confirm that, if anything, the peer variable of interest follows quadratic trends. I can show that this does not affect the main results of the empirical analysis, though.

[32] This set of regressions is also often referred to as balancing tests.

Hence, if the peer performance results are correlated with any observable, then the variation in the target variable is likely not exogenous.

Table 5 presents the results of these regressions. Odd (even) columns report the coefficients (standard errors clustered at the school level) of the predefined attribute—reported in the row header—on the peer average GPA in 1994 for three different specifications: simple OLS (Columns 1-2), a linear model with school and grade fixed effects (Columns 3-4), and school-specific linear trends (Columns 5-6).

Column (1) of Table 5 suggests that there is substantial selection into schools. As one would expect, students from better educated families—those that generally invest more in their children—tend to be systematically exposed to better-performing peers, while the opposite is true for students from larger and poorer families. Virtually all systematic correlations disappear as soon as school and grade fixed effects are added. Out of eleven coefficients, only one is statistically significant at the 10% level, but this precisely what one would expect to occur by chance. Furthermore, the coefficient is almost exactly zero and positive, which goes against what would be expected in the case of segregation of black students (see Column 1).[33]. Adding school-specific linear trends does not improve the picture. Instead of turning insignificant, the coefficient on "black" increases with regard to significance level. This indicates that controlling for school-specific linear trends in (1) may only introduce noise and thus be overly conservative for the case at hand.

### 3.4 Validity of the peer treatment

Before moving on to the results, there is one last aspect that may be a source of concern and that deserves discussion: the validity of the peer variable of interest.

Peer effect studies typically consider *predetermined* characteristics that are either inalterable, such as gender and race (Angrist and Lang, 2004; Hoxby and Weingarth, 2005; Lavy and Schlosser, 2011),[34] or were realized before assignment to the peer group.[35] In the present study, peer GPA is not predetermined in any of the two senses, but it is certainly realized prior to the realization of all outcomes. As discussed in Section 3.1, I restrict the sample to schools where the initial questionnaire was conducted between September and November 1994 to ensure that responses to the question "What was your grade in subject $X$ in the last grading period?" exclusively pertain to the grading period at the end of the 1993/94 school year, thereby predating any subsequent grading period referenced in in-home interviews of Waves I and II.

Nevertheless, because cohorts remain unchanged from year to year (with only the exception of grade-9 students), it is possible that the peer variable is influenced by past interactions with

[33]The positive sign likely arises from a negative mechanical relationship between one's own performance and that of one's peers (Caeyers and Fafchamps, 2020; Guryan, Kroft, and Notowidigdo, 2009). Students of color (as well as women) have lower GPAs on average; thus, the group average without them is by construction higher than the one with them

[34]Other examples of studies using gender or race include Anelli and Peri (2017); Black, Devereux, and Salvanes (2013); Whitmore (2005) for gender and Cho (2012); Diette and Uwaifo Oyelere (2014, 2017); Gould, Lavy, and Paserman (2009); Hanushek, Kain, and Rivkin (2009); Jensen and Rasmussen (2011) for race.

[35]The list of examples is long, including special educational needs (Balestra, Eugster, and Liebert, 2022; Fletcher, 2009), exposure to domestic violence (Carrell, Hoekstra, and Kuka, 2018), divorced parents (Kristoffersen et al., 2015), past academic achievement (Antecol, Eren, and Ozbeklik, 2016; Carman and Zhang, 2012; Feld and Zölitz, 2017; Griffith and Rask, 2014; Lyle, 2007; Sacerdote, 2002; Stinebrickner and Stinebrickner, 2006), indicators of grade repetition (Bietenbeck, 2020; Hill, 2014; Lavy, Paserman, and Schlosser, 2012) and giftedness (Balestra, Sallin, and Wolter, forthcoming), parental education and employment status (Bifulco, Fletcher, and Ross, 2011; Cools and Fernaández, 2022; Olivetti, Patacchini, and Zenou, 2020), and many others.

peers from the same cohort, thereby introducing a potential "contamination." This contamination is rather a concern for the outcomes realized during the period in high school and not for the outcomes in adulthood—in the high school stage, students are exposed to other peers. As a result, the potential existence of unobserved factors that could have affected both individual outcomes in 1995 and 1996, as well peer GPA in the 1993/94 school year, cannot be excluded a priori.

To solve this problem, I control for a large number of individual and peer covariates and test whether the residuals of the outcome and peer variable of interest obtained from (1) are significantly correlated. This test is similar in spirit to the serial correlation test proposed by Wooldridge (2002). The idea is that although it can never be 100% guaranteed that the variable of interest is independent of the error term, the presence of a nonzero and statistically significant correlation with the residual is a sufficient indicator of endogeneity.

Figure 5 shows the result of this test for outcomes for which the endogeneity of the peer variable would be most problematic. The correlation is exactly zero, and the relationship between the two residuals does not follow any distinguishable pattern. Although this does not preclude the existence of other sources of endogeneity, such as measurement error and omitted variable bias (which will be addressed in the robustness checks), for the time being, it can be concluded that the peer variable is not subject to significant contamination.

GPA is often considered to be a biased measure of student ability because teachers might be biased when grading, which could naturally result in two students with similar abilities having very different grades when graded by different teachers. Also, teacher often grade on a curve, which can easily result in two students with very similar abilities achieving slightly different grades even when graded by the same teacher. A better alternative to measure actual abilities would be using the score from an ability test, such as the Picture Vocabulary Test (PVT), as done in other studies (see for example, Elsner and Isphording, 2017).

Using the PVT score instead of the GPA would, however, go beyond the scope of this study. I am specifically interested in peer performance measured as GPA as main peer treatment because it is apter for testing the three channels. Firstly, GPA is observable and quantifiable. Hence, students can easily use it as information for comparing with other students and inferring their own abilities. Second, grade are decided by the teachers and this decision is often based on the whole classroom environment as well as the overall performance distribution of the classroom. Therefore, effects of peer performance could also be driven by the classroom environment. Thirdly, GPAs are highly predicted by behaviors and attitudes that are observable and imitable. Hence, effects of peer performance could also easily be driven by processes of social learning (e.g., engagement, discipline, perseverance; see Borghans et al., 2016; Heckman and Rubinstein, 2001).

In contrast, actual abilities are neither directly observable and quantifiable, nor are they imitable. Furthermore, the PVT was conducted during in-home Wave I only, which means that the test was conducted only on a fraction (approximately 20%) of the students from each school.[36] Consequently, using PVT scores instead of GPAs would entail even more serious measurement error problems.

[36] So-called *saturated* schools are an exception (see Badev, 2021). In these schools, all students were selected for the follow-ups, but the total number of students from these schools is rather small (approximately 3,000 students).

# 4 Results

This section presents the main results and tests their robustness by discussing the major potential confounders.

## 4.1 Main results

Table 6 presents the coefficients of one's own and peer performance on several outcomes. Panel A presents the results for cognitive and socioemotional skills measured in the spring of 1995, Panel B presents those for socioemotional skills in the spring of 1996,[37] and Panel C is for future outcomes. Tables 15 and 16 in Appendix A also report the results for the single items of the three socioemotional abilities.

All models differ only by the outcome variable reported in the column header. All specifications control for school and grade fixed effects, the individual covariates reported in Panels I-III of Table 2, and some of the peer covariates (e.g., fraction of female and black students and students with at least one college-educated parent), the fraction of missing GPAs in the school grade, and the within-school grade variation of individual GPAs.

Overall, Table 6 suggests that peer performance negatively affects one's own cognitive abilities, self-discipline, and probability of enrolling in and graduating from college. The coefficient on cognitive abilities is consistently negative and statistically significant over time, while the one on self-discipline is consistently negative but only significant for later realizations of self-discipline. Similarly, the coefficients of peer performance on the probability of enrolling in and graduating from college are both negative (i.e., consistent in the direction), although only the probability of graduating from college seems to be statistically significantly affected.

An increase of one standard deviation (SD)—or 0.3 points—in peer GPA leads to a decrease of 0.11 and 0.10 SD (or 1.45 and 1.6 points) in the PVT scores in 1995 and 2002, respectively, a decrease of 0.12 SD in self-discipline one year later, and a decrease of 0.13 SD (or 5 percentage points) in the probability of graduating from college.[38] All effects are also moderately economically significant and within the range of effect sizes found in previous studies (see Table 1 in Sacerdote, 2014 or Bifulco, Fletcher, and Ross, 2011 for outcomes in adulthood).[39]

As shown in Tables 17-19 of Appendix A the size and the statistical significance of the estimated coefficients do not vary substantially as I progressively add controls. The results of the PVT in 1995 are even robust to the introduction of school-specific linear trends. Furthermore, by comparing the OLS specifications (Column 1 of Tables 17-19) with the fixed effect specifications without covariates (Column 2 of Tables 17-19), one can notice that the sign of the coefficient on peer performance turns negative only after the introduction of school and grade fixed effects and remains negative even after adding numerous controls. This suggests that the effect might be driven by some specific mechanisms operating within schools.

[37] The PVT was only conducted during interviews in-home I and III. This is why Column (1) in Panel B is empty.

[38] The standardized effects are obtained by multiplying the coefficients by 0.3, the standard deviation of peer GPA (see first row, Column 5 of Table 2), and dividing by the standard deviation of the outcome variable (see Column 3 of Table 1).

[39] Bifulco, Fletcher, and Ross (2011) find that a 1 SD increase in the fraction of peers with college-educated mothers increases one's own probability of attending college by 5 percentage points. Similarly, Olivetti, Patacchini, and Zenou (2020) find that a 1 SD increase in the fraction of peers with employed mothers increases girls' own probability of being active in the labor market by 5-7%. The magnitude of both results is comparable to the one I find.

The effects of one's own GPA are, by contrast, all positive but not always larger in absolute terms than the peer effect. The effect of one's own GPA is larger on cognitive skills (+0.16 SD in 1995 and +0.13 SD in 2022 vs. 0.10-0.11 SD) and graduation from college (+0.34 SD or +13 percentage points vs. 0.13 SD) but is almost half the size of the peer effect on self-discipline in 1996 (0.07 SD vs. 0.12 SD). Since self-discipline is an index based on a set of behaviors reflecting study effort and discipline, this is in line with the conclusion drawn by Sacerdote (2014) that peers' influence is larger on actual, observable behaviors than on knowledge accumulation (i.e., achievement tests).

The difference in sign between the coefficients on one's own and peer GPA hints that one's own and peer academic performance capture different sets of behaviors or attributes that steer one's performance in different directions. However, before jumping to the interpretation of the potential mechanisms driving these estimates, it is important to verify that the estimated coefficients are not byproducts of one of the following confounders: exclusion bias (i.e., the mechanically negative relationship between own and LOO average), particular sample selection, the possibility that higher GPAs reflect selection into easier courses, measurement error, or multiple testing. In what follows, I address and discuss each of these concerns.

## 4.2 Robustness checks

**Mechanical negative relationship.** The first concern is whether the negative relationship between peer academic performance and the various outcomes is simply the byproduct of the so-called exclusion bias (see Caeyers and Fafchamps, 2020; Guryan, Kroft, and Notowidigdo, 2009). Exclusion bias entails that the peer average performance of good students is mechanically lower without their GPA on average, while the peer average of bad students is mechanically higher without their GPA on average. Since all the outcome variables considered increase in the own GPA, it could be that the negative coefficients simply reflect this mechanical negative relationship.

For this to be the case, one should observe a negative relationship between one's own and peer GPAs. From the auxiliary regression (i.e., regression of the peer GPA on the other controls), it turns out that the coefficient of one's own GPA on peer GPA is positive and almost zero.[40] This implies that the negative sign of the estimate of interest cannot be mechanically driven by the exclusion bias.

**Sample selection.** The second potential confounder could be driven by the particular sample selection described in section 3.1. As shown in Table 2, the peer average GPA is slightly larger than the individual average GPA, meaning that the participants of follow-up surveys were students who performed somewhat less well. Hence, the negative coefficients may simply mirror this particular sample selection and be solely driven by low-performance students.

If this was the case, one should expect different effect signs for different performance groups, such as negative for low performers and positive for high performers, or possibly larger effect sizes for low performers. To check whether this is the case, I re-estimate the model by tertiles of the GPA distribution for the four outcome variables on which I found statistically significant effects.

Table 7 reports the results of these estimations. Each column indicates the student subpopulation (defined by the GPA tertile), while each panel header reports the outcome variable considered. Contrary to the doubts raised by Table 2, all effects seem to be driven by students in the uppermost

[40]The results of the auxiliary regression are reported in Table 20 in Appendix A.

and middle parts of the GPA distribution. The group of students who seem to suffer most from the presence of higher-performing peers (on almost all dimensions except cognitive skills) appears to be the middle performance group.

**Selection into easier courses.** The third concern is that high GPAs are a proxy of more strategic students. For a student who cares more about a high GPA and less about the learning value, it is reasonable to choose easier courses to maximize the GPA while exerting the lowest possible effort.[41]

If this was the case, then the average GPA would be higher among students taking easier courses compared to those taking more advanced courses. To test this, I check the GPA distribution by course difficulty level. To gather the difficulty level of the courses taken in the 1994/95 school year in math, science, and English, I use information on high-school transcripts (AHAA data). Math and science courses are divided into nine[42] and six[43] levels, respectively, where lower values denote easier courses and higher values denote more advanced courses. For English, the course level is either regular or advanced, where advanced denotes either honorary or advanced placement (AP) levels.

The results are reported in Figure 2, which depicts the GPA distribution by difficulty level in math (Panel a), science (Panel b), and English (Panel c). In Panels (a) and (b), the value 0 stands for students who did not take math or science in 1994/95, whereas in Panel (c), 0 denotes students who took regular-level English classes. Figure 2 suggests that the average GPA increases with the difficulty level of the courses. This trend is more pronounced for math courses and more moderate for science courses. The lowest GPA in advanced math classes is even higher than the average GPA of basic and remedial math courses. This means that higher peer GPA does not proxy for more strategic or lazy students; rather, it reflects more able and ambitious students.

**Information incompleteness.** The fourth concern is that the negative sign is driven by measurement error due to missing information on student GPA.[44] The fact that in some schools the percentage of missing GPAs exceeds 50% in all grades, or that it reaches up to 75% in some grades while being almost 0 in others,[45] casts doubt on whether the estimated effect is the byproduct of an unevenly distributed, nonrandom measurement error in the peer variable of interest. As shown by Balestra, Eugster, and Puljic (2021), if the peer variable is measured with nonclassical (i.e., nonrandom) error, and this error is unevenly scattered across groups (i.e., in some groups it is disproportionately higher than in others), then this can even lead to a sign reversal (even when groups are randomly formed).

To verify whether missing information is a potential source of bias, I run two different tests. First, I group schools into three different groups defined by their intensity of missing GPAs and separately regress Model (1) for each of the groups. Groups are defined based on the distribution

[41] In contrast to European secondary education—where high school curricula are mostly standardized regardless of the specialization a student choses—in the US, high school students are given greater freedom in choosing their curricula, both in terms of content and difficulty level.

[42] 1, Basic/Remedial Math; 2, General/Applied Math; 3, Prealgebra; 4, Algebra I; 5, Geometry; 6, Algebra II; 7, Advanced Math (including Algebra III, Finite Math, Statistics); 8, Precalculus (including Trigonometry); and 9, Calculus.

[43] 1, Basic/Remedial Science; 2, General/Earth Science; 3, Biology I; 4, Chemistry; 5, Advanced Science (Biology II, Chemistry II); and 6, Physics.

[44] Information omission can typically cause greater bias than misreporting (Griliches, 1986).

[45] See panels of school 24 and 18 in Figure 6 of Appendix A.

of the school average within-grade fraction of missing GPAs. More precisely, the distribution is split into tertiles, with the first representing the school with the lowest attrition and the third representing the school with the highest attrition.

Second, I impute grades using two different methods. The first imputation method consists of substituting the missing grade with the average of the other two. The second method consists of substituting the missing grade with the only observable grade (when two out of three grades are missing) or the average of the other two (when only one grade out of three is missing). I then compute the peer GPA using the imputed individual GPAs.[46]

The results are reported in Table 8. Each panel presents the coefficient on the peer variable of interest under different situations that are described in the column headers. Columns (1)-(3) report the coefficients for schools with an average grade fraction of missing GPAs that is smaller than 15.8% (first tertile), larger than 17% but smaller than 26.8% (second tertile), and larger than 26.8% (third tertile) . Columns (4) and (5) report the results obtained using the first and second imputation methods, respectively. For the sake of an easier comparison, Column (6) also reports the main estimates from Table 6.

If the results were driven by missing observations of GPAs, one would expect the estimates to gradually increase from Column (1) to (3), as the degree of information incompleteness increases from one column to the other. The only panels where a progressive increase is observed are Panels I and III, where the outcomes are PVT scores in adolescence and in adulthood. For all the other variables, in Columns (1) and (3)—representing schools with the lowest and the highest share of attrition, respectively—the coefficients are very similar in magnitude and in most cases in statistical significance as well.

Similarly, if the estimates were driven by the rate of missing information on GPAs, we would expect that using imputed values reduces the bias. Assuming that the true effect of high-performing peers on their own outcomes is positive (common hypothesis, see (Ushchev and Zenou, 2020)), it follows that using imputed values should push all the estimates toward positive values. Hence, in absolute terms, one would expect coefficients to decrease. However, when comparing Columns (4) and (5) with Column (6), this seems to be especially the case for the two PVT measures, as well as for graduation from college.

In sum, Table 8 suggests that missing information on GPAs may be a concern only for a subset of results. On the one hand, it suggests that the negative effects found on cognitive abilities may need to be regarded with more caution. On the other hand, it also shows that measurement error due to information omission is unlikely to drive the negative effects on the other two outcomes: self-discipline and graduation from college.

**Multiple hypothesis testing.** A final concern is that the estimated effects might be artifacts of multiple nonindependent hypothesis tests. As the number of hypotheses tested increases, the probability of observing significant results purely by chance grows, even if no true effect exists, thereby heightening the likelihood of drawing erroneous conclusions.

In the main analysis, the estimate of interest is the effect of peer performance (i.e., $\beta_j$ in equation 1) on $J = 11$ different outcomes. This implies that I test the null hypotheses $H_0^j : \beta_j = 0$ eleven times

[46]The first imputation method allows me to obviate the missing GPA problem for almost 9,637 students in grades 9-12, reducing the fraction of missing GPAs by almost half. The second imputation method reduces the fraction of missing GPAs even more, i.e., by 63%.

in total (i.e., on four types of skills in 1995, three skills in 1996, and four outcomes in adulthood).

To control for multiple testing, I adopt the approach used by Bifulco, Fletcher, and Ross (2011) and Kling, Liebman, and Katz (2007), implementing the step-down resampling algorithm described in Westfall and Young (1993) and Anderson (2008).[47] From the eleven hypotheses, I select the smallest to be the family unadjusted $p$-value. Then, I reshuffle the sample 10,000 times by randomly reassigning students across grades of the same school (cornerstone of the identifying assumption) and retest all eleven hypotheses for each permutation, selecting the one with the smallest $p$-value. The family-adjusted $p$-value is calculated as the probability of finding a $p$-value smaller than or equal to the smallest $p$-value obtained from the actual data.

