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Self-, Peer-, and Teacher Perceptions under School Tracking

Ofer Malamud*

Andreea Mitrut+

Cristian Pop-Eleches±

Miguel Urquiola±

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Abstract

We examine student, teacher, and peer perceptions of effort, ability, performance, and self-confidence in Romania's highly tracked schools. We find that: (1) students just above a cutoff—tracked into high-achieving classes—have less favorable self-perceptions than those just below ("big-fish-little-pond" effects); (2) students perceive peers in their classes more favorably ("in-group bias"); (3) this bias is stronger in lower-achieving classes; (4) students perceive themselves more positively than others perceive them ("illusory superiority"); (5) this bias is stronger among lower-achieving students ("Krueger-Dunning effects"). In short, being tracked into lower-achieving classes does not appear to negatively affect self-perceptions.

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1. Introduction

School tracking, a policy that separates students by academic achievement, is widely debated. Economists have focused on estimating the causal effect of tracking on cognitive skills as measured by academic achievement (e.g., Figlio and Page 2002; Hanushek and Woessmann 2006; Duflo, Dupas, and Kremer 2011; Cohodes 2020; Antonovics et al. 2022). Such studies often highlight a potential tradeoff: tracking may allow for more targeted teaching, but it can also deny lower-achieving students the positive peer effects that emerge from interactions with higher-achieving students (Betts 2011).[1]

There is much less evidence on the causal impact of tracking on non-cognitive skills.[2] Moreover, work outside economics raises the concern that tracking may stigmatize students in lower tracks, hurting their self-perceptions and, thus, their later outcomes (e.g., Oakes 1985, Gamoran 1992).

This paper examines how assignment to a lower vs. higher track affects non-cognitive skills as captured by perceptions of self-confidence, academic effort, disruptive behavior, and self-esteem (Rosenberg 1965; Heckman, Stixrud, Urzua 2006). We consider this question within a causal framework—we ask whether

[1] The concern for inequality also arises in long-standing work in the social sciences (e.g., Slavin 1987, 1990; Hallinan 1994).

[2] The few studies in economics show mixed results for marginal students assigned to a higher track: they are more motivated to study but have worse relations with their peers (Belfield and Rasul 2020) and are more competitive but have lower academic self-concept (Korthals, Schils, and Borghans 2022).

Review of Economics and Statistics Just Accepted MS.
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the assignment to different tracks causally impacts how students perceive themselves relative to their peers and how their peers and teachers perceive them.

We explore this in the context of Romania's high school system, in which students apply to high schools and specializations. Specializations are self-contained programs within high schools, each with a specific curricular focus (e.g., humanities, mathematics). Students are allocated to specializations solely based on a standardized admission score. The result is a clear hierarchy of specializations by selectivity.

Many high schools use the same admission score to track students within a specialization into classes of 28 students each. For example, a school may divide a mathematics specialization into two classes. The "top" class contains the students with the highest 28 admission scores; the "bottom" class contains those with the 28 lowest. Classes always receive instruction separately in all subjects, although they cover the same curriculum, often delivered by the same teachers. These features enable us to isolate the role of student allocations from differences in curriculum and teacher quality.[3]

We selected 87 schools that tracked students in this fashion. At these schools, we implemented an individualized survey asking students about their perceived relative standing within specializations across both top and bottom classes. In each class, we surveyed five students from the top, middle, and bottom of the class based on their admission scores. We gave each of these students a list of ten of their peers' names: the five students surveyed from their own class (including the respondent) and the five surveyed from the

[3] This contrasts with studies examining gifted and talented programs in the U.S. (Card and Giuliano 2016, Cohodes 2020).

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

other class in their specialization. We asked surveyed students to rank themselves relative to this group along several domains, including academic self-confidence, ability, and effort. We administered an analogous survey to teachers who taught the same subject to the top and bottom classes.

In short, for each student X, we observe how X ranks herself relative to nine peers in her own and the adjacent class, how X is ranked by these peers, and how X is ranked (relative to the same nine peers) by a teacher who teaches the same subject to both classes.

This unique setup enables us to implement two empirical approaches. First, we use a regression discontinuity (RD) design to compare students who just missed or just got into the top class within a specialization. Second, we implement fixed effects (FE) specifications that compare how perceptions differ according to who reports them (oneself, one's peer, or one's teacher) and how student perceptions differ across classes. This strategy also allows us to explore heterogeneity over the admission score distribution. These approaches yield five findings.

First, the RD design reveals that being allocated to the top vs. the bottom class lowers a student's perception of how she ranks relative to her peers in the same specialization. This holds along academic domains like self-confidence, effort, and predicted performance. Being allocated to the top class also lowers self-esteem as measured by the Rosenberg index, an absolute rather than relative measure. These negative impacts on self-perception are consistent with *big-fish-little-pond* effects (Marsh and Parker 1984). Further, these negative impacts are in stark contrast to teachers' perceptions—teachers have similar assessments of students on either side of the cutoff.

Review of Economics and Statistics Just Accepted MS.
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Second, along almost all dimensions, students rank their own classmates significantly higher than their peers from other classes. This aligns with work on *in-group biases*, which emerge when individuals perceive members from their own group differently from others and tend to assume that in-group members share positive values and characteristics (Tajfel 1974; Tajfel and Turner 1979).

Third, the magnitude of the in-group bias is significantly stronger in the bottom classes than in the top classes. In other words, students in the bottom classes believe that their classmates perform relatively better compared to those in the top class than vice versa. This is consistent with evidence that in-group favoritism can be larger among low-status groups (Branthwaite, Doyle, and Lightbown 1979), although other studies find the opposite (Sachdev and Bourhis 1987).

Fourth, students rank themselves higher than the corresponding rankings coming from their peers and their teachers. This finding aligns with *illusory superiority*, a cognitive bias also known as superiority bias, that arises when individuals overestimate their abilities (Taylor and Brown 1988).

