Social Interactions and College Choice*

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Abstract

We examine the effect of peers on one of the most salient human capital investments affecting an individual's labor market outcomes: whether and where to go to college. Using rich administrative data from a large school district in Minnesota, we exploit detailed information about courses taken by students and random classroom assignments for identification of peer effects. We address the reflection problem by instrumenting the choices made by a student's direct peers by the decisions made by the peers of their peers. We find that peers have a significant positive effect on a student's probability of applying to a particular college. Moreover, the average quality of one's peers' applications increases own application quality sizably and significantly. On average, students respond more strongly to application decisions made by peers who are white, are of high socio-economic status (SES), and have a high GPA. Examining within-group peer effects, we find that the strong average response to high-SES peers is driven by high-SES students, while the low-SES students respond more to their low-SES peers. We do not detect effects of peers on students of the same type for any other demographic group. Using survey data on uptake of various school-provided counseling services, we illustrate that the flow of information from more informed peers to less informed ones is a potential mechanism through which peers affect their classmates.

JEL: I21, I23, I24

Keywords: Peer effects, college quality, college applications, human capital investment

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1 Introduction

College quality has been found to increase the return to college for minority and disadvantaged students in the United States (Dale and Krueger, 2002, 2014). Yet, even conditional on test scores, students of different socioeconomic backgrounds submit substantially different college application portfolios, with low-income and middle-class students relatively underrepresented in selective colleges (Hoxby and Avery, 2012; Black et al., 2015; Smith and Howell, 2017; Chetty, 2020). Information frictions, or the lack of alumni networks within districts too small to support selective public high schools, have been demonstrated to explain missing applications among low-income, high-achieving students (Hoxby and Turner, 2013, 2015; Gazmuri and Prager, 2024).

While existing empirical evidence points to the importance of environmental factors in determining college application behavior, there is little research on how social interactions in high school affect students' decision-making. In this paper, we examine the effect of peers on high school students' decision of whether and where to apply for colleges.

We examine this question in the context of a large school district in Minnesota. This is a heterogeneous environment, both economically and ethnically, with one unique high school offering a wide array of college and career path opportunities. For each high school student, we observe demographic characteristics, measures of achievement, courses and sections attended, and a list of the college applications submitted in the senior year. Our outcomes of interest are whether a student applies to any given institution, the average quality of the colleges to which a student applies, and the level of diversification within an application portfolio.

There are two empirical challenges in identifying the effect of peers' college choices on the student's college choices: endogeneity and reflection. Endogeneity refers to a set of challenges

arising from unobservable factors that affect both the outcomes of the individual and the outcomes of the peers. This includes the fact that individuals choose their own peer groups. The reflection problem arises from the simultaneity in behavior of students and their peers such that it is hard to identify whether a student's outcome is driven by the outcomes of the peers or from the composition of the peers in terms of observable characteristics.

To address these concerns, we exploit Bramoullé et al. (2009a) and De Giorgi et al. (2010)'s approach. It exploits the network structure implied by classroom formation to construct partially overlapping groups of peers such that peer groups of two peers do not perfectly overlap. These papers show that it is possible to use partially overlapping groups to address the reflection problem and, in combination with exogenous group assignments, address the endogeneity problem.

We construct the overlapping set of peers using information on classes students take in the last year of high school. In the beginning of the year, students list a set of courses they want to take. Most courses have multiple sections taught over different terms within the school year. For each course on their list, students are assigned to sections at random. Our data contain information on the composition of students in each section. We define peer groups of student i as consisting of all classmates of i across sections that student i attends. Since sections are created randomly, this process naturally forms partially overlapping peer groups. We rely on this information for identification of the peer effects: Since peer groups in high school are not perfectly overlapping, we instrument for the outcomes of student i's *direct* peers (classmates) by the outcomes of i's *excluded* peers, that is, students who are in class with at least one of i's peers, but not with i directly.

We find that one additional peer applying to a given college increases a student's own probability of applying to that same college by around 0.5 percentage points. Moreover, an increase

in the average quality of applications by peers increases one's own application quality sizably and significantly.

Our analysis reveals significant heterogeneity in peer response patterns across various demographic and academic groups. Students demonstrate consistently stronger responsiveness to college quality choices made by white peers compared to non-white peers; by peers from high socio-economic status (SES) families relative to those from low-SES backgrounds; and by high-GPA peers versus their low-GPA counterparts. Interestingly, we find no statistically significant difference in students' overall responsiveness to male versus female peers when examining gender effects in isolation.

We then examine whether significant within-group peer responses exist—specifically, whether students respond more strongly to peers from their own demographic group compared to those outside it. Interestingly, our analysis reveals limited evidence of such within-group effects, with one notable exception: socio-economic status. Low-SES students demonstrate significantly stronger responses to actions taken by their low-SES peers compared to actions of their high-SES counterparts.

Prior literature has demonstrated that top-achieving students from low socio-economic backgrounds tend to apply to less selective colleges than their higher socioeconomic peers. The gap is driven by low-SES students who are isolated, either geographically or in terms of the high school they attend. To investigate whether this pattern persists *within* our school of interest, we focus specifically on high-achieving students – those with GPAs in the top two deciles of their cohort, who are academically suited for selective institutions. Interestingly, among these high performers, the role of socioeconomic status virtually disappears. Students apply to colleges of comparable quality regardless of family income and respond to peer influences with similar sensitivity.

What is driving the patterns of peer effects we observe in our analysis? We shed light on one potential mechanism: information flow through peer networks. Using infromation from a survey administered to high school seniors in 2024, we examine the uptake of specialized counseling services offered by the school. These services provide additional and more tailored information to students about college applications than the general information provided by school counselors. On average, top achievers and females are more likley to avail of these services. There is no difference between low-SES and high-SES students in uptake of these services, suggesting that the access to counselor information across socio-economic groups is similar within the high school. We find that uptake of additional counseling services has positive effects on students' application outcomes and that students whose peers take up these services are more likely to take them up as well. In a sample of students who do not take up these specialized services (less informed students), we find that the average college quality and likelihood of getting a scholarship is affected more by peers who take up such services compared to peers who do not take up these services.

This paper contributes to three streams of literature. The first is on students' college application behavior (Hoxby and Avery, 2012; Hoxby and Turner, 2013, 2015; Black et al., 2015; Dillon and Smith, 2017; Delaney and Devereux, 2020; Gazmuri and Prager, 2024). Similar to contemporaneous work developed independently in Gazmuri and Prager (2024), we focus on peer effects as a determinant of college application behavior. In that paper, the authors find that a student's probability of applying to a particular undergraduate program to which no one from her high school previously applied doubles after a student in the preceding cohort applies. Our approach is different as we focus on peer effects operating through classroom networks rather than across cohorts. In particular, we investigate the role of within-classroom interactions as potential mediators of the application gap the literature has documented, even conditional on

achievement. Moreover, while our findings are consistent with theirs, we focus on heterogeneous effects across student socio-economic status, race, and achievement level. Empirically, our paper adds to the body of work exploring peer effects by gender and race (Hoxby, 2000; Hoxby and Weingarth, 2005; Lavy and Schlosser, 2011; Lavy et al., 2012; Black et al., 2013; Burke and Sass, 2013; Gibbons and Telhaj, 2016; Anelli and Peri, 2019).

