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RESEARCH ARTICLE

Peer desirability and academic achievement

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Summary

Using the random assignment of university engineering students to peer groups during introductory freshmen weeks, this paper studies how a student's parental income and facial attractiveness affect the grade outcomes of peers. The results show that exposure to highly desirable peers with respect to socioeconomic background and beauty improves grades. The results operate chiefly through a direct spillover channel and also through an indirect marriage market channel, through which exposure to high-desirability peers improves well-being. A field experiment suggests that the marriage market mechanism is likely to be limited to students not currently in a romantic relationship.

KEYWORDS

beauty, peer effects, socioeconomic status

1 | INTRODUCTION

Peer effects in education are one of the most studied phenomena in economics. In its most narrow sense, it refers to the observation that students perform better if exposed to classrooms with high-achieving classmates. Recently, economists have begun to explore how personality traits of peers affect academic outcomes. Examples of such traits include grit, self-confidence, and anxiety (Gerhards & Gravert, 2020; Golsteyn et al., 2021). In this paper, I examine how university students' socioeconomic status (SES) and physical beauty affect the academic performance of peers.

There are at least two reasons for why socioeconomic status and beauty would affect peer grades. First, socioeconomic status and physical attractiveness are significantly linked to academic outcomes. As an example of this, students with wealthy parents are more likely to interact with faculty, positively impacting grades by widening their information set (Kim & Sax, 2009). More generally, students from high-status backgrounds have more open social networks (Calvó-Armengol et al., 2009; Mehic, 2023). Since linkage to different social clusters reduces information redundancy and facilitates access to broader information, those with broader networks are likely to benefit academically. Other research has suggested that high-SES status students are more motivated to study and more altruistic than others (Falk et al., 2021). In terms of beauty, attractive college students receive higher grades than nonattractive peers (Hernández-Julián & Peters, 2017; Landy & Sigall, 1974). There is similar evidence about beautiful people being more likely to have broker positions in social networks (O'Connor & Gladstone, 2018). Any such positive effects on grades, regardless of whether driven by socioeconomy, beauty, or both, can cause positive spillovers to peers. Examples of propagation mechanisms include group assignments and informal study sessions.

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However, socioeconomic status and beauty are also seen as highly desirable traits on the marriage market.[1] Recent sociological evidence suggests that singles take into account these traits jointly when screening for a potential romantic partner and that couples are formed by matching on total desirability (McClintock, 2014).[2] Relatedly, besides being obvious predictors of dating success, social stratification and beauty are both status markers, and many people attribute desirable interpersonal qualities to high-SES and physically attractive individuals, even if they have no intent of pursuing a sexual relationship with that individual (Feingold, 1992; Lemay Jr et al., 2010; Webster & Driskell, 1983). Put simply, people enjoy being in the presence of beautiful and wealthy people, and individuals associate beauty and wealth with a wide range of positive attributes (Eagly et al., 1991; Marks et al., 1981; Paulus, 2016). Additional evidence shows that exposure to facial attractiveness increases neural activity (Chatterjee et al., 2009). Hence, being surrounded by highly desirable peers improves well-being, which should, in turn, positively affect academic performance (Cornaglia et al., 2015).[3]

Building on this theory, I construct a measure of a student's total desirability with respect to socioeconomic status and beauty. In the main model, these two traits are given equal weight in determining a student's desirability. For the identification strategy, I use data from the random assignment of undergraduate engineering freshmen into peer groups during orientation weeks at a Swedish university. The purpose of the orientation weeks is to familiarize newly admitted students with the university environment and to facilitate the creation of friendship bonds between the students. Since students are allocated to peer groups randomly, the setting eliminates the problem of students self-selecting into peer groups.

By matching data on peer group affiliation with 2 years of grade data for each student, detailed administrative records on parental income, as well as survey responses grading the physical beauty of each individual, I can causally identify the role played by peer desirability in terms of socioeconomic status and beauty on academic performance. Since all courses during the first 2 years of the engineering program are mandatory, there is no self-selection bias in the empirical design. Another advantage of the identification strategy is that students admitted to the engineering program in question are all on approximately the same academic level before commencing their studies. While the question on how peer effects in physical appearance affect academic performance has been studied previously (Hernández-Julián & Peters, 2018), this paper is the first to examine the role of peer beauty and socioeconomic status jointly. Additionally, this study is the first to use detailed administrative records to examine the academic consequences of peer socioeconomic status.

I have two main findings. First, a student's own desirability improves academic performance. This effect is particularly strong in courses with a high weight on group assignments and is driven primarily by socioeconomic status, although a student's own beauty is also positively related to grades. Second, the desirability of peers impacts academic achievement, with exposure to desirable peers significantly improving grades. The estimated peer effects are attenuated when considering the desirability characteristics individually, suggesting that these traits are to be taken into account jointly not to underestimate peer effects. An additional finding is that peer desirability affects major choice: Students allocated to groups with a high share of high-desirability opposite-sex peers are more likely to choose majors that lead to careers with more social interactions, such as in management consulting, as opposed to in finance or IT.

The finding that a student's own desirability impact grades positively implies the existence of direct spillover effects from peers. However, since peer effects are magnified when considered jointly, an indirect marriage market channel is likely to be an additional channel behind our results. I proceed by shedding light on the mechanisms behind this link. I design a field experiment among university students, in which the treatment group is shown a number of pictures of individuals perceived as beautiful, whereas the control group is shown a set of less attractive faces. The treatment is followed by a questionnaire, in which respondents are asked to rate their agreement with various statements on a 5-point Likert scale. Singles in the treatment group were significantly more optimistic about their subjective probability of passing the next exam and also rated their well-being higher vis-à-vis singles in the control group. This finding suggests that even ephemeral exposure to beauty has significant positive impacts on well-being, at least among those who are not currently in a romantic relationship. These positive effects on contentment are likely to cause academic spillovers, positively impacting in-class performance.

[1]Considering that college graduates are significantly more likely to be married to one another, higher education institutions are increasingly regarded as local marriage markets (Eika et al., 2019; Kirkebøen et al., 2022).

[2]This theory of assortative mating contrasts the more traditional beauty-status exchange model, under which it is assumed that one partner "exchanges" a high level of one trait for a high level of another trait (Buss, 1998; Juhn & McCue, 2017). Specifically, wealthy men desire attractive women, whereas physically attractive women trade beauty for a man's stratification status.

[3]In addition to socioeconomy and beauty, a variety of other potential "desirability pairs" have been suggested in recent research. These include couples matching on joint socioeconomy and health (Maralani & Portier, 2021), or in regions where HIV is endemic, on joint beauty, and sexual safety (Angelucci & Bennett, 2021).

This paper contributes to three different strands of work in economics and sociology. First, I contribute to the wide literature on peer effects in education (Carrell et al., 2013; Feld & Zöltz, 2017; Hill, 2015; Lavy & Schlosser, 2011; Sacerdote, 2001). Although most studies evaluate long-term interventions, a number of these papers have used a similar short-term intervention where students are randomly allocated to peer groups during freshman orientation weeks, albeit answering different questions than the ones posed in this article (Fisher & Rode, 2020; Thiemann, 2022). Most studies focus on the peer effect on grades, whereas a minority of papers examine other outcomes, most notably major choice (Aneli & Peri, 2019; Brenøe & Zölitz, 2020; Zöltz & Feld, 2021). My paper adds to this literature by examining the role played by the socioeconomic status and beauty of peers and how the interplay between these traits is shaping peer grades and major choice.

