University of Zurich

Department of Economics

Working Paper Series

ISSN 1664-7041 (print)
ISSN 1664-705X (online)

Working Paper No. 269

The Impact of Peer Personality on Academic Achievement

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November 2017

The Impact of Peer Personality on Academic Achievement*

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This paper provides evidence of a novel facet of peer effects by showing how peer personality affects educational achievement. We exploit random assignment of students to university sections and find that students perform better in the presence of more persistent peers and more risk-averse peers. In particular, low-persistence students benefit from highly-persistent peers without devoting additional efforts to studying. However, highly-persistent students are not affected by the persistence of their peers. The personality peer effects that we document are distinct from other observable peer characteristics and suggest that the personality traits of peers causally affect human capital accumulation. (JEL I21, I24, J24)

I. Introduction

The importance of people's personality traits for the trajectory of life has been recognized by a steadily growing body of literature in economics, psychology and sociology. Personality traits are predictive of many significant outcomes in life, including educational attainment, earnings, employment, health as well as participation in risky behavior and crime.[1] While evidence on the importance of personality traits is accumulating, there is virtually no evidence on the extent to which individual personality affects other people in their social environment. The literature on peer effects – which is dedicated to identifying social spillovers – has established that peer

* We thank Armin Falk, Jan Feld, Wolter Hassink, Ingo Isphording, Fabian Kosse, Nicolas Salamanca and seminar participants at briq, the University of Cologne, the University of Munich, Maastricht University, Utrecht University, the joined briq/IZA workshop on socio-emotional skills and the 2nd IZA education workshop for helpful discussions and comments. Golsteyn acknowledges financial support from the Netherlands Organization for Scientific Research (NWO VIDI grant). We thank Sophia Wagner for providing outstanding research assistance, and the Department of Education Research and Development at Maastricht University for sharing their data.
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[1] An often-used taxonomy in personality psychology is the Big Five. This entails openness to experiences, conscientiousness, extraversion, agreeableness and neuroticism. Big Five traits are predictive of many outcomes in life, including schooling, wages, crime, teenage pregnancy and longevity. Generally, conscientiousness and neuroticism are more predictive than the other traits (see Borghans et al. 2008, and Almlund et al. 2011). Borghans et al. (2016) show that personality traits have predictive power over and above pure cognition for life outcomes. Regarding economic preference parameters, recent studies reveal that time preferences (Golsteyn, Grönqvist and Lindahl 2014, Åkerlund et al. 2016), risk attitudes (Dohmen et al. 2011) and social preferences (Dohmen et al. 2009) predict outcomes in life such as educational attainment, wages and health outcomes.

characteristics such as race, gender and test scores affect the accumulation of human capital.[2] Surprisingly, the question whether the *personality* of peers affects educational outcomes has been neglected in the literature.

In this paper, we test whether peer personality affects performance in education. We use data from Maastricht University's School of Business and Economics (SBE), located in the Netherlands. Two key institutional features make SBE the ideal place to study peer effects. First, students are required to spend a significant amount of their study time in small teaching sections of up to sixteen students. These sections where students solve problems and discuss literature provide us with natural peer groups in which students engage in meaningful social interactions. Second, the assignment of students to these tutorial groups within each course is random, conditional on scheduling constraints. In most other educational settings, students are tracked or self-select into peer groups. Random assignment allows us to overcome this fundamental selection problem that typically plagues the identification of causal peer effects.

We measure personality at the beginning of students' study careers, before students were assigned to the groups in which we test for peer effects. This avoids the simultaneity problem arising from the fact that peers and students affect each other at the same time. We collect four distinct measures of students' personality traits related to education: *persistence*, which is a facet of conscientiousness and captures how much students keep trying to solve a problem even if it is challenging; *self-confidence*, which measures students' belief in their ability to do well and succeed in their studies; *anxiety*, which reflects how worried and nervous students are about succeeding in their studies; and *risk attitude*, which captures people's willingness to engage in risky behaviors. After combining students' self-assessed measures of these traits with their administrative records on grades, we observe a total of 8,288 student course observations of 2,375 unique students in three different study cohorts.

Our results show that students who were randomly assigned to a tutorial group of more persistent peers attain higher exam grades in centrally-graded exams. A one standard deviation increase in average peer persistence raises grades by 1.8 percent of a standard deviation. The impact of a one standard deviation increase in peer persistence is approximately twice as large as a one standard deviation increase of peer GPA as identified by Feld and Zölitz (2017) in the same setting. We further find that exposure to risk-tolerant peers negatively affects

[2] Prominent papers on peer effects focusing on peer race and gender include Angrist and Lang (2004), Hoxby (2000), Hoxby and Weingarth (2005), Lavy and Schlosser (2011), as well as Oosterbeek and Van Ewijk (2014). Papers that exploit random assignment to identify a causal achievement peer effect include, but are not limited to, Sacerdote (2011), Zimmerman (2003), Whitmore (2005), Carrell, Fullerton and West (2009), Carrell, Sacerdote and West (2013), Duflo, Dupas and Kremer (2011), Lyle (2009), De Giorgi and Pellizzari (2013), Booij, Leuven and Oosterbeek (2017) and Feld and Zölitz (2017).

performance. A one standard deviation increase in peers' risk tolerance lowers grades by 1.7 percent of a standard deviation. Peer anxiety and self-confidence do not significantly affect performance.

Since personality traits are likely to be correlated with other characteristics, we test whether the inclusion of peer GPA, peer gender and peer nationality affects our results. Our point estimates on the impact of peer personality are not affected by the inclusion of these observable peer characteristics. This result suggests that peer personality has a distinct effect from peer achievement.[3]

When looking at the heterogeneity of peer effects, we find that in particular students with low persistence benefit from having more persistent peers. This finding suggests that peer persistence may serve as a substitute for students' own persistence in the accumulation of human capital. We find no evidence that high-persistence students are affected by the presence of either low- or high-persistence peers. These non-linear effects suggest that grouping high- and low-persistence students together could be an effective policy to improve student performance without additional costs.[4]

In order to achieve a better understanding of the underlying mechanisms, we provide a simple theoretical model illustrating how peer personality enters the education production function. We derive two classes of mechanisms from the model, which are empirically distinguishable. First, peer personality may affect student achievement directly through 'effortless' learning spillovers in the classroom. In this case, exposure to peers with productive personality traits increases the efficiency of the learning process and makes a given time period spent in class more productive. Second, peer personality may affect student achievement indirectly through an adjustment of study effort. In this case, students with more productive personality traits encourage their peers to work harder or display study behavior that provides a reference point or social norm for their fellow students. Using students' reports on self-study hours, we reject the notion that study effort is significantly affected by the personality of their peers. Our evidence is thus consistent with the idea that more persistent peers enhance the productivity of other students, who benefit *without* devoting more effort to class preparations.

[3] In the spirit of Altonji, Elder and Taber (2005), these results also suggest that unobservables only play a limited role in creating an omitted variable bias and that we indeed identify the causal impact of peer personality.

[4] Note that Carrell, Sacerdote and West (2013) caution against this type of policy recommendations, since (1) we may not have sufficient underlying support in the data, and (2) the reassignment may change the underlying structure of social interactions between students that generate peer effects. An experimental validation of the policy implications that we suggest here would provide important additional insights into whether our results can be generalized.

The evidence on externalities arising from peer personality on educational outcomes is scarce. Most of the literature on peer effects in education focuses on how various measures of peer achievement affect performance, while other papers in this literature have focused on the role of peer race and gender (see Sacerdote (2011) for a review). Only a few papers have touched upon the effect of peer characteristics that are related to personality. Carrell, Hoekstra and Kuka (2016) show that being exposed to disruptive peers in elementary school reduces earnings at the age of 26 by 3-4 percent.[5] Figlio (2007) shows that boys with female-sounding names – who display more behavioral problems – negatively affect their peers' test scores. While the role of peer personality is not explicitly studied in Carrell, Hoekstra and Kuka (2016) or Figlio (2007), their findings suggest that those personality traits that underlie students' disruptive behavior may also negatively affect their classroom peers.