For the test, I use two alternative definitions of hypothesis families. In one scenario, I combine all hypotheses into a single family, while in the other, I group hypotheses by year (i.e., one for outcomes from 1995, one for 1996, and one for adulthood).[48] The unadjusted $p$-value for the single family is approximately 0.003, while the corresponding adjusted $p$-value is $p^* = 0.067$, indicating that in 6.7% of the cases, the family unadjusted $p$-value is smaller than or equal to the family unadjusted $p$-values.

A similar pattern emerges when conducting the test separately for by-year outcome families. The family unadjusted $p$-values are 0.003, 0.02, and 0.013 for 1995, 1996, and adulthood, respectively. In the same order, the respective family-adjusted $p$-values are 0.026, 0.086, and 0.078.

Based on both sets of calculations, I conclude that the overall patterns identified in the data are unlikely to have occurred by chance.

## 5 What drives the negative effects?

The primary empirical analysis reveals that exposure to higher-performing peers reduces one's cognitive abilities, self-discipline, and likelihood of attending and graduating from college. The results of various validity checks indicate that the observed effects are not attributed to sample selection, omitted variable bias, or multiple hypothesis testing. In the subsequent analysis, my primary objective is to delve into the factors driving these negative effects. To address this question, I investigate the three channels outlined in Section 2. Specifically, I will examine whether the negative effects stem from an unfavorable learning environment, if they follow from negative self-evaluation resulting from social comparisons, or if they are a consequence of the observation and imitation of specific behaviors strongly linked to academic performance.

To assess whether the observed peer effects stem from an unfavorable learning environment created by high performers, I examine the impact of peer academic performance on one's perception of the learning environment. More precisely, I follow the example of Lavy, Paserman, and Schlosser (2012) and Bifulco, Fletcher, and Ross (2011) and estimate the same regression model used in the main analysis and substitute the dependent variable with indicators of one's perception of the learning environment.[49]

[47] Details on the algorithm are provided in Appendix C.

[48] As Anderson (2008) suggests, the choice of outcome grouping can theoretically affect the final results, making it advisable to test different alternatives as a robustness check.

[49] The indicators are generated by transforming survey items measured on a Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree) into binary indicators. Each binary indicator takes the value of one if the answer to the original question is "agree" (i.e., 4) or "strongly agree" (i.e., 5). Questions on the perception of one's learning environment include the following statements: "You feel close to people at your school," "You feel like you are part of your school,"

Results (see Table 9) suggest that when comparing two students with the same GPA, the one exposed to peers who, on average, perform better is less likely to feel connected to these peers and the school. Instead, they are more inclined to perceive their peers as prejudiced, but interestingly, they do not have a significantly negative perception of teachers' fairness. Notably, the coefficient on one's own GPA is consistently positive across all seven outcomes. This suggests that the higher one's academic performance, the more they feel a sense of belonging within the school and among their peers. In line with the findings of Bursztyn, Egorov, and Jensen (2019), the positive sign of the coefficient on one's own GPA indicates that study effort is not penalized by the peer group. Taken together, the two coefficients suggest that a higher proportion of better-performing peers may lead to more competitive and potentially hostile learning environments.

To investigate whether the negative effects are a result of social comparisons, I adopt a similar approach as described earlier but focus on outcomes related to students' self-evaluation and future aspirations. For self-evaluation, I utilize the question, "Compared with other people your age, how intelligent are you?," This question is measured on a Likert scale ranging from 1 (moderately below average) to 6 (extremely above average). I categorize responses into three groups: 'About or below average' (for responses between 1-3), 'Slightly above average' (for responses of 4), and 'Considerably above average' (for responses between 5-6). For future aspirations, I consider two questions "How much do you want to go to college?" and "How likely is it that you will go to college?". I generate indicators of high willingness and certainty of attending college, with both variables taking a value of 1 when the highest response category is selected.

The results are presented in Table 10. In Columns (1)-(3), it is evident that exposure to better-performing peers significantly increases the likelihood of an individual perceiving themselves as being of average or below-average intelligence. Moving on to Columns (4) and (5), we find that exposure to high-achieving peers leads to a decrease in one's willingness to enroll in college (though not reaching statistical significance) and a decline in their confidence about attending college. Similar to the findings in Table 9, the coefficients for individual GPAs show an inverse relationship with the peer effect coefficients. As a student's academic performance improves, students are more likely to consider themselves as above average and express a greater willingness to attend college, believing it will happen. However, if we compare two students with the same GPA, those exposed to high-achieving peers exhibit, on average, less confidence in their own abilities and in the likelihood of attending college.

Finally, to verify whether the negative impact is attributed to the observation and imitation of specific behaviors exhibited by higher-achieving peers, I employ an IV approach. Namely, I instrument one's own behavior with the equivalent peer behavior in the previous period and consider only outcomes realized thereafter. The underlying premise is that if students observe and imitate one another, individual and peer behavior should be strongly, positively related, but peer behavior should not directly affect later outcomes.

In order to select the specific peer behaviors I restrict my choice to peer behavior that (i) are strongly predict peer GPAs in 1994, (ii) reflect high studying effort, (iii) are potentially observable and imitable, and (iv) are included in the follow-up interviews. Based on Based on these criteria I select three behaviors that indicate high study effort: hard working, highly attentive in the class,

"Students at your school are prejudiced," "You are happy to be at your school," "You feel safe in your school," "The teachers at your school treat students fairly," and "How much do you feel that your teachers care about you?"

and highly diligent.[50] As shown in Column (1) of Table 11 the selected peer behaviors jointly explain approximately 93% of the within-school cross-grade variation in peer GPA.

For this approach to be valid, peer behavior must be highly predictive of the individual behavior in 1995 and must not directly predict the outcomes. To test the relevance of the instrument I regress the individual behavior in 1995 on the same peer behavior in 1994 and control for all the covariates from the main estimation, as in equation (1). Columns (2)-(4) in Table 11 report the coefficients of peer behavior (indicated in the row header) on one's own future behaviors (indicated in the column header). The results suggest that only *working hard* (hereafter also study effort) seems to be a relevant instrument.[51] More precisely, when the proportion of peers who value hard work increases by 100% at the start of the school year, there is a 35% greater likelihood that an individual will also place a higher value on hard work by the school year's end (refer to Column 2). In practical terms, if, in a cohort of 200 students, an additional 20 students initially express a stronger appreciation for hard work, the probability of any individual student dedicating themselves to hard work by the end of the school year would increase by 3.5%. Hence, as commonly deemed in the peer effect literature (see Liu, Patacchini, and Zenou, 2014; Ushchev and Zenou, 2020), peer and own effort are highly correlated.

For this test to be valid, I must also verify that peer study effort does not directly affect later outcomes. To this end, I equation (1) substituting peer GPA with peer study effort.[52] Table 21 in Appendix A shows that peer behavior does not directly predict one's own future outcomes, with the only exception of enrollment into college.

Now, what remains to be verified is whether this pattern between peer and one's own study effort also translates into negative externalities on one's future outcomes, as established in the main analysis. The results from the second stage estimations are reported in Table 12: Panel A presents the results for outcomes in 1996, while Panel B shows the results for outcomes in adulthood. Overall, the estimates are noisy because of the weak instrument and Table 12 alone does not allow to draw meaningful conclusions.[53] However, this last analysis offers at least two insights that support results from the previous two sets of tests. First, cohorts that feature better students tend to also feature more hard working students, who promote higher study engagement (see Table 11). Second, being exposed to a higher fraction of hard working peers significantly reduces one's probability of enrolling into college (see Tabel 21).

Combined with the results from Tables 9, 10 this seems to suggest that the negative effects documented in this study could be side effects of competition.

First, students have different goals in competitive environments compared to noncompetitive ones, which ultimately leads to distinct performance and learning outcomes. As initially proposed by Ames and Ames (1984) and more recently demonstrated by Lam et al. (2004), students who are exposed to competitive conditions tend to have performance-oriented goals, while those in noncompetitive environments are more likely to have mastery-oriented goals. Having

[50] All behaviors are obtained by dichotomizing the original questions to 1 and 0, where 1 reflects the highest level of engagement in that behavior, and 0 reflects all other possible levels. The questions include: "In general, how hard do you try to do your school work well?," "Have you ever had trouble paying attention in school?," and"Have you ever had trouble getting your homework done?".

[51] This is also in line with other studies that also find a strong correlation between individual and peer study effort (Stinebrickner and Stinebrickner, 2006).

[52] Note that since only working hard turned out to be a relevant instrument, I test the exclusion restriction only for this specific behavior.

[53] Note that the $F$-statistic= 8.43 for regression (2) of Table 11.

performance-oriented goals can result in better performance (Cagiltay, Ozcelik, and Ozcelik, 2015; Lam et al., 2004), but not necessarily in higher learning (Chen, Law, and Huang, 2019). This observation aligns with the findings presented in Tables 12 and 21, particularly in Column (1) of both tables. Although the estimates in this column do not reach statistical significance, an interesting trend emerges. When the outcome variable is school performance in 1996, the coefficients exhibit a positive sign. In contrast, when the outcome variable shifts to cognitive abilities in adulthood, the sign of the coefficients changes to negative. These results may indicate that emulating peers by putting in extra effort is associated with improved academic performance but may have a contrasting impact on cognitive abilities.

Second, competition highlights distinct aspects of one's abilities, potentially leading to a reduction (or enhancement) in students' self-assessment of their own abilities when they find themselves in a losing (or winning) position. Ames and Ames (1981) show that in competitive environments, relative performance is the most salient information, as opposed to individualistic conditions where one's own performance history is the most important information for deciding the amount of study effort or study goal.[54] In competitive environments, students' self-perception of their abilities is almost entirely a function of how they perform relative to others (Ames and Ames, 1984). Performing worse than others tends to elicit a self-attribution of low ability, while the opposite is true when one performs better than others (Ames and Ames, 1981; Lam et al., 2004). Table 10 reflects precisely this pattern: Exposure to better peers lowers one's self-perception of the own abilities and decreases one's confidence of ever attending college.

Third, within Festinger's (1954) social comparison theory, two key hypotheses are prominent. The first is the 'similarity hypothesis,' which posits that individuals tend to compare themselves with others who are similar to them. The second is the 'drive for upward comparison,' which is motivated by the desire for self-improvement. The rationale is that individuals can attain more accurate self-evaluations by comparing themselves with those of similar abilities. However, to enhance their own abilities, they must engage in comparisons with individuals who outperform them.[55]

Following this line of reasoning, if the negative effects presented in this study were indeed driven by social comparison, we would expect these effects to be most pronounced among students in the middle of the distribution. These students are positioned in a way that they are more similar to the outperformers but not yet at their level, which suggests the potential for self-improvement. Table 7 supports precisely this hypothesis by showing that the middle tertile of the GPA distribution is the most negatively affected performance group on virtually all four outcomes, including self-discipline in the short run, cognitive abilities in the short-run and adulthood, and likelihood of graduating from college.

In summary, a higher fraction of outperformers in a cohort likely creates a competitive environment that on the one side fosters total effort but worsens one's perception of the own actual abilities and consequently dampens one's future aspiration.

[54] Individualistic conditions describe situations in which one works alone (i.e., other people's actions are not observable) and has only oneself as a reference point.

[55] See Dijkstra et al. (2008) for a review of psychology research offering empirical evidence of both hypotheses.

## 6 A network game with self-perception

Conventional theoretical frameworks for studying peer effects often rely on the assumption of uniformly positive peer effects, where everyone's effort increases in response to the average effort of their peers (see Liu, Patacchini, and Zenou, 2014; Ushchev and Zenou, 2020). As demonstrated in Table 11 this this assumption holds when examining the relationship between individual and peer similar behaviors. However, as shown in Tables 6 when the outcome diverges from the behavior exhibited by peers, the nature of the relationship is no longer strictly positive or uniform.

The positive and uniform peer effects hypothesis is strongly questioned by several other recent studies too. Most of these studies find negative impact of high performers on other students' achievement (Antecol, Eren, and Ozbeklik, 2016; Feld and Zölitz, 2017; Imberman, Kugler, and Sacerdote, 2012), and in particular so on low-ability student (Burke and Sass, 2013; Carman and Zhang, 2012; Carrell, Sacerdote, and West, 2013; Gibbons and Telhaj, 2016).

Similarly, other studies find that exposure to peers with similar abilities obtained through ability tracking do not have a negative impact on the academic performance of low-ability students (Booij, Leuven, and Oosterbeek, 2017; Duflo, Dupas, and Kremer, 2011). In contrast, other studies find that better-performing peers can also exert a positive effect of on low-ability students' academic achievement (Carrell, Fullerton, and West, 2009).

The empirical evidence presented in this study complements these findings by highlighting the most likely factor contributing to these mixed results: self-perception. For example, in cases where low-ability students are exposed to a higher proportion of outperforming peers, as examined in Carrell, Sacerdote, and West (2013), their academic deficiencies may become more salient to them. Consequently, this situation can discourage low-ability students from interacting with high-ability peers (as demonstrated by the authors) to avoid unfavorable comparisons. Additionally, the absence of slightly better-performing peers to compare themselves with may also lead to reduced effort on low-ability students' side.

A negative effect on other high-ability students, as documented by Antecol, Eren, and Ozbeklik (2016), could instead arise when students misjudge their abilities. Highly productive students may perceive themselves as not smart enough to realize the achievements of the outperformers, and be discouraged from exerting more effort when exposed to more competitive peers. Conversely, low-ability students with high confidence in their ability to learn might exert more effort when exposed to more hard-working peers and benefit from the presence of high-performers, as found by (Carrell, Fullerton, and West, 2009).

All these examples illustrate how self-perception can effectively offer an explanation for different empirical patterns that challenge the conventional wisdom regarding the direction of peer effects on ability. To further legitimate and rationalize these findings, I present a game-theoretic framework that builds upon the results of the present study and includes self-perception in one of the conventional theoretical frameworks used to describe the mechanics behind peer effects.

More precisely, I modify local-average model (Ushchev and Zenou, 2020), which is a static, full- information game, in two significant ways. First, agent are characterized by self-assessed relative abilities, besides the conventional productivities. Second, one's utility can both increase as well as decrease in the group average effort. Whether it increases or decreases depends on the self-assessment of the own abilities compared to the group.

## 6.1 Set-up

**The network.** Let us consider a network $\mathcal{G}$ of $N \geq 2$ students (or agents) described by the $N \times N$ *undirected adjacency matrix* $\mathbf{G} = [g_{ij}]$, with $g_{ij} = \{0, 1\}$ for all pairs of students $(i, j)$, where 1 indicates that $i$ and $j$ are connected while 0 indicates that they are not. The row-normalized version of matrix $\mathbf{G}$ is denoted by $\widehat{\mathbf{G}} = [\widehat{g}_{ij}]$, where $\widehat{g}_{ij} := \frac{g_{ij}}{d_i} \in [0, 1]$, with $d_i := \sum_{j=1}^{N} g_{ij}$ being student $i$'s degree. The tie between a pair of students can be thought of as either a friendship or as membership in the same social group (e.g., cohort). Therefore, $\mathbf{G}$ is by definition symmetric.

**Agents' attributes.** Each agent $i = 1, 2, ..., N$ is characterized by a certain *productivity* level, $\alpha_i \in \mathbb{R}_+$, and the centered *self-perceived ability rank* $r_i \in \left[-\frac{1}{2}, \frac{1}{2}\right]$, where $r_i < 0$ ($r_i > 0$) indicates that the student believes to have below (above) average abilities. Both characteristics are considered exogenous and independent of each other.

Productivity is to be thought of as a function of $q > 0$ individual exogenous characteristics, $\mathbf{x}_i \in \mathbb{R}^q$, such as knowledge, cognitive and socioemotional abilities, and parental investment.

Self-perceived ability rank, instead, is to be thought of as the level to which an individual believes in his or her own abilities. Importantly, self-perceived ability rank does not depend from and is not equivalent of the actual current performance rank. It is, however, reasonable to think of it as a function of *past* performance ranks, if these were made public. For this reason, treating self-perceived ability rank as exogenous is a reasonable simplification for the time being.

**Preferences and choice variable.** Students are assumed to care only about their *academic achievement*, $y_i \in \mathbb{R}_+$, such as their GPA, or the likelihood of graduating from college. Their primary objective is to maximize this outcome. In pursuit of this goal, they determine their optimal *study effort*, taking into account the personal information set, $\mathcal{I}_i$, available to them at the decision time. Formally, they address the following optimization problem:

$$e_i^* = \arg\max_{e_i} \ \mathbb{E}\left[y_i\left(\alpha_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i\right) \middle| \mathcal{I}_i\right], \tag{2}$$

where the academic achievement is assumed to depend on one's productivity, one's self-perception of own abilities, and one's own and peers' level of effort in the following way:

$$y_i\left(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i\right) = \alpha_i e_i - \frac{1}{2}e_i^2 + \phi \ln\left(r_i + 1\right) e_i \bar{e}_{-i} + \epsilon_i. \tag{3}$$

The parameter $0 \leq \phi \leq 1$ denotes the degree of *social comparison* in the network, $\bar{e}_{-i} := \sum_{j \neq i} \widehat{g}_{ij} e_j$ denotes the average effort among $i$'s peers, and $\epsilon_i$ is a random event that may affect a student's achievement, such as an illness or an accident.[56] For simplicity, students are assumed to know nothing about uncertain events. Hence, their best guess based on their information set, $\mathcal{I}_i$, is to expect no random event, neither for themselves, nor for anybody else in the network. That is, $\mathbb{E}[\epsilon_j | \mathcal{I}_i] = 0$ for any $i, j = 1, 2, \ldots, N$.

The initial component of the technology is standard in both the local-average model Ushchev and Zenou (2020) and the local-aggregate model Liu, Patacchini, and Zenou (2014). It reflects the

[56]To better understand what the parameter $\phi$ captures, consider a network of adolescents versus a network of retirees. For adolescents, who are more susceptible to social comparison, $\phi$ takes on a higher value than for retirees, who are also likely to compare themselves but to a much lesser extent than adolescents.

idea that academic performance increases in both productivity and effort but not indefinitely—resulting in a concave relationship with both arguments. Furthermore, the product between the two arguments implies that, everything else being equal, a high-productivity student must exert a lower level of effort to achieve the same outcome as a low-productivity student.

The novelty of the model lies in third term: product between $e_i$ and $\ln(r_i + 1)$, where the logarithmic function of the self-perceived ability rank is the mathematical formalization of self-perception (or self-concept)—the set of beliefs and self- perceptions one holds about oneself (Myers and Twenge, 2015). The product captures the idea that one's self-concept regulates one's level of effort (Honicke and Broadbent, 2016).