Secondly, the paper contributes to research on how student achievement varies by socioeconomic status (McEwan, 2004; Rivkin, 2001; Willms, 1986). However, these studies are oftentimes plagued with endogeneity concerns or unclear definitions of socioeconomic status (van Ewijk & Sleegers, 2010). Two recent random interventions from Peru and India, respectively, show that for low-SES students, exposure to high-status peers improves academic outcomes, whereas the effects on high-SES students are more modest (Adrianzén et al., 2019; Rao, 2019). Contrary to these findings, having high-status college peers in an elite US university in the early 1900s increased educational inequality through exposure to on-campus cliques that positively impact the academic and social outcomes of high-SES students, but not those from more frugal backgrounds (Michelman et al., 2022). I contribute to this literature by illustrating that peer socioeconomic status positively impacts grades; however, the results are considerably stronger when considering socioeconomic status jointly with peer beauty.

Finally, this paper complements the wide literature on the importance of beauty in shaping various outcomes, both in education and elsewhere. Being physically attractive is associated with a range of advantages in life: workers who are more attractive are more likely to be called back to an interview (Bóo et al., 2013), earn more money (Biddle & Hamermesh, 1998; Scholz & Sicinski, 2015), and are more satisfied with their careers (Hosoda et al., 2003). In addition, attractive teachers receive higher ratings from students (Hamermesh & Parker, 2005), beautiful politicians are more likely be elected to office (Berggren et al., 2010, 2017), while being unattractive increases a person's propensity for criminal activity (Mocan & Tekin, 2010). I add to this literature by illustrating the importance of peer beauty in shaping academic outcomes, at least when combined with peer socioeconomic status. Finally, if the positive grade effect stemming from peer beauty is a result of improved productivity, this finding has broader labor market implications, because it implies that hiring a physically attractive worker improves the productivity of that person's colleagues. This finding, thus, sheds new light on the origins and consequences of labor market discrimination.

The reminder of the paper is structured as follows. Section 2 describes the orientation weeks, and Section 3 presents the data. Section 4 outlines the empirical strategy and presents the main results. Section 5 discusses potential mechanisms. The paper concludes with Section 6.

2 | SETTING

2.1 | The industrial engineering program

At the Lund University, Faculty of Engineering, most undergraduate engineering programs are five-year programs leading to an MA in Engineering. The most competitive engineering program is the Industrial Engineering (denoted by I) program. Admission to Swedish universities is based solely on either high school grades or on the standardized entrance exams (equivalent to the SAT in the United States) and not on interviews or cover letters.[4] Regardless of whether a student is admitted through grades or through the standardized exam, all admitted students are approximately in the top 1.5% of university applicants nationally. This feature ensures that all students admitted to the program are on roughly the same academic level before starting their studies.

The first 2 years consist of mandatory courses in mathematics, physics, computer science, business administration, and economics, after which students choose one out of five possible specializations: business, finance, manufacturing, software engineering, and supply chain management, where the manufacturing and supply chain management majors are similar and are merged in the empirical analysis for simplicity. Majors are chosen towards the end of the third year. Students who choose the business and supply chain management majors are overrepresented in business development and management consulting in their later work lives, and underrepresented in finance and IT.

[4]Around two-thirds of applicants are admitted through high school grades and the reminder via the standardized admission test.

Table A.1 of Appendix A in the supporting information shows the year-by-year structure for the I program. The focus of this paper is on years 1 and 2, since all courses in the first 2 years are mandatory, and there is no selection into courses. Appendix B in the supporting information provides further details on the setting, including the admissions procedure described previously.

2.2 | The orientation weeks

The total number of students enrolled in the Industrial Engineering program is around 100 year per year, with around 80 completing the second year. To familiarize incoming freshmen with their future classmates, with the city of Lund, and with university life in general, the program starts with four student-led orientation weeks. When receiving their acceptance letter, admitted students are informed that the introduction meeting is 1 week before the start of lectures. This date, thus, marks the commencement of the orientation weeks. Hence, despite the orientation weeks being organized by the student union, the university facilitates and encourages participation. As a consequence, participation is *de facto* mandatory. At the start of the orientation weeks, students are allocated randomly to peer groups, the number of peer groups being around seven per year. In our sample, the average number of students per peer group is approximately 11. A student at the program describes the first day of the orientation weeks as follows:

> "It's kind of a lit thing really. On the first day, we have the introduction, we kind of meet all the teachers, or, rather, they present themselves. Then, directly afterwards, all the mentors enter and read out the names [of the peer group allocations] and then people run out, and they have pounding music outside and welcome everyone with hugs ..."[5]

As suggested by the quote, each peer group is allocated a number of senior students to act as mentors. The mentors are also allocated randomly among senior students interested in becoming mentors.[6] Importantly for the identification strategy, freshmen are not allowed to switch between different peer groups.

Table A.2 of Appendix A in the supporting information presents the schedule of a typical orientation week. The orientation weeks commence in Week 0, 1 week before the start of lectures. Whereas Week 1 is relatively "soft" in terms of scheduled classes, in Weeks 2 and 3, students are expected to spend around 40 h per week on their studies, so the number of freshmen activities is reduced. The end of the orientation weeks is marked by a large prom in Week 3. As indicated in Table A.2, there are some activities in which all freshmen regardless of peer group participate, but the lion's share of activities are separated by peer group. Since the bulk of the orientation weeks activities takes place before the start of lectures and assignments, there are no academic activities associated with the orientation weeks. Also, since the orientation weeks are strictly student-organized, the peer groups are unrelated to group allocations done by teachers and course administrators for educational purposes.[7] Thus, the only way that the orientation weeks can impact academic outcomes is through social interactions, not through variations in educational quality.

As the peer group teammates are the first classmates the freshman encounters, ties formed during the orientation weeks have potential to persist over time. Supporting this claim, several recent papers have found that friendship bonds formed early are predictive of persistent social ties throughout university (Back et al., 2008; Giese et al., 2020). Having a formal orientation week similar to the one in our setting reinforces these dynamics (Thiemann, 2022). In addition, in 4-year degree programs, there are only minor changes in interstudent social networks after 9 months (Overgoor et al., 2020), again pointing to the importance of early friendship connections.

3 | DATA

3.1 | Sample

At the Faculty of Engineering, passing grades are given by 3, 4, and 5, with 5 being the top grade.[8] The grading scale is absolute, meaning that the cutoff level for each grade is determined before the start of the course and is not affected by

[5]Transcription from an episode of a student-run podcast (Marhaug & Stefansson, 2020).

[6]Typically, a large majority (80%–90%) of the students in the previous cohort volunteer to be mentors for the younger cohort. Figure A.1 of Appendix A in the supporting information illustrates the partition into peer groups during the first day of the orientation weeks for one of the cohorts.

[7]For instance, allocations to TA sessions is typically based on surnames.