Fifth, the gap between a student's self-assessment and that provided by her peers and teachers is larger among students with lower admissions scores. This finding is consistent with the *Krueger-Dunning bias*, where low performers are typically more overconfident, while high performers assess their skills more accurately (Krueger and Dunning 1999).

To summarize, we observe five empirical patterns in Romania's high school system, in which the allocation to tracked classrooms is salient, but other school inputs are similar. These patterns mitigate the adverse effects that being assigned to a lower-achieving class has on self-perceptions. A natural question

Review of Economics and Statistics Just Accepted MS.
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is whether these empirical patterns affect students' educational outcomes. In the final part of our analysis, we describe some suggestive evidence of small but positive effects of attending a top class on a high-stakes exam taken at the end of high school.[4]

Overall, our results suggest that, while being tracked into a lower-achieving class does not produce stigma and negative self-perceptions, being tracked into a higher-achieving class may produce academic benefits. Whether self-perceived relative ranking under tracking has long-term consequences on later outcomes is an important topic for further study.

Our study contributes to the literature on the effect of school tracking, both inside and outside economics. Several studies also consider the role of school tracking on student self-perceptions and academic self-concept—defined as students' perceptions of their academic abilities (e.g., Trautwein et al. 2009, Chmielewski et al. 2013, Belfi et al. 2012). However, many of these studies have small samples or lack a compelling research design for causal identification. An exception is Korthals, Schils, and Borghans (2022), who show evidence that students placed in high tracks are less emotionally stable and have lower academic self-concept. In addition, studies in psychology and sociology explore the "big-fish-little-pond effect" in the context of school tracking (e.g., Liu, Wang, and Parkins 2005, Marsh and Scalas 2011). A related literature in economics examines whether a student's rank affects student perceptions and subsequent academic outcomes (Murphy and Weinhardt 2020, Carneiro et al. 2022).

[4] The evidence of the benefit of attending a top class within a specialization complements results in Pop-Eleches and Urquiola (2013). That paper finds clear evidence of the benefits of attending a better school or specialization.

Review of Economics and Statistics Just Accepted MS.
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Our study has several distinct features relative to existing research on tracking and student perceptions. First, we consider impacts on a broad set of self-perceptions, including academic self-concept of ability, effort, and performance, as well as self-confidence and disruptiveness. Second, we compare self-perceptions with the corresponding perceptions of peers and teachers. Third, we focus on relative measures that explicitly compare students within and across classrooms, but we also consider and validate our results with absolute measures of self-esteem and performance. Finally, we adopt empirical strategies designed to estimate causal impacts, such as regression discontinuity.

2. Institutional Background

As they prepare to transition into high school (grades 9-12), Romanian students receive a transition grade, which is a weighted average of their score on a national 8th-grade exam and their middle school (grades 5-8) grade point average. Students then submit a list of ranked schools and specializations they wish to attend. Specializations are self-contained units within high schools that vary in their curricular focus (e.g., Mathematics, Natural Sciences, Technical Studies, Social Studies, Literature). The students are allocated to specializations based on their transition score, using a computerized serial dictatorship algorithm.

Before the allocation process begins, the Ministry of Education announces the number of slots available in each high school's specializations. This number is a multiple of 28, the maximum class size allowed. In other words, each school can offer multiple classes of 28 students in each specialization.

Review of Economics and Statistics Just Accepted MS.
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All classes in a school/specialization follow the same curriculum and, for some subjects, share the same teachers. Despite this, the classes are self-contained. Although students in different classes may interact during breaks and share extracurricular activities (e.g., academic competitions and educational clubs), they do not receive instruction together. These classes remain unchanged during all four years of high school.[5]

Moreover, within specializations, some schools track students into classes based on the ordinal ranking of their transition score: the students with the top 28 scores are allocated to a top class.[6] Our study focuses on these types of schools. Thus, in a specialization with two tracked classes, two students with very similar scores (e.g., those ranked 28 and 29) end up in different classes: the top and the bottom class.

This allocation mechanism is salient to students, parents, and teachers. For example, at the beginning of the academic year, the names of the students assigned to each class—along with the ordinal rank of their

[5] Students can move across classes, schools, and specializations, but their ability to do so varies significantly across grades; it is harder to transfer during earlier grades. In particular, under the existing regulations, students in grade 9 are only allowed to change specializations/schools for medical reasons and if their admission score exceeds that of the lowest-scoring student in a given specialization/school. Our key results hold when restricting the sample to 9th-grade students.

[6] The tracked schools are not a random sample. For example, relative to other schools in Romania, they have slightly higher average transition scores and have more students enrolled in the more “competitive” specializations like mathematics and IT (about 25% vs. 18% in the other schools) or natural science (22% vs. 14%). The tracked schools account for roughly 14% of all high school students admitted in 2014-2017.

Review of Economics and Statistics Just Accepted MS.
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admission scores—are listed openly in schools and school websites. Further, in the Romanian context, students are likely to form perceptions of their peers in other classes through social interactions, teacher comments, extra-curricular activities, academic clubs, public awards to top students, and public sanctions (e.g., having to retake exams).

Upon completing high school, students take a high-stakes nationwide standardized *Baccalaureate* exam, which determines university admission and influences labor market outcomes. This national exam is identical for all students within the same specialization.

3. Data

We use three sources of data. First, we have administrative data from the Ministry of Education on four cohorts of students. These data contain students' transition scores and their school-grade specializations. We merge these data with school-level information on the allocation of students to classes. Thus, we observe each student's name and transition score in each top and bottom class in each school grade and specialization. We also have the names of all the teachers at these schools, along with a listing of the subjects they taught to each class. For three of the four cohorts, we can match these data to information on Baccalaureate exams taken at the end of high school.[7]

[7] The Baccalaureate consists of standardized tests in different subjects. These are graded on a scale of 1 to 10, and students need to obtain a minimum score of 5 on each test (and a minimum overall average of 6).