By further multiplying this product with peer average effort, $\bar{e}_{-i}$, the model posits that depending on how able one perceives themselves to be, peer externalities can be either positive or negative. If agents harbor doubts about their own abilities ($r_i < 0$), then the presence of peers with whom they compete or compare imposes extra psychological costs. As a result, given the same level of effort, outcomes are lower in the presence of social interaction than when realized individually. However, if agents perceive themselves as capable ($r_i > 0$), the presence of peers serves as an extrinsic motivator, spurring them to exert even greater effort than they would in isolation. In fact, if we assume a full-information game, where everybody knows the productivity and effort of everybody in the network, that is $\{\alpha_i, \boldsymbol{\alpha}_{-i}, e_i, \boldsymbol{e}_{-i}, \boldsymbol{g}_i\} \subseteq \mathcal{I}_i$, then the first order condition of (3) with respect to a peer $j$'s s effort yields

$$\frac{\partial y_i(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i)}{\partial e_j} \lesseqqgtr 0 \qquad \Leftrightarrow \qquad r_i \lesseqqgtr 0. \tag{4}$$

In contrast to the local-average model studied by Ushchev and Zenou (2020), efforts are not unconditionally strategic complements since

$$\frac{\partial^2 y_i(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i)}{\partial e_i e_j} \lesseqqgtr 0 \qquad \Leftrightarrow \qquad r_i \lesseqqgtr 0. \tag{5}$$

Rather, efforts are strategic complements only if one believes to have above-average abilities, strategic substitutes if one does not believe in their abilities, and independent if one believes to have average abilities.

The choice of the logarithmic function to express the notion of self-concept is motivated by three specific features of the function itself.

First, $\ln(r_i + 1)$ is monotonically increasing in $r_i$. From a purely technical point of view, this is a conventional property for differentiation with respect to $r_i$. From a more conceptual point of view, this reflects the empirical pattern shown by numerous studies, whereby students with higher confidence in their academic abilities tend to perform better academically, as well as to experience higher satisfaction than those with lower levels (see Doménech-Betoret, Abellán-Roselló, and Gómez-Artiga, 2017; Honicke and Broadbent, 2016). That is,

$$\frac{\partial y_i(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i)}{\partial r_i} > 0. \tag{6}$$

Second, $\ln(r_i + 1)$ takes positive values for $r_i > 0$ and negative values for $r_i < 0$. This formalizes Bandura's (1977) idea that negative beliefs in one's abilities to perform a given task can hijack one's perseverance in that task, while positive beliefs tend to boost it. Formally, let $r_i^H > 0$ and $r_i^L < 0$, then

$$y_i\left(\cdot, r_i^L\right) < y_i\left(\cdot, r_i^H\right). \tag{7}$$

Third, the slope of the function is steeper for lower values of $r_i$, implying that the marginal benefits of an improvement in one's self-concept are greater for students with lower self-confidence than those for students who already believe in their abilities. Formally,

$$\left.\frac{\partial y_i(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i)}{\partial r_i}\right|_{r_i=r_i^L} > \left.\frac{\partial y_i(\alpha_i, r_i, e_i, \mathbf{e}_{-i}, \mathbf{g}_i)}{\partial r_i}\right|_{r_i=r_i^H}. \tag{8}$$

## 6.2 Nash Equilibrium

When maximizing the utility function, individuals are assumed to choose $e_i$ simultaneously with other players. Hence, the effort choice of the other agents is taken for given, just as it is the network structure, $\mathbf{G}$. For the sake of simplicity, I consider the full information scenario, wherefore $\{\alpha_i, \boldsymbol{\alpha}_{-i}, e_i, \boldsymbol{e}_{-i}, \boldsymbol{g}_i\} \subseteq \mathcal{I}_i$.

By plugging (3) in (2) and computing the first-order condition (FOC) with respect to $e_i$, it follows that each student's best-response function yields:

$$e_i = \alpha_i + \phi w_i \bar{e}_{-i}, \tag{9}$$

where $w_i := \ln(r_i + 1)$. Let $\mathbf{W} := \ln(\mathbf{R} + \mathbf{I})$ be the logarithm matrix of the $N \times N$ diagonal matrix $(\mathbf{R} + \mathbf{I})$, where $\mathbf{I}$ is the identity, and $\mathbf{R}$ is a diagonal matrix, with $diag(\mathbf{R}) = (r_1, r_2, \ldots, r_N)^T$ and off-diagonal elements equal to zero.[57] Considering that $\bar{e}_{-i} := \sum_{j\neq i}^{N} \widehat{g}_{ij} e_j = \widehat{\boldsymbol{g}}_i \mathbf{e}$, we can re-express (9) in matrix form as follows:

$$\mathbf{e} = \boldsymbol{\alpha} + \phi \mathbf{W}\widehat{\mathbf{G}}\mathbf{e}, \tag{10}$$

where $\boldsymbol{\alpha} := (\alpha_1, \alpha_2, \ldots, \alpha_N)^T$ is the productivity vector and $\mathbf{e} := (e_1, e_2, \ldots, e_N)^T$ is the effort vector. By reshuffling and re-expressing (10) in terms of effort, one finds the equilibrium and with it Proposition 1.

**Proposition 1.** *(Equilibrium efforts, performance, and utilities) Consider a network described by the row-normalized $N \times N$ adjacency matrix $\widehat{\mathbf{G}}$, where $N \geq 2$ denotes the number of agents. Let $\boldsymbol{\alpha}$ be a $N \times 1$ vector describing agents' productivity, and $\mathbf{W}$ be a diagonal matrix that describes agents' self-perception, with $w_{ii} = \ln(r_i + 1)$, for all $i = 1, 2, ..., N$, and $r_i \in \left[-\frac{1}{2}, \frac{1}{2}\right]$. Assume that agents solve (2), then it can be shown that, for $0 \geq \phi \geq 1$, $\left(\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}\right)^{-1}$ exists and that the following results hold true.*

*(i) A unique (but not always interior) Nash equilibrium $\mathbf{e}^*$ of the following form exists:*

$$\mathbf{e}^* = \widehat{\mathbf{M}}\boldsymbol{\alpha}, \tag{11}$$

*where*

$$\widehat{\mathbf{M}} := \left(\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}\right)^{-1} = \sum_{k=0}^{\infty} \phi^k \left(\mathbf{W}\widehat{\mathbf{G}}\right)^k. \tag{12}$$

[57] Note that sum $(\mathbf{R} + \mathbf{I})$ is a diagonal matrix, precisely because both $\mathbf{R}$ and $\mathbf{I}$ are diagonal matrices. Therefore, to compute the matrix logarithm $\mathbf{W}$, the sum $(\mathbf{R} + \mathbf{I})$ does not need to be diagonalized first.

*(ii) Each student's equilibrium outcome is given by*

$$y_i^*(\alpha_i, r_i, e_i^*, \overline{e}_{-i}^*, \mathbf{g}_i) = \frac{1}{2}\widehat{m}_{ii}\alpha_i + \frac{1}{2}\sum_{j\neq i}^{N} \widehat{m}_{ij}\alpha_j. \tag{13}$$

Just as in the conventional local-average model, the equilibrium effort is a weighted average of individuals' productivities. However, in contrast to the existing models, weights not only depend on the the network structure but also on everybody's self-concept. To see the exact form that these weights take, one can use the Neumann series expansion and find the approximate form of the single elements of matrix $\widehat{\mathbf{M}}$:[58]

$$\widehat{m}_{ij} = \begin{cases} 1 + w_i \left(\phi^2 \sum_{k\neq i} w_k \widehat{g}_{ik}^2 + \phi^3 \sum_{k\neq i} \sum_{\ell\neq\{i,k\}} w_k w_\ell \widehat{g}_{ik}\widehat{g}_{k\ell}\widehat{g}_{\ell i} + ...\right) , & \text{if } j = i \\ w_i \left(\phi \widehat{g}_{ij} + \phi^2 \sum_{k\neq\{i,j\}} w_k \widehat{g}_{ik}\widehat{g}_{kj} + \phi^3 \sum_{k\neq\{i,j\}} \sum_{\ell\neq\{i,j,k\}} w_k w_\ell \widehat{g}_{jk}\widehat{g}_{k\ell}\widehat{g}_{\ell i} + ...\right) , & \text{if } j \neq i \, . \end{cases} \tag{14}$$

The first expression of (14) represents the diagonal elements of $\widehat{\mathbf{M}}$, and also the marginal effects of one's own productivity, $\alpha_i$, on the one's equilibrium effort. The second expression of (14) represents the off-diagonal elements of $\widehat{\mathbf{M}}$ and also the marginal effects of other agents' productivities on one's own equilibrium effort.

The marginal effect of one's own productivity is determined by two essential components. The first component is the direct effect (first term) of one's own productivity, while the second component is the indirect effect (second term) resulting from circular friendships. This indirect effect essentially represents the "reflected effect" of one's productivity on peers' effort.[59] It is important to note that the direct effect of one's own productivity on equilibrium effort is greater than the indirect effect. This difference in magnitude is due to the attenuation of the indirect effect, which becomes more pronounced as the size of the friendship circle grows.[60] As a direct consequence of this, one can easily conclude that both effort and academic performance always increase in one's own productivity, $\alpha_i$. That is,[61]

$$\widehat{m}_{ii} > 0 \, , \qquad \forall \, i = 1, 2, ..., N.$$

The marginal effect of a peer's productivity on one's equilibrium effort is influenced by two key components. The first component is the direct effect of that peer's productivity. The second component is the indirect effect, where the peer's productivity influences one's equilibrium effort through common friends. In scenarios where individuals are isolated from others, meaning they do not share any connections, the indirect effect of a peer's productivity becomes zero. However, the focus of this study lies in situations where everyone is interconnected within a social group, while there are no connections across different groups. This is a typical implicit assumption in nearly all empirical studies on peer effects in education.

This distinction is crucial because the role of self-perception varies depending on whether

[58] See Appendix D for more details.

[59] Circular friendships are defined as friendships that start and end at the same node.

[60] This happens for two reasons. On the one hand, since $0 \leq \phi \leq 1$, it means that $\lim_{k\to\infty} \phi^k = 0$. On the other hand, because $0 \leq \widehat{g}_{ij} \leq 1$, the more $\widehat{g}_{ij}$s are multiplied with each other, the smaller their product becomes.

[61] Formally, this result is a direct consequence of the spectral radius of $\widehat{\mathbf{WG}}$ being strictly smaller than 1 in absolute terms. Considering the first expression of (14), even if $w_i$ is negative, its product with other $w_j$'s and $g_{ij}$'s never exceeds 1. Hence, the expression of $\widehat{m}_{ii}$ must always be positive.

individuals share connections or not. When individuals like $i$ and $j$ have no common friends, the effect of $j$'s productivity on $i$'s effort and outcome is solely determined by $i$'s beliefs. If $i$ has confidence in their abilities ($r_i > 0$), the effect is positive; otherwise, it is negative.

Conversely, when $i$ and $j$ share common friends, as in a scenario where everyone is connected to everyone else within a cohort, the effect of $j$'s productivity on $i$'s effort and performance is influenced not only by $i$'s beliefs but also by the beliefs of all intermediary agents (denoted as $r_k$, where $k \neq i, j$). The ultimate direction of the total effect is still determined by one's own self-concept, but the magnitude of the effect can greatly vary depending on the distribution of self-perception within the network. From the second expression in (14) it is evident that the self-perception of less distant agents has the greatest impact on one's equilibrium effort. This influence fades out the higher the number of intermediary nodes between two agents becomes.

The fact that everybody's self-perception impacts individual effort also implies that the overall distribution of self-perception in the network can give rise to specific patterns in the overall effort choice in the network. Loosely speaking, a higher presence of less confident students may produce less stimulating and less fostering learning environments compared to situations where their presence is limited. To verify this conjecture, I rely on a simulation exercise in which I hold both the productivity distribution, the size, and structure of the network constant, varying only the distribution of $r_i$ among agents.

The simulation consists of the following steps. First, I draw a random Erdos-Renyi network of size $N = 20$ (i.e., approximately the size of a classroom) with medium density ($P(\mathbf{G}) = 0.30$) and a random vector of productivities $\boldsymbol{\alpha}$.[62]

Let $H$-types and $L$-types and denote agents with positive (i.e., ($r_i > 0$) and negative (i.e., $r_i < 0$) self-perceptions. The fraction of $L$-types is then defined as $\pi = P(r_i < 0)$. For all possible fractions $\pi \in [0, 1]$, I randomly draw 1,000 times $N \times 1$ random vectors of $\mathbf{r} = (r_1, r_2, ..., r_N)$ from the interval $[-0.5, 0.5]$. Since there are only 21 possible fractions of $L$-types in a network of 20 agents (with $\pi = 0$ included), I end up with a total of 21,000 different random vectors of $\mathbf{r}$.

To also explore the impact of social comparison, I consider three different levels of $\phi \in \{0.1, 0.5, 1\}$. Starting with one of these levels, I compute the vector of equilibrium efforts for each of the 21,000 random vectors $\mathbf{r}$ by using expression (11). The average equilibrium effort is then calculated as the arithmetic mean of the resulting effort vector. The result of the simulation exercise is presented in Figure 3, which presents how the mean equilibrium effort evolves as the fraction of $L$-types increases.

As the proportion of agents holding pessimistic beliefs about their abilities increases, the average optimal effort in the network decreases. The steepness of the lines becomes more pronounced with higher values of $\phi$, indicating that when individuals engage in more frequent comparisons, the overall effort level in the network undergoes a more significant decrease as the fraction of pessimistic agents increases.

Another interesting detail of Figure 3 is that all lines intersect at a specific point. This intersection point is where the average optimal effort equals the average productivity. This can be inferred from the fact that all lines intersect with the dark-gray horizontal line where $\phi = 0$. In fact, when $\phi = 0$, the equilibrium solution is simply $\mathbf{e}^* = \boldsymbol{\alpha}$.

[62]The random vector of productivities is drawn from a normal distribution centered at 0.5 and with standard deviation of 0.15. Potential negative values are substituted with 0.05.

Now, this implies the existence of a threshold (of approximately 40% in Figure 3) in the fraction of individuals with negative self-perceptions for any $\phi > 0$. Below this threshold, the average optimal effort exceeds what is expected in the absence of social comparison or of social interactions, while above this threshold, the mean optimal effort falls below the level that is observed without social comparison or social interactions.

From Figure 3 one can draw at least two policy-relevant conclusions. First, it confirms the initial conjecture that everybody's self-perception matters for the overall effort choice in the network. Second, it suggests that the presence of individuals with negative self-perceptions is not unconditionally harmful to the entire network. While it is true that when the fraction of these individuals increases the average effort in the equilibrium decreases, their presence leads to inefficiencies only when their fraction exceeds a given threshold. The latter is reached when the average optimal effort is equal to the effort level that would be observed in the absence of social comparison or social interactions.

### 6.3 Discussion

Before concluding, it is essential to discuss how this model complements the empirical analysis presented in the first part of this study, as well as how it contributes to explaining the empirical results from previous studies.

To illustrate how this model complements the empirical analysis let us consider a concrete example. Consider graduation from college be the outcome of interest. From the empirical analysis we concluded that being exposed to outperformers worsens one's academic self-concept during high-school. According to the model, entering college with a low self-confidence in the own academic abilities results in a lower likelihood of graduating from college as one selects into a peer group with higher average abilities as compared to high school. This prediction is in line with one of the main results from the empirical analysis presented in Section 4.

Equation (9) provides the explanations for why this is the case. By computing the first order condition of (9) with respect to a peer's effort we finds that

$$\frac{\partial e_i^*}{\partial e_j} = \phi \ln(r_i + 1) \gtreqless 0 \quad \Leftrightarrow \quad r_i \gtreqless 0\,. \tag{15}$$

That is, as peer effort increases one's own effort increases, but only if one believes to have above-average abilities (i.e., $r_i > 0$), otherwise it decreases (when $r_i < 0$) or it remains unchanged (when $r_i = 0$). In other words, if students believe in their abilities to learn, they are by construction inclined to follow the example of more hard working peers. However, if they lack self-confidence, they are discouraged from the start and exert even a lower effort than they would were they exposed to nobody.

This threefold nature is the core peculiarity of this model that also distinguishes it from the two canonical models, the local-average and the local-aggregate models. While the latter models allow for positive peer effects only, here, the relationships between one's own and peer effort can potentially take three turns: (i) *complementarity at the top*, (ii) *discouragement at the bottom*, and (iii) *indifference in the middle*. In fact, thanks to its versatility, the present model provides a theoretical foundation for virtually all studies, where one's effort and peer effort do not exhibit strategic complementarity (see for example Antecol, Eren, and Ozbeklik, 2016; Carman and Zhang, 2012;

Carrell, Sacerdote, and West, 2013; Feld and Zölitz, 2017; Imberman, Kugler, and Sacerdote, 2012).

## 7 Conclusion

The last twenty years of research on peer effects in education reveal that peer ability impacts various groups differently and can yield both positive and negative consequences (see Cools and Patacchini, 2021; Sacerdote, 2011, 2014, for reviews). Yet, the understanding of the underlying mechanisms driving these effects and the factors influencing their positive or negative trajectories is still limited (de Gendre Alexandra and Salamanca, 2020). The literature has identified three potential channels through which peer effects operate—learning environment, social learning, and social comparison—but the limited simultaneous testing of more than channel at a time leaves uncertainties about the existence and identity of the dominant mechanism.

This study addresses this gap by taking a comprehensive approach. Firstly, I consider a broader set of outcomes, including both cognitive and socio-emotional abilities in the short run, as well as education attainment in adulthood. Secondly, I investigate all three potential channels within the same institutional and empirical setting. Leveraging cross-cohort, within-school variation in a representative sample of American high school students, the findings indicate that exposure to better performing peers negatively impacts various outcomes, including one's cognitive abilities, self-discipline, and likelihood of graduating from college. The mechanism analysis points to social comparison as the primary driver of these adverse effects, as that exposure to better-performing peers negatively influences self-perception of abilities and future aspirations.

This study's primary contribution lies in the comprehensive analysis of the mechanisms and the emphasis on self-perception. The findings highlight the pivotal role of self-perception in determining the direction of peer effects on individual outcomes. This assertion is substantiated by proposing a novel theoretical framework of peer effects that incorporates the concept of self-perception. The framework demonstrates how using self-perception as a 'switcher,' turning the presence of more engaged peers into either a bonus or a penalty, effectively explains a broader range of empirical findings.

These findings offer valuable insights for both the political debate on tracking vs. inclusive education as well as the theoretical framework guiding our understanding of peer effects in general. Policymakers should not only consider the effects that a specific grouping scheme has on school performance but also its impact on students' academic self-concept and general well-being. Similarly, scholars developing mathematical models to describe how others' behavior influences individual outcomes should account for agents' personal beliefs, as it can considerably enhance the accuracy of predicting observed outcomes.