Our paper also contributes to a broad literature estimating peer effects on student outcomes in school (Hanushek et al., 2003; Angrist and Lang, 2004; Whitmore, 2005; Burke and Sass, 2013; Angrist and Lang, 2004; Imberman et al., 2012) and college (Sacerdote, 2001; Zimmerman, 2003; Stinebrickner and Stinebrickner, 2006; Fletcher and Tienda, 2010). While most of these studies do not address the mechanisms driving peer effects, our study exploits survey data to provide suggestive evidence that information flow from more informed peers to less informed peers is a potential channel. Methodologically, our main analysis relies on the identification strategy based on "excluded peers" proposed by De Giorgi et al. (2010). That paper shows that an individual is more likely to choose a college major when more of her peers make the same choice. It also documents that peers can divert students from majors in which they have a relative ability advantage, with adverse consequences on academic performance, entry wages, and job satisfaction.

This paper also complements the body of work investigating the determinants of college major choice. In their handbook chapter, Altonji et al. (2016) observe that "the role played by students' peers on the decision to enroll in a given college major is an important question, which has not been the object of much attention in this literature" (p. 377.)[1] This paper focuses on elected institutions, rather than majors, by examining the factors influencing college application decisions instead of the selection of specific fields of study, as both dimensions have been proven

[1]Notable exceptions include Sacerdote (2001) and De Giorgi et al. (2010)

highly consequential for labor market outcomes.

The rest of this paper is structured as follows: Section 2 describes the data; Section 3.1 defines own and excluded peers and illustrates the identification approach; Section 4 describes the results; Section 5 provides suggestive evidence for a potential mechanism; and Section 6 concludes.

2 Data

Our analysis is based on administrative data from a large school district in Minnesota (the District, henceforth). We complement this source with information from Naviance, a system that students use to send applications to colleges, and data on college quality collected by the Integrated Postsecondary Education Data System (IPEDS). Our analysis consists of cohorts of students who graduated from high school in the District between 2009 and 2015.

We use data on students enrolled in Grade 12 at the District's only public high school. The students in our sample take several mandatory classes, along with optional classes of their choice.[2] Most classes have a large total enrollment, and students are divided across sections *at random*. That is, students do not select which section to attend; conditional on the choice of class, students are assigned to sections randomly via an algorithm that the administration of the District has been using for several years now.[3] In the data, each section of a class has a unique identifier, which allows us to identify students who take the same class in the same section. The average size of a section in our sample is 21 students. We also observe students' grades in each

[2]Our analysis includes both instructional and non-instructional courses, based on course titles. We adopt a restrictive definition of instructional courses, i.e., one that only includes academic and non-vocational courses. Examples of courses in our sample that we label as non-instructional are Ceramics, Culinary, Drawing and Painting, Guitar, Jewel and Metal-smithing, Sculpture, and Video Production. Later in the paper, we discuss how our results vary as attention is restricted to instructional or non-instructional courses.

[3]Once courses have started, students can potentially ask to be transferred to a different section by getting an appointment with their counselors, as long as this is compatible with the rest of their school schedule. However, we have confirmation from the school administration that this happens rarely.

Table 1: Descriptive statistics of students with non-zero application

Variable	Mean	SD	Min	Max	N
No. of applications	4.51	3.35	1	29	3,603
1 = female	0.50	-	0	1	3,603
1 = white	0.79	-	0	1	3,603
1 = low SES	0.25	-	0	1	3,603
GPA	3.21	0.63	0.41	4	3,603

N in the last column refers to the number of students.

class taken.

We analyze students' college application patterns using combined data from the school district and Naviance, the platform students use to submit their college applications.[4] To protect student privacy, colleges were assigned unique identifiers by the school district rather than being identified by name. For each institution, we observe two key characteristics: whether it was a two-year or four-year college and its state location.

To analyze college quality, we complement our dataset with publicly available information from the Integrated Postsecondary Education Data System (IPEDS), which maintains statistics for approximately 1,000 U.S. colleges. Among the various metrics IPEDS collects on incoming student cohorts, we select the 75th percentile of the ACT math score in 2018 as our measure of institutional quality. Before anonymizing college identifiers, the District matched the Naviance application data with these IPEDS quality metrics using institution names.

Tables 1 and 2 present summary statistics of students' application patterns. Among the sampled students, 83% submitted at least one college application. Of these applicants, more than half submitted four or fewer applications, with 21% submitting just one application. Table 1 describes the distribution of the number of submitted applications in our sample, alongside student demographic characteristics (gender, race, and socioeconomic status) and GPA.

[4]We note that Naviance captures all relevant applications. If a college requires a high school transcript, then the application is channeled via Naviance. In the years we study, all colleges required high school transcripts.

Table 2: Distribution of colleges across quality categories

ACT math score	16–22	23	24	25	26	27	28	29	30	31	32–36
U.S. college	0.18	0.10	0.11	0.14	0.16	0.10	0.06	0.04	0.03	0.02	0.06
in sample applications	0.01	0.03	0.05	0.06	0.06	0.12	0.12	0.05	0.13	0.06	0.14

Notes: The first row shows the distribution of colleges across quality categories in IPEDS. The second row shows the distribution of applications in our sample across quality categories, conditional on the college being ranked in IPEDS.

Students in our sample sent a total of 33,403 college applications. Of these, 222 were sent to schools outside the US and 405 to institutions that are not ranked in IPEDS. The ACT math test score is on a scale of 1–36. In our sample, 9% of the applications were sent to colleges with an ACT math score at entry (75th percentile) less than 25, 14% to colleges greater than 32. 42% of the applications were sent to colleges with an ACT math score between 27–30, which in the ranking accounts for about 23% of colleges. Overall, students tend to send applications to better colleges than what corresponds to a "random" sample of colleges, as shown in Table 2.

2.1 Application Patterns

This section describes the application patterns of the students in our sample on the basis of three characteristics of a student's application portfolio: the number of applications; the average quality of the colleges applied to; and the variation (standard deviation) in the application quality.

Appendix Figures A1, A2, and A3 show how the distributions of these variables vary across gender, race, and socio-economic status (SES), respectively. There is a relatively larger concentration of males, non-white, and low-SES students who submit at most two applications and with an average quality in the bottom bin of the distribution. Moreover, females tend to diversify their application portfolios more than their male schoolmates. Appendix Figures A4, A5, and A6 show how these distributions vary across deciles of the applicant GPA distribution: Both the size of the application portfolio, and its average quality, and the level of portfolio diversification

Table 3: Application Patterns by Demographics for Bottom and Top Achievers

	Bottom achievers		Top achievers	
Average	Low SES	High SES	Low SES	High SES
Pf size	2.86 (3.21)	2.64 (2.87)	6.14 (5.34)	6.51 (4.25)
Pf quality	*2.22* (1.81)	*2.40* (1.93)	**5.40** (2.84)	**7.21** (2.15)
Pf quality sd	1.62 (1.38)	1.71 (1.43)	2.82 (1.35)	2.76 (1.38)
Average	Nonwhite	White	Nonwhite	White
Pf size	*3.05* (3.49)	*2.44* (2.58)	6.79 (4.78)	6.57 (4.42)
Pf quality	2.25 (1.76)	2.41 (2.03)	**6.16** (2.84)	**7.18** (2.18)
Pf quality sd	1.67 (1.35)	1.56 (1.38)	2.91 (1.31)	2.77 (1.34)
Average	Female	Male	Female	Male
Pf size	*3.17* (3.60)	*2.55* (2.79)	**6.94** (4.74)	**6.06** (3.98)
Pf quality	2.27 (1.73)	2.34 (1.96)	**6.82** (2.25)	**7.32** (2.42)
Pf quality sd	1.68 (1.37)	1.59 (1.36)	**2.92** (1.32)	**2.58** (1.35)

Note: This table reports averages of three variables (rows), each computed at the student level: the number of applications submitted (*Pf size*), the average quality of the colleges applied to (*Pf quality*), and the variation (standard deviation) in the quality of the applications submitted (*Pf quality sd*). Such averages are reported for different groups of students, identified among students with a GPA (weakly) above the 9th decile of the applicant distribution (*Top achievers*, right panel) and among those with a GPA (weakly) below the 2nd decile (*Bottom achievers*, left panel). Within each panel, students are divided by socio-economic status (*Low SES* v. *High SES*), race (*Nonwhite* v. *White*), and gender (*Female* v. *Male*). Pairs of averages in bold (italics) are significantly different at the 1% (10%) level.