Review of Economics and Statistics Just Accepted MS.
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The second data source is a unique Spring 2017 survey that we administered to students in grades 9-12 at 87 schools in 74 towns. We selected these schools because they track students into at least two classes based on admission scores.[8] Due to time and budget constraints, we could only survey some of the students in these schools. We chose to survey five students in each class according to their transition score—specifically, students with the highest, lowest, and median scores and two additional students closest to the cutoff (i.e., the next two highest-scoring students in the bottom class or the next two lowest-scoring students in the top class). Out of a target sample of 4,350 students, we received 2,865 responses for a response rate of 66 percent.

The survey elicited students' perceptions of themselves and their peers. We gave students a list of 10 student names, ordered alphabetically: 5 from their own class (including the respondent) and 5 from the other class. We asked them to rank themselves and their peers along four *academic* domains:

- *Self-confidence* (e.g., expresses opinions in class, takes risks, asks/answers questions),
- *Effort* (e.g., does homework, pays attention in class),
- *Ability* (e.g., understands hard concepts easily, has high native/innate ability), and
- *Expected performance* (e.g., will score well on the Baccalaureate exam).

[8] We targeted 95 schools for the survey but received positive responses from only 87 of them. After obtaining parental and teacher consent, enumerators conducted the surveys during meetings held in school. Approximately 80% of the school-grade specializations in our sample have two (top and bottom) classes; the rest have three or more.

Review of Economics and Statistics Just Accepted MS.
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For each domain, we assign the highest-ranked student a 10 and the lowest-ranked student a 1 (e.g., higher values should be interpreted as higher ability, self-confidence, academic performance, etc.).[9] Students also ranked themselves and their peers on *disruptiveness* (e.g., harasses/disparages peers); in this case, higher values indicate more disruptive peers. Appendix Table A1 shows the correlation between the different student perceptions. Academic effort, ability, and performance are highly correlated with one another; self-confidence and disruptive behavior are less correlated with each other or with the other domains. To provide a further sense of these measures, Appendix Table A2 shows the differences in self-reported perceptions by gender. It shows that boys are more self-confident and report more disruptive behavior than girls, while girls report higher academic effort and performance than boys; there are no significant differences in self-reported ability.

Students also completed questionnaires covering:

- family background information (e.g., gender, number of siblings, ethnicity, parental education),
- a peer victimization index (taking higher values if students agreed that their peers are more likely to hit them, take their belongings, or exclude them), and
- a standard 10-item scale measuring the Rosenberg self-esteem index (i.e., higher values indicating a more positive attitude towards oneself).

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[9] Approximately 90% of students who responded to our survey provided rankings. Among these, almost all ranked at least 5 students, and about 45% provided complete rankings for all 10 students, depending on the domain. Our results remain unchanged when we restrict the sample to students with complete rankings. Note that in cases where not all students are ranked, we normalize the rankings so that they are equally spaced from 1 to 10.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

Appendix Table A3 describes these data.

The third source of data is a survey of teachers. We surveyed all teachers who taught the *same* subject to both the top and bottom classes, asking them to rank the same 10 students across the same domains.[10] The subjects these teachers cover include some that are tested on the Baccalaureate exam (e.g., math, biology, Romanian) and some that are not (e.g., music, religion). Teachers also completed a questionnaire about their family background and career (e.g., years of experience, tenured position). Out of a target sample of 3,131 teachers, who taught students in both top and bottom classes, we received responses from 1,843 teachers for a response rate of 59 percent. Appendix Table A4 describes these data.

Thus, our final sample comprises 2,865 students and 1,843 teachers across 435 discontinuities in 87 schools.

4. Empirical Strategy

We use two strategies to explore how student, peer, and teacher perceptions vary under school tracking. First, we use a regression discontinuity (RD) design to estimate the effect of being assigned to the top relative to the bottom class on student, peer, and teacher perceptions. Second, we use student fixed effects

[10] Approximately 85% of teachers who responded to our survey provided some rankings. Among these, a further 85% provided complete rankings of all 10 students. We also normalize the teacher rankings in cases where not all students are ranked.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

(FE) when directly comparing student perceptions to teacher perceptions, and when directly comparing peer perceptions of one's own classmates to those of students in other classes. To set out terms, let:

- i index students who responded to our survey,
- j index teachers who responded to our survey, and
- k index students whose names appear on our survey (including some non-respondents).

4.1 Regression discontinuity

Our RD analysis is based on the following basic regression model:

$$Y_{id} = \alpha_0 + \alpha_1 Above_{id} + f(score_{id}) + \eta_d + \varepsilon_{id} \qquad \text{(1a)}$$

where Y_{id} is the outcome of interest as self-reported by student i in discontinuity d, $Above_{id}$ is an indicator for students whose transition score is above the cutoff used to assign students to the top class, $f(score_{id})$ is a flexible function of the admission score, which serves as our running variable, and η_d are discontinuity fixed-effects, i.e., fixed effects for each pair of top and bottom classrooms. We allow for robust standard errors and cluster at the level of the student being reported on.[11]

[11] In school-grade specializations with more than two classes, we have multiple discontinuities, such that some students appear more than once in the analysis. We stack these discontinuities and cluster by student to account for multiple observations. Our results are robust to keeping school-grade specializations with only two classes.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

For simplicity, our preferred specifications control for linear splines of the admission score with a rectangular kernel and do not include any covariates except for a constant, α_0, although our results are robust to various alternative specifications and the inclusion of control variables, as discussed below. The coefficient α_1 represents the "reduced-form" or "intent-to-treat" effect of being assigned to the top class within a given school's specialization.

Since children just above and below the transition score cutoff should have very similar background characteristics, we expect our RD design (if correctly specified) to yield causal estimates of how being assigned to a top class affects perceptions. Appendix Table A5 tests this assumption, showing estimates from a regression discontinuity of demographic characteristics on the cutoff for being assigned to a top class, i.e., using a specification analogous to equation (1). The absence of significant coefficients confirms that these characteristics are smooth around the cutoff. Thus, comparisons of perceptions just above and below the cutoff are unlikely to be confounded by other factors.