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# Figures

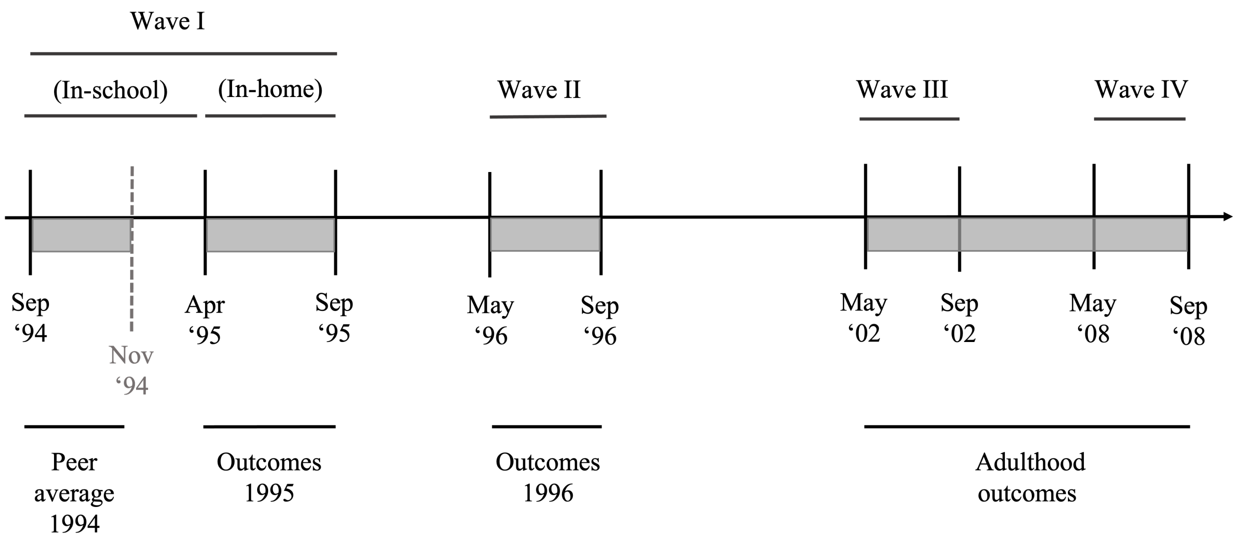



Figure 1: Timeline of data collection.

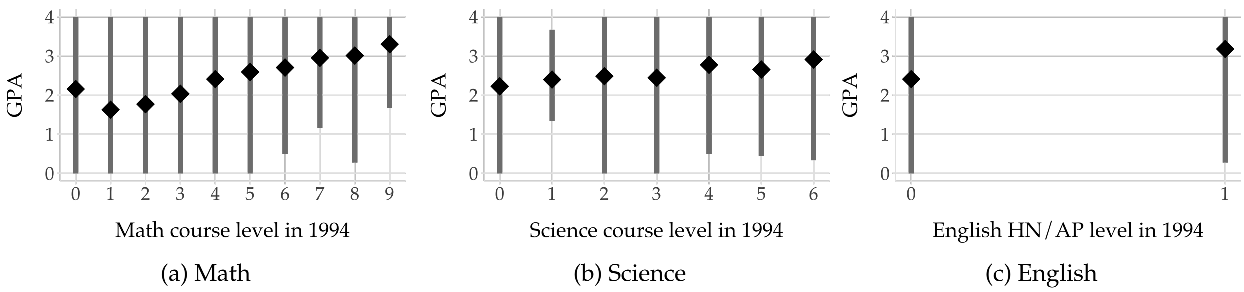



Figure 2: Average GPA by course difficulty level

*Note*: in Panels (a) and (b), the value zero represents all students who do not take a math or science course at all. This is more common among 11th and 12th graders who have already completed their coursework in math and science.

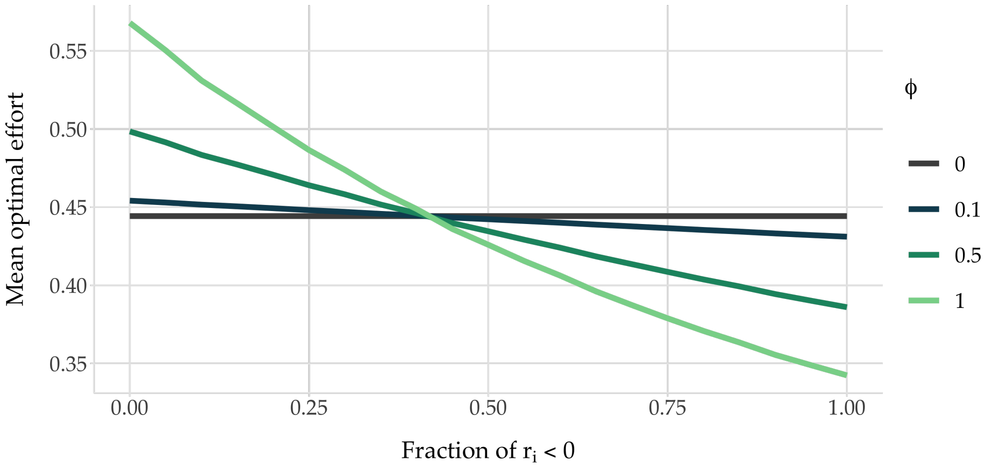



Figure 3: MEAN EFFORT GIVEN THE FRACTION OF *L*-TYPE INDIVIDUALS.

## Tables

Table 1: Outcomes summary.

| | N (1) | Mean (2) | Std. dev. (3) | [min;max] (4) |
|---|---|---|---|---|
| *Panel I: Spring 1995* | | | | |
| PVT in 1995 | 5,801 | 103.55 | 13.51 | [14;136] |
| Own self-discipline index in 1995 (standardized) | 6,003 | 0.01 | 0.94 | [-3.73;1.37] |
| Own self-esteem index in 1995 (standardized) | 6,064 | -0.04 | 0.99 | [-5.26;1.49] |
| Own emotional stability index in 1995 (standardized) | 6,067 | -0.03 | 1.00 | [-5.71;1.29] |
| *Panel II: Spring 1996* | | | | |
| Own self-discipline index in 1996 (standardized) | 3,770 | 0.01 | 0.96 | [-3.96;1.35] |
| Own self-esteem index in 1996 (standardized) | 4,116 | -0.02 | 0.99 | [-4.89;1.39] |
| Own emotional stability index in 1996 (standardized) | 4,113 | -0.05 | 0.98 | [-4.72;1.37] |
| *Panel III: Adulthood* | | | | |
| PVT in 2002 | 4,580 | 102.11 | 15.82 | [7;122] |
| Graduated from high school | 5,396 | 0.93 | 0.26 | [0;1] |
| Attended college | 5,396 | 0.74 | 0.44 | [0;1] |
| Graduated from college | 5,396 | 0.39 | 0.49 | [0;1] |

*Note*: The table reports the various outcome variables. *Panel I* reports outcomes collected between May and September 1995 during in-home Wave I. *Panel II* reports outcomes collected between May and September 1996 during Wave II. *Panel III* reports adulthood outcomes collected between May 2002 and September 2008 during Wave III and Wave IV. PVT stands for Picture Vocabulary test. Standardization of the non-cognitive skills has been performed over the whole sample. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 2: Sample description.

| | Individual | | | Peer averages | | |
|---|---|---|---|---|---|---|
| | Mean (1) | Std. dev. (2) | [min;max] (3) | Mean (4) | Std. dev. (5) | [min;max] (6) |
| *Panel I: Abilities* | | | | | | |
| Own GPA in 1994 | 2.62 | 0.88 | [0; 4] | 2.72 | 0.3 | [2.06; 3.38] |
| Own self-discipline index (standardized) | 0.09 | 0.96 | [-2.11; 1.42] | 0.05 | 0.14 | [-0.65; 0.69] |
| Own self-esteem index (standardized) | -0.04 | 0.98 | [-3.76; 1.51] | -0.05 | 0.16 | [-0.47; 0.53] |
| Own emotional stability index (standardized) | -0.09 | 1.01 | [-4.02; 1.37] | -0.05 | 0.15 | [-0.62; 0.36] |
| Ever repeated a grade | 0.17 | 0.37 | [0; 1] | | | |
| *Panel II: Attitudes and believes* | | | | | | |
| Part of a sport club | 0.52 | 0.5 | [0; 1] | 0.48 | 0.14 | [0.19; 0.91] |
| Part of a foreign language club | 0.15 | 0.36 | [0; 1] | 0.14 | 0.1 | [0; 0.7] |
| Part of an arts club | 0.32 | 0.46 | [0; 1] | 0.27 | 0.1 | [0.03; 0.62] |
| Part of a STEM club | 0.08 | 0.28 | [0; 1] | 0.06 | 0.05 | [0; 0.36] |
| Part of a politics club | 0.22 | 0.41 | [0; 1] | 0.19 | 0.09 | [0.07; 0.53] |
| Working hard in 1994 | 0.34 | 0.47 | [0; 1] | 0.33 | 0.08 | [0.13; 0.62] |
| Expects to earn middle-class income | 0.21 | 0.41 | [0; 1] | 0.2 | 0.05 | [0; 0.41] |
| Expects to marry by age 25 | 0.13 | 0.33 | [0; 1] | 0.13 | 0.05 | [0.02; 0.41] |
| Expects to be killed by age 21 | 0.02 | 0.13 | [0; 1] | 0.02 | 0.01 | [0; 0.06] |
| Risky behaviors index (standardized) | 0.08 | 1 | [-0.85; 3.2] | 0.11 | 0.26 | [-0.41; 1.1] |
| Regular truant in 1994 | 0.15 | 0.36 | [0; 1] | 0.15 | 0.09 | [0; 0.47] |
| *Panel III: Demographics and family inputs* | | | | | | |
| Female | 0.52 | 0.5 | [0; 1] | 0.49 | 0.08 | [0; 0.63] |
| White | 0.56 | 0.5 | [0; 1] | 0.53 | 0.35 | [0; 1] |
| Black | 0.19 | 0.39 | [0; 1] | 0.16 | 0.22 | [0; 0.94] |
| Hispanic | 0.15 | 0.35 | [0; 1] | 0.17 | 0.22 | [0; 0.92] |
| At least one parent on public assistance | 0.01 | 0.11 | [0; 1] | 0.01 | 0.01 | [0; 0.08] |
| At least one college-educated parent | 0.31 | 0.46 | [0; 1] | 0.36 | 0.17 | [0.03; 0.93] |
| Parental investment (score) | 0.5 | 0.32 | [0; 1] | | | |
| Permissive parenting style (score) | 0.9 | 0.21 | [0; 1] | | | |
| Household size (wo/ interviewee) | 3.52 | 1.51 | [1; 17] | | | |
| *Panel IV: School characteristics* | | | | | | |
| Mixed-race school | 0.63 | 0.48 | [0; 1] | | | |
| Public school | 0.92 | 0.27 | [0; 1] | | | |
| Urban and suburbarn area | 0.81 | 0.4 | [0; 1] | | | |
| Rural area | 0.19 | 0.4 | [0; 1] | | | |
| Large/mid-large (>=351) | 0.95 | 0.21 | [0; 1] | | | |
| Mid-small (126-350) | 0.05 | 0.21 | [0; 1] | | | |
| Grade 9 | 0.21 | 0.41 | [0; 1] | | | |
| Grade 10 | 0.28 | 0.45 | [0; 1] | | | |
| Grade 11 | 0.29 | 0.45 | [0; 1] | | | |
| Grade 12 | 0.22 | 0.41 | [0; 1] | | | |
| School-grade frac. of missing GPAs | 0.24 | 0.15 | [0.01; 0.75] | | | |
| No. grades by school | 3.86 | 0.35 | [3; 4] | | | |

*Note*: The table reports summary statistics on the sample composition, including individual covariates (Columns 1-3, Panels I-III), peer covariates (Columns 4-6, Panels I-III), and information on selected schools. The sample counts 6,069 students from 58 schools. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 3: Raw and residual variation in peer average GPA.

| | N (1) | Mean (2) | Std. dev. (3) | Min (4) | Max (5) |
|---|---|---|---|---|---|
| *Panel A: Raw variation* | | | | | |
| Peer GPA in 1994 | 6,069 | 2.72 | 0.30 | 2.06 | 3.38 |
| *Panel B: Residuals net of school and grade FE* | | | | | |
| Peer GPA in 1994 | 6,069 | 0.00 | 0.10 | -0.36 | 0.36 |
| *Panel C: Residuals net of school and grade FE, and school-specific linear trends* | | | | | |
| Peer GPA in 1994 | 6,069 | -0.00 | 0.07 | -0.29 | 0.28 |

*Note*: the table presents the variation in the peer variable of interest for three different cases: raw (Panel A), net of school and grade fixed effect (Panel B), net of school, grade fixed effects, and school-specific linear trends (Panel C). *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 4: Test for school-specific linear trends across grades.

| | | *Panel A: Outcomes in 1995* | | | |
|---|---|---|---|---|---|
| | Peer GPA (1) | PVT in 1995 (2) | Self-discipline (3) | Self-esteem (4) | Emotional stability (5) |
| Grade | 0.016 | 0.757*** | 0.013 | 0.019 | -0.014 |
| | (0.012) | (0.148) | (0.016) | (0.012) | (0.012) |
| R-squared | 0.869 | 0.201 | 0.033 | 0.024 | 0.019 |
| N | 6,069 | 5,801 | 6,003 | 6,064 | 6,067 |
| | | *Panel B: Outcomes in 1996* | | | |
| | Peer GPA (1) | (2) | Self-discipline (3) | Self-esteem (4) | Emotional stability (5) |
| Grade | 0.016 | | 0.075*** | -0.01 | -0.025 |
| | (0.012) | | (0.023) | (0.017) | (0.022) |
| R-squared | 0.869 | | 0.061 | 0.036 | 0.021 |
| N | 6,069 | | 3,770 | 4,116 | 4,113 |
| | | *Panel C: Outcomes in adulthood* | | | |
| | Peer GPA (1) | PVT in 2002 (2) | Graduation from high school (3) | Enrollment in college (4) | Graduation from college (5) |
| Grade | 0.016 | 1.205*** | 0.033*** | 0.02*** | 0.034*** |
| | (0.012) | (0.174) | (0.004) | (0.006) | (0.007) |
| R-squared | 0.869 | 0.192 | 0.043 | 0.07 | 0.129 |
| N | 6,069 | 4,580 | 5,396 | 5,396 | 5,396 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Each panel presents the estimate of the continuous variable for grade on the outcome indicated in the panel column. Outcomes are grouped in different panels according to their time of realization: spring 1995 (Panel A), spring 1996 (Panel B), and adulthood (Panel C). Each panel presents the results for the regressor of interest: peer GPA. The result is the same for all panels because the same, baseline sample is used for all three of them. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 5: Balancing tests.

| | *Outcome: Peer average GPA in 1994* | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | + School & grade fixed effects | | + School-specific linear trends | |
| | Coefficient (1) | Std. error (2) | Coefficient (3) | Std. error (4) | Coefficient (5) | Std. error (6) |
| *Predetermined variable:* | | | | | | |
| Ever repeated a grade | -0.09546*** | (0.02972) | 0.00196 | (0.00468) | 0.00359 | (0.00244) |
| Part of a cultural club | 0.06883*** | (0.022) | -0.00343 | (0.00287) | -0.00126 | (0.00193) |
| Part of a sport club | 0.07802** | (0.03157) | 0.00146 | (0.00288) | -0.00098 | (0.00175) |
| White | 0.18166** | (0.08431) | -0.00303 | (0.00328) | -0.00249 | (0.0025) |
| Black | -0.12055* | (0.06956) | 0.00536* | (0.00282) | 0.00548** | (0.00228) |
| Hispanic | -0.22919* | (0.1156) | 0.00022 | (0.00399) | -0.00106 | (0.00288) |
| At least one parent on public assistance | -0.08044 | (0.06789) | 0.00383 | (0.01633) | -0.00332 | (0.0085) |
| At least one college-educated parent | 0.10528*** | (0.03414) | -0.00084 | (0.00266) | 0.00016 | (0.00223) |
| Parental investment (score) | 0.0343* | (0.0185) | 0.0029 | (0.00389) | 0.00043 | (0.00261) |
| Permissive parenting style (score) | 0.11392*** | (0.03769) | 0.00452 | (0.0052) | -0.00275 | (0.00392) |
| Household size | -0.01336* | (0.00725) | 0.00017 | (0.00091) | -5e-05 | (6e-04) |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Observations $N = 6,069$. The table presents the coefficients of the predetermined variables indicated in the row headers on the treatment of interest: peer GPA in 1994. Each regression is a univariate regression, that is the outcome is regressed on one characteristic at a time. Different pairs of columns represent different models: Columns (1)-(2) are obtained with a simple OLS, Columns (3)-(4) additionally control for school and grade fixed effects, while Columns (5)-(6) additionally control for school-specific linear trends. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 6: Main effects.

| | *Panel A: Outcomes in spring 1995* | | | |
|---|---|---|---|---|
| | PVT<br>(1) | Self-discipline<br>(2) | Self-esteem<br>(3) | Emotional stability<br>(4) |
| Own GPA in 1994 | 2.511*** | 0.127*** | -0.003 | 0.035** |
| | (0.219) | (0.015) | (0.014) | (0.015) |
| Peer GPA in 1994 | -4.826*** | -0.181 | 0.183 | 0.068 |
| | (1.574) | (0.147) | (0.135) | (0.124) |
| R-squared | 0.341 | 0.248 | 0.331 | 0.341 |
| N | 5,801 | 6,003 | 6,064 | 6,067 |
| | *Panel B: Outcomes in spring 1996* | | | |
| | (1) | Self-discipline<br>(2) | Self-esteem<br>(3) | Emotional stability<br>(4) |
| Own GPA in 1994 | | 0.077*** | 0 | 0.052*** |
| | | (0.024) | (0.017) | (0.017) |
| Peer GPA in 1994 | | -0.399** | -0.032 | 0.145 |
| | | (0.167) | (0.180) | (0.137) |
| R-squared | | 0.193 | 0.28 | 0.268 |
| N | | 3,770 | 4,116 | 4,113 |
| | *Panel C: Outcomes in adulthood* | | | |
| | PVT (2002)<br>(1) | Graduation from HS<br>(2) | Enrollment in college<br>(3) | Graduation from college<br>(4) |
| Own GPA in 1994 | 2.281*** | 0.049*** | 0.103*** | 0.151*** |
| | (0.283) | (0.006) | (0.011) | (0.009) |
| Peer GPA in 1994 | -5.369** | 0.05 | -0.048 | -0.17** |
| | (2.089) | (0.058) | (0.078) | (0.071) |
| R-squared | 0.278 | 0.143 | 0.228 | 0.317 |
| N | 4,580 | 5,396 | 5,396 | 5,396 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. All specifications control for school and grade fixed effects, the individual covariates indicated in Panels I-III of Table 2, and some of the peer covariates (e.g., fraction of female and black students, and students with at least one college-educated parent), the fraction of missing GPAs in the school-grade, and the within-school-grade variation of individual GPAs. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 7: MAIN EFFECTS BY TERTILES OF THE GPA DISTRIBUTION.