The only paper to explicitly consider the association between peer personality and educational outcomes is by Shure (2017), who investigates the relationship between peer personality and grades in secondary school. In order to identify peer effects, she exploits idiosyncratic variation in peer personality in a school fixed effects framework. Consistent with our results, Shure (2017) documents a positive relationship between peer conscientiousness and student performance. Moreover, she finds a negative association between performance and peer extraversion. The key difference between our study and Shure's (2017) lies in the empirical strategy: while Shure (2017) relies on school fixed effects, we exploit the random assignment of students into teaching sections. The benefit of our approach is that it alleviates concerns related to non-random student sorting into peer groups.

We believe that this paper establishes a novel connection between the peer effects literature and a growing body of evidence documenting the importance of individuals' personality traits. We make two contributions to these two strands of literature: First, by studying the role of peer personality instead of achievement, gender or race, we focus on a novel facet of peer effects in human interaction. Second, we provide the first causal evidence that personality traits of people around us affect educational performance. Our key finding that peer personality affects performance has important implications for the social returns of any intervention that affects socio-emotional skills. For instance, the social returns of interventions like the Perry Preschool Project – which enhanced socio-emotional skills – will be underestimated if spillovers driven by peer personality are neglected. Such spillovers may arise

[5] Using similar data, Carrell and Hoekstra (2010) show that children who experienced domestic violence also have a direct negative impact on their peers as they lower their reading and math test scores.

– for instance – if children affected by the intervention in turn affect their siblings, friends, neighbors or classmates.

The remainder of the paper is structured as follows. Section II discusses *why* peer personality may affect educational achievement using an education production framework. Section III describes the institutional environment and the assignment procedure of students to sections. Section IV describes the dataset. Section V discusses the empirical strategy and shows evidence that the assignment to sections is random. Section VI provides results and investigates changes in study effort as an underlying channel. Section VII concludes the article.

II. Peer Personality in the Education Production Function

Why would the personality of peers have an effect on students' educational attainment? In this section, we describe one way in which peer personality may enter the education production function and affect students' accumulation of human capital. We distinguish between two possible channels: (1) peer personality affects the classroom environment, which changes the *efficiency* of learning; and (2) peer personality affects the *effort* that students devote to their studies.

Based on Almlund et al. (2011), student achievement can be described as a function of IQ, effort and environment:

$$A_{ig} = f\left(IQ_i\,, effort_i, environment_{ig}\right), \tag{1}$$

where A_{ig} denotes the achievement of student i in group g. Extending Almlund (2011), the environment may not only include aspects like teacher quality, class size and parental background, but also peer personality. The environment may be affected by peer personality if – for example – more persistent students prepare better for class or self-confident students are more willing to contribute to classroom discussions.[6] Peers with such productive traits thus raise the quality of classroom interactions and consequently student achievement. Alternatively, risk-seeking students may introduce fellow students to unproductive behavior such as binge drinking and the use of drugs. Since we are interested in the impact of student personality, we abstract from the predetermined characteristics and describe the classroom environment of student i in group g as a positive function of fellow students' personalities:

[6] Another possibility is that there may be direct peer-to-peer instruction depending on students' personalities.

$$environment_{ig} = f\left(peer\ personality_{-ig}{}'\right), \tag{2}$$

where $peer\ personality_{-ig}{}'$ represents a vector of the personality traits of all students in group g excluding student i.

In addition to the classroom environment, students' performance A_{ig} also depends on effort, e.g. the amount of time that students invest in their studies or the intensity of studying. It is natural to assume that effort depends on students' own personality, as personality is supposed to affect outcomes through students' behavior. Other potentially important determinants of effort are IQ and classroom environment. One possible reason why classroom environment and hence peer personality affects effort is that peers with a more productive personality put more pressure on fellow students to perform well, or establish higher working norms in the classroom. Therefore, the behavior of these peers may induce students with less productive traits to work harder.

$$effort_{ig} = f\left(personality_i, IQ_i, environment_{ig}\right). \tag{3}$$

To assess how achievement changes in peer personality, we substitute equations (2) and (3) into equation (1) and take the derivative with respect to peer personality:

$$\frac{\partial A_{ig}}{\partial peer\ personality_{-ig}{}'} = \frac{\partial environment_{ig}}{\partial peer\ pers._{-ig}{}'}\left[\frac{\partial A_{ig}}{\partial environment_{ig}} + \frac{\partial effort_i}{\partial environment_{ig}}\frac{\partial A_{ig}}{\partial effort_i}\right] \tag{4}$$

Equation (4) shows the partial derivative of achievement with respect to peer personality. It implies that peers with more productive personality traits improve the classroom environment, which affects performance through two channels: a direct positive effect on achievement $\frac{\partial A_{ig}}{\partial environment_{ig}}$, and an indirect effect via effort $\frac{\partial effort_i}{\partial environment_{ig}}\frac{\partial A_{ig}}{\partial deffort_i}$. Note that the direction of the latter effect is ambiguous: prepared fellow students may stimulate effort or invite free-riding of students. Therefore, the total effect of having peers with productive traits on achievement depends on behavioral responses that are difficult to predict.[7]

Conceptually, own and peer traits may work as substitutes or complements in the education production function. For example, when highly-persistent peers come to class well

[7] See Todd and Wolpin (2003) for a similar discussion in the context of cognitive achievement of children. In their model, better school inputs influence achievement directly, as well as via their effect on parents' input choices, i.e. via effort.

prepared, it might be the case that other well-prepared students benefit most from high-quality classroom discussions, as understanding the details of the discussion requires significant prior knowledge. In this case, own and peer personalities are complements, i.e. $\frac{\partial^2 A_{ig}}{\partial peer\ personality_{-ig}{}'\partial personality_i} > 0$. An example of the case where own and peer traits are substitutes is when students who lack persistence to study independently particularly benefit from good classroom discussions with their persistent and prepared peers. Students who are persistent and well prepared benefit less because they have already gained ample knowledge of the material themselves. Mathematically, this case holds when $\frac{\partial^2 A_{ig}}{\partial peer\ personality_{-ig}{}'\partial personality_i} < 0$.

It is important to note that substitution effects can be non-linear, i.e. the second derivative $\frac{\partial^3 A_{ig}}{\partial peer\ personality_{-ig}{}'\partial^2 personality_i}$ may not be constant. This implies that the effect of adding a peer with productive traits may be large in some parts of the distribution (e.g. those who do not possess the traits themselves), but small for others. Understanding heterogeneity and non-linear effects is crucial for the design of optimal group assignment policies that maximize learning spillovers between students.

III. Institutional Background

In order to test how peer personality affects achievement, we collected data at Maastricht University's School of Business and Economics (SBE).[8] Maastricht is located in the south of the Netherlands. At present, there are about 4,300 students enrolled at SBE in bachelor, master and PhD programs. The language of instruction at SBE is English.

In contrast to the US college system, all students who enroll at SBE are committed to studying a specific program from the first year onwards. In all bachelor programs, students have to take eight compulsory courses in the first year.[9] Some of those courses are program-specific. In the second and third year, students choose a number of elective courses in addition to the compulsory courses. Students enrolled in the Economics and Business bachelor programs also choose one out of eight majors. The major choice implies that students have to take a number of major-specific compulsory courses. In this paper, we concentrate on performance in the first

[8] For similar but more detailed information on the institutional environment, see Feld, Salamanca and Hamermesh (2016), Feld and Zölitz (2017) as well as Zölitz and Feld (2017).