Another common specification check is verifying that the observations' density is continuous around the cutoff (McCrary 2008). Figure 1 shows the density of student observations stacked around the cutoff for being assigned to a top class for the target sample (Panel A) and for the sample of respondents (Panel B). There is a higher density near either side of the cutoff because we sampled more students close to the cutoff, but no visible discontinuity around the cutoff. This suggests that students and schools did not manipulate the admission score.

Panel C of Figure 1 also tests for non-response rates around the cutoff and suggests no differential responses for any outcomes. This graphical pattern is confirmed by Column (1) of Appendix Table A6,

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

where we regress an indicator for whether students responded to the survey on the cutoff for being assigned to a top class, as in specification (1); the coefficient on "Above" is small and not significantly different from zero. There are also no significant effects in student responses to any specific question asking students to rank their peers.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

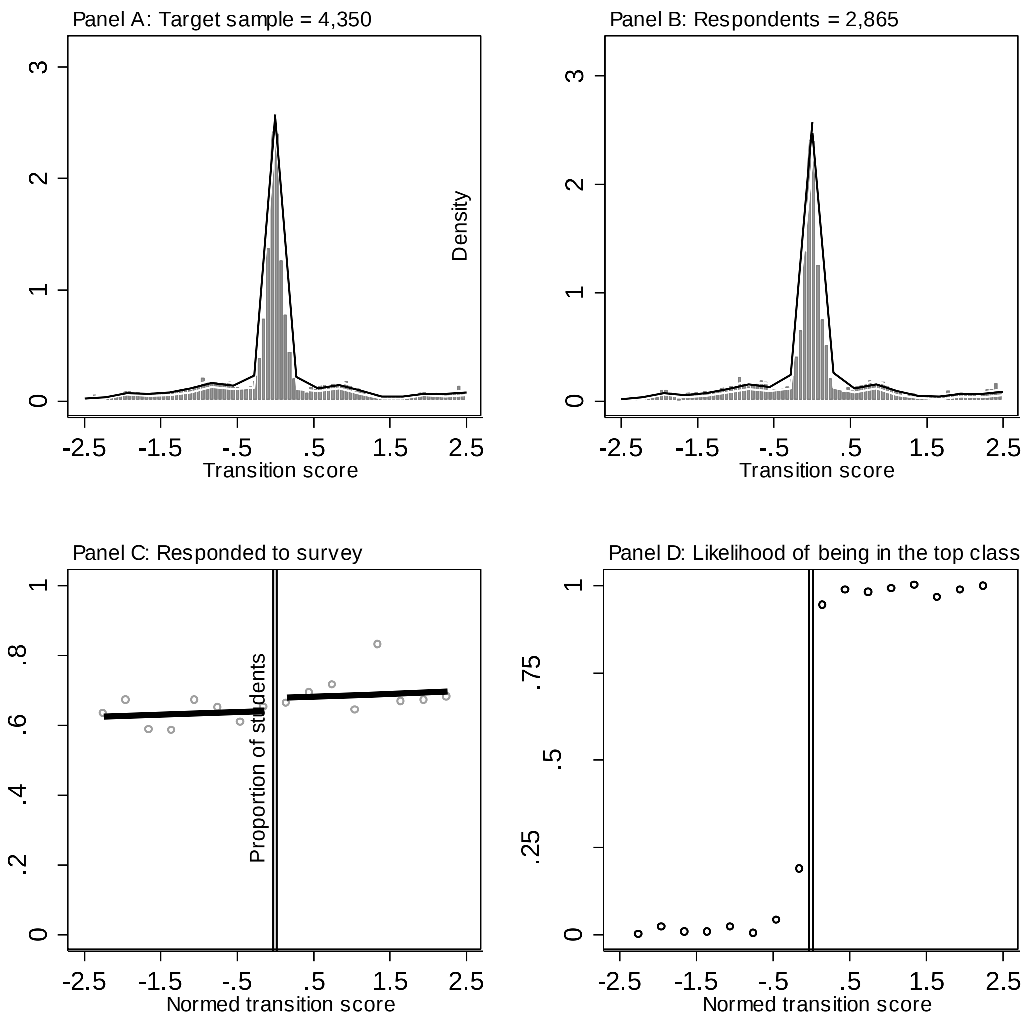

Figure 1: Density checks, response rates, and compliance

Notes: Test of differences in discontinuity, p-value = 0.661 in Panel A, and p-value = 0.415 in Panel B.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

Panel D of Figure 1 verifies that students comply with their assignment to top and bottom classes. It displays the likelihood of enrolling in a top class as a function of the transition score. We observe strong, albeit imperfect, compliance. A small fraction of students below the cutoff ends up in the top class, and vice versa. Using specification (1), we estimate that the probability of enrolling in a top class increases by 77 percentage points at the discontinuity—a highly significant effect (shown in column (1) of Table 1 below). Thus, for simplicity, we will focus on the intent-to-treat effect of being assigned to a top class, ignoring the deviations from perfect compliance around the cutoff.

We also conduct an RD analysis to compare the effect of students being assigned to a top vs. bottom class based on reports by teachers:

$$Y_{ijd} = \beta_0 + \beta_1 Above_{id} + f(score_{id}) + \eta_d + \varepsilon_{ijd} \tag{1b}$$

where Y_{ijd} is our outcome of interest for student *i* as reported by teacher *j* in discontinuity *d*. Note that we usually have multiple teachers per student, so (1b) will include more observations than the preceding regression model (1a). We cluster observations at the level of the student who is being reported on.

We also conduct an RD analysis to compare the effect of students being assigned to a top vs. bottom class based on reports by peers:

$$Y_{ikd} = \gamma_0 + \gamma_1 Above_{id} + f(score_{id}) + \eta_d + \varepsilon_{ikd} \tag{2}$$

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

where Y_{ikd} (with $i \neq k$) is our outcome of interest for student i as reported by peer k in discontinuity d. We implement this analysis separately for reporting students from the top and bottom classes. Since we have multiple peers reporting on the same students, we have more observations than in the self-reports equation (1a). Again, we cluster observations at the level of the student being reported on.