| | Lowest tertile (1) | Middle tertile (2) | Uppermost tertile (3) | Lowest tertile (4) | Middle tertile (5) | Uppermost tertile (6) |
|---|---|---|---|---|---|---|
| | *Panel A: PVT in 1995* | | | *Panel B: Self-discipline in 1996* | | |
| Peer GPA in 1994 | -4.989* | -3.506 | -6.714** | -0.387 | -0.629* | -0.138 |
| | (2.868) | (2.965) | (2.933) | (0.371) | (0.348) | (0.286) |
| R-squared | 0.342 | 0.339 | 0.367 | 0.225 | 0.199 | 0.234 |
| N | 2,132 | 1,823 | 1,846 | 1,239 | 1,201 | 1,330 |
| | *Panel C: PVT in 2002* | | | *Panel D: Graduation from college* | | |
| Peer GPA in 1994 | -4.879 | -12.904*** | -3.27 | -0.183* | -0.351*** | 0.134 |
| | (3.767) | (3.876) | (3.026) | (0.095) | (0.123) | (0.154) |
| R-squared | 0.277 | 0.293 | 0.282 | 0.287 | 0.285 | 0.253 |
| N | 1,797 | 1,418 | 1,365 | 2,042 | 1,674 | 1,680 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. The table shows the estimates of the peer variable of interest on different outcomes for different subpopulation of students. The subpopulations are defined by the tertiles of the GPA distribution across all students, and are indicated in the column headers. Each panel indicates the results for a different outcome including PVT in spring 1995 (Panel A), Self-discipline in spring 1995 (Panel B), PVT in 2002 (Panel C), and graduation from college (Panel D). All specifications control for school and grade fixed effect, the individual and peer covariates, fraction of missing GPAs in the school-grade, and the within-school-grade variation of individual GPAs. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 8: Main effects by degrees of GPA's missingness rate and with imputed GPA.

| | First tertile (1) | Middle tertile (2) | Uppermost tertile (3) | Imputation type 1 (4) | Imputation type 2 (5) | Main effect (6) |
|---|---|---|---|---|---|---|
| *Panel I: PVT in 1995* | | | | | | |
| Peer GPA in 1994 | 7.161 | -5.982*** | -7.75** | -2.659 | -2.065 | -4.826*** |
| | (6.702) | (2.154) | (2.998) | (1.702) | (1.658) | (1.574) |
| N | 1,083 | 3,313 | 1,405 | 5,801 | 5,801 | 5,801 |
| R-squared | 0.245 | 0.344 | 0.316 | 0.34 | 0.34 | 0.341 |
| *Panel II: Self-discipline in 1996* | | | | | | |
| Peer GPA in 1994 | -1.241*** | -0.189 | -0.881*** | -0.409** | -0.355* | -0.399** |
| | (0.304) | (0.234) | (0.298) | (0.18) | (0.187) | (0.167) |
| N | 767 | 2,140 | 863 | 3,770 | 3,770 | 3,770 |
| R-squared | 0.242 | 0.196 | 0.202 | 0.193 | 0.193 | 0.193 |
| *Panel III: PVT in 2002* | | | | | | |
| Peer GPA in 1994 | 1.13 | -2.082 | -13.747*** | -4.116* | -4.629** | -5.369** |
| | (8.978) | (2.855) | (4.707) | (2.183) | (2.173) | (2.089) |
| N | 841 | 2,614 | 1,125 | 4,580 | 4,580 | 4,580 |
| R-squared | 0.245 | 0.254 | 0.323 | 0.277 | 0.277 | 0.278 |
| *Panel IV: Graduation from college* | | | | | | |
| Peer GPA in 1994 | -0.485* | 0.01 | -0.337** | -0.138* | -0.13* | -0.17** |
| | (0.227) | (0.073) | (0.127) | (0.073) | (0.073) | (0.071) |
| N | 998 | 3,111 | 1,287 | 5,396 | 5,396 | 5,396 |
| R-squared | 0.384 | 0.306 | 0.3 | 0.317 | 0.317 | 0.317 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Each panel presents results for a different outcome, including PVT in spring 1995 (Panel I), self-discipline in spring 1996 (Panel II), PVT in 2002 (Panel III), and graduation from college (Panel IV). Columns (1)-(3) present the results for different subpopulations that are defined by the tertiles from the average fraction of missing GPAs within schools. Schools with average fractions below 15.8% compose the first tertile, larger than 17% but smaller than 26.8 the middle tertile, and larger than 26.8% the uppermost tertile. Columns (4)-(5) present the baseline results using imputed values of peer GPA. *Imputation 1* consists in substituting the missing grade with the average of the other two. *Imputation 2* consists in substituting the missing grade with the only observable grade (when two out three grades are missing) or the average of the other two (when only one grade out of three is missing). I then compute the peer GPA using the imputed individual GPAs. Column (6) reports the effects from Table 6 for the respective outcome. All specifications control for school and grade fixed effects as well as the covariates from the main specifications. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 9: Perception of school environment vs. peer average GPA.

| | Feeling close to peers (1) | Perceiving peers as prejudiced (2) | Feeling as part of the school (3) | Feeling happy at school (4) | Feeling safe at school (5) | Perceiving teachers as fair (6) | Perceiving great care from teachers (7) |
|---|---|---|---|---|---|---|---|
| Own GPA in 1994 | 0.004 | -0.006 | 0.017*** | 0.019** | 0.028*** | 0.024*** | 0.033*** |
| | (0.008) | (0.009) | (0.005) | (0.009) | (0.007) | (0.008) | (0.009) |
| Peer GPA in 1994 | -0.086 | 0.142** | -0.101* | -0.067 | -0.15** | -0.021 | -0.063 |
| | (0.057) | (0.070) | (0.059) | (0.058) | (0.070) | (0.073) | (0.077) |
| R-squared | 0.083 | 0.156 | 0.132 | 0.117 | 0.143 | 0.086 | 0.127 |
| N | 6,004 | 5,999 | 6,005 | 6,004 | 6,005 | 6,005 | 6,069 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. The table presents the coefficients of own and peer GPA on different outcomes, which are indicated in the column header is the outcome. All specification control for school and grade fixed effect as well as all the covariates used for the main specifications from Table 6. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 10: Self-assessment and aspirations vs. peer average GPA.

| | Considerably above average (1) | Slightly above average (2) | About or below average (3) | Wants to attend college badly (4) | Will certainly attend college (5) |
|---|---|---|---|---|---|
| Own GPA in 1994 | 0.127*** | 0.018** | -0.145*** | 0.084*** | 0.107*** |
| | (0.013) | (0.008) | (0.010) | (0.008) | (0.008) |
| Peer GPA in 1994 | -0.141** | -0.034 | 0.175** | -0.072 | -0.196*** |
| | (0.064) | (0.075) | (0.072) | (0.068) | (0.068) |
| R-squared | 0.178 | 0.024 | 0.187 | 0.184 | 0.259 |
| N | 6,069 | 6,069 | 6,069 | 6,069 | 6,069 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. The table presents the coefficients of own and peer GPA on different outcomes, which are indicated in the column header is the outcome. All specification control for school and grade fixed effect as well as all the covariates used for the main specifications from Table 6. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 11: Peer behaviors and own similar behaviors in 1995.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Peer GPA (1) | Working hard (2) | Highly focused (3) | Always completing homeworks (4) |
| *Peer study behavior:* | | | | |
| Frac. of peers working hard | 0.472** | 0.346** | | |
| | (0.195) | (0.166) | | |
| Frac. of highly focused peers | 0.508** | | -0.021 | |
| | (0.220) | | (0.180) | |
| Frac. of peers always completing homeworks | 0.539*** | | | 0.195 |
| | (0.174) | | | (0.189) |
| R-squared | 0.927 | 0.063 | 0.144 | 0.172 |
| N | 6,069 | 6,060 | 5,997 | 5,995 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. The table presents the estimates of the peer study behavior indicated in the row headers on the dependent variables indicated in the column headers. All regressions control for school and grade fixed effects, as well as all the covariates used in the main specification from Table 6, i.e., including the same past behaviors that were collected in the school questionnaire in 1994. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

Table 12: Own effort in 1995 on outcomes in 1996 and adulthood (second stage).

| | *Panel A: Outcomes in 1996* | | | |
|---|---|---|---|---|
| | GPA in 1996 (1) | Self-discipline (2) | Self-esteem (3) | Emotional stability (4) |
| Working hard | 2.709 | 1.623 | 1.623 | -0.438 |
| | (4.16) | (1.778) | (1.778) | (1.217) |
| R-squared | 0.461 | 0.201 | 0.201 | 0.27 |
| N | 3,053 | 3,764 | 3,764 | 4,107 |
| | *Panel B: Outcomes in adulthood* | | | |
| | PVT (2002) (1) | Graduation from HS (2) | Enrollement in college (3) | Graduation from college (4) |
| Working hard | -14.752 | 0.18 | -0.939 | 0.336 |
| | (15.942) | (0.349) | (0.733) | (0.605) |
| R-squared | 0.275 | 0.144 | 0.227 | 0.316 |
| N | 4,575 | 5,388 | 5,388 | 5,388 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. The table presents the 2SLS estimates of own study effort in 1995 on the outcomes indicated in the panel columns, where own study effort is instrumented with peer study effort in 1994. Outcomes are grouped by realization time: spring 1996 (Panel A) versus adulthood (Panel B). All specifications control for school and grade fixed effects, as well as all the covariates used in the main specification from Table 6, i.e., including individual study effort in 1994. *Source*: Own computations. Data are drawn from National Longitudinal Survey of Adolescents (Add Health).

# A Supplemental material

## Sample selection

Table 13: Sample selection.

| | | |
|---|---|---|
| Participated to both interviews of Wave I | **15,350** | |
| Keep in-school questionnaires conducted before December 1994 | | – 1,300 |
| Keep 9th-12th grade | | – 3,654 |
| Keep schools w/ 10th through 12th grade in the same building | | – 383 |
| Keep school-grades w/ at least 20 observable GPAs | | – 366 |
| Keep obs. with all key information observable | | –3,534 |
| Keep schools with at least 3 grades | | –44 |
| **Baseline sample** | | **6,069** |

## Validity of the empirical strategy

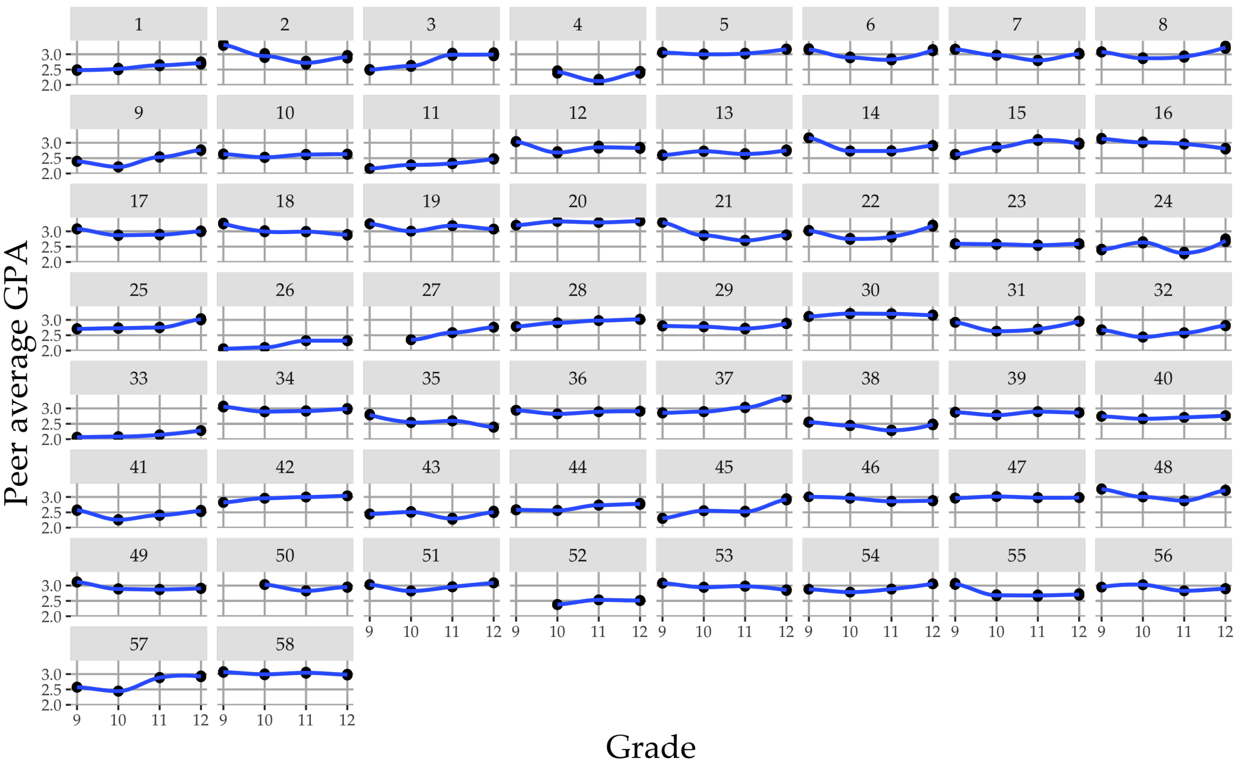


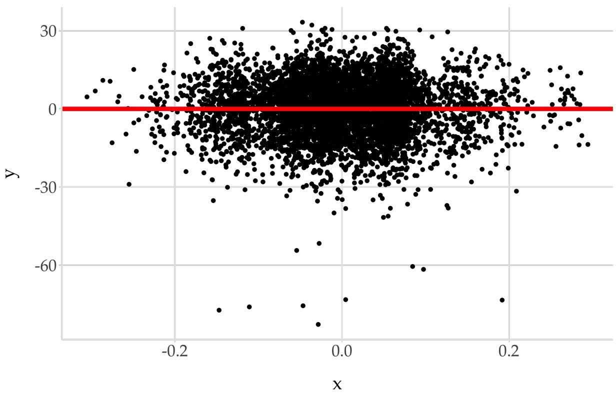

Figure 4: Peer average GPA vs. grade by school.

## Empirical analysis

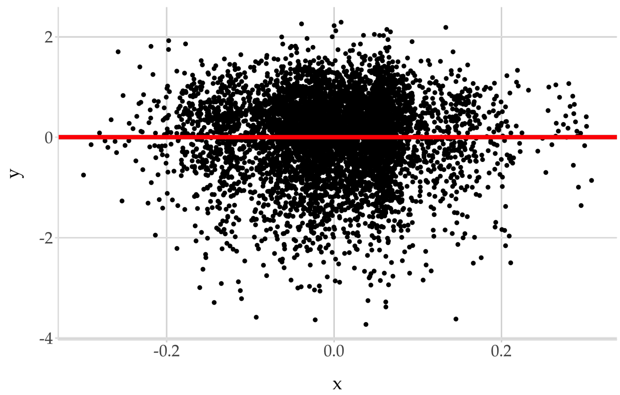
Table 14: Test for school-specific quadratic trends across grades.

| | | *Outcomes in 1995* | | | |
|---|---|---|---|---|---|
| | Peer average GPA (1) | PVT in 1995 (2) | Self-discipline (3) | Self-esteem (4) | Emotional stability (5) |
| Grade | 1.242 | 61.838*** | 1.016 | 1.486 | -1.155 |
| | (0.911) | (11.832) | (1.239) | (1.042) | (1.035) |
| Grade2 | 3.067*** | 17.228 | 2.737** | 1.953 | 2.091* |
| | (0.674) | (11.678) | (1.028) | (1.358) | (1.136) |
| R-squared | 0.886 | 0.201 | 0.034 | 0.025 | 0.02 |
| N | 6,069 | 5,801 | 6,003 | 6,064 | 6,067 |
| | | *Outcomes in 1996* | | | |
| | Peer average GPA (1) | (2) | Self-discipline (3) | Self-esteem (4) | Emotional stability (5) |
| Grade | 1.242 | | 8.693*** | -0.716 | -1.468 |
| | (0.911) | | (1.723) | (1.659) | (1.807) |
| Grade2 | 3.067*** | | 3.997** | 0.287 | 1.138 |
| | (0.674) | | (1.810) | (1.512) | (1.811) |
| R-squared | 0.886 | | 0.063 | 0.036 | 0.021 |
| N | 6,069 | | 3,770 | 4,116 | 4,113 |
| | | *Outcomes in adulthood* | | | |
| | Peer average GPA (1) | PVT in 2002 (2) | Graduation from high school (3) | Enrollment in college (4) | Graduation from college (5) |
| Grade | 1.242 | 98.632*** | 2.739*** | 1.671*** | 2.793*** |
| | (0.911) | (14.165) | (0.329) | (0.476) | (0.546) |
| Grade2 | 3.067*** | 9.396 | 0.098 | 0.011 | 0.032 |
| | (0.674) | (14.086) | (0.282) | (0.450) | (0.526) |
| R-squared | 0.886 | 0.192 | 0.043 | 0.07 | 0.129 |
| N | 6,069 | 4,580 | 5,396 | 5,396 | 5,396 |

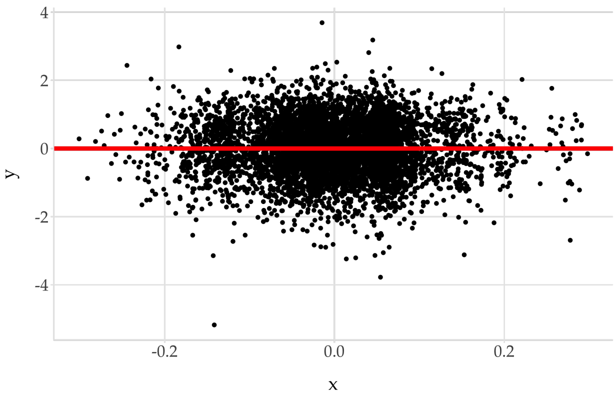
*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. All specifications control for school and grade fixed effects, as well as all the covariates from the main specifications.