[9] Courses held at the time when personality is measured are excluded from the analysis to avoid the reflection problem (Manski 1993).

year. Due to endogenous course selection and different grading standards across courses, grades from non-compulsory courses in later years might not be comparable.

The academic year at SBE is divided into four regular teaching periods of two months and two skills periods of two weeks. Students usually take two courses at the same time in each regular period and one course in each skills period. In our analysis, we focus on the courses taken during the regular teaching periods because students are often not graded in skills courses or we could not identify the relevant peer group.[10]

Importantly, the bulk of teaching at SBE occurs in sections. Sections are small groups of up to sixteen students, taught by one instructor. This peer group will be the focus of our analysis. Students typically meet twice per week for two hours with their section peer group to discuss the course material. These discussions follow the Problem-Based Learning (PBL) approach, in which students generate questions about a topic, try to answer these questions in self-study and then discuss their findings with their peers in the next session.[11] The role of the teacher in the PBL system is to monitor and guide the classroom discussion. However, courses differ in the extent to which they follow this PBL approach. In most courses, students solve problem sets or read textbook chapters or papers at home and then come together to discuss the material and solutions to the problem sets. Additionally, most courses have lectures that are attended by students of all sections.

A. Assignment of Students to Sections

The Scheduling Department of SBE assigns students to sections, teachers to sections, and allocates sections to time slots and rooms.[12] Before the start of each period, students register online for the courses that they want to take. After the registration deadline, the scheduler receives a list of registered students for each course. A computer program then randomly allocates all students who have registered for a given course to sections. The allocation of bachelor students to sections is additionally stratified by nationality.[13] After the assignment of

[10] In almost all skills courses, students are scheduled in different sections but end up sitting together in the same room. Furthermore, some skills courses have only a “pass” or a “fail” grade.

[11] See http://www.umpblprep.nl/ for a more detailed explanation of PBL at Maastricht University.

[12] See also Feld and Zölitz (2017) for a similar but more detailed description of the section assignment procedure.

[13] This was introduced in the academic year 2010/2011. The stratification occurs as follows: the scheduler first selects all German students (who are not ordered by any observable characteristic) and then uses the option “Allocate Students set SPREAD,” which assigns an equal number of German students to all sections. Subsequently, the scheduler repeats this process with the Dutch students and finally distributes the students of all other nationalities to the remaining spots. Until the academic year 2013/14, about ten percent of the slots in each section were initially left empty and were filled with students who register late. This procedure balances the

students to sections, teachers are assigned to sections, and then sections are assigned to available time slots and rooms.[14] After this assignment, the program Syllabus Plus Enterprise Timetable indicates scheduling conflicts.[15] These conflicts arise for about 5 percent of the initial assignments. If the computer program indicates a scheduling conflict, the scheduler manually moves students between different sections until all scheduling conflicts are resolved. After this, the section and teacher assignments are published.

Schedulers typically do not know the students and do not observe their previous grades, gender or student personality in the scheduling program. There are a few exceptions to this general procedure, e.g. when the course coordinator requests to manipulate the section composition. We remove all such exceptions from the random assignment procedure from the estimation sample. Importantly, in the estimation sample that we use throughout this paper, neither teachers, students nor course coordinators influence the section assignment.

IV. Data

A. Sample and Descriptive Statistics

In the academic years from 2012/13 to 2014/15, we collected data on students' personality and attitudes using online questionnaires that students were required to fill out at the beginning of their introductory course in quantitative methods. This course takes place in the first period of the first academic year, and is obligatory for all Economics and Business students at SBE. Since the survey was part of a compulsory assignment students completed for the course, virtually all students filled out the questionnaires. Only a handful of students who dropped out of the study program during the first weeks did not answer the survey.[16] Our sample thus comprises three full SBE study cohorts.[17]

number of late registration students over the sections. Since 2013/14, SBE no longer admits students to courses after expiration of the registration deadline.

[14] About ten percent of teachers indicate time slots when they are not available for teaching. This happens before they are scheduled and requires the signature of the department chair.

[15] There are three reasons for students' scheduling conflicts: (1) the student takes another elective course at the same time; (2) the student is also working as a teaching assistant and is scheduled for teaching at the same time; and (3) the student indicates non-availability for evening education. Evening sessions are scheduled from 6 p.m. to 8 p.m. By default, all students are recorded as available for evening sessions, although they can opt out by filling out an online form. About three percent of all sessions in our sample are scheduled for this time slot.

[16] Students were informed that their responses remain confidential, and are only used in anonymous format for research purposes as well as the improvement of education.

[17] Administrative data on all scheduled sections are provided by the Scheduling Department of SBE. The data on student course registrations, grades and student background characteristics are provided by the Examinations Office of SBE.

Table 1 provides descriptive statistics. Panel A in Table 1 shows that there are 2,375 students in our sample, around 40 percent of whom are female. Since Maastricht is located close to the German border, around 50 percent of the students are German, while 24 percent of students are Dutch. We follow their performance throughout the first year, although we exclude courses in the first course period of the first year to avoid problems arising from simultaneity. We also exclude one course where students were not randomly assigned to sections. Overall, we observe 654 unique teaching sections, which constitute the peer groups of interest in this paper. Panel C of the table shows that the sample contains 8,288 student course registrations. Course drop-out rates are relatively low at around 6 percent.

B. Measures of Student Personality and Attitudes

Table 2 provides an overview of the personality measures that we use in this paper.[18] All measures are self-reported on a scale from 1-7. The personality traits persistence, self-confidence and anxiety are measured using the Student Motivation Scale as proposed by Martin (2009). Each of the traits is measured by four questions.[19] This scale is specifically developed for the measurement of student motivation in education. Hence, all questions are framed in the context of education. Our measure of risk attitudes is the widely-used question: "In general, how willing are you to take risks?", whereby higher values indicate higher risk tolerance. Dohmen et al. (2011) and Vieider et al. (2015) show that this measure predicts behavior in incentivized lottery experiments, and that it is correlated with risky behaviors in several domains across different cultures (see also Falk et al., 2016).

C. Data on Student Performance and Student Course Evaluations

The performance indicator in this study is the grade that students achieve in the exam at the end of each course. The exam is written by each individual student and does not have a group component. We only use the results of the first central exam in a course and do not take the grades of the resit exam into consideration, as these are not comparable with the grades in the first sit. As can be seen in Table 1, the average grade that students obtain is 6.5.[20]

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[18] Table A1 in the appendix shows the correlations between these variables.

[19] The underlying questions are not publicly available. Table B1 in the appendix – which is exclusively available for referees – shows the separate questions.

[20] The Dutch grading scale ranges from 1 to 10, with 5.5 usually being the lowest passing grade. If the grade of a student is lower than 5.5, the student fails the course and has the possibility to take a second and third attempt at the exam.

We obtain data on self-reported study hours from online course evaluations. Given that not all students complete all course evaluations, the sample size is limited to 2,766 student course observations. Students report that they study on average around thirteen hours per week for one course, excluding the six hours per week during which they meet in the sections and lectures. Given that the students take two courses per period, this number of study hours is close to the 40 hours per week that full-time students are supposed to invest in their studies according to the European Credit Transfer System (ECTS) framework.

V. Empirical Strategy

Our goal in this paper is to estimate the effect of peer personality on students' grades. Throughout this paper, we define peer groups at the section level and when referring to peers we mean students' section peers.

Before we test how peer personality affects outcomes, we investigate whether students' *own* personality traits predict their outcomes. We estimate the following model:

$$GPA_i = P_i \, \delta' + X_i \theta' + \varepsilon_i, \tag{4}$$

where GPA_i is the grade point average of student *i* at the end of the first study year.[21] The vector of personality traits P_i includes the student's persistence, self-confidence, anxiety and risk attitude. X_i is a vector of control variables that includes student gender, nationality, as well as cohort and study program fixed effects. The vector δ' captures the predictive power of personality traits for student performance.