[8]The failing mark is "U" (Swed. *underkänd*, meaning "failed"). If a student did not take an exam, that particular course is treated as a missing observation. If the student did take the exam, but failed, I assign the value 1 to the course in question.

the relative performance of students. I use data from five cohorts, namely, from students starting their studies in 2015, 2016, 2017, 2018, and 2019. The cohorts are thus denoted I-15, I-16, I-17, I-18, and I-19, respectively. In total, the full sample includes 307 students, which is slightly lower than the total number of students who have completed the second year.[9] There are no significant differences between cohorts in terms of the share of students with missing personal data (one-way ANOVA F statistic 0.51, $p = 0.73$).[10]

As discussed previously, during the first 2 years, all courses are mandatory, meaning that students cannot self-select into courses. This also means that during the first 2 years, students cannot self-select into a particular section of a course. Hence, I restrict the sample to include all courses in the first 2 years of the program. In all, students take 15 courses during the first 2 years. Most courses run for one term only, and students always have two or three courses in parallel. Another feature is that every second exam during the first 2 years is typically in a mathematics course, whereas the other is in business administration, economics, or physics. Although there are a number exceptions to this principle, it will be of some importance for the econometric framework.

An advantage with this empirical setting is that a majority of the courses taken by students are taken by Industrial Engineering students only. That is, the freshmen orientation peer group is also the student's classroom peers. In courses where Industrial Engineering students have lectures together with students from other engineering tracks (chiefly first-year mathematics courses), allocation to TA sessions and seminars is normally based on engineering tracks, meaning that students in the Industrial Engineering program are not likely to encounter students from other engineering programs other than during lectures, even in this subset of courses. While acknowledging that classroom peers also matter, another, more general, motivation for focusing on orientation peer group friends is that friendship bonds formed outside formal academic settings, such as during orientation weeks or in conjunction with assignment to roommates, are likely to be stronger than classroom peer effects (Fisher & Rode, 2020; Jain & Kapoor, 2015). A self-reinforcing mechanism in the present context is that the student union for the Industrial Engineering program frequently arranges social events for its members during the semester, again suggesting that the orientation week peers are more likely to be encountered by the students outside the classroom, even after the orientation weeks.

3.2 | Measure of desirability and control variables

In this paper, I define desirability to consist of two distinct traits, namely, socioeconomic status and physical beauty. To operationalize socioeconomic status, I use register data from the Swedish Tax Authority to calculate the average labor income of both parents, measured in the same year that their children started their studies. The average income is then standardized at the total sample level (i.e., when including all five cohorts), so that the average income is equal to zero, and the standard deviation is equal to unity.

To quantify physical beauty, I recruit a jury consisting of 74 individuals. Since the number of students in the full sample is over 300, each jury member rates one-half of the sample only. Thus, each face receives an average of 37 independent ratings. The jury members are selected so that their average age and gender composition is not statistically different from the values observed in sample.[11] By using publicly available pictures of all students, I let each juror grade the faces using a scale from 1 to 10, where 1 is extremely unattractive and 10 is extremely attractive. Intercoder reliability was excellent (Cronbach's alpha = 0.94). I standardize the measure of physical beauty by rater and sex, so that the mean is zero, and the standard deviation is equal to 1. After taking the average of the standardized parental income and beauty variables, the total desirability variable is restandardized to ensure that the standard deviation is equal to unity. The average of a student's standardized parental income and her standardized physical beauty is then the individual's total desirability. This variable is also the main independent variable of interest in the paper. As control variables, I include data on the students' gender at birth and age.

[9] Of the 307 students, 37% are female. Of these, 270 remained until at least the third year, when majors are chosen. In terms of the gender distribution in choice of major, the merged supply chain management and manufacturing majors have an approximately equal gender distribution, the finance and software engineering majors are strongly male-dominated, and the business major is somewhat female-dominated. Of the 270 students, 101 selected the supply chain/manufacturing major (of which 47% were women), 82 selected the business major (with 59% women), 62 chose the finance major, and 25 selected the software major, with female shares of 19% and 8%, respectively.

[10] The most common reason behind this is if the student's parents are nonresidents of Sweden. In that case, the parent has no personal identity number in the population registry, and it is not possible to retrieve any income data.

[11] The average age of the raters is 19.73 years, which is not statistically different from the average age of the students when starting the program (20.06 years, $p = 0.14$). Among jury members, 44.6% were women, compared with 37.0% of the students in the sample ($p = 0.23$).

Figure A.2 of Appendix A in the supporting information illustrates the box-and-whisker diagrams of the nonstandardized values of parental income and beauty for each of the five cohorts. Table A.3 of Appendix A in the supporting information presents the summary statistics for all variables used in the empirical analysis. The average face rating was 4.72, and the average pretax parental income was around SEK 800,000.[12] A caveat to note is that while Swedish administrative records are considered high-quality (Maret-Ouda et al., 2017), using average income tends to lead to right-skewed values. Considering this, and the possible challenges with using a fairly “elite” sample of students, the presentation of the results in Section 4 provides additional discussions about the external validity of the findings, as well as a number of robustness checks. Appendix C in the supporting information presents the data sources for all variables and provides more detailed definitions.

In terms of the two variables used in the measure of desirability, it is generally assumed to exist a positive relationship between socioeconomic status and beauty. This is because better off people can afford more expensive clothes, spend more money on make-up and personal hygiene, may have different diets, and so on (Mafra et al., 2016). In addition, since attractiveness is associated with a wage premium, and because beauty is at least partially a genetic attribute, a positive relationship between parental income and student beauty is to be expected. On the other hand, it is possible that this effect is partially mitigated by, for instance, attractive mothers having married more well-off (but less attractive) men, diluting the relationship between parental income and the beauty of their children (Carmalt et al., 2008; Taylor & Glenn, 1976). Figure A.3 of Appendix A in the supporting information visualizes this relationship by showing a scatter plot of average parental income and beauty, showing a positive, albeit numerically insignificant correlation between the two traits.

3.3 | Survey data

As an additional way of examining potential mechanisms, I perform an online survey combined with a field experiment, which was implemented in February 2022. The purpose of the field experiment is to evaluate whether short-term exposure to attractive faces improves well-being and exam optimism and views about the future among a representative sample of students. If ephemeral exposure to aesthetically pleasing faces increases self-reported grit and well-being, longer-term exposure to beautiful classmates may have even greater positive effects, thus improving academic outcomes. The respondents are students at the Lund University School of Economics and Management, as well as students at the Industrial Engineering program at Uppsala University, Sweden. To increase the sample size, I use students enrolled in several different courses (not all majoring in Economics) and include course fixed effects to account for differences between cohorts. Two versions of the questionnaire are distributed. Allocation to treatment and control groups is done as good as randomly and is described in additional detail in Appendix C in the supporting information. The exact wording of the questions and answers available to respondents are presented in Appendix D in the supporting information, whereas Appendix E in the supporting information presents the full results for each question in the survey.

1. *Questionnaire outline*

   Both versions of the survey begin by asking respondents a number of basic questions about gender, socioeconomy, and relationship status.[13] In addition, this part of the questionnaire asks students about what traits they find important in romantic and nonromantic relationships, where each respondent rates the importance of various traits on a five-step Likert scale from “not at all important” to “very important”. I further include questions about study habits, namely, to what extend students participate in lectures and TA sessions and to what extent they communicate with teachers outside of class.
2. *Experiment design*

   The second part of the online survey differs between the treatment and control groups. Approximately half the sample grades 10 attractive faces, whereas the other half rates 10 nonattractive faces. Both for the treatment and the control group, there are five female and five male faces. Akin to the rating of the student pictures, the photos in the field experiment are rated on the 1–10 scale, where 1 is extremely unattractive and 10 is extremely attractive. The final section of the survey is again identical between groups. It asks about future career prospects (dream sector and starting salary), a yes/no question on whether the respondent would like to be a manager in the future and a number

[12] 1 USD = 9.96 SEK at the time of writing.