(variation) shift to the right as GPA increases, and the dispersion in the distributions of size and quality rises as well.

Table 3 shows differences by gender, race, and socio-economic status for top achievers (i.e., students with a GPA in the ninth decile or above) and bottom achievers (i.e., students with a GPA in the first or second decile). Among students at the top of the GPA distribution, high-SES and white students apply to more and higher-quality colleges, on average. Females submit more applications than males and choose a lower average quality, along with a higher level of diversification. The differences in means are statistically significant at the 1% level. In the left tail of the GPA distribution, high-SES students are associated with a higher average quality, while non-white and female students have larger application portfolio, on average. In this case, such differences are only marginally significant.

The next section introduces our analysis of how college application decisions are affected by peers.

3 Peer Effects

3.1 Empirical Strategy

Identifying peer effects poses two key empirical challenges. The first is determining causality (i.e., the reflection problem; Manski, 1993): Do peers influence an individual, or does the individual influence their peers? The second is disentangling the direct effect of peers' outcomes on an individual's outcome (endogenous peer effects) from correlated effects, where shared environmental factors affect all students in a group, and selection effects emanating from self-selection into groups based on pre-existing characteristics (also called exogenous peer effects).

We define peer groups as students who take one or more classes in the same section. Within each subject, the school randomly assigns students to sections. This random assignment at baseline ensures that peer groups are formed exogenously, thereby significantly alleviating selection concerns in our analysis. Furthermore, since students take different combinations of classes, each with its own random composition of students, this creates a network structure with partially overlapping peer groups. This variation in the composition of the peer group enables us to identify the effects of the peers based on the identification results in Bramoullé et al. (2009b) and De Giorgi et al. (2010).

We closely follow the notation in Bramoullé et al. (2009b) to introduce the model, which is a standard linear-in-means social interaction model. Students are indexed by i, $i = 1, \ldots n$. Let y_i denote the outcome variable and x_i the vector of student i's characteristics. Each student has a group of peers that is denoted by P_i and of size n_i. This group contains students who can influence student $i's$ decisions. We assume that student i is excluded from her own peer group,

$i \notin P_i$.

The structural model is given by

$$y_i = \alpha + \beta \frac{1}{n_i} \sum_{j \in P_i} y_j + \gamma x_i + \delta \frac{1}{n_i} \sum_{j \in P_i} x_j + \varepsilon_i, \tag{1}$$

where β is the endogenous peer effect, with the standard restriction that $|\beta| < 1$, and δ captures the exogenous peer effect.

Equation (1) in matrix notation is

$$\boldsymbol{y} = \alpha \boldsymbol{e} + \beta G\boldsymbol{y} + \gamma \boldsymbol{x} + \delta G\boldsymbol{x} + \boldsymbol{\epsilon}, \tag{2}$$

where $\boldsymbol{y}$ is a $n \times 1$ vector of outcome values, $\boldsymbol{x}$ is the $n \times 1$ vector of observable characteristics, G is an $n \times n$ matrix of interactions with $G_{ij} = 1/n_i$ if $j \in P_i$ and zero otherwise, and $\boldsymbol{e}$ is an $n \times 1$ vector of ones.

Assuming no correlated effects, $E[\varepsilon_i|x] = 0$, and that $\gamma\beta + \delta \neq 0$, then Proposition 3 in Bramoullé et al. (2009b) states that parameters $\alpha, \beta, \gamma, \delta$ are identified in a setting where students do not interact in groups. That is, there exists a triplet of students i, j, k such that $i \in P_j$, $j \in P_k$ but $k \notin P_i$. Bramoullé et al. (2009b) denote this condition as an intransitive triad, while De Giorgi et al. (2010) pin the name of excluded peers. Both papers show that the mean characteristic of the excluded peers, $G^2\boldsymbol{x}$, is a valid instrument for $G\boldsymbol{y}$ to address the reflection problem. With random classroom assignments, $G^2\boldsymbol{y}$ is also a valid instrument and is the one we use in this paper.

In classroom settings, students are exposed to shared environmental factors, such as teachers, physical spaces, and curricula, which can generate correlated effects among peers. Hence, it is very likely that the assumption of $E[\varepsilon_i|x] = 0$ is violated. Bramoullé et al. (2009b) suggest dealing with correlated effects by de-meaning the variables, as is typical in fixed effects setups.

De Giorgi et al. (2010) argue that the instrument $G^2\boldsymbol{y}$, which denotes the average outcome variable of excluded peers, also tackles endogeneity due to correlated effects: Excluded peers are not affected by group-specific shocks to student i, but are correlated with the mean outcome of i's direct peers due to social interactions. We follow this approach in our paper.

3.2 Definition of a Peer Group

To analyze peer effects, we first define each student's peer network. For student i, we designate their peer group P_i as those students who share classes with them in Grade 12. We focus on Grade 12 classmates because they are likely to have the strongest influence on college-related decisions, which occur during the same academic year.

In our baseline specification, student j belongs to peer group P_i if students i and j shared at least one class section.[5] Given the definition of peer group, we can construct the network matrix G. The excluded peer group is then described by G^2, which means that a student k is in the excluded peer group of student i if $k \notin P_i$ but there exists a student $j \in P_i$ such that $k \in P_j$.

While we acknowledge that students may interact with peers outside their defined group P_i, we limit our analysis to within-group interactions for several reasons. First, classroom interactions provide structured, sustained opportunities for meaningful peer influence, particularly regarding academic decisions. Second, the regular contact during class time facilitates information sharing about college applications and choices. Third, shared academic experiences create natural contexts for discussions about future educational plans. Although this assumption may not capture all peer effects, it allows us to identify the impact of the most likely and frequent peer interactions while maintaining analytical tractability.

The next section builds on the arguments developed above to present our empirical results.

[5]Recognizing that interaction opportunities vary by class type, we explore how our results change as attention is restricted to peers from instructional vs non-instructional courses only.

4 Results

4.1 College Application Patterns

The first step in our peer effect analysis is asking whether a student's decision of where to apply to college is affected by their peers applying to the same institution. For each college m in our sample, we define an outcome variable y_i^m taking value one if student i applies to college m, zero otherwise. Using the notation from section 3.1, for every college m, our structural model is then

$$y_i^m = \alpha + \beta \frac{1}{n_i} \sum_{j \in P_i} y_j^m + \gamma x_i + \delta \frac{1}{n_i} \sum_{j \in P_i} x_j + \varepsilon_i^m, \tag{3}$$

where we impose that structural parameters $\alpha, \beta, \gamma, \delta$ are the same for all colleges.