To test how peer personality affects student performance, we estimate the following model:

$$A_{ig} = \overline{PP}_{g-i} \, \alpha' + P_i \, \beta' + X\gamma' + u_{ic}, \tag{5}$$

where A_{ig} is the grade of student *i* in section g. The vector $\overline{PP}_{g-i}$ refers to the mean personality traits of all students in section g excluding the individual her-/himself, i.e. the leave-out-mean. We control for several variables to enhance the precision of our estimates: students' own personality measures and a vector of other control variables X that includes course-year fixed

[21] We use GPA at the end of the first study year since this measure is available for all students in our sample and comparable for all students in a given study program. Due to endogenous course selection and different grading standards across courses, grades from non-compulsory courses in later years might not be comparable.

effects and indicators for scheduling conflicts. We include the latter to account for potential non-random assignment due to scheduling conflicts. To further increase the precision of the estimates, X also includes indicators for students' own gender, nationality and their GPA at the start of the course. u_{ic} is the error term. We follow the guidelines of Abadie et al. (2017) and cluster standard errors at the level of randomization, which is at the course level in our case.

We estimate additional models where we control for other peer characteristics such as GPA, gender and nationality to disentangle the impact of peer personality from these characteristics. The difference in the peer personality coefficient in the model with and without these controls provides information on the extent to which observables affect the relationship between peer personality and performance. If the estimates remain robust to the inclusion of these important observables, it is likely that they also are robust to factors not included in the estimations (see Altonji, Elder and Taber 2005). This would make us more confident that the parameters of interest α' capture the causal effect of peer personality on students' course grades. In order to investigate heterogeneous treatment effects, we also estimate a variant of (5) where we allow α' to vary by students' own level of the respective trait.

Feld and Zölitz (2017) have shown that classical measurement error in the peer characteristic of interest can lead to substantial overestimation of peer effects when peer group assignment is non-random. When peer group assignment is random – as is the case in our setting – classical measurement error will attenuate peer effects estimates, i.e. bias them towards zero. Since peer personality is arguably measured with a substantial amount of error, we can expect that our estimates of α' will be significantly attenuated. This implies that we identify lower bounds and that the true underlying effect is likely to be larger than our estimates.

In order to simplify the interpretation of our estimates, we standardize own and peer personality measures as well as course grades to have a mean of zero and unit variance.

A. Tests for Random Assignment

The key identifying assumption of this paper is that the assignment of students to sections (i.e. peer groups) is random. The scheduling procedure described in Section III ensures that student assignment to sections is random, conditional on scheduling conflicts. Using data from the same environment, Feld and Zölitz (2017) have shown that section assignment has the properties that one would expect under random assignment. In order to confirm this result with respect to the sample we study in this paper and with respect to peer personality, we perform two randomization tests. First, we test whether student personality relates to average peer personality in the assigned section. This randomization check closely follows Guryan, Kroft and Notowidigdo (2009) and controls for the course-level leave-out mean of the respective characteristic to account for the mechanical relationship between own- and peer-level variables. Table 3 reports the results of this analysis and shows that peer personality is not systematically related to students' own personality. All coefficients are small and not statistically significant, which confirms that the section assignment is random.

Second, we perform a more flexible randomization check that tests our key identifying assumption in a different way. Since we are interested in whether students with specific observables cluster in the same section, we regress pre-treatment student characteristics on a vector of section dummies. This exercise reveals whether the assigned section is systematically related to student characteristics. The results of this exercise are reported in Table A2 and show that the section assignment has the characteristics that we would expect under random assignment.

VI. Results

A. The Relationship between Students' Own Personality and Performance

Are personality traits relevant predictors of students' own performance? We investigate this question by looking at how students' own personality traits measured at the beginning of the first study year relate to student GPA at the end of their first year in university. Table 4 shows that all personality traits that we measure are significantly correlated with GPA. A one standard deviation increase in persistence is correlated with .11 standard deviations higher GPA. Self-confidence is also positively related to GPA with a similar magnitude. We further find that anxiety is negatively related to GPA. A one standard deviation increase in anxiety is associated with a .16 standard deviation reduction in GPA. We also find that students who are more risk seeking have lower GPAs, whereby a one standard deviation increase in risk tolerance is related to a .11 decrease in standardized GPA. For reference purposes, we also estimate a regression of GPA on a dummy variable that equals one if a student has a high school math major. As can be seen in Column (5), the size of the personality coefficients is roughly equal to one-third of the size of the high school math major indicator. In Column (6), we include all personality measures in one model. While the magnitude of some point estimates changes to by a small degree, all personality measures remain highly statistically significant. Figure 1 provides an illustration of these relationships. The plots in Figure 1 visualize the regression results reported in Column 6 of Table 4. The construction of these binned scatter plots follows Chetty, Friedman and Rockoff

(2014). We first regress course grades on the set of controls included in Column 6 of Table 4 to obtain the residualized course grades. Next, we rank-order our measures of personality and split them into seven equally-sized bins (i.e. septiles). Subsequently, we plot the mean of the residualized course grades within each bin against the normalized mean value of personality in that bin. Figure 1 shows that the relationships found in Table 4 are fairly linear.

Taken together, the results in Table 4 and Figure 1 show that students' own personality traits are relevant predictors of study success. Our findings are broadly consistent with previous work on the relationship between educational attainment and personality.[22]

B. The Impact of Peer Personality on Performance

Table 5 displays the estimation results of our main analysis, showing the extent to which peer personality affects students' grades.[23] We find that students who were randomly assigned to more persistent peers obtain higher exam grades. A one standard deviation increase in peer persistence raises grades by 1.8 percent of a standard deviation. We also find that exposure to risk-tolerant peers negatively affects grades negatively. A one standard deviation increase in peers' risk tolerance lowers grades by 1.5 percent of a standard deviation.

We do not find that peers' self-confidence or anxiety are significantly related to grades. We also do not find that peer GPA calculated based on all previously-taken courses at SBE is related to performance. This seems to contrast the earlier study by Feld and Zölitz (2017), who find small positive achievement peer effects in a larger sample of students at the same institution. One possible explanation for this could be that we measure GPA in the first year of studies, while Feld and Zölitz (2017) measure GPA based on a longer period. As our measure of GPA is constructed based on only a handful of grades, it plausibly contains more noise. This measurement error in ability likely attenuates the peer GPA coefficient, which makes it difficult to identify an effect here.[24]

Since our measures of peer personality might be collinear to some degree, we include all peer personality variables in one model in Column (6) of Table 5. Importantly, point

[22] Our concepts relate to Big Five traits typically studied in the literature on personality traits. Persistence is a facet of Big Five conscientiousness. Anxiety is a facet of Big Five neuroticism. Self-Confidence is a facet of Locus of Control. Borghans et al. (2008) show in their overview of the literature that conscientiousness is by far the best predictor of grades among the personality traits (r = .22), and that it is – after openness to experience – the best predictor of years of education (r = .11).

[23] Prior to testing whether peer personality affects grades, we tested whether first year study dropout is affected by peer personality (see Table A3). This was not the case.

[24] Note that our confidence interval includes the 0.0126 standard deviations estimated effect size of Feld and Zölitz (2017).

estimates remain very similar when we include all peer personality measures at once, instead of estimating models with one peer characteristic at a time. This suggests that our measures of peer personality capture distinct components of students' personality traits. In Column (7), we additionally include fixed effects for scheduling conflicts. Their inclusion does not substantially affect our point estimates, which is perhaps unsurprising given that scheduling conflicts are relatively rare and not related to grades or student personality.