[13] Since it can be difficult for respondents to precisely estimate their parents' income, I construct a socioeconomic index based on student's demographic characteristics, standardized so that its mean is zero, and standard deviation is equal to unity. See Appendix C in the supporting information for details.

of questions where respondent is asked to rate their agreement with various statements on a 1–5 Likert scale. These include statements about the probability of passing the next exam, whether the respondent thinks that grades are important for future prospects and a general statement on future professional life and present well-being.

4 | EMPIRICAL STRATEGY AND RESULTS

4.1 | Own desirability and grade outcomes

I begin with examining whether a student's own desirability is related to academic performance. Unlike peer desirability, which can be considered exogenous through the orientation week allocation, the relationship between a student's own desirability and grade is not to be interpreted causally. Nevertheless, it serves as a preliminary step before introducing peer desirability in Section 4.2. The relationship between a student's own desirability and grades can be examined by estimating

$$y_{ict} = \rho_1 y_{ic,t-1} + \rho_2 y_{ic,t-2} + \xi X_{ic} + \lambda' \boldsymbol{W}_{ic} + \psi_c + \omega_t + \epsilon_{ict} \quad (1)$$

where y_{ict} is the grade of student i in cohort c in the course (subject) t, X_{ic} is the desirability of individual i, $\boldsymbol{W}_{ic}$ is a vector of individual-level controls, ψ_c are cohort fixed effects, ω_t are course fixed effects, and ϵ_{ict} is an idiosyncratic error term. The coefficient of interest is ξ. In this specification, the AR(1) term, namely, the one-period lagged grade $y_{ic,t-1}$, denotes the grade in the previous exam. Most applications of the dynamic panel model in economics make use of the one-period lagged dependent variable only. However, due to the course structure of the program discussed in Section 3.1, if y_{ict} is the grade in a mathematics course, the two-period lagged term $y_{ic,t-2}$ often represents the grade in a previous mathematics course and vice versa for nonmathematics courses. Considering that some students are innately better at mathematics, whereas others are not, we can expect significant persistence over two time periods.[14]

Table 1 gives the results of this regression. Columns (1) and (2) show the results when estimating the model using pooled ordinary least squares (OLS), columns (3) and (4) utilize the Arelleno–Bover system generalized method of moments (GMM), and columns (5) and (6) use the Blundell–Bond system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998). Since we have not yet introduced peer groups, I cluster standard errors at the cohort level. First, both the AR(1) and AR(2) coefficients are highly significant, suggesting that there is persistence both over one and two periods. Second, a student's own desirability significantly improves academic achievement; one standard deviation higher desirability improves grades by around 0.05 standard deviations when using GMM with the full set of controls. This coefficient is significant at the 1% level. There are only minor differences between the two versions of the GMM in terms of coefficient magnitude. Although the OLS and GMM estimates are numerically close, the OLS estimates are both biased and inconsistent and should be interpreted with some caution. Section 4.2 addresses a number of potential econometric concerns with the empirical strategy.

Considering that income distribution is right-skewed, I perform a robustness check by replacing the average parental income with the median income of the student's home municipality in the measurement of desirability. Table A.4 of Appendix A in the supporting information presents the results of this regression. The results are robust to this change, with the coefficient estimates increasing slightly in magnitude.

4.2 | Peer desirability characteristics and grade outcomes

1. *Main results*

   Having established the link between a student's own desirability and academic outcomes, this section examines the role of desirability on peer grade outcomes. Here, I use the following AR(2) dynamic panel variation of the standard linear-in-means peer effects model (Manski, 1993):

$$y_{icgt} = \phi_1 y_{icg,t-1} + \phi_2 y_{icg,t-2} + \beta X_{icg} + \gamma \bar{X}_{(i)cg} + \delta S_g + \boldsymbol{\theta}' \boldsymbol{W}_{icg} + \eta_c + \pi_t + \varepsilon_{icgt} \quad (2)$$

[14] In addition to this intuitive explanation behind including the AR(2) term, dropping it from equation causes the Arellano–Bond test for serial correlation (Arellano & Bond, 1991) to indicate that the idiosyncratic error term in levels is not serially uncorrelated. This technical point further motivates the inclusion of the AR(2) term.

TABLE 1 Impact of own desirability on grades.

Outcome variable: Standardized grades	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Grade$_{t-1}$	0.222***	0.222***	0.301***	0.312***	0.268***	0.267***
	(0.026)	(0.026)	(0.089)	(0.087)	(0.068)	(0.068)
Grade$_{t-2}$	0.323***	0.323***	0.162***	0.164***	0.169***	0.169***
	(0.019)	(0.019)	(0.023)	(0.022)	(0.023)	(0.023)
Own desirability	0.036**	0.039***	0.043***	0.046***	0.045***	0.049***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.003)	(0.005)
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Method	OLS	OLS	AB GMM	AB GMM	BB GMM	BB GMM
Observations	3645	3645	3645	3645	3645	3645
R^2	0.311	0.311				
Mean dep. var.	0.000	0.000	0.000	0.000	0.000	0.000
Hansen *J* test *p*-value			[1.00]	[1.00]	[1.00]	[1.00]
AR(3) test *p*-value			[0.51]	[0.51]	[0.39]	[0.39]

Note: Outcome variable: Standardized grades. Controls: The student's gender and age. Standard errors clustered by cohort in brackets.

Abbreviations: GMM, generalized method of moments; FE; fixed effects; OLS, ordinary least squares.

**Denotes significance at the 5% level.

***Denotes significance at 1% level.

TABLE 2 Impact of own and peer desirability on grades.

Outcome variable: Standardized grades	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Grade$_{t-1}$	0.221***	0.221***	0.294***	0.300***	0.260***	0.264***
	(0.026)	(0.026)	(0.088)	(0.086)	(0.067)	(0.066)
Grade$_{t-2}$	0.321***	0.321***	0.161***	0.163***	0.168***	0.169***
	(0.019)	(0.019)	(0.023)	(0.023)	(0.023)	(0.023)
Own desirability	0.036**	0.038**	0.048**	0.045***	0.045***	0.047***
	(0.014)	(0.014)	(0.021)	(0.016)	(0.017)	(0.016)
Peer desirability	0.030**	0.028**	0.034**	0.033**	0.037**	0.035**
	(0.013)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Method	OLS	OLS	AB GMM	AB GMM	BB GMM	BB GMM
Observations	3645	3645	3645	3645	3645	3645
R^2	0.312	0.312				
Mean dep. var.	0.000	0.000	0.000	0.000	0.000	0.000
Hansen *J* test *p*-value			[1.00]	[1.00]	[1.00]	[1.00]
AR(3) test *p*-value			[0.47]	[0.48]	[0.35]	[0.35]

Note: Outcome variable: Standardized grades. Controls: The student's gender, age, and the peer group size. Standard errors clustered by peer group in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Abbreviations: GMM, generalized method of moments; FE; fixed effects; OLS, ordinary least squares.

where y_{icgt} denotes the grade of student i in cohort c, and in peer group g in the course t, X_{icg} is the desirability of student i in cohort c and in peer group g, $\bar{X}_{(i)cg}$ is the average value of desirability of all members of group g in cohort c excluding i (known as the leave-out-mean), S_g is the number of students in group g, $\boldsymbol{W}_{icg}$ is a vector of individual-level controls, η_c are cohort fixed effects, π_t are the course fixed effects, and ε_{icgt} is an idiosyncratic error term. In this specification, the coefficient of interest is γ. Table 2 reports the results. Again, columns (1) and (2) give the pooled OLS estimates, while columns (3) and (4) and (5) and (6) use the Arellano–Bover and Blundell–Bond GMM estimates, respectively. We see that both own desirability and, importantly, peer desirability have a positive impact on academic outcomes. The main result from this part of the paper is that exposure to a one standard deviation higher average peer desirability raises grades by around 3.5% of a standard deviation. Previous studies on peer effects commonly estimate magnitudes of peer effects ranging from 0.02 to 0.08 standard deviations (cf. Brenøe & Zölitz, 2020; Gibbons, 2016; Thiemann, 2022).