Table 4 shows the results obtained from estimating regression (3) on both college applicants and non-applicants (i.e., in this part of the analysis, we include in our sample students that submit no college applications). The variable of interest is the fraction of own peers applying to that same college, Gy^m in matrix notation introduced earlier, and is instrumented by the share of excluded peers submitting an application to that college, G^2y^m. All regressions include the measure of college quality described in Section 2 and student fixed effects, which absorb all the time-invariant characteristics that are specific to each student.

Our findings indicate that, as the share of peers that apply to a certain college increases from 0 to 100%, the probability that a student also applies to that college increases by more than 90 percentage points on average (Column (2)). In other terms, since the average size of the pool of own peers in our sample is approximately 200, one additional peer applying for a certain college increases the own probability of applying by around 0.5 percentage points. This estimate is small in magnitude compared to De Giorgi et al. (2010), who find that one additional peer choosing economics as a major increases the likelihood of opting for economics by 7.4 percentage points.

Table 4: Peer effects in applying to a specific college

	First Stage (% Peers Applying) (1)	IV Estimate (Applying) (2)
% PoP Applying	0.991***	
	(0.005)	
% Peers Applying		0.897***
		(0.014)
College quality	Y	Y
Student fixed effects	Y	Y
Obs. (student x college)	1,814,554	1,814,554
N. students	4,373	4,373
N. colleges	403	403

Notes: Results from 2SLS regressions at the student-by-college level. Graduating cohorts 2009–2015 are included in the sample. The analysis extends to students that submit no college applications. The dependent variable "(Applying)" takes value 1 if there is an application on record for the corresponding student-college pair, zero otherwise. The main explanatory variable is the fraction of own peers applying for a given college and is instrumented with the fraction of excluded peers (PoP) who apply for that college, see Section 3.2 for details on the definition of own and excluded peers. The regression includes both instructional and non-instructional courses. Standard errors are clustered at the student level and reported in parentheses.

Besides the difference between our research question and theirs, this is expected, as the average size of the peer group in their context is much smaller (around 18), which suggests that their larger marginal effect is probably due to stronger peer-to-peer interactions.

Table 5 uses the same sample to explore how the peer effect documented in Table 4 varies across students of different genders, ethnic and socio-economic backgrounds, and levels of school performance. While females and males seem to be equally responsive to their peers' behavior (column (2)), students who are non-white (column (3)), come from a low-income family[6] (column (4)), or have a high GPA (column (5)) are more responsive to their peers' application decision. Column (6) shows that when we include all interaction terms in the same regression model, the interaction with economic status and GPA remain statistically and economically significant. Our results suggest that students from low-income families and with lower GPAs are less responsive to their peers' actions. Students from low-income backgrounds potentially face

[6]We use low-income and low-SES interchangeably

Table 5: Individual heterogeneity in peer effects in applying to a specific college

	(1)	(2)	(3)	(4)	(5)	(6)
% Peers Applying	0.897***	0.893***	0.694***	0.989***	1.086***	1.108***
	(0.014)	(0.019)	(0.029)	(0.016)	(0.018)	(0.045)
% Peers Applying*		0.041				−0.018
Female(own)		(0.027)				(0.027)
% Peers Applying*			0.287***			0.045
Non-White(own)			(0.033)			(0.039)
% Peers Applying*				−0.331***		−0.171***
*Low Income(own)				(0.030)		(0.036)
% Peers Applying*					−0.397***	−0.357***
*Low GPA(own)					(0.026)	(0.030)
College quality	Y	Y	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y	Y	Y
Obs. (student x college)	1,732,482	1,732,482	1,732,482	1,732,482	1,732,482	1,732,482
N. students	4,217	4,217	4,217	4,217	4,217	4,217
N. colleges	403	403	403	403	403	403

Notes: Results from 2SLS regressions at the student-by-college level. Graduating cohorts 2009–2015 are included in the sample. The analysis extends to students who submit no college applications. The dependent variable takes value 1 if there is an application on record for the corresponding student-college pair, zero otherwise. The main explanatory variable is the fraction of own peers applying for a given college and is instrumented with the fraction of excluded peers who apply for that college: see Section 3.2 for details on the definition of own and excluded peers. GPA is defined on a scale from 0 to 4, with larger values corresponding to a better average school performance. Standard errors are clustered at the student level, reported in parentheses.

additional responsibilities that might make them less susceptible to peer influence. Furthermore, these students might identify more strongly with peers of similar socioeconomic backgrounds, effectively creating different reference groups that shape their behaviors, independently from the broader student population. Similarly, students with lower GPAs might be less invested in the academic environment overall, contributing to diminished responsiveness to their peers.

4.2 Effects on Application Quality

Students' tendency to "follow" their peers significantly impacts the quality of institutions to which they ultimately apply. Table 6 extends our analysis from Table 5, with several adjustments: We conduct the analysis at the student level rather than at the student-college level; we use the average quality of a student's college applications as the dependent variable; and we employ both the average quality of the student's own applications and those of their excluded peers as explanatory variables and instruments, respectively. Moreover, as we now have one observation per student, we cannot include student fixed effects but control for several observable characteristics.

The magnitude of this peer quality effect is substantial. Our preferred specification in Column (6) of Table 6 reveals that when the average quality of peers' applications increases by 1 point on our quality scale (detailed in Section 2), a student's application quality increases by 1.8 points on average, holding other student characteristics fixed. This represents a remarkable 29% increase relative to the baseline average application quality of 6.3 points. The effect demonstrates notable heterogeneity across demographic groups: Students from low-income families exhibit the strongest response, with their average application quality increasing by 2.5 points (approximately 40% above baseline), while non-white students show the least responsiveness among all subgroups examined. Interestingly, for students with below-median GPAs, the peer effect is somewhat attenuated, as evidenced by the negative and statistically significant interaction term. These findings suggest that the effects of peers on the quality of the application vary considerably according to socioeconomic status, racial background, and levels of academic performance.

Table 6: Peer effects in application quality

	(1)	(2)	(3)	(4)	(5)	(6)
Average quality of peers' applications	1.666*** (0.115)	1.815*** (0.141)	1.688*** (0.111)	1.574*** (0.116)	1.667*** (0.115)	1.769*** (0.138)
Peers' app quality* *Female (own)		−0.293* (0.163)				−0.390** (0.181)
Peers' app quality* *Non-White (own)			0.112 (0.363)			−0.098 (0.459)
Peers' app quality* *Ec. disadv. (own)				0.579** (0.294)		0.773** (0.298)
Peers' app quality* *Low GPA (own)					−0.050** (0.023)	−0.072*** (0.027)
Female (own)	−0.662*** (0.092)	1.190 (0.1.041)	−0.668*** (0.094)	−0.659*** (0.093)	−0.664*** (0.092)	1.807 (1.143)
White (own)	−0.386*** (0.148)	−0.407*** (0.149)	0.262 (2.097)	−0.423*** (0.151)	−0.374** (0.147)	−1.017 (2.652)
Economically Disadvantaged (own)	−0.686*** (0.141)	−0.710*** (0.142)	−0.675*** (0.145)	−4.065** (1.708)	−0.694*** (0.141)	−5.236*** (1.744)
GPA (own)	2.489*** (0.144)	2.477** (0.144)	2.461*** (0.145)	2.459*** (0.151)	2.314*** (0.163)	2.170*** (0.206)
Graduating year (own)	Y	Y	Y	Y	Y	Y
Obs. (students)	3,716	3,716	3,716	3,716	3,716	3,716
Avg dep. var.	6.2	6.2	6.2	6.2	6.2	6.2

Notes: Results from 2SLS regressions at the student level. Graduating cohorts 2009–2015 are included in the sample. The analysis is limited to students who submit at least one college application. The dependent variable is the average quality of the colleges for which a student applies. College quality is defined based on the 75th percentile of the admission Math SAT score, and split into 16 categories. Larger values of the variable correspond to higher scores. The main explanatory variable is the average quality of the colleges where own peers apply and is instrumented with the average quality of the colleges where excluded peers apply, along with excluded peers' demographic characteristics; see Section 3.2 for details on the definition of own and excluded peers. High and low GPA are defined relative to the sample median. GPA is defined on a scale from 0 to 4, with larger values corresponding to a better average school performance. Standard errors are in parentheses.