In Column (8) of Table 5, we additionally include other observable peer characteristics as control variables. In particular, we include the proportion of female peers, the proportion of Dutch and German peers as well as the percentage of peers who have a high school math major. If peer personality affects performance mainly through these peer characteristics, we would expect the inclusion of these variables to reduce the effect size of the peer personality coefficients. Column (8) shows that this is not the case and that point estimates remain almost unchanged when we control for other peer observables. In the spirit of Altonji, Elder and Taber (2005), this result supports the idea that omitted variables bias can only play a limited role for our estimates.

Taken together, the point estimates presented in Table 5 show that peer personality has a causal impact on student achievement and that this personality peer effect is distinct from achievement, gender or country of origin peer effects. Figure 2 shows that the impact of peer persistence and peer risk tolerance on performance is fairly linear over the range of available support.

In order to assess the magnitude of our peer effect estimates, we can compare the effect size of peer persistence and risk tolerance to the relationship between one's own personality traits and educational outcomes. The size of peer persistence effects is approximately 17 percent of the relationship between one's own persistence and performance, while the size of peer risk tolerance effects is around 13 percent of the relationship between one's own risk tolerance and performance.

B. Heterogeneous Effects

From a policy perspective, an important question is how peer groups should be designed to maximize benefits arising from peer personality. In order to answer this question, we next investigate whether the impact of peer personality is heterogeneous, depending on students' own level of the respective trait. Based on students' own trait measures, we categorize students as low, medium or high types of a trait depending on the tertile to which they belong.[25] We then interact students' own type with the peer personality measure. Table 6 reports the estimates of this model, which allows for heterogeneous effects. Column (1) in Table 6 shows that only students in the bottom tertile of the persistence distribution benefit from a group of peers with high persistence. A one standard deviation increase in peer persistence raises grades of students with low persistence by 3.2 percent of a standard deviation. Students with medium and high persistence do not achieve significantly higher grades when they are exposed to more persistent peers.[26] Table 6 also shows that the negative impact of risk-tolerant peers is driven by students with medium risk tolerance. Column (2) shows that the results are again robust to the inclusion of other peer characteristics.[27]

Taken together, the results show that students who have little persistence benefit most from having highly-persistent peers. This finding suggests that own and peer persistence enter as substitutes in the education production function. Therefore, one plausible mechanism is that students who are less persistent and do not prepare well for class benefit most from the discussions with their well-prepared and highly-persistent peers. Importantly, we do not find evidence that highly-persistent peers are harmed by working with less-persistent peers. This finding suggests that mixing low- and high-persistence students together would lead to a Pareto improvement in achievement.[28]

We next turn to the question of whether personalities of peers in the tails of the distribution of the respective trait influence performance in the same way as average peer personality in the group. For instance, having very persistent peers (shining lights) may be particularly beneficial for performance. On the other hand, peers who have very limited persistence (bad apples) may be particularly detrimental for performance. We examine this by making an adjustment to equation (5): we replace the average peer personality by a variable measuring the average personality of the three peers with the highest level of personality traits in the group, as well as a variable with the average personality of the three peers with the lowest level of personality traits.

[25] Tertiles are defined based on the global distribution, and thus not at the section level.
[26] We formally test whether coefficients in Column (2) of Table 6 are statistically different from each other. Low-persistence students are not significantly more sensitive to peer persistence than medium persistence students. The difference between low- and high-persistence students is statistically significant at the 10% level.
[27] We also tested whether peer effects are heterogeneous by GPA of the student. Consistent with the findings discussed above, we find that students with low GPA benefit most from having peers with high persistence. Additionally, we do not find evidence that highly-persistent students are harmed by working with low GPA peers.
[28] Note that Carrell, Sacerdote and West (2013) caution against this type of prediction, as policies that manipulate the peer group composition may also lead to unintended changes in social interactions within the group that affect the outcomes of interest.

The results in Table 7 show that students benefit particularly from having very persistent peers in the group. However, peers who score very low on persistence do not seem to harm the group. The results indicate that when the average persistence of the three most persistent peers in a section is increased by one standard deviation, the grade increases by around five percent of a standard deviation. Similar to our results in the previous section, the persistence of peers at the bottom of the persistence distribution has no impact on student achievement. Moreover, we do not find that changes in the top and bottom of the self-confidence distribution in a group significantly affect performance, while the same holds for anxiety and risk tolerance. Taken together, our results suggest that particularly peers on the right tail of the persistence distribution boost academic performance.

C. Channels

How does the personality of peers affect students' grades? While there are many possible underlying mechanisms, our framework in Section 2 provides us with two classes of explanations. On the one hand, exposure to peers with more productive personality traits may prompt students to work harder. Peer pressure or reference group effects may induce students to prepare better for class, which could help them to achieve a higher grade. On the other hand, exposure to peers with more productive personality traits may simply make the time students spend in their peer group more productive. For example, peers with more productive traits may increase the level of classroom discussions, improve teacher motivation or engage in directly instructing their fellow students. As a result, students obtain higher grades without spending more time on their studies.

Using individual-level data from students' course evaluations, we can empirically distinguish between these two classes of explanations. At the end of each term, before learning about their grade students fill out an online evaluation questionnaire, which asks students to indicate the average number of hours that they studied for the course per week.[29]

First, before looking at the impact of peers, we analyze the extent to which own personality traits relate to study hours. Table A4 in the appendix shows that personality traits predict the number of hours that students study. As expected, persistent students study for more hours than less-persistent students. The effect is sizable: a one standard deviation increase in persistence is associated with 1.2 additional study hours, which is almost a 10 percent increase

[29] Since participation in the questionnaire is voluntary, not all students fill out the course evaluation forms. In the Appendix Table A3, Column (2), we reject that peer personality affects students' probability of responding to the student course evaluation survey.

from the baseline. We find similar effects for anxiety, while self-confidence and having a high school math major are negatively related to study effort. We do not find that risk tolerance is significantly related to study hours.

Table 8 shows estimates of how peer personality affects students' self-reported study hours using the same set of controls as in the previous regressions. Columns (1) and (2) show that exposure to more persistent peers does not significantly increase study hours. Both point estimates are small and not statistically significant. Therefore, we conclude that an increase in study effort is not the key mechanism behind our finding that persistent peers increase achievement. Students thus seem to benefit from more persistent peers without actually working harder.

We further find that peers' self-confidence and peers' risk tolerance are not significantly related to study effort. Perhaps surprisingly, the estimation results suggest that exposure to more anxious peers systematically increases students' study hours. A one standard deviation increase in peer anxiety increases weekly study hours by 0.4 hours, i.e. a 3 percent change from the baseline. Given the results of our main analysis – reported in Table 5 – the increased study efforts prompted by exposure to anxious peers does not lead to any measurable impact on performance.

Taken together, our analysis of student effort as an underlying channel suggests that grade improvements are not driven by an adjustment of study hours with respect to the peer composition. This points to the idea that more persistent peers create 'effortless' spillovers that make the fixed amount of time that students spend in their classroom section more productive.

VII. Conclusion

Previous literature on peer effects has studied the extent to which student performance depends on fellow students' achievement, gender and race. This paper focuses on a different aspect of student interaction and shows that peer personality causally affects student achievement in university. In order identify the causal impact of peers, we exploit the random assignment of students to university teaching sections.

Our results indicate that students who are exposed to more persistent peers and less risk-tolerant peers achieve higher grades. We find no evidence that peers' self-confidence or anxiety affect performance. We also study the heterogeneity of personality peer effects and while we find that students who have little persistence benefit most from having highly-persistent peers, we do not find evidence that highly-persistent peers are harmed by working with less-persistent peers. Moreover, we exploit data on self-reported study hours to investigate possible underlying mechanisms. We find no evidence that students change their study effort when exposed to persistent peers. Low-persistence students thus benefit from interacting with more persistent peers without any additional preparation efforts on their part.