Hence, the effect size is in line with most standard estimates of peer effects. The coefficient, denoted $\hat{\gamma}$, is statistically significant at the 5% level, and the result holds regardless of estimation method. The estimates are only marginally impacted by the inclusion of the controls for age, gender, and peer group size, suggesting that these traits are not driving the findings. In addition, the coefficient for a student's own desirability remains significant and is only marginally decreased, when including the variable for peer desirability.

Before examining heterogeneous effects, I will briefly address four potential econometric concerns. First, one might worry that the number of clusters is too low. In the specification in Section 4.1, which discusses the link between a student's own desirability and grades, I cluster standard errors by cohort, of which there are only five. In the current specification with peer effects, there are 32 orientation week peer groups. Although the latter number is larger, it could be considered low in certain situations (Cameron & Miller, 2015). Tables A.5 and A.6 of Appendix A in the supporting information replicate the results in Tables 1 and 2, correcting for potentially low cluster sizes by providing adjusted p-values using the wild clustered bootstrap technique (Cameron et al., 2008).[15] I use bootstrap weights drawn from the Webb distribution, which has been shown to perform well when the number of clusters is low (Webb, 2014). After correction, the estimated p-values increase slightly, particularly for the case with only five clusters. Importantly, however, none of our previous conclusions are altered by this procedure.

Second, considering that the number of observations is fairly large, there will be a large number of instruments as the GMM generates one instrument for each available lag and time period, the latter being equivalent to courses in our case. The "too good to be true" p-value of the Hansen J test in specifications (3)–(6) of Tables 1 and 2 is a possible indication of instrument proliferation. Two potential solutions include to limit the number of lags used as instruments or to collapse the instrument matrix (Roodman, 2009). Collapsing the instrument set in specification (6) in Table 2 gives similar estimates of the impact of peer desirability ($\hat{\gamma} = 0.044, p = 0.027$ for Blundell–Bond GMM). Returning to the results in Table 1, namely, when considering a student's own desirability only, collapsing the instrument matrix also yields similar estimates of the impact of own desirability ($\hat{\xi} = 0.061, p = 0.007$ for Blundell–Bond GMM), using the full set of controls in both cases.

A third potential concern is that the results could be sensitive to the inclusion of lagged grades. Disregarding the lagged grades gives estimates that are larger in magnitude, both for peer desirability in Table 2 ($\hat{\gamma} = 0.067, p = 0.014$) and for own desirability in Table 1 ($\hat{\xi} = 0.090, p = 0.001$), using the Blundell–Bond GMM with the full set of controls. On the other hand, both in Tables 1 and 2, the lagged coefficients are highly significant, suggesting that failing to correct for the lag structure of the grade data would lead to upwards biased coefficient estimates for own and peer desirability.

Finally, a concern is that teacher fixed effects might affect the results. A majority of teachers teach one course only and have had course responsibility for all five cohorts, meaning that this is not likely to be a major threat to the findings. Accordingly, augmenting with teacher fixed effects yields only minor changes in the main results presented in column (6) of Table 2 for peer desirability ($\hat{\gamma} = 0.049, p = 0.032$) and in column (6) of Table 1 for own desirability ($\hat{\xi} = 0.066, p = 0.004$). In sum, the main findings are robust to several alternative econometric specifications.

2. *Relative importance of peer socioeconomic status and beauty for grades*

What is the relative importance for peer effects of each of the two characteristics that constitute a student's total desirability? In the previous analyses, parental income and beauty were given equal weight when defining desirability. This section examines the effects on peer effects when giving different weight to socioeconomic status and beauty.

Figure 1 illustrates the point estimates $\hat{\gamma}$ and the 95% confidence bands associated with $\hat{\gamma}$ when re-estimating Equation (2) for various combinations of socioeconomic status and beauty. The horizontal axis shows the relative weight of beauty in constructing the standardized desirability measure. Hence, a value of 0 means that the measure is based fully on income, whereas 100 means that it is based fully on beauty. The coefficients are estimated using Blundell–Bond system GMM including the full set of controls, corresponding to column (6) in Table 2 when parental income and beauty were given equal weight. The results suggest that the largest peer effects occur when the relative weight of beauty is around 40%–60%, that is, when we give approximately equal weight to socioeconomic status and beauty. Conversely, there were no statistically significant peer effects when considering only parental income or beauty. Focusing on these measures individually instead of considering them jointly is thus likely to underestimate peer effects.

We may perform a similar decomposition when considering the impacts of a student's own characteristics. Table A.7 of Appendix A in the supporting information reports the results when re-estimating (1) separately for parental income

[15] Inference in the wild cluster bootstrap is based on p-values only. The algorithm does not produce any standard errors; instead, the bootstrap p-value is the share of the bootstrap statistics that are more extreme than the one from the original sample.

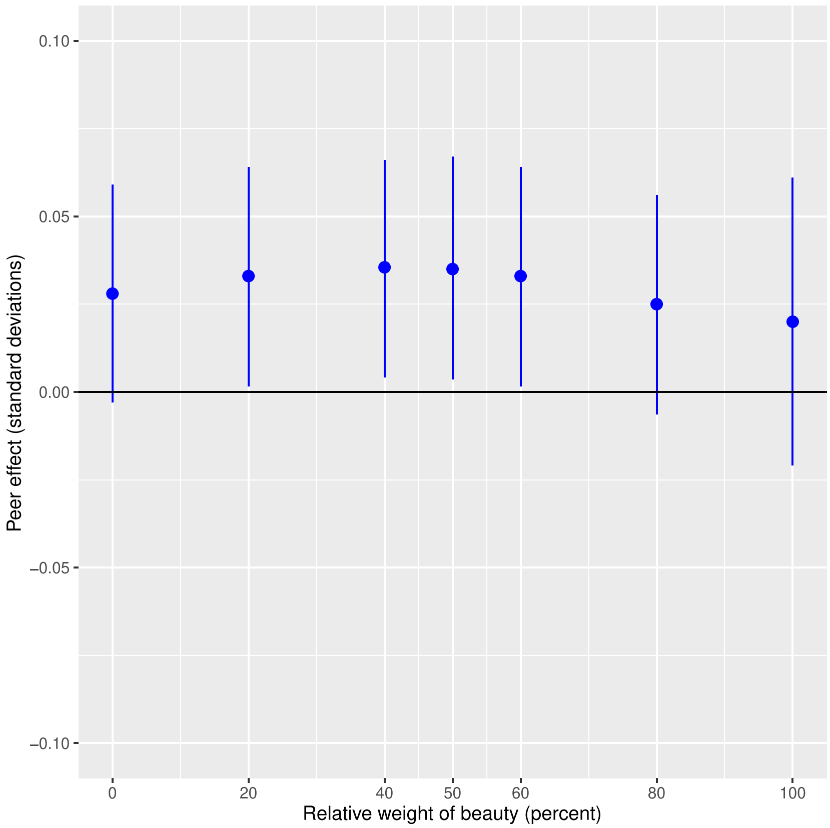

FIGURE 1 Coefficient estimates ($\hat{\gamma}$) and 95% confidence bands corresponding to re-estimating Equation (2) using Blundell–Bond GMM with the full set of controls, varying the relative weight of beauty compared with parental income in determining peer desirability.