4.2 Student-fixed effects

We also estimate regression models that directly compare self-reports to teacher reports, where we include student fixed effects as follows:

$$Y_{ij} = \mu_0 + \mu_1 SelfReports_{ij} + \sigma_i + \varepsilon_{ij} \quad (3)$$

where Y_{ij} is our outcome of interest for student i, who is taught by teacher j, $SelfReports_{ij}$ is an indicator for student perceptions of their academic attributes as opposed to teacher perceptions of these same attributes, and σ_i are student fixed effects. Specifically, we stack self-reports by students and reports by teachers about these same students. Therefore, the coefficient μ_1 captures the average difference in rankings of students' self-reports and their rankings by teachers.

5. Results

Figure 2 displays all our main findings. It describes how being assigned to a top vs. a bottom class affects students' self-perceptions, teacher perceptions, and peer perceptions along several dimensions: academic

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

self-confidence (panels A and B), academic effort (C and D), academic ability (E and F), and academic performance (G and H).[12] In each panel:

- The vertical line indicates the admission cutoff that determines whether a student is assigned to a top or a bottom class,
- The transition scores are normalized such that 0 represents the cutoff, and
- The symbols (circles and triangles) plot mean rankings in bins of 0.25 standard deviation units from the cutoff.

Self-reports are indicated by heavy continuous lines (and small circles), teacher rankings are given by thin continuous lines (and triangles), rankings by students in the top class are indicated by short-dashed lines (and small circles), and rankings by students in the bottom class are in long-dashed lines (and small circles).

[12] Perceptions of disruptive behavior are shown in Appendix Figure A1.

Review of Economics and Statistics Just Accepted MS.
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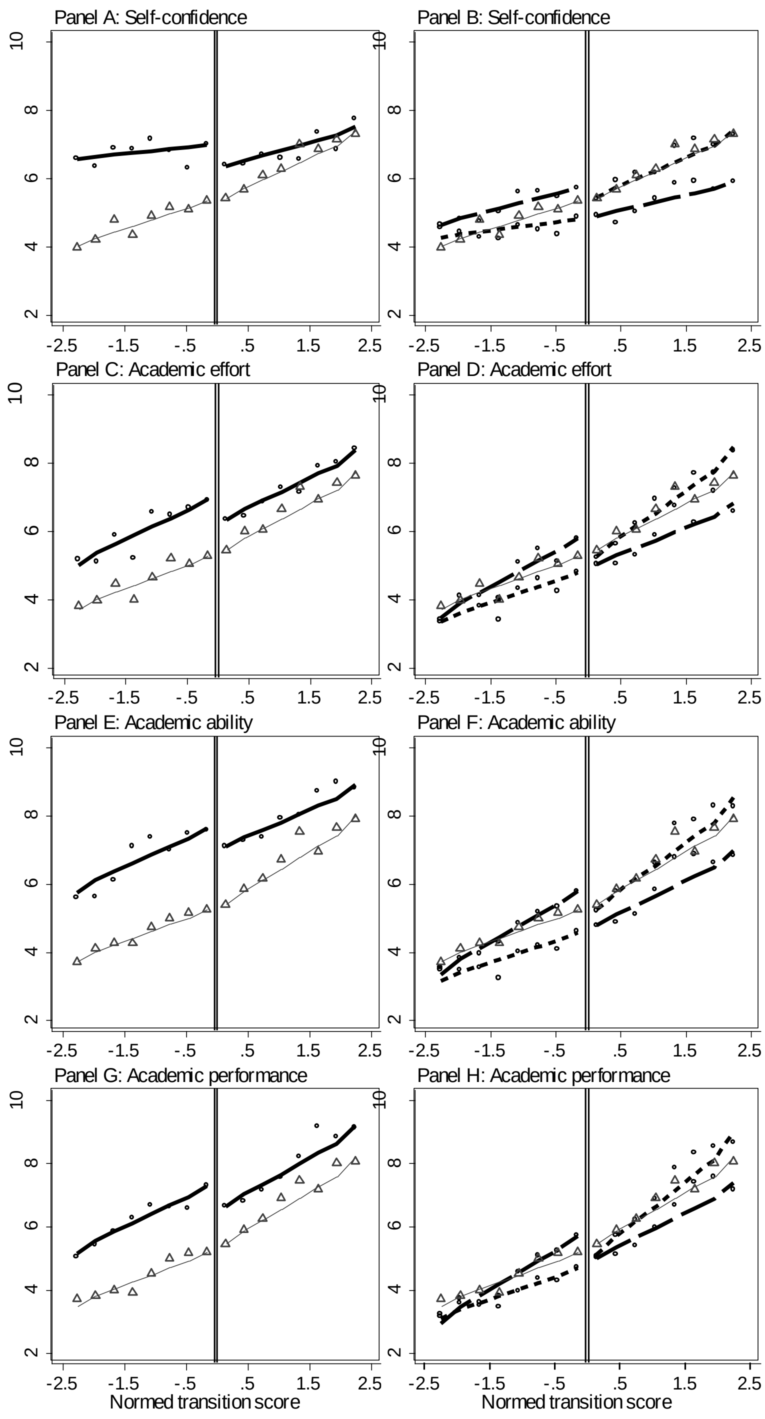

Figure 2: Self-perceptions, peer perceptions, and teacher perceptions

Notes: Self-reports are indicated by heavy continuous lines (and small circles), teacher rankings by thin continuous lines (and triangles), rankings by students in the top class are indicated by short-dashed lines (and small circles), and rankings by students in the bottom class by long-dashed lines (and small circles).

Review of Economics and Statistics Just Accepted MS.
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5.1 "Big-fish-little-pond" effects

Panels A, C, E, and G of Figure 2 present the effects of assignment to top vs. bottom classes on self-perceptions and teacher perceptions. We observe clear discontinuities in student self-perceptions (in heavy lines and small circles) around the cutoff. Students who barely got into a top class view themselves as having lower self-confidence, academic effort, academic ability, and academic performance compared to those who barely missed the cutoff and were assigned to the bottom class. In stark contrast, teachers' perceptions (in thin lines and triangles) display no clear discontinuities around the cutoff, suggesting that teachers perceive that these students are quite similar—at least based on their admissions scores.