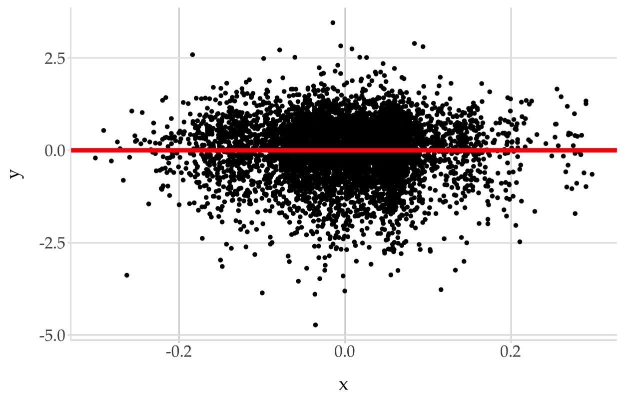

(a) PVT 1995



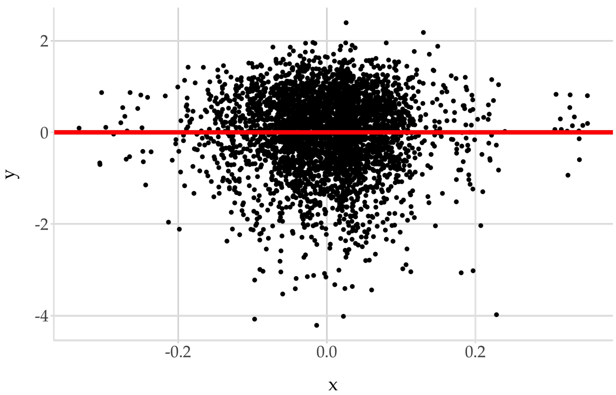

(b) Self-discipline 1995



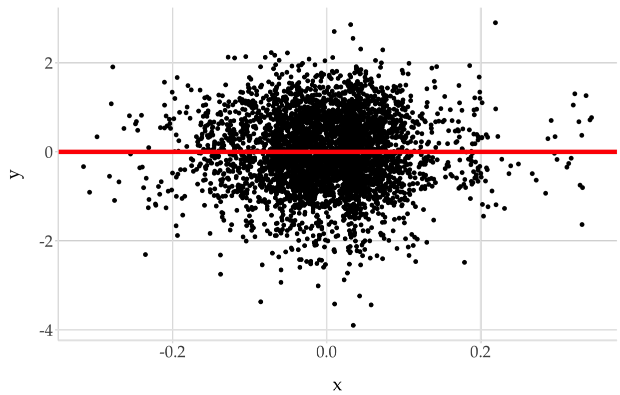

(c) Self-esteem 1995



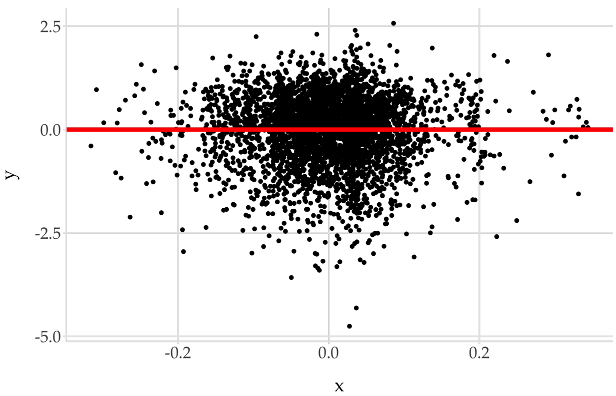

(d) Emotional stability 1995



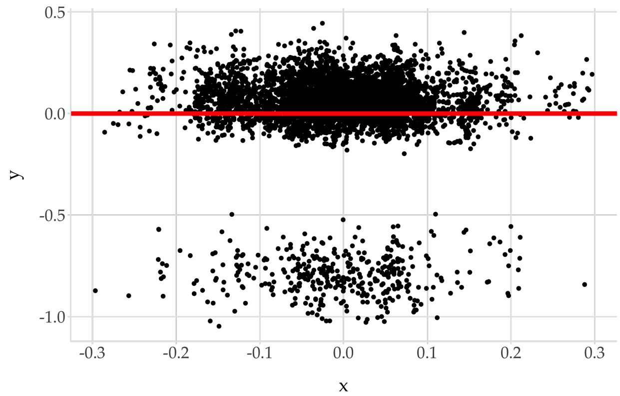

(e) Self-discipline 1996




(f) Self-esteem 1996




(g) Emotional stability 1996




(h) Emotional stability 1996

Figure 5: Outcome on peer performance residuals from equation (1).

Table 15: Socio-cognitive skills' single items in 1995.

| | Own GPA | | School-grade avg. GPA | | |
|---|---|---|---|---|---|
| | Coefficient (1) | Std. error (2) | Coefficient (3) | Std. error (4) | N (5) |
| *Panel A: Self-discipline* | | | | | |
| Focus | 0.089*** | (0.017) | 0.004 | (0.147) | 6,003 |
| Self-control | 0.149*** | (0.019) | -0.299** | (0.149) | 6,003 |
| Good rel. w/ teacher | 0.06*** | (0.016) | -0.131 | (0.161) | 6,003 |
| *Panel B: Self-esteem* | | | | | |
| Self-worth | 0.009 | (0.010) | -0.068 | (0.089) | 6,064 |
| Self-pride | 0.028*** | (0.009) | 0.073 | (0.110) | 6,064 |
| Self-satisfaction | -0.006 | (0.013) | 0.323*** | (0.121) | 6,064 |
| Competence | 0.002 | (0.015) | 0.187* | (0.110) | 6,064 |
| Social acceptance | -0.029** | (0.013) | 0.039 | (0.114) | 6,064 |
| Feeling loved | -0.013 | (0.011) | 0.098 | (0.100) | 6,064 |
| *Panel C: Emotional stability* | | | | | |
| Good appetite | 0.049*** | (0.011) | 0.031 | (0.092) | 6,067 |
| Good sleep | -0.047*** | (0.016) | 0.089 | (0.124) | 6,067 |
| Happiness | 0.057*** | (0.012) | 0.095 | (0.096) | 6,067 |
| No anxiety | -0.016 | (0.016) | -0.066 | (0.124) | 6,067 |
| Stable mood | 0.018 | (0.019) | -0.01 | (0.132) | 6,067 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 16: Socio-cognitive skills' single items in 1996.

| | Own GPA | | School-grade avg. GPA | | |
|---|---|---|---|---|---|
| | Coefficient (1) | Std. error (2) | Coefficient (3) | Std. error (4) | N (5) |
| *Panel A: Self-discipline* | | | | | |
| Focus | 0.037 | (0.026) | -0.295* | (0.155) | 3,770 |
| Self-control | 0.071** | (0.030) | -0.374* | (0.188) | 3,770 |
| Good rel. w/ teacher | 0.067*** | (0.018) | -0.235 | (0.173) | 3,770 |
| *Panel B: Self-esteem* | | | | | |
| Self-worth | 0.002 | (0.012) | -0.073 | (0.110) | 4,116 |
| Self-pride | 0.018 | (0.011) | -0.059 | (0.118) | 4,116 |
| Self-satisfaction | 0.01 | (0.020) | -0.06 | (0.167) | 4,116 |
| Competence | 0.007 | (0.015) | -0.062 | (0.176) | 4,116 |
| Social acceptance | -0.03** | (0.012) | 0.135 | (0.127) | 4,116 |
| Feeling loved | -0.006 | (0.012) | 0.007 | (0.111) | 4,116 |
| *Panel C: Emotional stability* | | | | | |
| Good appetite | 0.068*** | (0.014) | -0.001 | (0.138) | 4,113 |
| Good sleep | -0.024 | (0.018) | 0.146 | (0.140) | 4,113 |
| Happiness | 0.042*** | (0.014) | 0.104 | (0.126) | 4,113 |
| No anxiety | -0.042* | (0.021) | 0.144 | (0.138) | 4,113 |
| Stable mood | 0.065*** | (0.016) | 0.087 | (0.194) | 4,113 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 17: Robustness of estimated impacts on outcomes in 1995.

| | OLS<br>(1) | + school & grade fixed effects fixed effects<br>(2) | + individual covariates covariates<br>(3) | + peer covariates covariates<br>(4) | + school-grade GPA dispersion & frac. of missing GPAs<br>(5) | + school-specific across-grade linear trends<br>(6) |
|---|---|---|---|---|---|---|
| *Dependent variable: PVT in 1995* | | | | | | |
| Own GPA in 1994 | 3.529*** | 3.396*** | 2.526*** | 2.523*** | 2.515*** | 2.53*** |
| | (0.343) | (0.288) | (0.216) | (0.218) | (0.219) | (0.223) |
| Peer GPA in 1994 | 8.785*** | -5.221*** | -3.942** | -4.063** | -4.567*** | -4.576* |
| | (2.782) | (1.738) | (1.530) | (1.633) | (1.617) | (2.410) |
| R-squared | 0.116 | 0.245 | 0.339 | 0.34 | 0.341 | 0.347 |
| N | 5,801 | 5,801 | 5,801 | 5,801 | 5,801 | 5,801 |
| *Dependent variable: Self-discipline (standardized index) in 1995* | | | | | | |
| Own GPA in 1994 | 0.25*** | 0.26*** | 0.115*** | 0.116*** | 0.115*** | 0.117*** |
| | (0.019) | (0.020) | (0.014) | (0.014) | (0.014) | (0.015) |
| Peer GPA in 1994 | -0.378*** | 0.034 | -0.031 | -0.014 | -0.08 | -0.076 |
| | (0.090) | (0.145) | (0.121) | (0.122) | (0.131) | (0.191) |
| R-squared | 0.053 | 0.087 | 0.272 | 0.273 | 0.274 | 0.284 |
| N | 6,003 | 6,003 | 6,003 | 6,003 | 6,003 | 6,003 |
| *Dependent variable: Self-esteem (standardized index) in 1995* | | | | | | |
| Own GPA in 1994 | 0.05*** | 0.06*** | -0.015 | -0.013 | -0.013 | -0.013 |
| | (0.018) | (0.017) | (0.014) | (0.014) | (0.014) | (0.014) |
| Peer GPA in 1994 | -0.085 | 0.147 | 0.169* | 0.156 | 0.18 | 0.449** |
| | (0.063) | (0.110) | (0.093) | (0.100) | (0.111) | (0.182) |
| R-squared | 0.002 | 0.027 | 0.348 | 0.35 | 0.35 | 0.356 |
| N | 6,064 | 6,064 | 6,064 | 6,064 | 6,064 | 6,064 |
| *Dependent variable: Emotional stability (standardized index) in 1995* | | | | | | |
| Own GPA in 1994 | 0.072*** | 0.07*** | 0.031** | 0.03* | 0.03* | 0.029* |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Peer GPA in 1994 | -0.075 | 0.11 | 0.043 | 0.081 | 0.06 | -0.042 |
| | (0.058) | (0.127) | (0.107) | (0.104) | (0.110) | (0.172) |
| R-squared | 0.004 | 0.024 | 0.344 | 0.345 | 0.345 | 0.35 |
| N | 6,067 | 6,067 | 6,067 | 6,067 | 6,067 | 6,067 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 18: Robustness of estimated impacts on outcomes in 1996.

| | OLS (1) | + school & grade fixed effects fixed effects (2) | + individual covariates covariates (3) | + peer covariates covariates (4) | + school-grade GPA dispersion & frac. of missing GPAs (5) | + school-specific across-grade linear trends (6) |
|---|---|---|---|---|---|---|
| *Self-discipline (standardized index) in 1996* | | | | | | |
| Own GPA in 1994 | 0.17*** | 0.182*** | 0.068*** | 0.066*** | 0.066*** | 0.066** |
| | (0.024) | (0.027) | (0.025) | (0.025) | (0.025) | (0.025) |
| Peer GPA in 1994 | -0.39*** | -0.2 | -0.264* | -0.312* | -0.408*** | -0.068 |
| | (0.087) | (0.159) | (0.144) | (0.161) | (0.143) | (0.247) |
| R-squared | 0.027 | 0.087 | 0.207 | 0.208 | 0.208 | 0.226 |
| N | 3,770 | 3,770 | 3,770 | 3,770 | 3,770 | 3,770 |
| *Dependent variable: Self-esteem (standardized index) in 1996* | | | | | | |
| Own GPA in 1994 | 0.055*** | 0.067*** | -0.012 | -0.011 | -0.011 | -0.011 |
| | (0.019) | (0.019) | (0.016) | (0.016) | (0.016) | (0.016) |
| Peer GPA in 1994 | -0.002 | -0.04 | -0.12 | -0.128 | -0.073 | 0.165 |
| | (0.084) | (0.180) | (0.154) | (0.168) | (0.177) | (0.290) |
| R-squared | 0.002 | 0.04 | 0.297 | 0.298 | 0.298 | 0.312 |
| N | 4,116 | 4,116 | 4,116 | 4,116 | 4,116 | 4,116 |
| *Dependent variable: Emotional stability (standardized index) in 1996* | | | | | | |
| Own GPA in 1994 | 0.08*** | 0.077*** | 0.048*** | 0.048*** | 0.048*** | 0.043** |
| | (0.019) | (0.019) | (0.016) | (0.016) | (0.016) | (0.017) |
| Peer GPA in 1994 | -0.082 | 0.125 | 0.057 | 0.086 | 0.038 | -0.007 |
| | (0.078) | (0.156) | (0.112) | (0.123) | (0.119) | (0.221) |
| R-squared | 0.005 | 0.026 | 0.269 | 0.27 | 0.271 | 0.281 |
| N | 4,113 | 4,113 | 4,113 | 4,113 | 4,113 | 4,113 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

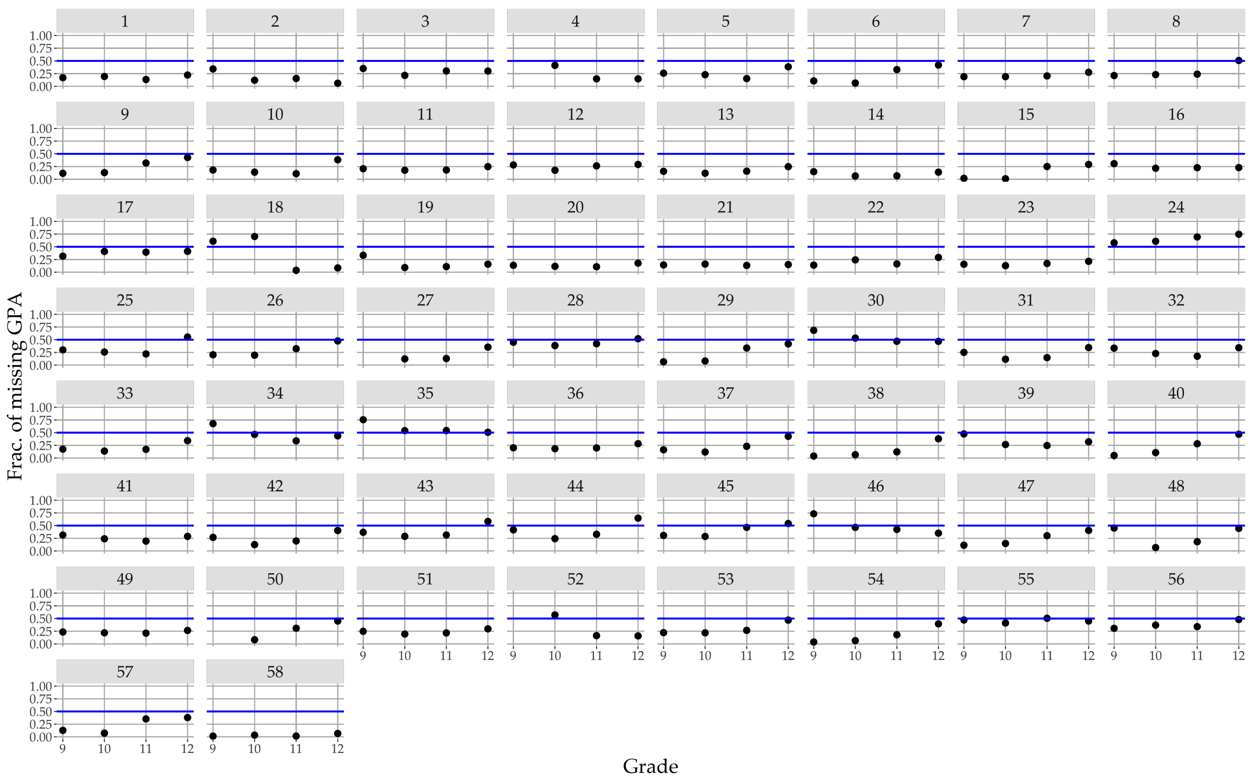



Figure 6: Fraction of missing GPAs by grade within single schools.

Table 19: Robustness of estimated impacts on outcomes in adulthood.

| | OLS<br>(1) | + school & grade fixed effects fixed effects<br>(2) | + individual covariates covariates<br>(3) | + peer covariates covariates<br>(4) | + school-grade GPA dispersion & frac. of missing GPAs<br>(5) | + school-specific across-grade linear trends<br>(6) |
|---|---|---|---|---|---|---|
| *Dependent variable: PVT in 2002* | | | | | | |
| Own GPA in 1994 | 3.465*** | 3.415*** | 2.274*** | 2.283*** | 2.282*** | 2.335*** |
| | (0.359) | (0.280) | (0.276) | (0.279) | (0.278) | (0.281) |
| Peer GPA in 1994 | 9.782** | -5.219*** | -4.13** | -5.131*** | -5.1** | -5.392 |
| | (3.903) | (1.691) | (1.597) | (1.661) | (1.954) | (3.603) |
| R-squared | 0.093 | 0.225 | 0.276 | 0.278 | 0.278 | 0.284 |
| N | 4,580 | 4,580 | 4,580 | 4,580 | 4,580 | 4,580 |
| *Dependent variable: Graduated from high school* | | | | | | |
| Own GPA in 1994 | 0.067*** | 0.071*** | 0.047*** | 0.047*** | 0.047*** | 0.049*** |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| Peer GPA in 1994 | 0.027* | 0.057 | 0.059 | 0.055 | 0.07 | 0.09 |
| | (0.015) | (0.041) | (0.040) | (0.047) | (0.056) | (0.087) |
| R-squared | 0.056 | 0.096 | 0.143 | 0.144 | 0.144 | 0.157 |
| N | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 |
| *Dependent variable: Attended college* | | | | | | |
| Own GPA in 1994 | 0.154*** | 0.155*** | 0.1*** | 0.101*** | 0.101*** | 0.103*** |
| | (0.009) | (0.01) | (0.011) | (0.011) | (0.011) | (0.011) |
| Peer GPA in 1994 | 0.038 | -0.055 | -0.039 | -0.049 | -0.053 | 0.025 |
| | (0.053) | (0.07) | (0.069) | (0.071) | (0.075) | (0.097) |
| R-squared | 0.102 | 0.158 | 0.227 | 0.229 | 0.229 | 0.24 |
| N | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 |
| *Dependent variable: Graduated from college* | | | | | | |
| Own GPA in 1994 | 0.21*** | 0.212*** | 0.15*** | 0.15*** | 0.15*** | 0.151*** |
| | (0.009) | (0.010) | (0.009) | (0.009) | (0.009) | (0.009) |
| Peer GPA in 1994 | 0.12* | -0.101 | -0.09 | -0.111* | -0.166*** | -0.097 |
| | (0.071) | (0.069) | (0.060) | (0.056) | (0.062) | (0.084) |
| R-squared | 0.169 | 0.261 | 0.316 | 0.318 | 0.318 | 0.326 |
| N | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 20: Auxiliary regression on peer GPA.