and beauty. The grade effects of own desirability are mostly driven by socioeconomic status. A student's own beauty is positively related to grades but is insignificant when considered individually. Taken together, these results imply that high-desirability students perform better academically. Since the same traits are associated with positive peer effects, this finding indicates the presence of direct spillover effects to peers.

3. *Peer effects when conditioning on own desirability*
   I now turn to investigating whether the peer effects are driven by high- or low-desirability students, by splitting the sample by students' own standardized desirability (see, e.g., Algan et al., 2019). The results are presented in Table A.8 of Appendix A in the supporting information, indicating that peer effects are stronger for students with low values of own desirability. For high-desirability students, the estimated coefficients are close to zero. Taken together with the findings from Table 1, namely, that a student's own desirability is positively related to grades, these results speak in favor of a direct spillover mechanism, through which low-desirability students benefit from being allocated to peer groups with relatively many high-desirability students. This finding that peer effects are lower for high-desirability students is consistent with previous studies showing that high-SES students are less likely to benefit academically from interacting with low-SES students when randomized into peer groups (Rao, 2019).

4.3 | Robustness checks

In addition to the concerns about cluster size and instrument proliferation, this section briefly performs a number of supplementary robustness checks.

1. *Test for random assignment*
   The identification strategy relies heavily on the assumption that assignment to peer groups was random with respect to peer desirability. Intuitively, since the students responsible for the allocation to peer groups have no information on these traits, it seems unlikely that beauty and parental income would effect allocation.[16] To test this claim formally, I perform a standard randomization check. It involves regressing the students' own standardized desirability on the standardized leave-out-mean of the desirability in the assigned peer group. However, a problem with this procedure

[16]The peer group allocation is done before the mentors meet the students.

is that randomization induces a negative correlation between own and peer desirability. The reason for this bias is that students cannot be their own peers. Thus, students with a high value of desirability draw peers from an urn of students with, on average, lower values of the trait. I correct for this bias by using a standard approach in the peer effects literature, namely, controlling for the leave-out-one mean at the level of randomization (Feld & Zöltz, 2017; Golsteyn et al., 2021; Guryan et al., 2009). In our case, randomization is performed at the cohort level. To further increase the precision of the estimates, I include controls for student age, gender, as well as the group size variable S_g, and the cohort fixed effect η_c. In addition to total desirability, I perform the same randomization check for parental income and beauty separately. Table A.9 of Appendix A in the supporting information reports the results. The small and statistically insignificant coefficients are consistent with assignment to peer groups being random with respect to desirability and also with respect to the two traits separately.

2. *The importance of peer group member for future friendship bonds*

   Another key assumption is that the peer groups are predictive of friendship bonds. In other words, that students remain friends with their orientation week group members. If this were not the case, we would not be able to credibly estimate any peer effects. To test this claim more formally, I use that during one course early in the second year of the program, students self-select into groups of three to four classmates when writing a mandatory group assignment. If peer group members are disproportionately represented in student's assignment groups, it is possible to conclude that the peer groups formed during the orientation week predict persisting friendship bonds. For each student, I calculate the number of assignment group members that were also in the student's orientation week peer group. With this information, it is straightforward to calculate the empirical distribution of overlapping friends. That is, the share of students with no peer group members in their assignment group, the share with one friend, and so on. Using basic combinatorics, I proceed by calculating the corresponding shares if assignment group members were chosen randomly.[17]

   Figure 2 plots the observed and approximate theoretical (expected) distributions of overlapping friends. We can see that a majority of students, 54%, chose to partner with at least one of their peer group friends, which significantly contrasts the expected share: If assignment group members were chosen randomly, only 32% would have at least one peer group friend in their assignment team. There are similar discrepancies for other values of the number of overlapping friends. For example, the expected share of students partnering with exactly two friends was around 11%, which is considerably higher than the predicted 3.5%. Overall, the difference between the empirical and theoretical distributions is highly significant, with the p-value of Fisher's exact test equal to 0.00036. This finding suggests that the orientation weeks groups, although not meant to last long, are indeed predictive of future within-cohort friendship bonds.

3. *The impact of the COVID-19 pandemic*

   Although Sweden had fewer restrictions than most countries during the COVID-19 pandemic, however, during the entire 2020/21 academic year, teaching was chiefly online, with the exception of some small-group TA sessions during September and October 2020. This change impacted the I-19 cohort. Table A.10 of Appendix A in the supporting information presents the results when re-estimating the main specification, excluding the I-19 cohort during the 2020/21 academic year. While the number of observations decreases from 3645 to 3021, the coefficient estimates for peer and own desirability are only marginally affected, and the results remain statistically significant, albeit at the 10% level for peer desirability.

4. *Differential effects in courses with self-selection to group assignments*

   Eight of the 15 courses have some type of group assignments in which students self-select into peer groups. In these courses, peer effects are likely to be even stronger if students self-select to be with their orientation week friends. Table A.11 of Appendix A in the supporting information re-estimates the main results for these courses only. While the estimates of the effect from own desirability stay unchanged, the coefficient estimates for peer desirability are around 40% higher in these courses compared with the baseline estimates in Table 2, which is reasonable, given that students are more likely to self-select to join their orientation weeks peers.

5 | EVIDENCE ON MECHANISMS

The main finding of this paper is that socioeconomic status and beauty are jointly associated with significant peer effects. This could be due to two mechanisms. First, there is a *direct academic channel*, where the higher academic performance of high-SES and physically attractive students causes spillover effects to peers. Another potential channel is an indirect

[17]See Appendix B in the supporting information for the derivation of the expected shares.