4.3 Focus on Top-Achievers

The literature highlights an interesting finding: low-income students often apply to lower-quality colleges despite being qualified for better ones (see Hoxby and Avery, 2012). One possible explanation is lack of information. Building on this insight and considering peer effects as a potential information channel, we focus on high-achieving students—defined as those in the 9th decile of their cohort's GPA distribution. Within this group, we examine the role of peers in shaping college application decisions, particularly the differences between high- and low-income students.

The results are summarized in Table 7. Columns (1) and (2) compare college quality choices across demographic groups. Low-income students tend to apply to slightly lower-quality colleges, though the effect is economically small and not statistically significant. In contrast, female students apply to colleges of lower quality than their male counterparts. Columns (3) and (4) add peer effects. We find that the peer effect in this group is strong, even somewhat stronger than among all students reported in Table 6. Interestingly, we do not find evidence that economically disadvantaged students respond less to their peers.

This finding aligns with the patterns documented in Hoxby and Avery (2012) by showing that, conditional on attending a school with a record of admissions that includes top universities and several counseling services (see Section 5), low-SES top-achievers apply similarly to their high-SES counterparts. Furthermore, thinking of peers as a potential information vehicle, these results are consistent with the findings in Hoxby and Turner (2013, 2015) as they illustrate that top-achievers' college application choices are malleable to new information.

Table 7: Peer effects in application quality among top-achievers

	(1)	(2)	(3)	(4)
Average quality of peers' applications			1.974***	2.003***
			(0.309)	(0.347)
Peers' app quality* *Ec. disadv. (own)				−0.275
				(1.053)
Economically Disadvantaged (own)	−0.055	−0.019	0.307	2.267
	(0.648)	(0.684)	(0.660)	(7.380)
Female (own)		−1.296***	−1.346***	−1.343***
		(0.282)	(0.278)	(0.279)
White (own)		−0.561	−0.613	−0.593
		(0.809)	(0.776)	(0.790)
Graduating year (own)	Y	Y	Y	Y
Obs. (students)	372	372	372	372
Avg dep. var.	9.8	9.8	9.8	9.8

Notes: Results from 2SLS regressions at the student level. Graduating cohorts 2009–2015 are included in the sample. The analysis is limited to students who submit at least one college application. The dependent variable is the average quality of the colleges for which a student applies. College quality is defined based on the 75th percentile of the admission Math SAT score, and split into 16 categories. Larger values of the variable correspond to higher scores. The main explanatory variable is the average quality of the colleges where own peers apply and is instrumented with the average quality of the colleges where excluded peers apply, along with excluded peers' demographic characteristics; see Section 3.2 for details on the definition of own and excluded peers. High and low GPA are defined relative to the sample median. GPA is defined on a scale from 0 to 4, with larger values corresponding to a better average school performance. The sample is restricted to students with a GPA in the ninth decile of the applicant distribution or above. Standard errors are in parentheses.

4.4 Within-Group Analysis

We uncovered substantial heterogeneity in peer effects in Table 6, which we explore next in further details. Specifically, we explore whether students respond more to peers with certain characteristics, and whether this response depends on students' own characteristics.

We start with gender. For each student, we construct two separate peer groups, one that includes only females and one that includes only males. Within each group, we construct the average quality of the students' applications, which we instrument for by the average quality

of excluded peers' applications of the same gender. We then use the average quality of the student's applications as the dependent variable and regress it either on the average quality of female peers' applications or on the average quality of male peers' applications.

Table 8: Heterogeneity in application quality, by gender and race

	First Stage (1)	2SLS (2)	2SLS (3)	First Stage (4)	2SLS (5)	2SLS (6)
Gender						
	Female peers			Male peers		
PoP's avg app quality	-1.796^{***}			-2.114^{***}		
	(0.062)			(0.050)		
PoP share nonwhite	0.759			0.203		
	(0.996)			(0.928)		
PoP share low-SES	-0.394			-2.243^{***}		
	(0.874)			(0.816)		
PoP share low-GPA	-2.406^{***}			-1.422^{***}		
	(0.535)			(0.503)		
Peer's avg app quality		1.446^{***}	1.674^{***}		1.377^{***}	1.193^{***}
		(0.109)	(0.189)		(0.073)	(0.094)
Peers' app quality*			-0.400			0.326^{***}
own gender			(0.294)			(0.118)
(Obs.) N. students	3,715	3,715	3,715	3,709	3,709	3,709
Average dep. var.	6.2	6.2	6.2	6.2	6.2	6.2
Race						
	Non-White Peers			White Peers		
PoP's avg app quality	-1.989^{***}			-2.088^{***}		
	(0.038)			(0.076)		
PoP share female	-0.140			-2.513^{***}		
	(0.531)			(0.544)		
PoP share low-SES	0.092			-0.569		
	(0.644)			(0.667)		
PoP share low-GPA	3.282^{***}			-4.646		
	(0.440)			(0.609)		
Peer's avg app quality		1.038^{***}	1.088^{***}		1.890^{***}	2.768^{***}
		(0.073)	(0.102)		(0.124)	(0.524)
Peers' app quality*			-0.275			-0.988^{*}
own race			(0.330)			(0.540)
(Obs.) N. students	3,709	3,709	3,709	3,715	3,715	3,715
Average dep. var.	6.2	6.2	6.2	6.2	6.2	6.2

Notes: Results from the first stage and 2SLS regressions at the student level, graduating cohorts 2009–2015. The analysis is limited to students who submit at least one college application. The dependent variable is the average quality of the colleges that a student applies to. The main explanatory variable is the average quality of the colleges where peers from the given group (male/female, white/non-white) apply and it is instrumented with the average college quality of excluded peers, along with selected excluded peers' demographic characteristics. We preserve the network structure when defining excluded peers.