| Control variable | Coefficient | Std. error | Control variable | Coefficient | Std. error |
|---|---|---|---|---|---|
| Own GPA in 1994 | 0.0018 | (0.00193) | Hispanic | -0.00117 | (0.0043) |
| Own self-discipline index (std.) | 0.00207** | (0.00094) | At least one parent on public assistance | -0.0057 | (0.01268) |
| Own self-esteem index (std.) | -0.00121 | (0.00117) | At least one college-educated parent | 0.00046 | (0.00219) |
| Own emotional stability index (std.) | 0.00179 | (0.0012) | Parental investment (score) | -0.00092 | (0.00309) |
| Ever repeated a grade | 0.00577 | (0.00382) | Permissive parenting style (score) | 0.00313 | (0.00455) |
| Part of a sport club | 7e-05 | (0.00255) | Household size (wo/ interviewee) | 4e-04 | (0.00076) |
| Part of a foreign language club | 0.00182 | (0.0044) | Risky behaviors index (std.) | 0.00067 | (0.00143) |
| Part of an arts club | -0.00507 | (0.00303) | Regular truant in 1994 | 0.00257 | (0.0031) |
| Part of a STEM club | 0.01081* | (0.00628) | School-grade frac. of missing GPAs | 0.22189*** | (0.08072) |
| Part of a politics club | -0.00412 | (0.00293) | Within-school-grade GPA dispersion | -0.91814*** | (0.18499) |
| Working hard in 1994 | 0.0014 | (0.00267) | Frac. of female peers | 0.0393 | (0.22838) |
| Expects to earn middle-class income | -0.00058 | (0.00303) | Frac. of black peers | 0.08343 | (0.42732) |
| Expects to marry by age 25 | 0.00021 | (0.00293) | Frac. of peers w/ college-educ. parent | 0.44089* | (0.23374) |
| Expects to be killed by age 21 | 0.00054 | (0.00772) | Frac. of peers working hard | 0.62445*** | (0.1885) |
| Female | 0.00497* | (0.00252) | Peer self-discipline (std.) | 0.22771*** | (0.08331) |
| White | 0.00208 | (0.00522) | Frac. of regulary truant peers | -0.09766 | (0.20444) |
| Black | 0.00771* | (0.00455) | | | |
| School FE | ✓ | ✓ | School FE | ✓ | ✓ |
| Grade FE | ✓ | ✓ | Grade FE | ✓ | ✓ |
| N | 6,069 | | N | 6,069 | |
| R-squared | | | R-squared | 0.926 | |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

Table 21: Peer effort on outcomes in 1996 and adulthood (exclusion restriction test).

| | *Panel A: Outcomes in 1996* | | | |
|---|---|---|---|---|
| | GPA<br>(1) | Self-discipline<br>(2) | Self-esteem<br>(3) | Emotional stability<br>(4) |
| Frac. of peers working hard | 0.62<br>(0.586) | 0.46<br>(0.536) | 0.46<br>(0.536) | -0.19<br>(0.458) |
| R-squared | 0.461 | 0.203 | 0.203 | 0.27 |
| N | 3,053 | 3,764 | 3,764 | 4,107 |
| | *Panel B: Outcomes in adulthood* | | | |
| | PVT (2002)<br>(1) | Graduation from HS<br>(2) | Enrollement in college<br>(3) | Graduation from college<br>(4) |
| Frac. of peers working hard | -6.142<br>(5.831) | 0.054<br>(0.103) | -0.294*<br>(0.17) | 0.11<br>(0.205) |
| R-squared | 0.276 | 0.144 | 0.227 | 0.316 |
| N | 4,575 | 5,388 | 5,388 | 5,388 |

*Note*: Clustered (school) standard errors in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

# B Data

## B.1 Non-cognitive skill estimation

Table 22: Non-cognitive skills: Question selection and classification.

| | Add Health Question | Wave (1) | Label/Coding (2) | Reference (3) |
|---|---|---|---|---|
| *Conscientiousness* | | | | |
| 1. | How often have you had trouble paying attention? | S12 | Focus (*SD1*) | Hofstee, de Raad, and Goldberg (1992) |
| 2. | How often have you had trouble getting homework done? | S12 | Self-control (*SD2*) | Peterson and Seligman (2004) |
| 3.a. | How hard do you try to do your school work well? | S | Perseverance (*SD3*) | Peterson and Seligman (2004) |
| 3.b. | When you get what you want, it's usually because you worked hard for it. | 12 | Perseverance (*SD3*) | Levenson (1981) |
| *Self-esteem* | | | | |
| 4. | You have a lot of good qualities. | S12 | Self worth (*SE1*) | Rosenberg (1965) |
| 5. | You have a lot to be proud of. | S12 | Self pride (*SE2*) | Rosenberg (1965) |
| 6. | You like yourself just the way you are. | S12 | Self satisfaction (*SE3*) | Rosenberg (1965) |
| 7. | You feel like you are doing everything just about right. | S12 | Competence (*SE4*) | Rosenberg (1965) |
| 8. | You feel socially accepted. | S12 | Social acceptance (*SE5*) | Branden (1994) |
| 9. | You feel loved and wanted. | S12 | Feeling loved (*SE6*) | Branden (1994) |
| *Emotional stability* | | | | |
| 10. | Did you have trouble eating, or a poor appetite? | S12 | Good appetite (*ES1*) | CES-D, Lewinsohn et al. (1997) |
| 11. | Did you have trouble falling asleep or staying asleep? | S12 | Good sleep (R, *ES2*) | CES-D, Lewinsohn et al. (1997) |
| 12. | Did you feel depressed or blue? | S12 | Happiness (R, *ES3*) | CES-D, Lewinsohn et al. (1997) |
| 13. | Did you have trouble relaxing? | S12 | No anxiety (R, *ES4*) | NEO-PI-R, (Costa and McCrae, 1995) |
| 14. | Were you moody? | S12 | Stable mood (R, *ES5*) | NEO-PI-R, Costa and McCrae (1995) |
| 15. | Did you (feel like) cry(-ing) a lot? | S12 | No crying (R, *ES5*) | CES-D, Lewinsohn et al. (1997) |
| 16. | Were you fearful, or afraid of things? | S12 | No fears (R, *ES7*) | CES-D, Lewinsohn et al. (1997) |
| *Agreeableness/Gregariousness* | | | | |
| 17. | How often did you have trouble getting along with teachers? | S12 | Good rel. w/ teachers (R) | Heckman, Stixrud, and Urzua (2006) |
| 18. | How often did you have trouble getting along with other students? | S12 | Good rel. w/ peers (R) | Heckman, Stixrud, and Urzua (2006) |
| 19. | I feel like I am part of this school. | S12 | Feeling part of the school | Heckman, Stixrud, and Urzua (2006) |
| 20. | I feel close to people at this school. | S12 | Feeling close to peers | Heckman, Stixrud, and Urzua (2006) |
| *Risk proneness* | | | | |
| 21. | How often did you lie to your parents? | S12 | Lying (*RB1*) | Humphries and Kosse (2017) |
| 22. | How many times have you skipped school for a full day without an excuse? | S12 | Truancy (*RB2*) | Humphries and Kosse (2017) |
| 23. | How many times have you skipped school for a full day without an excuse? | S12 | Fight involvement (*RB3*) | Humphries and Kosse (2017) |
| 24. | How many times have you skipped school for a full day without an excuse? | S12 | Smoking (*RB4*) | Humphries and Kosse (2017) |
| 25. | How many times have you skipped school for a full day without an excuse? | S12 | Alcohol consumption (*RB5*) | Humphries and Kosse (2017) |
| 26. | How many times have you skipped school for a full day without an excuse? | S12 | Binge drinking (*RB6*) | Humphries and Kosse (2017) |

*Notes*: (R) stands for *reversed*. When reported in column (3) it indicates that a in the reference study or scale an item with opposite meaning relative to the question asked in the Add Health survey was used. If reported in column (4), instead, it indicates that the item reported in column (3) was intended to measure the opposite the trait of the one reported in column (4). Column (2) reports the labels that are going to be used in the subsequent figures and tables.

To construct measures of skills I follow the common psychometric procedure of exploratory and confirmatory factor analysis (EFA and CFA, respectively). The EFA procedure entails the following steps:

1. Select blocks of items that are observed across all first three surveys based on validated psychological scales. Table 22 is the result from this initial selection.

2. Re-define items by grade using information across waves. That is, the value of item *i* among 9th graders is obtained by combining the information reported by 9th graders at the end of school year 1994/95 (i.e., during in-home I) when they are supposed to have acquired the grade-9 level of all skills, and the information reported 10th graders at the beginning of school year 1994/95, assuming that they have acquired grade-9 level of all skills when entering grade 10, but have still to master the grade-10 level of skills.[63] Table 23 should further clarify the logic with which the by-grade versions of the various items are constructed.

Table 23: Construction of by-grade variables

| *Skill of* | Beginning of school year 94/95 (1) | End of school year 94/95 (2) | End of school year 95/96 (3) |
|---|---|---|---|
| 8th graders | Grade 7 level | Grade 8 level | Grade 9 level |
| 9th graders | Grade 8 level | Grade 9 level | Grade 10 level |
| 10th graders | Grade 9 level | Grade 10 level | Grade 11 level |
| 11th graders | Grade 10 level | Grade 11 level | Grade 12 level |
| 12th graders | Grade 11 level | Grade 12 level | – |

3. Run a principal component analysis (PCA) jointly on all blocks of items, and separately for each grade. Results are reported in in Figure 7.

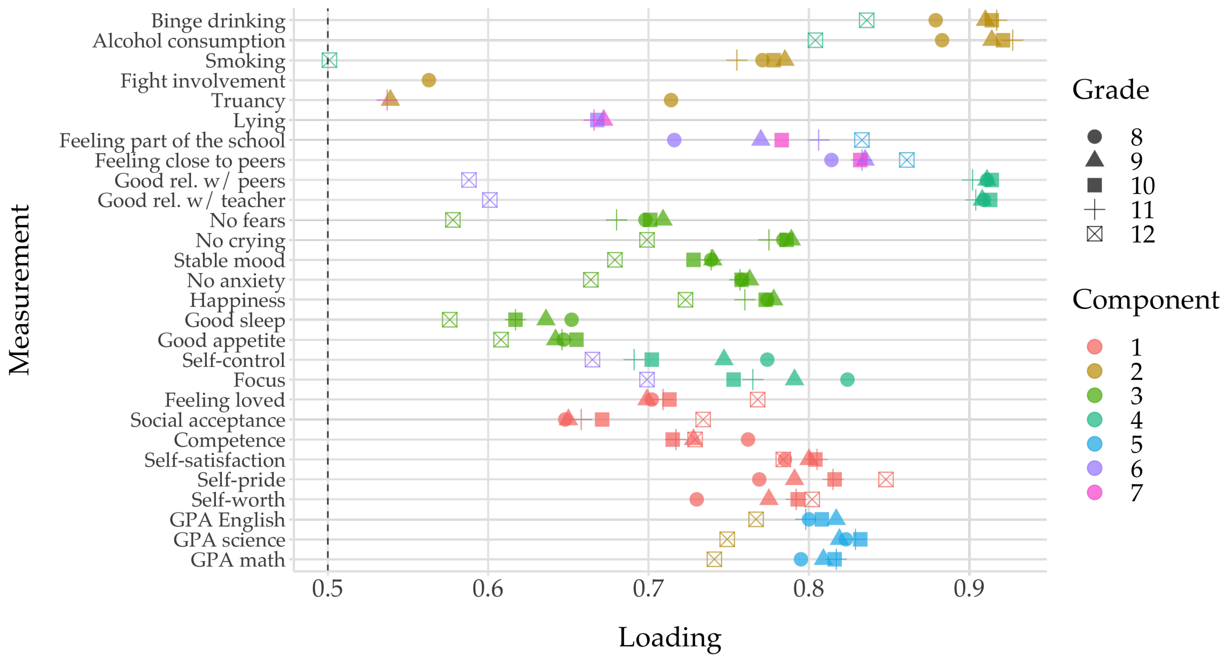



Figure 7: Rotated loadings from PCA (all grades). *Note*: only loadings that are > 0.5 in absolute value are showed.

[63] In doing so I use the whole universe of 8th through 12th grade students, and the their reported information from all three initial surveys (i.e., in-school, in-home I and II).

Table 24: Cronbach's alphas between selected items

| Latent factor | Grade 8 (1) | Grade 9 (2) | Grade 10 (3) | Grade 11 (4) | Grade 12 (5) |
|---|---|---|---|---|---|
| Self-esteem | 0.86 | 0.86 | 0.85 | 0.85 | 0.84 |
| Self-discipline | 0.82 | 0.79 | 0.77 | 0.77 | 0.61 |
| Emotional stability | 0.81 | 0.81 | 0.81 | 0.81 | 0.73 |
| Risk proneness | 0.81 | 0.80 | 0.80 | 0.78 | 0.44 |

4. Select items whose loadings are consistently above 0.5 across all by-grades decompositions. Concretely, this means that I keep all groups of items that *always* feature same shape and color in Figure 7.

5. Compute the indexes as row-wise means across the selected items.

## B.2 Parental inputs estimation

To select the questions for estimating the index of parental time investment and parents' authoritative parenting style I proceed in a similar fashion as for the estimation of non-cognitive skills. That is I first select questions that potentially measure parental investment and permissive (or authoritative) parenting style following the example by Agostinelli et al. (2020). The selected questions are summarized in Table 25.

Table 25: Parental investment and parenting style: Question selection

| Question | Wave (1) | Label (2) |
|---|---|---|
| *Permissive parenting style* | | |
| Do your parents let you make your own decisions about... | | |
| 1. ... the time you must be home on weekend nights? | W1 | Curfew |
| 2. ... the people you hang out with ? | W1 | Friends |
| 3. ... what you wear? | W1 | Clothing |
| 4. ... how much television you watch? | W1 | Amount of TV |
| 5. ... which television programs you watch? | W1 | TV programs |
| 6. ... what time you go to bed on week nights= | W1 | Bed time |
| 7. ... what you eat? | W1 | Food |
| *Parental investment* | | |
| Which of the things listed have your done with your mother in the past four weeks? | | |
| 8. Gone shopping. | W1 | Shopping |
| 9. Played a sport. | W1 | Sport |
| 10. Talked about someone you are dating or a party you went to. | W1 | Dating |
| 11. Had a talk about a personal problem you were having. | W1 | Personal problem |
| 12. Talked about your school work or grades. | W1 | School performance |
| 13. Worked on a project for school together. | W1 | School project |
| 14. Talked about other things you were doing in school. | W1 | School life |

Next, I run a PCA separately on the two blocks of variables. Results are reported in Table 26. For each of the two blocks I only choose the items whose loading is above 0.5 on the first component. That is, for parental investment I select all the items reflecting at least one parent's interest in the child's school work, whereas for permissive parenting style essentially all items expect decision of the curfew are selected to generate the final index.

The final indexes are estimated through a multi-group factor model that is fitted under the assumptions that single items are determined only by one latent factor at a time (i.e., parental investment or parenting style). The factor model builds upon the assumptions that latent factors are mean-zero and variance-one, and that they are orthogonal to each others' items, but not to each

Table 26: VARIMAX-ROTATED LOADINGS FOR SELECTED MEASUREMENTS OF PARENTAL INVESTMENT AND PARENTING STYLE

| Measurement | Component 1<br>(1) | Component 2<br>(2) | Component 3<br>(3) |
|---|---|---|---|
| *Parental investment* | | | |
| Shopping | | | 0.692 |
| Sport | | | 0.831 |
| Dating | | 0.848 | |
| Personal problem | | 0.823 | |
| School project | -0.749 | | |
| School performance | -0.859 | | |
| School life | -0.89 | | |
| | | | |
| Eigenvalues | 2.687 | 1.184 | 1.081 |
| Proportion of Variance | 0.384 | 0.169 | 0.154 |
| Cumulative Prop. Variance | 0.384 | 0.553 | 0.707 |
| *Permissive parenting style* | | | |
| Curfew | | | |
| Friends | -0.648 | | |
| Clothing | -0.738 | | |
| Amount of TV | -0.783 | | |
| TV programs | -0.758 | | |
| Bed time | -0.641 | | |
| Food | -0.664 | | |
| | | | |
| Eigenvalues | 3.243 | | |
| Proportion of Variance | 0.463 | | |
| Cumulative Prop. Variance | 0.463 | | |

*Note*: Loadings that are smaller than 0.5 are concealed.

other. In other words, factors are not assumed to be independent of each other (as it is typically done in the literature), because it is reasonable to think that skills are interdependent.[64]

The factor scores used in the main analysis are the predicted scores from the above described fitted factor model.

The goodness-of-fit measures presented in Table 27 are within the canonical ranges considered as good fits (Gorsuch, 2015; Mair, 2018). Namely, the comparative fit index (CFI) is $\geq 0.95$, the root mean squared error (RMSEA) is $\leq 0.05$, the upper CI upper bound is $\leq 0.10$, and the standardized root mean square residual (SRMR) is $\leq 0.08$.

Furthermore, when considering Table 28 one concludes that the fraction of noise in most measurements is sufficiently small to be considered random or source of substantial measurement error.[65]

[64] Cuhna and Heckman (2007) and Cuhna, Heckman, and Schennach (2010) use the alternative approach to grantee unique identification, namely they fix one of loadings to one.

[65] As a term of comparison, Cuhna, Heckman, and Schennach (2010) report measurement with 90% of noise in their Table IIB.

Table 27: Multifactor model of parental investment and parenting style

| Statistic | Value |
|---|---|
| Chi-square statistic | 484.21 |
| Degrees of freedom | 26.00 |
| p-value (Chi-square) | 0.00 |
| Comparative Fit Index (CFI) | 0.98 |
| Tucker-Lewis Index (TLI) | 0.97 |
| Root Mean Squared Error of Approximation (RMSEA) | 0.03 |
| p-value (RMSEA) | 1.00 |
| 90% CI upper (RMSEA) | 0.04 |
| Standardized Root Mean Square Residual (SRMR) | 0.05 |
| Average residual variance | 0.29 |
| N. observations | 15048.00 |
| N. parameters | 19.00 |

Table 28: Parental investment and parenting style: Signal and noise fractions

| Measurement | Signal | Noise |
|---|---|---|
| *Permissive parenting style* | | |
| Friends | 0.37 | 0.63 |
| Clothing | 0.64 | 0.36 |
| Amount of TV | 0.79 | 0.21 |
| TV programs | 0.71 | 0.29 |
| Bed time | 0.37 | 0.63 |
| Food | 0.46 | 0.54 |
| *Parental investment* | | |
| School project | 0.53 | 0.47 |
| School performance | 0.82 | 0.18 |
| School life | 0.95 | 0.05 |
| Average | 0.63 | 0.37 |

## C Calculation of adjusted p-values

This appendix describes the algorithm I use for calculating the family-wise adjusted p-values. The calculation of is based on a free step-down resampling method, as described by Anderson (2008) and Westfall and Young (1993) (pp. 62-68).[66]

Let $J$ denote the total number of outcomes, which in this specific case are 11 (i.e., four for 1995, three for 1996, and four for adulthood). For each parameter of interest $\beta_j$, let $\widehat{\beta_j^o}$ denote the estimated peer effect on outcome $j$, and $p_j^o$ be its $p$-value in the actual data.[67] For each simulation $s = 1, ..., S$ let $\widehat{\beta}_{js}$ and $p_{js}$ be the simulated estimate of $\beta_j$ and its $p$-value, respectively. Finally, let $p^k$ denote the family adjusted p-value for family $k$. The family adjusted $p$-value is derived as follows.