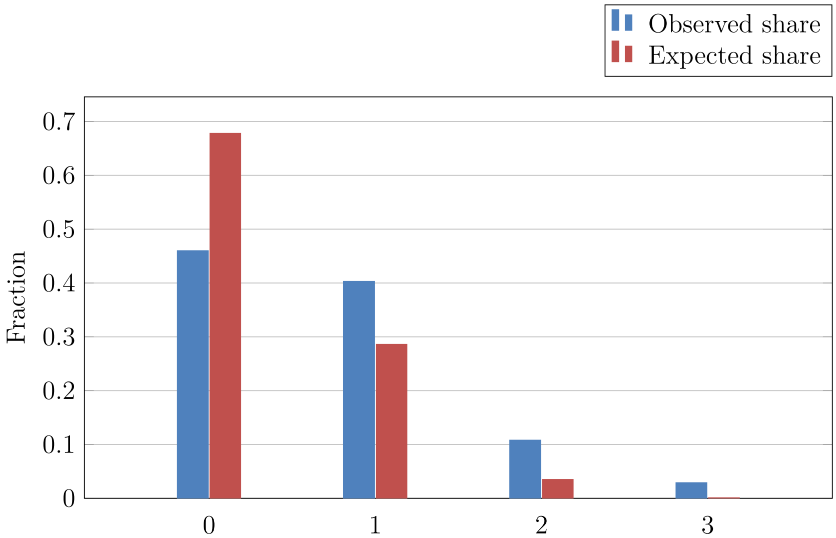

FIGURE 2 The observed and expected frequencies of the number of friends from the freshman week in the student's assignment group. The observed shares are based from the universe of available observations from cohorts I-18 and I-19; $N = 139$. The Fisher exact p-value is 0.00036 under the null hypothesis of equal distributions. For additional details, see Appendix B in the supporting information.

link, through which exposure to peer beauty creates positive externalities, improving a student's exam optimism and well-being. We may interpret this as a *marriage market channel*. Although we cannot exclude such a link in the opposite direction, where exposure to high-SES classmates improves well-being, this direction is likely to be of less importance, due to the relatively lower weight that students place on the socioeconomic status of a romantic partner. In the following section, I attempt to distinguish between these potential mechanisms and provide additional evidence on the relationship between exposure to attractiveness and the well-being of students.

5.1 | Direct versus indirect effects of peer desirability on grades

This subsection discusses briefly a number of ways to distinguish between the direct spillover mechanism and the indirect marriage market mechanism.

1. *Effects of lagged peer grades*
   I begin by including a control for the average peer grade in the previous course. If peer grades in the previous course are important, it speaks in favor of the direct spillover mechanism, as it would indicate that desirable students help their peers learn more. A simple fixed effects regression with standardized grades as the outcome variable, and the standardized lagged peer grades as the independent variable, shows that one standard deviation higher average peer grades in the previous course increases a student's own grades by about 0.08σ ($p = 0.000$), suggesting that there are indeed direct spillover effects from peers. Importantly, however, including the average peer grades in the previous course does not significantly affect the results about peer desirability; the coefficient estimate for peer effects in Table 2 is even increased to 0.061 ($p = 0.017$). Similarly, the results are robust to including the two-period lagged average peer grade. Table A.12 of Appendix A in the supporting information presents these results in table format.
2. *Major choice, gender composition of the peer group, and differential effects depending on student gender*
   Another way through which peer socioeconomic status and beauty can affect human capital formation is through effects on major choice. Table 3, column (1), presents the logit estimates when regressing a binary variable equal to unity if the student has selected either the business or supply chain major. The results indicate that there is no significant overall relationship between peer desirability and major choice. However, to differentiate between the spillover mechanism and the marriage market mechanism, the gender composition of the peer group could be of importance. This could give rise to heterogeneous effects on major choice, since a heterosexual male student is likely to be affected by the appearance of his female peers, but not by that of his male peers. Thus, if the gender composition matters for major choice, it would speak in favor of the marriage market mechanism. Assuming that a majority of the students are heterosexual, I define the gender composition as the share of female peers in the orientation group for male students, and the share of male peers for female students, and interact this variable with peer desirability.

   The interaction between peer desirability and gender composition is significant at the 10% level, as seen in Table 3, columns (2) and (3), which report the logit and probit estimates, respectively. This finding suggests that male students in peer groups with relatively many high-desirability women, and female students in peer groups with a large share of

TABLE 3 Impact of own desirability on major choice.

Outcome variable: Business or supply chain major	(1)	(2)	(3)
Own desirability	−0.169	−0.208	−0.134
	(0.215)	(0.203)	(0.112)
Peer desirability	0.171	−0.703	−0.411
	(0.197)	(0.544)	(0.319)
Gender composition		−1.320	−0.876
		(0.922)	(0.538)
Peer desirability × gender composition		2.073*	1.140*
		(1.115)	(0.644)
Course FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Method	Logit	Logit	Probit
Observations	269	269	269
Pseudo R^2	0.125	0.134	0.137
Mean dep. var.	0.000	0.000	0.000

Note: Outcome variable: A binary variable taking the value 1 if the student majored in business or supply chain management. Controls: The student's gender, age, and the peer group size. Standard errors clustered by peer group in brackets.
Abbreviation: FE; fixed effects.
**Denotes significance at the 5% level.
***Denote significance at the 1% level.

high-desirability men, were more likely to choose the business or supply chain majors. Professions such as business development and consulting typically place high weight on social skills, and the workplaces tend to feature more equal gender distributions, compared to the finance or IT sectors.[18] However, the results on grades, as opposed to major choice, are not affected by the gender composition of the peer group. Adding the variable for gender composition, and its interaction with peer desirability to the main results presented in Table 2, gives a statistically insignificant coefficient for the interaction term (0.021, $p = 0.84$). More broadly, it is possible to examine whether the main results in Table 2 differ between male and female students. Subsetting the sample by gender yields coefficient estimates of 0.051 ($p = 0.16$) for the males and 0.026 ($p = 0.18$) for the females, respectively. While reducing the number of students leads to a loss of statistical power and insignificant estimates, the coefficient estimates are still informative, suggesting that peer effects of desirability on grades are around twice as high for the male students.

3. *Heterogeneity depending on course type*

   Previous studies have suggested that peer effects in education are likely to be more pronounced in mathematics and natural sciences, compared with in the humanities and social sciences (Carrell et al., 2009; Brunello et al., 1998). In the Industrial Engineering program, there are both quantitative courses, such as in mathematics and physics, and courses in business administration and supply chain management, which focus less on mathematical calculations. Repeating the main results from Table 2 for the courses in mathematics and physics only yields somewhat larger estimates of peer effects ($\hat{\gamma} = 0.050, p = 0.071$), with the coefficient estimate significant at the 10% level despite the reduction in sample size. Additionally, this finding speaks more in favor of the direct spillover mechanism, as a potential marriage market mechanism should not be dependent on the type of course.

5.2 | A field experiment on the effects of exposure to physical beauty

The previous analysis suggests that both the direct spillover mechanism as well as the indirect marriage market mechanism are possible explanations for the findings about the impact of peer desirability on grades. The purpose of this field experiment is to examine how exposure to beauty affects the well-being, exam optimism, and future career plans of a similar sample of students.

1. *Preliminary analyses*

[18] Since peer desirability impacts major choice in the third year and beyond, this result complements previous findings about the long-term strength of the friendship bonds created during the orientation weeks.

Before analyzing the role of exposure to beautiful faces in creating positive externalities, I begin by evaluating descriptively what characteristics respondents find important in a romantic partner. Notably, over 72% respondents reported that beauty was "somewhat important" in a potential romantic partner, while 11% found it to be "very important". If we consider the rating scale as a 1–5 Likert scale instead of a nonnumeric scale, where "not at all important" is given the value 1, "not so important" the value 2, and so on, we may note that male students placed significantly more weight on beauty than females (coefficient estimate 0.258, $p = 0.002$). Examining the views on the second trait of interest, a plurality of respondents, 39.6%, regarded the income of a potential partner as "neither important nor unimportant", although 31.5% found it to be at least somewhat important. This finding also suggests that any marriage market mechanism is likely to chiefly operate through exposure to beauty, and not through exposure to socioeconomic status. Again converting to the 1–5 scale, women were significantly more likely than men to find income important in a romantic partner (coefficient estimate 0.627, $p < 0.001$).