Our results have important implications for policies related to student tracking and the design of peer groups. They suggest that mixing low- and high-persistence students in study groups would increase overall achievement. The results documented in this paper also have two important implications for the design of interventions and education policies that aim to improve socio-emotional skills. First, in settings where treated and non-treated students interact, changes in peer personality may positively affect the educational attainment of non-treated students, which will make it more difficult to detect an intervention impact. Second – and more generally – the social returns of any intervention that enhances socio-emotional skills will be underestimated if positive spillovers of personality on other individuals outside the studied environment are neglected.

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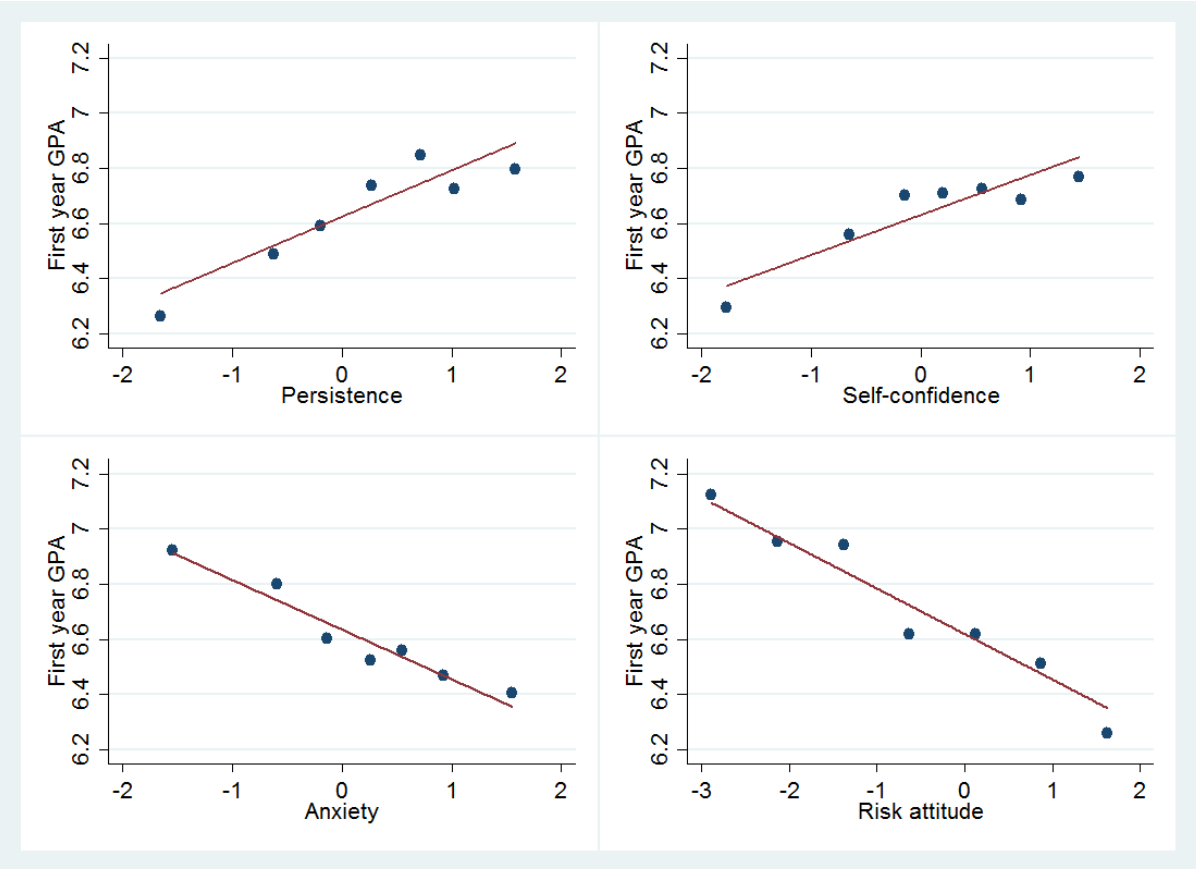
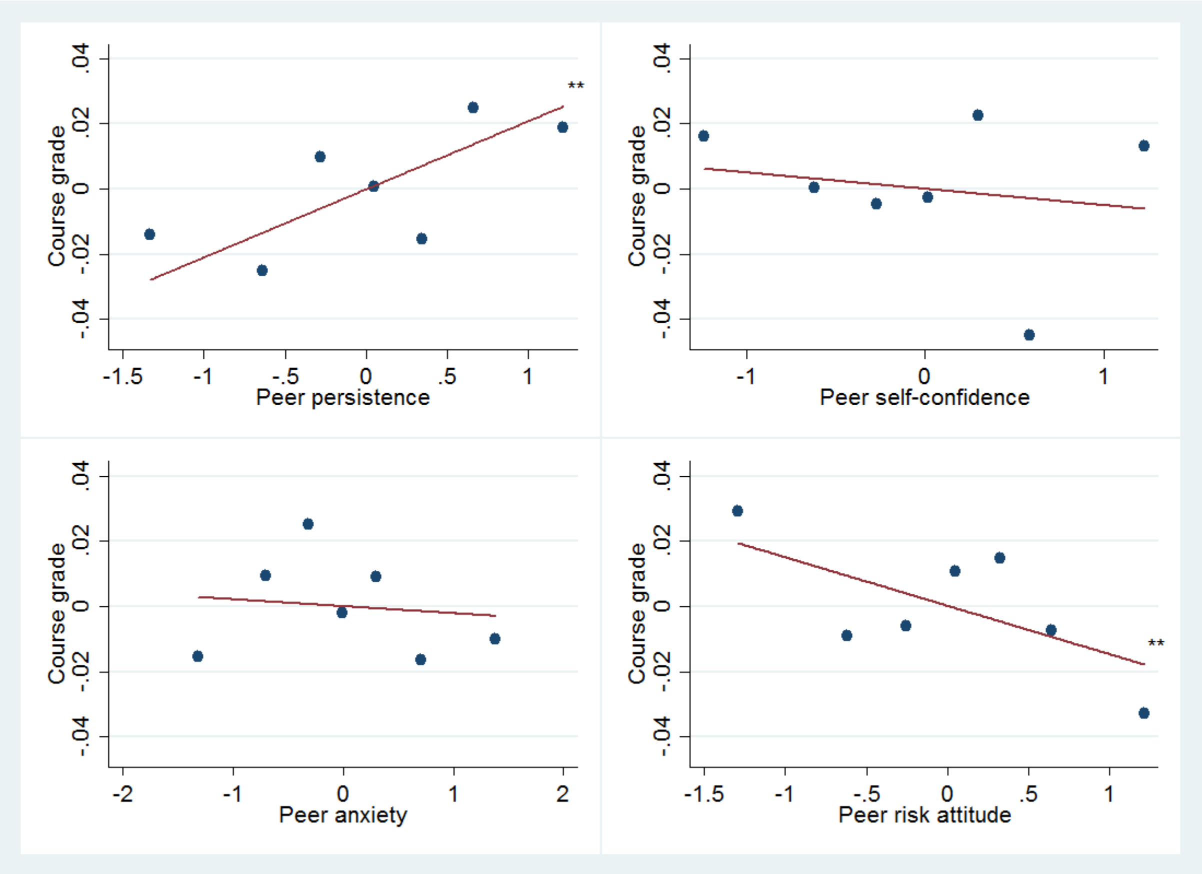
FIGURES AND TABLES

Figure 1: Student Personality and Performance



NOTE.— These plots visualize the regression results reported in Column 6 of Table 4. The construction of these binned scatter plots follows Chetty, Friedman and Rockoff (2014). We first regress course grades on the set of controls included in Column 6 of Table 4 to obtain the residualized course grades. Next, we rank-order our measures of personality and split them into seven equally-sized bins (i.e. septiles). We then plot the mean of the residualized course grades within each bin against the normalized mean value of personality in that bin. N=2,375.