1. Rank the observed $p$-values in an increasing order, so that $p_1^o < p_2^o < ... < p_J^o$.
2. Simulate $S$ times the data set by randomly re-assigning students to grades within single schools.[68]
3. For each simulated data set, estimate $\widehat{\beta}_{js}$ for all outcomes $j = 1, ..., J$ and compute the simulated $p$-values, $p_{js}$.
4. Sort the simulated p-values in an increasing order and define $p_{1s} < p_{2s} < ... < p_{Js}$.
5. Define the vector of smallest simulated $p$-values as $p^* = (p_{11}, p_{12}, ..., p_{1S})$.
6. Compare each element of $p^*$ with the observed smallest $p$-value, and compute the family adjusted p-value as $p^k = \sum_{s=1}^{S} \mathbb{1}\{p_{1s} < p_1^o\}$.

In essence, the family adjusted p-value represents the probability of estimating an effect with a $p$-value that is smaller than the smallest one obtained from the actual data.

[66] Note that Kling, Liebman, and Katz (2007) follow a similar algorithm, with the only difference that they bootstrap (i.e., sample with replacement from the original sample) instead of permuting the observational units.

[67] I will refer to these two also as observed estimate and observed $p$-value.

[68] The data simulation is directly dictated by identification strategy which relies on as-good-as random variation within school.

# D Proofs of the model

## A.1 Proof of Proposition 1

***Proof of part (i).*** The equilibrium effort is given by expression (11), where $\widehat{\mathbf{M}} := \left(\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}\right)^{-1}$. Hence, the equilibrium *exists* and is *unique* if $\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}$ is invertible, and thus *nonsingular*. Concretely, we need to prove that

$$\det\left(\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}\right) \neq 0\,.$$

Since matrix $\mathbf{W}\widehat{\mathbf{G}}$ is not nonnegative—i.e., its elements can be negative due to $\mathbf{W}$—one cannot directly apply Theorem III of (Debreu and Herstein, 1953, p. 601) as done by Ballester, Calvó–Armengol, and Zenou (2006) to prove the existence of the inverse.

However, matrices of the form $\mathbf{I} - \mathbf{A}$ are always invertible as long as $\rho(\mathbf{A}) < 1$, where $\rho(\cdot)$ denotes the spectral radius (see Mayer, 2000, p. 618). This also ensures a stable equilibrium and asymptotic convergence in case of multiple transformations through the same matrix, which is very important for approximating $\widehat{\mathbf{M}}$ through the Neumann series as in equation (12).

In the specific case, this means that one needs to prove that

$$\phi\rho(\mathbf{W}\widehat{\mathbf{G}}) < 1\,, \tag{A.2}$$

for any $0 \leq \phi \leq 1$ and $r_i \in \left[-\frac{1}{2}, \frac{1}{2}\right]$, for all $i = 1, 2, ..., N$. This can be accomplished by using Gerschgorin circle theorem (Mayer, 2000, p. 498).

The theorem states that all eigenvalues of a square matrix $\mathbf{A} = [a_{ij}]$ lie within the union of the so-called Gerschgorin disks. Each disk is a circle centered around a diagonal entry, $a_{ii}$, and radius $r_i = \sum_{j=1}^{N} |a_{ij}|$, which is equal to the sum of the absolute values of the off-diagonal entries in the corresponding row $i$.

Since $\mathbf{W}$ is a diagonal matrix while $diag(\widehat{\mathbf{G}}) = \mathbf{0}$, it means that the diagonal of their matrix product must also be a zero vector. Namely,

$$\mathbf{W}\widehat{\mathbf{G}} = \begin{pmatrix} w_1 & 0 & 0 & ... & 0 \\ 0 & w_2 & 0 & ... & 0 \\ 0 & 0 & \ddots & & 0 \\ 0 & 0 & \dots & & w_N \end{pmatrix} \begin{pmatrix} 0 & \widehat{g}_{12} & \widehat{g}_{13} & \cdots & \widehat{g}_{1N} \\ \widehat{g}_{21} & 0 & \widehat{g}_{23} & \dots & \widehat{g}_{2N} \\ \vdots & & 0 & \dots & \vdots \\ \widehat{g}_{N1} & \widehat{g}_{N2} & \widehat{g}_{N3} & \dots & 0 \end{pmatrix} = \begin{pmatrix} 0 & w_1 \cdot \widehat{g}_{12} & \dots & w_1 \cdot \widehat{g}_{1N} \\ w_2 \cdot \widehat{g}_{21} & 0 & \dots & w_2 \cdot \widehat{g}_{2N} \\ \vdots & \vdots & \dots & \vdots \\ w_N \cdot \widehat{g}_{N1} & w_N \cdot \widehat{g}_{N2} & \dots & 0 \end{pmatrix}.$$

Now, from Gerschgoring theorem it follows that all Gerschgorin disks are centered around zero. This means that the Gerschgorin disk with the largest radius contains all the other disks. In other words the largest Gerschgorin disk must contain all the eigenvalues, including the spectral radius.[69] Therefore, to prove (A.2) it suffices to prove that the sum of the absolute value of the

[69]Technically, the spectral radius is nothing but the largest eigenvalue of a matrix in absolute terms, that is

$$\rho(A) = \max\left\{|\lambda_1|, |\lambda_2|, ..., |\lambda_n|\right\},$$

where $\lambda_k$, with $k = 1, 2, ..., N$ denote all the eigenvalues of the generic matrix $\mathbf{A}$.

off-diagonal elements is smaller than one for all rows of the matrix $\mathbf{W}\widehat{\mathbf{G}}$. That is,

$$\sum_{j=1}^{N} |w_i \widehat{g}_{ij}| \overset{?}{<} 1, \quad \forall\, i = 1, 2, ..., N. \tag{A.3}$$

Notice that $w_i$ is the same for the same row and that $0 \leq \widehat{g}_{ij} \leq 1$, and that $\sum_{j=1}^{N} \widehat{g}_{ij} = 1$ because $\widehat{\mathbf{G}}$ is row-normalized. This means that (A.3) can be rewritten as follows:

$$|w_i| \sum_{j=1}^{N} \widehat{g}_{ij} = |w_i|\,. \tag{A.4}$$

But since $w_i := \ln(r_i + 1)$, with $r_i \in \left[-\frac{1}{2}, \frac{1}{2}\right]$, and both $|\ln(0.5)| < 1$ and $|\ln(1.5)| < 1$, it follows that for any $r_i \in \left[-\frac{1}{2}, \frac{1}{2}\right]$ the largest Gerschgorin radius is smaller than one. Given Gerschgorin theorem this means that all eigenvalues of the matrix $\mathbf{W}\widehat{\mathbf{G}}$, including its spectral radius, $\rho\left(\mathbf{W}\widehat{\mathbf{G}}\right) < 1$.

Since $\phi$ is defined as a ratio (i.e., it never exceeds 1), with this I proved that $\left(\mathbf{I} - \phi\mathbf{W}\widehat{\mathbf{G}}\right)^{-1}$ exists and that the Nash equilibrium is unique and asymptotically converges to a fixed point under the specific parametrization of the model.

Even if the equilibrium is always unique, it is not guaranteed that it is also always interior. In fact, if one considers the best-response function in equation (9), it is easy to see that if $r_i < 0$ (i.e., if student $i$ is pessimistic about the own abilities relative to others), then if might happen that $\alpha_i + \phi \ln(r_i + 1)\bar{e}_{-i} < 0$. This would cause the optimal effort to be negative, which is not an admissible solution given that I defined effort as a positive choice variable.

Players' best-response is thus given by

$$e_i = \max\left\{0, \alpha_i + \phi \ln(r_i + 1)\bar{e}_{-i}\right\}. \tag{A.5}$$

More in general, the equilibrium is not interior when at least one student is pessimistic about their abilities (i.e., $r_i < 0$ for at least one student) and $r_i < \exp\left(-\frac{\alpha_i}{\phi\bar{e}_{-i}}\right) - 1$.

□

***Proof part (ii).*** To prove that the *equilibrium performance* is given by (13) one needs to use equation (9) and express $\bar{e}_{-i}$ in terms of the individual equilibrium effort as follows:

$$\bar{e}_{-i} = \frac{1}{\phi \ln(r_i + 1)} \left(e_i^* - \alpha_i\right). \tag{A.6}$$

By replacing $\bar{e}_{-i}$ in (3) with (A.6) it can be found that:

$$y_i^* = \frac{1}{2} e_i^*. \tag{A.7}$$

Finally, using (11) one can re-write the optimal performance as follows

$$\begin{aligned} y_i^* &= \frac{1}{2}\sum_{j=1}^{N} m_{ij}\alpha_j \\ &= \frac{1}{2}\widehat{m}_{ii}\alpha_i + \frac{1}{2}\sum_{j\neq i}^{N} \widehat{m}_{ij}\alpha_j \end{aligned}$$

where $\widehat{m}_{ij}$ iw the $ij$-th element of matrix $\widehat{\mathbf{M}}$. □

***Proof part (iii).*** To proof that the *equilibrium utility* is given by (**??**) we need to substitute $y_i$ with the equilibrium performance using equation (13). In a context with *full information* where all students know both own and others' productivity and self-efficacy levels, as well as the network structure, i.e., $\{\boldsymbol{\alpha}, \mathbf{W}, \widehat{\mathbf{G}}\} \subseteq \mathcal{I}_i$, this means that

$$\begin{aligned} E\left[y_i^* \middle| \mathcal{I}_i\right] &= \frac{1}{2}E\left[\sum_{j=1} \widehat{m}_{ij}\alpha_j \middle| \mathcal{I}_i\right] \\ &= \frac{1}{2}\sum_{j=1} \widehat{m}_{ij}\alpha_j \\ &= \frac{1}{2}\widehat{m}_{ii}\alpha_i + \frac{1}{2}\sum_{j\neq i}^{N} \widehat{m}_{ij}\alpha_j . \end{aligned}$$

□

### A.2 Proofs on marginal effects of productivity (14)

***Proof of equation (14).*** To compute the effect of anybodies' productivity on own equilibrium effort, it is useful to start from the individual formulation of optimal effort, that is,

$$e_i^* = \sum_{j=1}^{N} \widehat{m}_{ij}\alpha_j \ ,$$

which is obtained by multiplying the $i$th row of $\widehat{\mathbf{M}}$ with the productivity vector, $\boldsymbol{\alpha}$.

The first-order derivative with respect to all $\alpha_j$'s (i.e., with respect to the vector $\boldsymbol{\alpha}$) of the above expression gives,

$$\frac{\partial e_i^*}{\partial \boldsymbol{\alpha}} = \left(\widehat{m}_{i1}, \widehat{m}_{i2}, \ldots, \widehat{m}_{ii}, \ldots, \widehat{m}_{iN}\right) \ ,$$

which corresponds to the $i$-th row of matrix $\widehat{\mathbf{M}}$. This also means that the matrix of all first-order derivatives of equilibrium effort with respect to all productivities is

$$\frac{\partial \mathbf{e}^*}{\partial \boldsymbol{\alpha}} = \begin{pmatrix} \frac{\partial e_1^*}{\partial \alpha_1} & \dots & \frac{\partial e_1^*}{\partial \alpha_i} & \dots & \frac{\partial e_1^*}{\partial \alpha_N} \\ & \ddots & & & \\ \frac{\partial e_i^*}{\partial \alpha_1} & \dots & \frac{\partial e_i^*}{\partial \alpha_i} & \dots & \frac{\partial e_i^*}{\partial \alpha_N} \\ \vdots & & & \cdots & \\ \frac{\partial e_N^*}{\partial \alpha_1} & \dots & \frac{\partial e_N^*}{\partial \alpha_i} & \dots & \frac{\partial e_N^*}{\partial \alpha_N} \end{pmatrix} = \begin{pmatrix} \widehat{m}_{11} & \dots & \widehat{m}_{1i} & \dots & \widehat{m}_{1N} \\ & \ddots & & & \\ \widehat{m}_{i1} & \dots & \widehat{m}_{ii} & \dots & \widehat{m}_{iN} \\ \vdots & & & \cdots & \\ \widehat{m}_{N1} & \dots & \widehat{m}_{Ni} & \dots & \widehat{m}_{NN} \end{pmatrix} = \widehat{\mathbf{M}}.$$

This means that $\widehat{\mathbf{M}}$ is to be seen as a sort of Jacobian matrix of first-order derivatives with respect to productivities of all individuals in network $\mathbf{g}$.

To see why $|\widehat{m}_{ij}| < 1$, for all $i, j = 1, ..., N$ it is useful to decompose $\widehat{\mathbf{M}}$ in its single components using the Neumann series expansion (12) as follows:

$$\phi^0 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^0 = 1 \cdot \begin{pmatrix} 1 & 0 & 0 \dots & 0 \\ \vdots & 1 & \dots & \vdots \\ 0 & \dots & \ddots & 0 \\ \vdots & & & 1 \end{pmatrix}$$

$$\phi\left(\mathbf{W}\widehat{\mathbf{G}}\right) = \phi \cdot \begin{pmatrix} 0 & w_1 \widehat{g}_{12} & \dots & w_1 \widehat{g}_{1N} \\ w_2 \widehat{g}_{21} & 0 & \dots & w_2 \widehat{g}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_N \widehat{g}_{N1} & w_N \widehat{g}_{N2} & \dots & 0 \end{pmatrix}$$

$$\phi^2 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^2 = \phi^2 \begin{pmatrix} w_1 \sum_{k\neq 1} w_k \widehat{g}_{1k}^2 & \dots & & w_1 \sum_{k\neq\{1,N\}} w_k \widehat{g}_{1k}\widehat{g}_{kN} \\ w_2 \sum_{k\neq\{1,2\}} w_k \widehat{g}_{2k}\widehat{g}_{k1} & w_2 \sum_{k\neq 2} w_k \widehat{g}_{2k}^2 & & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ w_N \sum_{k\neq\{1,N\}} w_k \widehat{g}_{Nk}\widehat{g}_{k1} & \dots & & w_N \sum_{k\neq N} w_k \widehat{g}_{Nk}^2 \end{pmatrix}$$

$$\phi^3 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^3 = \phi^3 \begin{pmatrix} w_1 \sum_{\ell\neq 1} \sum_{k\neq\{1,\ell\}} w_k w_\ell \widehat{g}_{1\ell}\widehat{g}_{\ell k}\widehat{g}_{k1} & \dots & & w_1 \sum_{\ell\neq N} \sum_{k\neq\{1,\ell\}} w_k w_\ell \widehat{g}_{Nk}\widehat{g}_{k\ell}\widehat{g}_{\ell 1} \\ w_2 \sum_{\ell\neq 1} \sum_{k\neq\{2,\ell\}} w_k w_\ell \widehat{g}_{1k}\widehat{g}_{k\ell}\widehat{g}_{\ell 2} & w_2 \sum_{\ell\neq 2} \sum_{k\neq\{2,\ell\}} w_k w_\ell \widehat{g}_{2\ell}\widehat{g}_{\ell k}\widehat{g}_{k2} & & w_2 \sum_{\ell\neq N} \sum_{k\neq\{2,\ell\}} w_k w_\ell \widehat{g}_{Nk}\widehat{g}_{k\ell}\widehat{g}_{\ell 2} \\ \vdots & \vdots & \ddots & \vdots \\ w_N \sum_{\ell\neq 1} \sum_{k\neq\{N,\ell\}} w_k w_\ell \widehat{g}_{1k}\widehat{g}_{k\ell}\widehat{g}_{\ell N} & \dots & & w_N \sum_{\ell\neq N} \sum_{k\neq\{N,\ell\}} w_k w_\ell \widehat{g}_{N\ell}\widehat{g}_{\ell k}\widehat{g}_{kN} \end{pmatrix}$$

Since

$$\widehat{\mathbf{M}} = \phi^0 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^0 + \phi^1 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^1 + \phi^2 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^2 + \phi^3 \left(\mathbf{W}\widehat{\mathbf{G}}\right)^3 + \dots \tag{A.8}$$

this means that $\widehat{m}_{ij}$ corresponds to the sum of $ij$-th elements from the above matrices. That is,

$$\widehat{m}_{ij} = \begin{cases} 1 + w_i \left(\phi^2 \sum_{k\neq i} w_k \widehat{g}_{ik}^2 + \phi^3 \sum_{k\neq i} \sum_{\ell\neq\{i,k\}} w_k w_\ell \widehat{g}_{ik}\widehat{g}_{k\ell}\widehat{g}_{\ell i} + \dots\right), & \text{if } j = i \\ w_i \left(\phi \widehat{g}_{ij} + \phi^2 \sum_{k\neq\{i,j\}} w_k \widehat{g}_{ik}\widehat{g}_{kj} + \phi^3 \sum_{k\neq\{i,j\}} \sum_{\ell\neq\{i,j,k\}} w_k w_\ell \widehat{g}_{jk}\widehat{g}_{k\ell}\widehat{g}_{\ell i} + \dots\right), & \text{if } j \neq i\,. \end{cases}$$

Since $0 \leq \phi, \widehat{g}_{ij} \leq 1$, and $|w_i| < 1$, for all $i = 1, ..., N$, for all $i, j = 1, ..., N$, it means that when $i \neq j$, the productivity effect of other students on own equilibrium effort must be smaller than 1 in absolute terms. Note that this is a direct consequence of the spectral radius of $\mathbf{W}\widehat{\mathbf{G}}$ being strictly smaller than 1 in absolute terms. $\square$

***Marginal effect of peer productivity.*** Starting from (13) and deriving with respect to $\alpha_j$, on finds that

$$\frac{\partial y_i^*}{\partial \alpha_j} = \frac{1}{2}\widehat{m}_{ij},$$

where $\widehat{m}_{ij}$ is defined as in (14) for the case when $j \neq i$.

As explained in the text, the determinants influencing the direction of the marginal effect of productivity can be inferred from the second expression of equation (14) when $j \neq i$, where

$$\frac{\partial e_i^*}{\partial \alpha_j} = \begin{cases} \phi w_i \widehat{g}_{ij} & , \text{ if } i \text{ and } j \text{ are direct friends} \\ \phi^2 w_i \sum_{k \neq \{i,j\}} w_k \widehat{g}_{ik} \widehat{g}_{kj} & , \text{ if } i \text{ and } j \text{ are one node apart} \\ \phi^3 w_i \sum_{\ell \neq j} \sum_{k \neq \{i,\ell\}} w_k w_\ell \widehat{g}_{jk} \widehat{g}_{k\ell} \widehat{g}_{\ell N} & , \text{ if } i \text{ and } j \text{ are two nodes apart} \\ ... & , \text{ if } i \text{ and } j \text{ are } h \text{ nodes apart} \end{cases}$$

As it can be seen above, a derivatives depend from $w_i$, which represents individual beliefs about one's own abilities. Furthermore, the second and the third expressions—i.e., the cases of indirect friendships—also depend on the intermediary nodes' beliefs, denoted as $w_k$ and $w_\ell$. $\square$

***Marginal effect of own productivity.*** That the return to own productivity is always positive it can be seen from the first expression of (14). Since the spectral radius of $\widehat{\mathbf{WG}}$ being strictly smaller than one, one can confidently conclude that the sum of the various products between $w_i$'s and $\widehat{g}_{ij}$'s is smaller than one absolute value. Consequently, the sum of 1 plus something the is smaller than 1 in absolute value must be strictly positive. $\square$