2. *Main experiment results*

Proceeding from here, I examine the role of treatment, that is, exposure to aesthetically pleasing faces, in shaping views about future academic and professional outcomes. Table A.13 of Appendix A in the supporting information presents the balance tests between treatment and control groups with respect to socioeconomic status, gender, and relationship status. There are no significant differences between the treatment and control groups in terms of these traits. As expected, the average beauty of all 10 faces was estimated to be significantly higher in the treatment group compared with the control group (6.59 and 3.79, respectively, $p < 0.001$). However, there is nothing to suggest that singles were more generous in their ratings.[19]

Table 4 reports the OLS results when regressing the outcome on the 1–5 scale on the treatment dummy and a set of student-specific controls. Both for the question about anticipated performance on future exams, as well as for the general question about well-being, there is a positive and significant effect of treatment when interacted with the indicator for being single. This finding is important for understanding why grades improved when students were exposed to attractive classmates, as it suggests that even ephemeral exposure to beautiful faces increases optimism and self-estimated well-being among single respondents. This finding further suggests that any peer effects from beauty is likely to be driven by singles and not by those in a committed relationship. Table A.14 of Appendix A in the supporting information includes an indicator variable taking the value 1 if the respondent claimed that beauty is "very important" in a romantic partner. The results are somewhat stronger when augmenting with this variable, although the numerical differences are relatively minor.

It should be acknowledged that just having seen pictures of attractive individuals is different from having interacted with them, and the effect from interacting with attractive peers may not last over the academic year. On the other hand, since students in the program spend considerable time with their peer group friends, the true underlying effect is likely to be magnified by, for instance, networking. An additional caveat to note in this experiment is the possibility of self-evaluation bias. Although studies generally show a positive association between motivational beliefs and grades (Corkin et al., 2017; Morisano et al., 2010), overconfidence may be detrimental to achievement, for instance, through reducing study hours (Wilkinson & Klaes, 2012, pp. 124–126). In the present setting, a potential problem is that the increased optimism and well-being observed by singles in the treatment group could make them more likely to be overconfident about their anticipated performance on future exams. Previous studies in psychology generally support a positive, albeit numerically small, relationship between positive mood and overconfidence, suggesting that any overconfidence induced by exposure to attractive faces is unlikely to significantly affect the results (Allwood et al., 2002; Ifcher & Zarghamee, 2014).

To address the concern that when using OLS, the distance between the options available to respondents is all assumed to be equal, which is a strong assumption if the outcome variable is a rating scale score.[20] Relaxing this assumption, Table A.15 of Appendix A in the supporting information shows the results when using ordered logit in lieu of OLS. The results are robust to this modification.

Moving on to evaluating the students' views about their future careers, as reported in Table A.16 of Appendix A in the supporting information, there is no effect of treatment on estimated starting salaries or the willingness to become a manager. It should be noted that a large majority of respondents preferred the private sector, and an even larger share

[19]A simple linear regression with the average rating as the dependent variable on a constant and the dummy for being single gives a coefficient estimate of 0.267, and a corresponding robust standard error is equal to 0.252 ($p = 0.290$). Additionally controlling for treatment gives a corresponding coefficient estimate of 0.042, and a robust standard error is equal to 0.151 ($p = 0.780$).

[20]Often, respondents tend to place themselves in the "middle" of the option set, in this case around 3.

TABLE 4 Experiment results.

	Probability of passing upcoming exams		Importance of grades for future career		View on future professional life		"How do you feel right now?"	
Treatment	0.092	−0.285	0.114	−0.078	0.022	−0.116	−0.066	−0.447*
	(0.135)	(0.199)	(0.200)	(0.153)	(0.129)	(0.182)	(0.156)	(0.235)
Single		−0.316		0.103		−0.381**		− 0.605**
		(1.697)		(0.229)		(0.177)		(0.235)
Treatment × single		0.548**		0.292		0.200		0.611**
		(0.256)		(0.309)		(0.251)		(0.308)
Controls included	No	Yes	No	Yes	No	Yes	No	Yes
Observations	195	195	194	194	197	197	196	196
R^2	0.002	0.156	0.003	0.036	0.000	0.072	0.001	0.080
Mean dep. var.	3.15	3.15	3.49	3.49	3.98	3.98	3.43	3.43

Note: OLS estimates. Outcome variable: Agreement on a 1–5 Likert scale. Controls: Gender, socioeconomic status, relationship status, and course and university fixed effects. White heteroscedasticity robust standard errors are in brackets.

*Denotes significance at the 10% level.

**Denotes significance at the 5% level.

would be interested in becoming a manager in the future (68% and 83%, respectively). This means that variation is relatively low between treatment and control groups for these two questions.

3. *Overall assessment about mechanisms* The results presented in this section, suggest that, overall, there is more support for the direct spillover mechanism. However, since the gender composition of the peer group is of importance for major choice, and since the peer effects are stronger when beauty is considered jointly with socioeconomic status, the marriage market, or optimism, mechanism cannot be excluded. While the results of the field experiment should be viewed with some caution, there is reason to believe that a potential marriage market mechanism is driven by students not currently in a romantic relationship.

6 | CONCLUDING REMARKS

In this paper, I study the role of peer desirability with respect to socioeconomy and beauty in shaping academic outcomes, using the random allocation of engineering students to peer groups during freshman orientation weeks. I show that students allocated to peer groups with highly desirable classmates with respect to socioeconomic status and beauty have better grades. In addition, a student's own socioeconomic status and beauty impact grades positively. Using a field experiment, I further show that single respondents exposed to physically attractive faces are more optimistic about passing exams and report higher levels of well-being. This finding suggests that peer effects operate, at least partially, by an indirect channel, in addition to a direct spillover channel, through which variations in peer beauty affect well-being.

Improvements in grades reflect, at least to some extent, increases in student productivity. Thus, a natural extension is to examine the role of peer desirability in other settings, for instance, in the labor market. The results of this paper imply that hiring a high-SES or physically attractive worker improves the productivity of that person's co-workers. These effects are likely to be particularly strong for unmarried junior professionals and can have significant long-term ramifications (Hamermesh, 2011). Taken together, the findings in this paper expand our knowledge about labor market discrimination.

There are a number of directions for future research. Similar to other studies that rely on data from one specific institution, more work is required to understand how these findings translate to other contexts. For example, the peer effects from socioeconomic status and beauty may matter less in settings where there is less contact between students, for instance, in distance education. On the other hand, the peer effects are likely to be more pronounced in college programs that place an even greater weight on group assignments. A second perspective is that the present study relies on data from high-preforming students. It could be the case that socioeconomic status and physical attractiveness are even more salient than in the general population in this high-performing sample of students, since other aspects of desirability are likely to be similar among the students. A possible extension would be to examine the role of peer desirability in shaping academic outcomes in settings with more disadvantaged individuals, for instance, low-SES students, or students enrolled in less competitive programs.

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OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at https://doi.org/10.15456/jae.2023262.0850171527.

DATA AVAILABILITY STATEMENT

Data is available through the journal data archive page (https://journaldata.zbw.eu/journals/jae).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of the article.

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