Figure 2: Impact of Peer Personality on Performance



NOTE.—These plots visualize the regression results reported in Column 6 of Table 5. The construction of these binned scatter plots follows Chetty, Friedman and Rockoff (2014). We first regress course grades on the set of controls included in Column 6 of Table 5 to obtain the residualized course grades. Next, we rank-order our measures of peer personality and split them into seven equally-sized bins (i.e. septiles). We then plot the mean of the residualized course grades within each bin against the normalized mean value of peer personality in that bin. N=7,800.

Table 1: Descriptive Statistics

Panel A: Student-level characteristics	(1) N	(2) mean	(3) sd	(4) min	(5) max
Female	2,375	0.40	0.49	0.00	1.00
German	2,375	0.50	0.50	0.00	1.00
Dutch	2,375	0.24	0.43	0.00	1.00
GPA	2,375	6.97	1.49	2.00	10.00
Risk attitude	2,375	4.76	1.31	1.00	7.00
Self-confidence	2,375	5.84	0.70	3.00	7.00
Persistence	2,375	5.43	0.80	1.75	7.00
Anxiety	2,375	4.60	1.25	1.00	7.00
High school math major	2,375	0.33	0.47	0.00	1.00

Panel B: Section-level peer characteristics	(1) N	(2) mean	(3) sd	(4) min	(5) max
Peer persistence	654	5.39	0.25	4.42	6.50
Peer self-confidence	654	5.84	0.23	4.75	7.00
Peer anxiety	654	4.56	0.38	3.19	7.00
Peer risk attitude	654	4.84	0.51	3.00	7.00
Proportion of peers with high school math major	654	0.34	0.16	0.00	1.00
Peer GPA	654	6.81	0.61	3.50	8.62

Panel C: Student performance and study effort	(1) N	(2) mean	(3) sd	(4) min	(5) max
Course dropout	8,288	0.06	0.24	0.00	1.00
Course grade	7,789	6.48	1.60	1.00	10.00
Self-reported study hours	2,766	13.15	8.33	0.00	60.00

NOTE.—This table is based on our estimation sample.

Table 2: Measurement of Student Personality

Trait	Definition	Measurement
Persistence	How much students keep trying to work out an answer or to understand a problem even when that problem is difficult or is challenging.	Four items, e.g. "If my assignment is difficult, I keep working at it trying to figure it out."
Self-confidence	Students' belief and confidence in their ability to understand or to do well in their studies.	Four items, e.g. "If I try hard, I believe I can do my university work well."
Anxiety	Feeling nervous when thinking about their studies and worrying about not doing well in their studies.	Four items, e.g. "When exams and assignments are coming up, I worry a lot."
Risk attitude	Willingness to take risks.	"In general, how willing are you to take risks?"

NOTE. — All concepts are measured on a scale of 1-7. Persistence, Self-confidence, and Anxiety were taken from the Student Motivation Scale (Martin, 2009). For a discussion and validation of the measure of risk attitude, see Dohmen et al. (2011).

Table 3: Test for Random Assignment

	(1) Peer persistence	(2) Peer self-confidence	(3) Peer anxiety	(4) Peer risk attitude	(5) Peers high school math major
Persistence	0.0042				
	(0.007)				
Self-confidence		-0.0034			
		(0.005)			
Anxiety			-0.0027		
			(0.005)		
Risk attitude				0.0059	
				(0.005)	
High school math major					-0.0007
					(0.005)
Observations	8,288	8,288	8,288	8,288	8,288
R-squared	0.157	0.193	0.208	0.346	0.255
Course x year FE	YES	YES	YES	YES	YES
Indicators for scheduling conflicts	YES	YES	YES	YES	YES

NOTE.— The dependent variable in all columns is the standardized section-level leave-out mean of the respective characteristic, i.e. the average personality in a section excluding the student's own personality. Following the Guryan, Kroft and Notowidigdo (2009) correction method, we control for the course-level leave-out mean in all estimations. Robust standard errors clustered at the course level. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Student Personality and Student Achievement

	(1)	(2)	(3)	(4)	(5)	(6)
	Std. first year GPA	Std. first year GPA	Std. first year GPA	Std. first year GPA	Std. first year GPA	Std. first year GPA
Persistence	0.1054***					0.0751***
	(0.021)					(0.023)
Self-confidence		0.0991***				0.0439**
		(0.020)				(0.022)
Anxiety			-0.1588***			-0.1436***
			(0.021)			(0.021)
Risk attitude				-0.1093***		-0.1272***
				(0.020)		(0.020)
High school math major					0.3697***	0.3209***
					(0.041)	(0.041)
Observations	2,375	2,375	2,375	2,375	2,375	2,375
R-squared	0.098	0.097	0.109	0.098	0.117	0.157

NOTE.— All columns are estimated with ordinary least squares regressions that include cohort and study program fixed effects and control for gender and nationality (Dutch, German, other). Robust standard errors are in parentheses. * p<0.1, **p<0.05, ***p<0.01.

Table 5: The Effect of Peer Personality on Student Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Std. grade	Std. grade	Std. grade	Std. grade	Std. grade	Std. grade	Std. grade	Std. grade
Peer persistence	0.0181**					0.0204**	0.0187**	0.0181**
	(0.009)					(0.009)	(0.009)	(0.009)
Peer self-confidence		0.0041				-0.0046	-0.0037	-0.0038
		(0.008)				(0.009)	(0.009)	(0.009)
Peer anxiety			-0.0001			-0.0032	-0.0019	-0.0030
			(0.007)			(0.007)	(0.007)	(0.007)
Peer risk attitude				-0.0145*		-0.0161**	-0.0170**	-0.0169**
				(0.007)		(0.007)	(0.008)	(0.008)
Peer GPA					-0.0021	-0.0062	-0.0062	-0.0071
					(0.009)	(0.009)	(0.009)	(0.010)
Observations	7,789	7,789	7,789	7,789	7,789	7,789	7,789	7,789
R-squared	0.617	0.617	0.618	0.617	0.617	0.618	0.621	0.621
Indicators for scheduling conflicts	NO	NO	NO	NO	NO	NO	YES	YES
Controlling for peer gender, nationality and high school math major	NO	NO	NO	NO	NO	NO	NO	YES

NOTE.— All columns are estimated with ordinary least squares regressions that include measures for the respective own personality trait as well as course-year fixed effects, cohort dummies, female, Std. GPA, Dutch and German. Robust standard errors clustered at the course level are in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 6: Effect of Peer PersonaIity on Student Performance – Heterogeneous Effects

	(1) Std. grade	(2) Std. grade
Low persistence * Peer persistence	0.0318**	0.0307**
	(0.014)	(0.014)
Medium persistence * Peer persistence	0.0143	0.0138
	(0.014)	(0.013)
High persistence * Peer persistence	0.0090	0.0085
	(0.013)	(0.013)
Low self-confidence * Peer self-confidence	-0.0030	-0.0022
	(0.012)	(0.012)
Medium self-confidence * Peer self-confidence	0.0105	0.0101
	(0.012)	(0.013)
High self-confidence * Peer self-confidence	-0.0239	-0.0244
	(0.018)	(0.018)
Low anxiety * Peer anxiety	-0.0136	-0.0165
	(0.015)	(0.015)
Medium anxiety * Peer anxiety	0.0048	0.0026
	(0.014)	(0.014)
High anxiety * Peer anxiety	0.0073	0.0056
	(0.010)	(0.010)
Low risk * Peer risk attitude	-0.0074	-0.0079
	(0.006)	(0.006)
Medium risk * Peer risk attitude	-0.0410**	-0.0420**
	(0.017)	(0.017)
High risk * Peer risk attitude	-0.0123	-0.0136
	(0.032)	(0.032)
Observations	7,789	7,789
R-squared	0.622	0.622
P-value joint significance of peer variables	.0648	.0472
Controlling for peer gender, peer nationality and peer GPA	NO	YES