The first panel of Table 8 presents our analysis of gender-specific peer effects. All students

Table 9: Heterogeneity in application quality, by socio-economic status and GPA

	First Stage (1)	2SLS (2)	2SLS (3)	First Stage (4)	2SLS (5)	2SLS (6)
Socio-economic status						
	Low SES Peers			High SES Peers		
PoP's avg app quality	-1.844^{***}			-1.859^{***}		
	(0.035)			(0.025)		
PoP share females	-1.146^{**}			-2.568^{***}		
	(0.483)			(0.544)		
PoP share non-white	-2.211^{***}			-0.041		
	(0.679)			(0.757)		
PoP share low-GPA	4.493^{***}			-3.364^{***}		
	(0.413)			(0.599)		
Peer's avg app quality		1.125^{***}	1.063^{***}		1.931^{***}	0.293
		(0.075)	(0.105)		(0.155)	(0.672)
Peers' app quality*			0.177			1.893^{**}
own status			(0.289)			(0.748)
(Obs.) N. students	3,716	3,716	3,716	3,716	3,716	3,716
Average dep. var.	6.2	6.2	6.2	6.2	6.2	6.2
GPA						
	Low GPA Peers			High GPA Peers		
PoP's avg app quality	-1.801^{***}			-1.518^{***}		
	(0.036)			(0.066)		
PoP share females	-1.927^{***}			-1.838^{***}		
	(0.331)			(0.623)		
PoP share non-white	1.849^{***}			-1.151		
	(0.592)			(1.116)		
PoP share low-SES	-0.275			-1.591		
	(0.537)			(1.025)		
Peer's avg app quality		1.786^{***}	1.789^{***}		2.145^{***}	2.076^{***}
		(0.104)	(0.110)		(0.327)	(0.306)
Peers' app quality*			-0.003			0.115^{***}
own status			(0.036)			(0.029)
(Obs.) N. students	3,713	3,713	3,713	3,715	3,715	3,715
Average dep. var.	6.2	6.2	6.2	6.2	6.2	6.2

Notes: Results from the first stage and 2SLS regressions at the student level, graduating cohorts 2009–2015. The dependent variable is the average quality of the colleges that a student applies to. The main explanatory variable is the average quality of the colleges where peers from the given group (low-/high-income, low-/high-GPA) apply and it is instrumented with the average college quality of excluded peers, along with selected excluded peers' demographic characteristics. We preserve the network structure when defining excluded peers.

are included in this analysis; columns (1)–(3) use only female peers as explanatory variables, while columns (4)–(6) only male peers. Comparing coefficients in columns (2) and (5), we observe that, on average, students respond with similar magnitude to both female and male peers' application choices. However, when we interact peer application quality with students' own

gender, female students exhibit a somewhat diminished response to same-gender peers compared to male students' response to female peers, as evidenced by the negative coefficient in column (3), although this difference does not reach statistical significance. Column (6) reveals a more pronounced pattern regarding male peers: Male students demonstrate stronger responsiveness to their male peers' application choices than to their female peers. This asymmetry in gender-based peer effects suggests that male students may be particularly influenced by the collegiate aspirations of their male counterparts, while female students display a more consistent response pattern across peer gender groups.

The second panel of Table 8 extends our analysis to examine race-based peer effects. Comparing columns (2) and (5), we observe an asymmetric patter: Students respond more strongly to their white peers' application choices than to those of non-white peers. This disparity is particularly pronounced, with the coefficient in column (5) exceeding that in column (2) almost twofold, indicating a greater influence of white peers' decisions on application behavior. Notably, the interaction terms in column (3) and (6) are either not statistically significant or only marginally so, suggesting that a student's own racial background does not significantly moderate these peer effects. If anything, the large magnitude of the interaction coefficient in column (6) suggests that non-white students respond to white peers even more strongly than white students. Nevertheless, since this coefficient is only marginally significant, we cannot confidently rule out that the heightened influence of white peers' application choices operates similarly across students of all racial backgrounds, pointing to potential structural factors in college application dynamics rather than in-group preferences.

The first panel in Table 9 analyzes heterogeneity by the socio-economic status, finding that all students respond substantially more to high-income peers than low-income peers (comparing coefficients in columns (2) and (5)). In contrast to results on race-based peer effects, we find

that low-income students respond more to applications decisions of other low-income students than do high-income students, even though the interaction term is not significant (column (3)). Results in column (6) indicate that the strong response to the high-income peers is driven almost entirely by high-income students, as the interaction term is high and strongly significant. Hence, overall, low-income students are much less responsive to the actions of their high-SES peers.

Finally, the second panel of Table 9 reveals compelling patterns in peer effects across academic performance levels. Comparing columns (2) and (5), we observe that students across all GPA levels demonstrate stronger responsiveness to the application choices of high-GPA peers compared to choices of low-GPA peers. This insight does not depend on student's own GPA. Indeed, the interaction term in column (3) is not significant, and the interaction term in column (6) is rather small in magnitude. Hence, high-performing students serve as influential reference points for all students regardless of their own academic standing.

5 Mechanism: Role of Information

In the previous section, we showed that student college application decisions are affected by the application decisions of their peers. The question we address in this section is whether the peer effects simply capture students imitating the decisions of one another or whether there is flow of information through peers that affects student decisions. The distinction has important policy implications. If imitation is the only channel, the school district will need to optimally mix students in classrooms to improve student outcomes. If the flow of information is an important channel, then the school district can improve access to information without resorting to changing peer networks.

Using information on uptake of various counseling services provided by the school, we illustrate that information flow is one of the mechanisms driving the observed peer effects. The

additional data needed to study the information mechanism comes from a survey taken by high school seniors who apply to colleges. This survey includes information on which college they plan to attend, whether and how much scholarship they received from any of the colleges where they were accepted, whether they are the first-generation college students in their family, and what types of counseling services they used in making their decisions. Appendix B provides the list of questions students respond to. This survey can be linked to administrative data containing demographic information about students and their classrooms. The survey data used in this section was administered to students who graduated from Grade 12 in 2024. There are 373 respondents to the survey.

The main source of general information about college applications is the high school student counselors. The counselors provide services that are available to all high school students and offer individual meetings throughout the year. They share general information about college admissions and answer specific queries about the process. While almost all students work with one of the counselors in the high school, there are other services geared towards college admissions that the high school provides.

There are three additional services that are captured in the survey. The first is meetings with the school's College and Career Readiness Coordinator, who is an expert in college preparedness; provides individualized and student-centered college advising; and also connects students to various resources and opportunities. The second service is meetings with college representatives either on school visits or through virtual sessions. The college reps provide information to students about tuition, fees, financial aid, and other information about the application process to specific institutions. The third service reflected in the survey is participation in a college preparatory course offered by the school. This prep course explains to students the various steps in the application process and helps them complete the applications.

Table 10: Summary statistics from survey responses

	Statistic
Share who took up additional college counseling services	41.8
Share received scholarship	44.8
Average college quality of accepted offers	28.2
Standard deviation of college quality of accepted offers	2.6
Share first generation college goers	28.2
Sample size	373

Table 10 provides summary statistics of the responses to the survey. The share of students who take up one or more additional counseling services described above is 41.8%. Looking at the extensive margin for whether or not a student received a scholarship, we find that about 45% of the students do so from at least one of the colleges from which they received an acceptance offer. The average quality of enrolling colleges in the sample, as measured by the 75th percentile of the math ACT scores of incoming students, is 28.2 and the standard deviation is 2.6. The additional family background information we obtained from the survey is whether or not the student's parents completed a 4-year college degree. The share of respondents who are first generation college goers is 28.2%.

We begin our analysis by examining whether uptake of additional counseling services matters for students' college application outcomes. We run the following regression:

$$y_i = \alpha + X_i'\beta + \gamma U_i + \varepsilon_i$$

where y_i is the outcome variable (standardized college quality or a dummy for whether the student received any scholarship), X_i is a vector of student's characteristics including family background, GPA, and demographics. Our main variable of interest is U_i which is an indicator for whether a student takes up any additional college services.

Table 11 presents the OLS estimates for this regression. Column (1) shows the unconditional

Table 11: Why does up take of additional college counseling services matter?