Table 1 confirms these graphical patterns using models (1a) and (1b).[13] Column (1) presents the first stage effect of being assigned to a top class, as discussed in section 4.1. Columns (2)-(5) display the RD estimates corresponding to the effects for panels A, C, E, and G, respectively, in Figure 2. Panel A covers self-reports, where the coefficients on "Above" in columns (2) to (5) are highly significant and range from -0.62 for self-confidence to -0.83 for academic performance. Thus, students just above the cutoff rank themselves approximately one half-rank lower than their counterparts just assigned to the bottom class.

One exception to this pattern arises for disruptive behavior (column (6)), for which the discontinuity is not significant.[14]

[13] Sample sizes vary across columns in Table 1; our results are robust to keeping the same number of observations across the columns and panels.

[14] A possible explanation is that the perceived relative rankings on negative traits like disruptiveness are less affected than those for more positive traits like self-confidence (Suls et al. 2002).

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

Table 1: RD estimates of self-perceptions and teacher perceptions

	Top class	Self-confidence	Academic Effort	Academic Ability	Academic Performance	Disruptive behavior	Rosenberg index	Peer victimization index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Self reports								
Above	0.7651***	-0.6240***	-0.6879***	-0.7194***	-0.8283***	0.1185	-0.0830*	-0.0342
	[0.0152]	[0.1604]	[0.1327]	[0.1220]	[0.1186]	[0.1555]	[0.0487]	[0.0492]
Observations	2,865	2,513	2,494	2,472	2,501	2,440	2,865	2,837
Mean of dependent variab	0.549	6.737	6.675	7.376	7.040	4.139	0.000	0.000
R-squared	0.779	0.179	0.239	0.234	0.269	0.191	0.187	0.155
Panel B: Teachers								
Above	0.7710***	-0.0801	0.0289	-0.0178	0.0679	-0.1263		
	[0.0137]	[0.0748]	[0.0839]	[0.0801]	[0.0820]	[0.0931]		
Observations	18,430	14,485	14,437	14,137	14,137	12,184		
Mean of dependent variab	0.540	5.500	5.500	5.500	5.500	5.500		
R-squared	0.763	0.058	0.082	0.096	0.118	0.044		

Notes: Each column presents results from regression (1). Estimates are based on a rectangular kernel and all observations. All regressions feature linear splines of the transition score and include discontinuity fixed effects. Robust standard errors in brackets are clustered at the reported-on student level. *** p<0.01, ** p<0.05, * p<0.1.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

The estimates based on teacher perceptions in Panel B are insignificant and substantially smaller in magnitude. As in Figure 2, teachers do not appear to rank students on either side of the cutoff very differently. While teacher perceptions may also be subject to biases, they appear to be more accurate than student perceptions. We validate this using data on actual performance on the Baccalaureate exam in subsequent years for three of the four cohorts in our sample. Appendix Figure A2 (left panel) replicates Panel G of Figure 2 and adds a plot of academic performance ranks based on actual performance on the Baccalaureate exam. Teacher reports (in black) of academic performance are mostly in line with actual academic performance (in yellow); they display a high level of accuracy in predicting actual performance across the transition score distribution, particularly around the discontinuity.

In addition to the relative measures of student perceptions, Table 1 presents results for two absolute measures: the Rosenberg self-esteem index and a "peer victimization" index. Column (7) shows that students who just got into the top classes report having lower self-esteem compared to those who just barely landed in the bottom classes—although the difference is only marginally significant. Column (8) shows no significant effect on students' likelihood of reporting that their peers victimize them.

To summarize, being allocated to a top class lowers students' self-perceived rankings along the academic domains of effort, ability, self-confidence, and predicted performance. It also negatively affects an absolute measure of self-esteem (the Rosenberg index). These adverse effects are in stark contrast with teacher perceptions of these same academic characteristics. Thus, for students on the margin, being assigned to a lower class positively affects how they perceive themselves—consistent with a *big-fish-little-pond effect*.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

5.2 In-group bias

Panels B, D, F, and H of Figure 2 compare perceptions of students' peers in top classes (in short dashed lines and small circles) and peers in bottom classes (in long dashed lines and small circles) across the transition score distribution. As before, we show teacher perceptions (thin lines and triangles), and vertical lines indicate admission score cutoffs. To elaborate, the circles to the right of the cutoff refer to students assigned to the top class; the length of the dash distinguishes who they are evaluated by. Similarly, the circles to the left of the cutoff refer to students assigned to the bottom class, and the length of the dash indicates who they are evaluated by.

The patterns are striking, with clear discontinuities in the peer rankings provided by students in top and bottom classes and substantial level differences between the rankings originating from students in one's own class as compared to students in the other class.[15] The patterns indicate that students in *both* the top and bottom classes rank their fellow classmates significantly higher than their peers in other classes.

Table 2 confirms the patterns at the discontinuities based on model (2), displaying the corresponding RD estimates for the effect of being assigned to a *top vs. bottom* class on peer perceptions based on reports by students in the top class (Panel A) and bottom class (Panel B).