NOTE.— All columns are estimated with ordinary least squares regressions that include measures for the respective own personality trait as well as course-year fixed effects, indicators for scheduling conflicts, cohort dummies, female, Std. GPA, Dutch and German. Robust standard errors clustered at the course level are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Peer Personality - Bad Apples and Shining Lights

	(1) Std. grade	(2) Std. grade
Persistence of top 3 peers	0.0490**	0.0468**
	(0.022)	(0.021)
Persistence of bottom 3 peers	0.0098	0.0090
	(0.014)	(0.014)
Self-confidence of top 3 peers	0.0038	0.0047
	(0.026)	(0.027)
Self-confidence of bottom 3 peers	-0.0003	-0.0010
	(0.017)	(0.017)
Anxiety of top 3 peers	-0.0075	-0.0147
	(0.019)	(0.020)
Anxiety of bottom 3 peers	0.0125	0.0122
	(0.011)	(0.011)
Risk attitude of top 3 peers	0.0056	0.0080
	(0.027)	(0.027)
Risk attitude of bottom 3 peers	-0.0180	-0.0196
	(0.014)	(0.013)
Observations	7,752	7,752
R-squared	0.620	0.620
Controlling for peer gender, nationality and GPA	NO	YES

NOTE.— All columns are estimated with ordinary least squares regressions that include measures for the respective own personality trait as well as course-year fixed effects, indicators for scheduling conflicts, cohort dummies, female, Std. GPA, Dutch and German. The number of observations in this Table is lower than in the previous Tables since we lose all sections with fewer than six students. Robust standard errors clustered at the course level are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Mechanisms: Peer Personality and Student Effort

	(1) Study hours	(2) Study hours
Peer persistence	-0.1533	-0.1510
	(0.213)	(0.217)
Peer self-confidence	-0.1491	-0.1500
	(0.211)	(0.220)
Peer anxiety	0.3616**	0.3726**
	(0.145)	(0.149)
Peer risk attitude	0.2016	0.2036
	(0.150)	(0.154)
Peer GPA	0.2091	0.1741
	(0.186)	(0.174)
Observations	2,766	2,766
R-squared	0.114	0.115
Controlling for peer gender nationality and high school math major	NO	YES
Indicator for scheduling conflicts	YES	YES

NOTE.— All columns are estimated with ordinary least squares regressions that include measures for own study effort as well as course-year fixed effects, indicators for scheduling conflicts, cohort dummies, female, Std. GPA, Dutch and German. Robust standard errors clustered at the course level are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

APPENDIX

Table A1: Pairwise Correlations between Measures of Student Personality

	(1) Anxiety	(2) Risk attitude	(3) High school math major	(4) Persistence
Self-confidence	-0.1520***	0.1345***	0.0255	0.4757***
	(0.026)	(0.027)	(0.054)	(0.023)
Anxiety		-0.1643***	-0.1786***	0.0285
		(0.026)	(0.053)	(0.027)
Risk attitude			-0.1409***	0.0462
			(0.052)	(0.028)
High school math major				0.0469
				(0.052)

NOTE.— N=2,375

Table A2: Summary of Flexible Randomization Test

Does the Assigned Section Predict Individual Characteristics?

	(1) Number significant at the:			(2) Percent significant at the:			(3)	(4)	(5) P-value of test
Dependent variable:	5%	1%	0.1%	5%	1%	0.1%	Total tests performed	Mean of p-value	Mean of p-value different from 0.5
Female	2	0	0	4.3%	0.0%	0.0%	47	.4846	.7189
GPA	4	0	0	8.5%	0.0%	0.0%	47	.4908	.8304
Age	1	0	0	2.1%	0.0%	0.0%	47	.5003	.9917
ID rank	2	0	0	4.3%	0.0%	0.0%	47	.5368	.3744
Persistence	4	0	0	8.5%	0.0%	0.0%	47	.4660	.4522
Anxiety	2	0	0	4.3%	0.0%	0.0%	47	.5453	.2518
Self-confidence	2	1	0	4.3%	2.1%	0.0%	47	.5436	.3006
Risk attitude	4	0	0	8.5%	0.0%	0.0%	47	.4660	.4522
All characteristics	21	1	0	5.6%	0.3%	0.0%	376	.5042	.5465

NOTE.—This table provides evidence concerning the number of cases in which dummies for the assigned section significantly predict individual characteristics. The table is based on 376 separate OLS regressions with gender, GPA, age, ID rank, persistence, anxiety, self-confidence and risk attitude as dependent variables. The explanatory variables are a set of section dummies and dummies for scheduling conflicts and the nationality indicators German and Dutch. Column (1) shows in how many regressions the F-test on joint significance of all included section dummies is statistically significant at the 5 percent, 1 percent and .1 percent level, respectively. Column (2) shows the percentage of the regressions for which the F-test rejected the null hypothesis at the respective levels. In the absence of systematic sorting, we would expect 5 percent of tests to be significant at the 5 percent level, 1 percent to be significant at the 1 percent level, and .1 percent to be significant at the .1 percent level. For a more detailed explanation of this randomization check, see Feld and Zölitz (2017).

Table A3: Peer Personality and Course Dropout and Survey Response

	(1) Course dropout	(2) Survey response
Peer persistence	-0.0002	-0.0071
	(0.003)	(0.007)
Peer self-confidence	0.0013	-0.0092
	(0.003)	(0.006)
Peer anxiety	-0.0008	0.0102
	(0.003)	(0.006)
Peer risk attitude	-0.0046	-0.0046
	(0.003)	(0.007)
Proportion of peers with high school math major	0.0021	-0.0321
	(0.021)	(0.042)
Observations	8,288	8,288
R-squared	0.051	0.128

NOTE.— All columns are estimated with ordinary least squares regressions that include measures for the respective own personality trait as well as course-year fixed effects, indicators for scheduling conflicts, cohort dummies, female, Std. GPA, Dutch and German. Robust standard errors clustered at the course level are in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A4: Personality and Study Hours

	(1) Study hours	(2) Study hours	(3) Study hours	(4) Study hours	(5) Study hours	(6) Study hours	(7) Study hours	(8) Log study hours
Persistence	1.6703***	1.2147***					1.6703***	0.1244***
	(0.192)	(0.196)					(0.192)	(0.013)
Self-confidence	-0.7349***		-0.1730				-0.7349***	-0.0515***
	(0.123)		(0.150)				(0.123)	(0.011)
Anxiety	1.0236***			0.9729***			1.0236***	0.0876***
	(0.167)			(0.148)			(0.167)	(0.012)
Risk attitude	-0.0267				-0.1668		-0.0267	-0.0041
	(0.182)				(0.166)		(0.182)	(0.013)
High school math major	-0.4977*					-0.4811**	-0.4977*	-0.0382**
	(0.252)					(0.231)	(0.252)	(0.016)
Observations	2,766	2,766	2,766	2,766	2,766	2,766	2,766	2,763
R-squared	0.112	0.089	0.071	0.083	0.071	0.071	0.112	0.133

NOTE.— All columns are estimated with ordinary least squares regressions that include course-year fixed effects, indicators for scheduling conflicts, cohort dummies, female, Std. GPA, Dutch and German. Robust standard errors clustered at the course level are in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.