	Standardized College quality		Received scholarship	
	(1)	(2)	(3)	(4)
Uptake additional services	0.39***	0.42***	0.16***	0.10**
	(0.13)	(0.12)	(0.05)	(0.05)
First Gen		0.07		-0.09
		(0.19)		(0.06)
Low income		0.09		-0.14**
		(0.19)		(0.06)
Top achiever		0.69***		0.29***
		(0.14)		(0.06)
Female		-0.14		0.25***
		(0.13)		(0.05)
Black		-0.32		0.08
		(0.22)		(0.07)
Hispanic		-0.38*		-0.01
		(0.20)		(0.08)
Asian		0.86***		0.03
		(0.23)		(0.13)
N	235	232	373	357

Notes: Robust standard errors in parenthesis. All specifications control for other races.

correlation and column (2) shows the conditional correlation between uptake of additional services and college quality. Students who take up additional services enroll into colleges that are of higher quality by an average of 0.42 standard deviations. In column (4), we see that students who take up additional services have a 10% higher likelihood of receiving a scholarship, even after controlling for family background, demographics, and student GPA. Hence, we find a significant correlation between uptake of additional counseling service and students' college application outcomes.

Who takes up additional counseling services and what role do peers play in this decision? To address this question we now estimate the following regression model

$$U_i = \alpha + X_i'\beta + \theta P_i + \varepsilon_i$$

Table 12: Role of peers in take up of additional college counseling services

	OLS	OLS	2SLS
	(1)	(2)	(3)
First Gen	-0.05	-0.03	-0.03
	(0.06)	(0.07)	(0.07)
Low income	0.04	0.05	0.06
	(0.07)	(0.07)	(0.07)
Top achiever	0.14**	0.11	0.13*
	(0.07)	(0.07)	(0.07)
Female	0.11**	0.12**	0.12**
	(0.05)	(0.05)	(0.05)
Black	0.00	-0.02	-0.01
	(0.08)	(0.08)	(0.08)
Hispanic	-0.01	-0.04	-0.04
	(0.08)	(0.09)	(0.08)
Asian	-0.09	-0.13	-0.14
	(0.14)	(0.14)	(0.14)
Peers' uptake share		1.55*	2.16**
		(0.89)	(1.03)
N	351	344	341

Notes: Robust standard errors in parenthesis. All specifications control for other races.

where U_i is an indicator for whether a student takes up additional college services, P_i is the share of peers of student i that take up any additional services, and X_i captures student characteristics. Column (1) of Table 12 shows estimates of β when P_i is not included in the regression model. We find that females and students in the top two deciles of the GPA distribution are significantly more likely to take up additional counseling services. There is no difference in uptake across students of different family backgrounds (first gen or SES) and across students of different racial groups.

In column (2) of Table 12, we add as an explanatory variable the share of direct peers who take up additional counseling services. We find that there are significant peer effects - students are more likely to take up additional services if their peers are also doing so. To make a causal statement about peer effects in uptake of services, we instrument the decisions of direct peers

Table 13: Which type of peers affect students who do not take up additional services?

	College quality		Scholarship received	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
College quality of uptake peers	0.29***	0.44***		
	(0.10)	(0.17)		
College quality of non-uptake peers	0.01	0.49		
	(0.12)	(0.41)		
Scholarship share of uptake peers			1.22**	2.11**
			(0.50)	(0.99)
Scholarship share of non-uptake peers			0.35	1.64*
			(0.51)	(0.94)
Student Characteristics	Y	Y	Y	Y
N	111	111	203	200

Notes: Robust standard errors in parenthesis.

by the decisions made by the excluded peers. This is the same empirical strategy we used in section 3 except that the decision we were examining there was choice of college rather than the choice of taking up counselor services. The IV estimates are larger and more precisely estimated compared to the OLS estimates, strengthening our results.

So far, we have illustrated that taking up additional counseling services has positive effects on application outcomes and that students whose peers take up these services are more likely to take them up as well. We now examine how the outcomes of students who do not take up any additional services are affected by two types of peers: uptake peers (those who take up additional counselor services and are well informed) and non-uptake peers (those do not take up additional services and are less informed). The information flow channel would suggest that the student outcomes should be more affected by the outcomes of their uptake peers and less by the outcomes of their non-uptake peers.

Table 13 presents evidence in support of the information flow hypothesis. We restrict attention to the sample of "less informed" students, that is, students who do not take up additional services. In columns (1) and (2), we regress the standardized quality of college for the less in-

formed students on the standardized college quality of uptake peers and the college quality for non-uptake peers. The OLS estimates in column (1) show that a one standard deviation increase in the college quality of uptake peers is associated with a 0.29 standard deviation rise in the average standardized quality of non-uptake students, holding other factors fixed. The coefficient is statistically significant. The coefficient on non-uptake peers is, instead, close to zero, and the standard errors are large. The estimates are larger for the 2SLS coefficients[7] in column (2), and the estimates for both types of peers are similar in magnitude. However, the standard error on non-uptake peers is significantly larger, implying that the corresponding estimate cannot be statistically distinguished from zero. The coefficient on uptake peers remains significant at the 1% level.

In columns (3) and (4) of Table 13, we find a similar pattern for whether students received a scholarship: Uptake peers affect the less informed students' likelihood of getting scholarship significantly more than non-uptake students.

The main takeaway from the results presented in this section is that there is flow of information through classroom networks from more informed peers to less informed ones and that this could be a potential mechanism through which peers effects operate.

6 Conclusion

In this paper, we investigate how school peer influences shape students' college application decisions. We identify peer effects by leveraging non-fully overlapping peer groups (classmates) and comprehensive administrative student data. Our findings reveal that, when peers apply to higher-quality institutions, students significantly elevate their own application standards.

[7]For the IV specifications in this table, there are two endogenous variables: the outcome of direct uptake peers and outcome of direct non-uptake peers. We instrument these by the outcome of indirect uptake peers and indirect non-uptake peers.

Students demonstrate stronger responses to application choices made by white, high-income, and high-GPA peers. However, we observe notable heterogeneity in these patterns. While both low- and high-GPA students respond more robustly to high-GPA peers, low-income students display stronger responses to their low-income peers than to high-income counterparts. Interestingly, non-white students show heightened responsiveness to their white peers—even more pronounced than white students' responses to white peers. Gender, however, does not appear to drive differential responses; female and male students respond similarly to peers of either gender. While these patterns hold for average application quality, in future work, we will also examine the effect of peers on how diversified students' application portfolios are. Moreover, having illustrated that flow of information from more informed students to less informed ones could be a potential mechanism through which our observed peer effects operate, in future work we will further explore how information flows through classroom networks.

Our finding that within-group peer responses are not significantly stronger than across-group responses is encouraging for schools aiming to improve outcomes for disadvantaged students. In particular, integrating students from diverse backgrounds has the potential to enhance overall achievement. For example, our research demonstrates that all students respond strongly to high-GPA peers, regardless of their own academic standing. This suggests that deliberately increasing lower-GPA students' exposure to high-performing peers could yield substantial benefits. We will evaluate such potential policies by more explicitly examining the role of teachers and counselors in creating such an environment.