[15] Students are more likely to report on their fellow classmates than on their peers in other classes. Results are largely unchanged for a "balanced" sample of students who report on peers in both their own and the other class.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

Table 2: RD estimates of peer perceptions

	Top class	Self-confidence	Academic Effort	Academic Ability	Predicted Performance	Disruptive behavior
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reported by students in top classrooms						
Above	0.7666***	0.6091***	0.3886***	0.6182***	0.3333***	-0.2677**
	[0.0132]	[0.0929]	[0.0992]	[0.0923]	[0.0963]	[0.1053]
Observations	13,185	9,182	9,108	9,039	9,167	8,994
Mean of dependent variable	0.490	5.343	5.314	5.216	5.255	5.704
R-squared	0.755	0.085	0.163	0.192	0.214	0.051
Panel B: Reported by students in bottom classrooms						
Above	0.7680***	-0.9986***	-0.9817***	-1.2601***	-0.9499***	0.1186
	[0.0134]	[0.0956]	[0.1032]	[0.1015]	[0.1045]	[0.1038]
Observations	12,600	8,718	8,635	8,535	8,602	8,480
Mean of dependent variable	0.584	5.309	5.356	5.257	5.313	5.676
R-squared	0.768	0.026	0.057	0.071	0.089	0.026

Notes: Each column represents an independent regression. All regressions include reported-on student fixed effects. Robust standard errors in brackets are clustered at the reported-on student level. *** p<0.01, ** p<0.05, * p<0.1.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

For reports by *top* class students, we observe positive and highly significant effects on self-confidence, academic effort, ability, and performance. Thus, students in top classes rank their fellow classmates who are just above the cutoff approximately 0.33 to 0.62 ranks higher in terms of these academic characteristics than peers from other classes who are just below the cutoff. These effects correspond to the discontinuities in the short-dashed lines in Figure 2.

For reports by students in *bottom* classes, we observe negative and significant effects on self-confidence, academic effort, ability, and performance. Thus, students in the bottom classes rank their peers who are just above the cutoff to the top class as worse in terms of these academic characteristics compared to their peers who are just below the cutoff, with even larger magnitudes of 0.95 to 1.26 ranks. These effects correspond to the discontinuities in the long dashed lines in Figure 2.

These results align with research on *in-group bias* in which individuals perceive people in their own group differently from those outside their groups.[16] This bias is present in both the top and bottom classes, but

[16] The mechanism for in-group bias could arise from several factors, such as stronger friendships with immediate classmates, resentment towards students placed in the other class, or feelings of affinity with students in the same group due to shared circumstances. Disentangling such mechanisms would require sources of variation beyond our score-based cutoffs.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

its magnitude is even more pronounced in the bottom class. An interacted specification confirms that these differences in magnitude are statistically significant (available upon request).[17]

In addition to the differences at the discontinuities, the pattern of "in-group bias" is also apparent across the transition score distribution. We observe substantial level differences between the rankings of students in one's own class as compared to students in the other class (i.e. the short-dotted lines are higher than the long-dotted lines above the cutoff and lower than the long-dotted lines below the cutoff in Figure 2). This is true for self-confidence as well as academic effort, ability, and performance, although not for disruptive behavior (as seen in Panel B of Appendix Figure A1).

To quantify these differences, Appendix Table A7 estimates the differences between how students in the top (Panel A) and bottom (Panel B) classes are ranked by their own classmates and by their counterparts in the other classes, as compared to teachers.[18] For most domains in panel A, we observe that students in

[17] This specification includes interactions of the indicator for being above the cutoff with indicators for both top-class reporters and bottom-class reporters (while allowing for separate intercepts and slopes for each group) and tests whether these interactions are statistically different from one another.

[18] This is based on regressions that compare student attributes as reported by peers in the top class and peers in the bottom class, relative to teachers in both cases, and including student fixed effects: $Y_{ik} = \mu_0 + \mu_1 TopClassReports_{it} + \mu_1 BottomClassReports_{it} + \sigma_i + \epsilon_{ik}$. where Y_{it} is our outcome of interest for student i who is taught by peer k, $TopClassReports_{ik}$ is an indicator for perceptions by peers in the top class, $BottomClassReports_{ik}$ is an indicator for perceptions by peers in the bottom class, and

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

the top class are ranked fairly similarly by their fellow classmates as by teachers, but ranked substantially lower by students in the bottom class. In panel B, we observe that students in the bottom class are ranked higher by their fellow classmates than by teachers, but ranked lower by the students in the top class relative to teachers.

Unsurprisingly, the "in-group bias" pattern we observe for students is not apparent for teacher reports. This is also the case when we compare performance predictions on the Baccalaureate schooling-leaving exam with the actual performance in Appendix Figure A2, right panel (which adds actual performance to Panel H of Figure 2).

5.3 Illusory superiority and Krueger-Dunning effects

In addition to the differences at the discontinuity in Panels A, C, E, and G of Figure 2, there is a striking level difference between student self-perceptions and teacher perceptions (i.e., the distance between the dotted and thin solid lines). Students rank their own self-confidence, academic effort, academic ability, and academic performance much more highly than their corresponding rankings by teachers. Table 3 elaborates on this by estimating student self-reports relative to teachers using model (3).

perceptions by teachers are the omitted category. We estimate these regressions separately for students (being reported on) in the top and bottom classes.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

The coefficients on the indicator for "self-reports" in columns (1) to (4) are highly significant and range from 1.08 for academic effort to 1.78 for academic ability. Thus, students rank themselves approximately 1 to 2 ranks (out of 10) more highly than they are rated by their teachers. The coefficient on "self-reports" for disruptiveness in column (5) is negative and significant indicating that students rank themselves as less disruptive by approximately 1.3 ranks (out of 10) lower than teachers.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

Table 3: Self-perceptions relative to teachers

	Differences relative to teachers				
	Self-confidence	Academic Effort	Academic Ability	Predicted Performance	Disruptive behavior
	(1)	(2)	(3)	(4)	(5)
Panel A: Average differences					
Self reports	1.1580***	1.0795***	1.7725***	1.4109***	-1.3323***
	[0.0781]	[0.0646]	[0.0643]	[0.0619]	[0.0788]
Panel B: Average differences by transition score					
Self reports	1.2139***	1.1024***	1.8085***	1.4390***	-1.3684***
	[0.0777]	[0.0650]	[0.0649]	[0.0627]	[0.0791]
Self reports x Transition score	-0.5727***	-0.2269***	-0.3471***	-0.2665***	0.3692***
	[0.0782]	[0.0698]	[0.0665]	[0.0620]	[0.0800]
Obs	16,998	16,931	16,609	16,638	14,624
Mean of dependent variable	5.683	5.673	5.779	5.732	5.273
R-squared	0.353	0.434	0.437	0.460	0.446

Notes: Each column represents an independent regression. Observations include student's self-reports and teacher reports. All regressions include reported-on student fixed effects. Robust standard errors in brackets are clustered at the reported-on student level. *** p<0.01, ** p<0.05, * p<0.1.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

This finding aligns with the notion of *illusory superiority*, a cognitive bias that arises when individuals overestimate their own abilities relative to others (Taylor and Brown 1988; Colvin, Block, and Funder 1995). Illusory superiority is also apparent when focusing on self-perception of academic performance, which we validate using academic performance on the Baccalaureate schooling leaving exam (Appendix Figure A2, left panel). Except at the very top of the transition score distribution, there is a clear gap between self-perceptions of predicted performance and actual performance.

Additionally, the interaction of self-reports with the transition score in Panel B of Table 3 is negative and significant for all the outcomes that have a positive illusory superiority, and positive for disruptiveness which has a negative illusory superiority. This pattern confirms that the absolute level of illusory superiority is declining with transition scores. It is also consistent with the Krueger-Dunning effect, which suggests that low performers are typically more overconfident, while high performers assess their skills more accurately (Krueger and Dunning 1999).

5.4 Educational effects

We also examine the educational impacts of being assigned to a top class by linking students to administrative data on their Baccalaureate exams. Appendix Table A8 presents the results. There does not appear to be a large or significant effect of being assigned to a top class on whether students took this exam; the estimates in column (1) are approximately 1 or 2 percentage points in magnitude on a base of 94 percent, and marginally significant only with the inclusion of additional controls. However, column (2) reveals that being assigned to a top class has a more significant effect on Baccalaureate grades. This effect corresponds to 0.10-0.16 standard deviations (the standard deviation of the raw score is

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

approximately 1). The effects appear somewhat larger when they are used to rank the students across classrooms, as in column (3), similar to the way we framed the questions about academic characteristics to students, peers, and teachers. Indeed, we can compare them directly to the teacher predictions of student success in the Baccalaureate exam in column (4). These results suggest there may be educational benefits to being tracked into a higher-achieving class.[19,20]

5.5 Robustness

Appendix B presents tables showing robustness checks for the results in the main RD tables: (i) the inclusion of control variables (tables B1-B2), (ii) quadratic trends in the running variables (tables B3- B4), (iii) local linear specifications using alternative bandwidths (tables B5-B6), (iv) collapsing our ordinal

[19] The effects on educational outcomes are not as robust as our results for self, teacher and peer perceptions; e.g. the estimates on ranked Baccalaureate grades are not significant with quadratic functions of the transition scores and some bandwidths do not show significant effects on ranked or raw Baccalaureate grades.

[20] We also explored a mediation analysis where we conditioned for self-reported rankings of academic attributes (i.e. self-confidence, academic effort, etc.) when estimating the effect of being assigned to a higher-achieving class on Baccalaureate grades. As expected, given the negative effects on most measures of self-perceptions, the educational effects on Baccalaureate grades were substantially larger (and more significant) with the inclusion of these covariates. However, these estimates must be interpreted with caution because self-perceptions are likely endogenous to academic achievement.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

ranks into dichotomous outcomes of high vs. low ranks (tables B7-B9),[21] (v) using only students in grade 9 since these students are much less likely to be affected by selective mobility and dropouts (tables B10-B12), and (vi) using only a sample of students and teachers who provided a complete ranking of all students (tables B13-B15). In each case, the main results remain qualitatively unchanged.

5.6 Heterogeneity

Appendix C presents tables showing the heterogeneity of impacts by gender (tables C1-C3) and grade level of the students being ranked (tables C4-C6). While relatively few interactions are significant, we observe that illusory superiority is weaker among girls than boys. Furthermore, in-group bias among students in the bottom class is weaker in later grades than in earlier grades. This is consistent with students in the bottom class gaining a more accurate perception of their relative ranking over time. We do not find much evidence of heterogeneous effects by SES (these results are available upon request).

6. Conclusion

School tracking has long been controversial. A standard concern is that it could hurt lower-achieving children by denying them the chance to interact with higher-achieving peers. Economists have concluded that, at least in some settings, this concern is unwarranted. In fact, tracking can causally raise overall learning even as it improves that of lower-achieving children (Duflo, Dupas, Kremer 2011; Riehl 2023).

[21] This partially addresses the concern that we treat our ordinal rankings as cardinal scales in OLS regressions.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01555

This paper considers another concern: because tracking renders some children's low achievement salient, it may stigmatize them, hurting their self-perceptions. We analyzed this in the context of Romania's high school system, one of the most explicitly tracked in the world. Using unique data on student and teacher perceptions, we find surprisingly little evidence that tracking adversely affects the self-perceptions of lower-achieving students: students in lower-achieving (bottom) classes display patterns of perception consistent with "big-fish-little-pond" effects, "illusory superiority," and in-group bias. Furthermore, the effects of illusory superiority and in-group bias appear to be larger relative to their peers in higher achieving classes. Thus, these perceptions may act as a defensive adaptation and mitigate a perception of inferiority.

While our findings may mitigate concerns regarding adverse effects on self-perceptions in the short run, whether they have positive or negative long-term effects is an empirical question.[22] Moreover, at some point, students' perceptions will likely be contradicted by long-term outcomes, such as placements into college or jobs. Whether students maintain these perceptions into the future, or whether these perceptions engender feelings of unfairness, are important open questions.

[22] On the one hand, psychologists suggest that "self-enhancement" biases may promote psychological health, resilience, and subjective well-being (Taylor and Brown 1988, Taylor et al. 2003, Sedikides et al. 2007). On the other hand, they could cause anti-social behavior, impact mental health, or reduce engagement with schoolwork (Colvin et al. 1995, Robins and Beer 2001, Sedikides et al. 2007).

Review of Economics and Statistics Just Accepted MS.
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