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A Appendix: Additional Figures

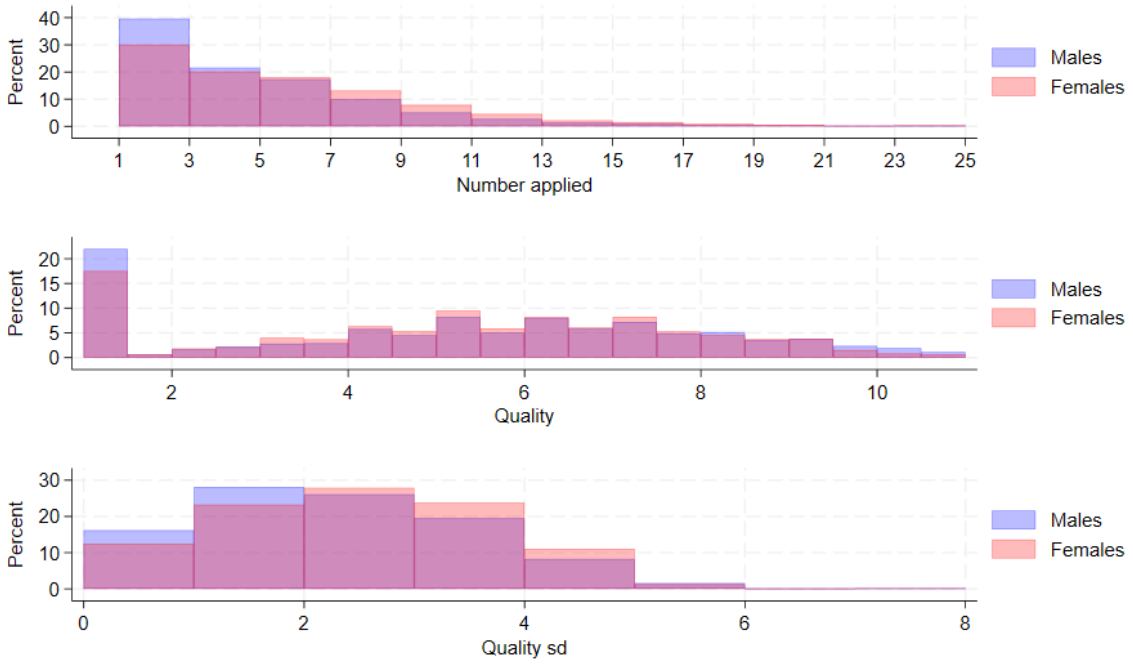


Figure A1: Application Patterns by Gender

Number applied denotes the number of applications submitted; *Quality* is the average quality of the colleges applied to; *Quality sd* denotes the variation (standard deviation) in the quality of the applications submitted. All variables are defined at the student level.

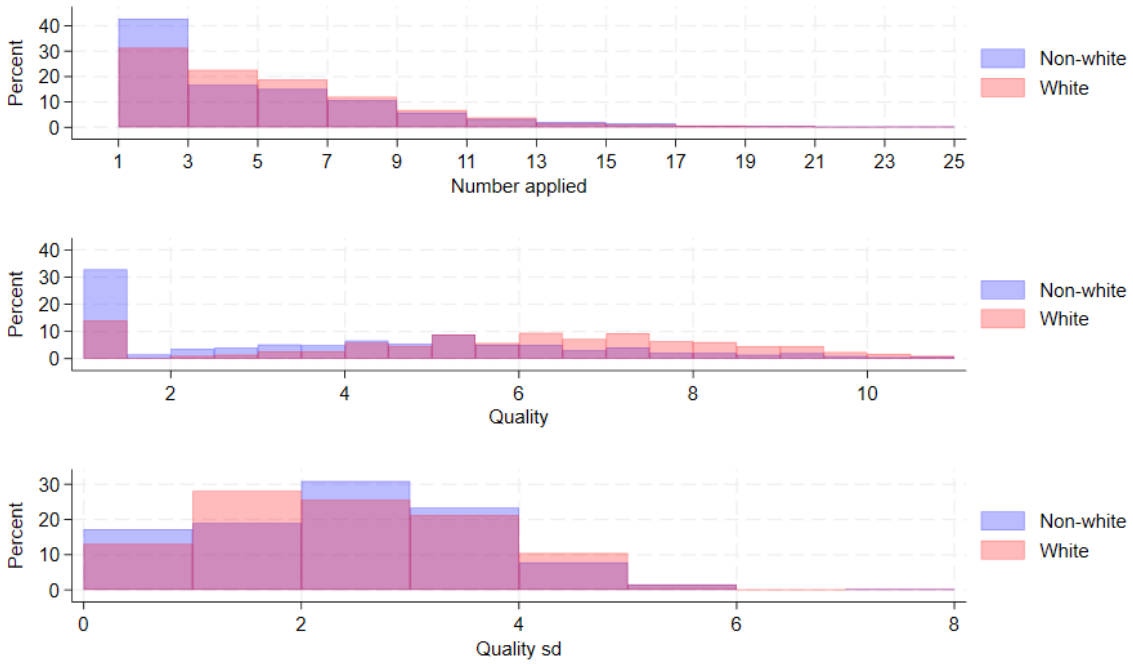


Figure A2: Application Patterns by Race

Number applied denotes the number of applications submitted; *Quality* is the average quality of the colleges applied to; *Quality sd* denotes the variation (standard deviation) in the quality of the applications submitted. All variables are defined at the student level.

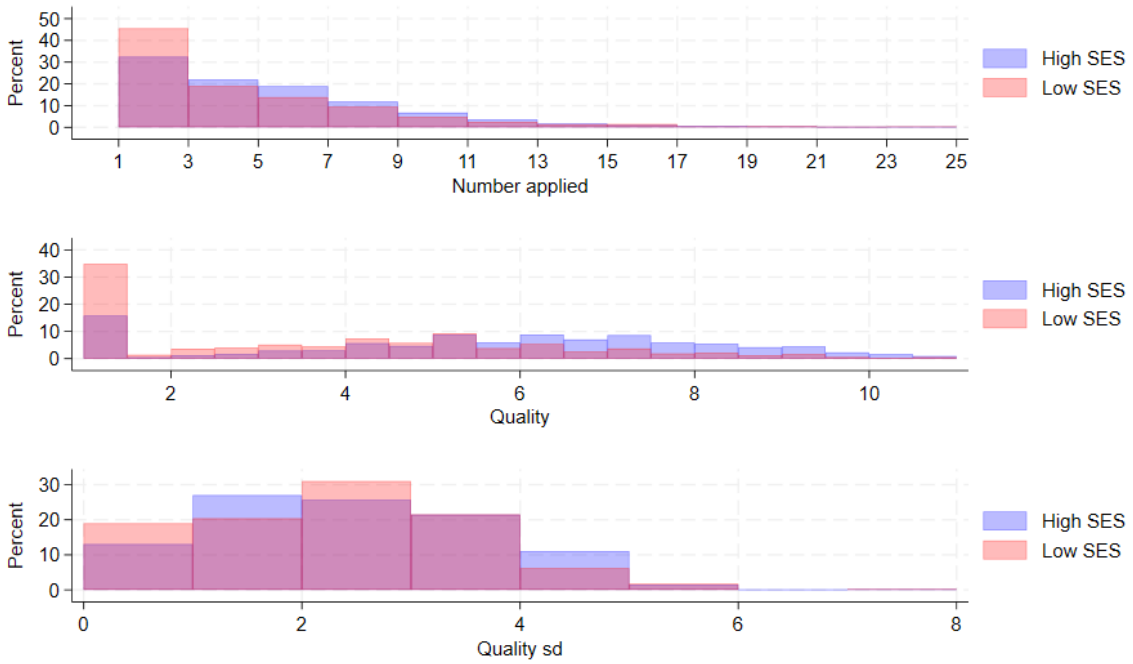


Figure A3: Application Patterns by Socio-Economic Status

Number applied denotes the number of applications submitted; *Quality* is the average quality of the colleges applied to; *Quality sd* denotes the variation (standard deviation) in the quality of the applications submitted. All variables are defined at the student level.

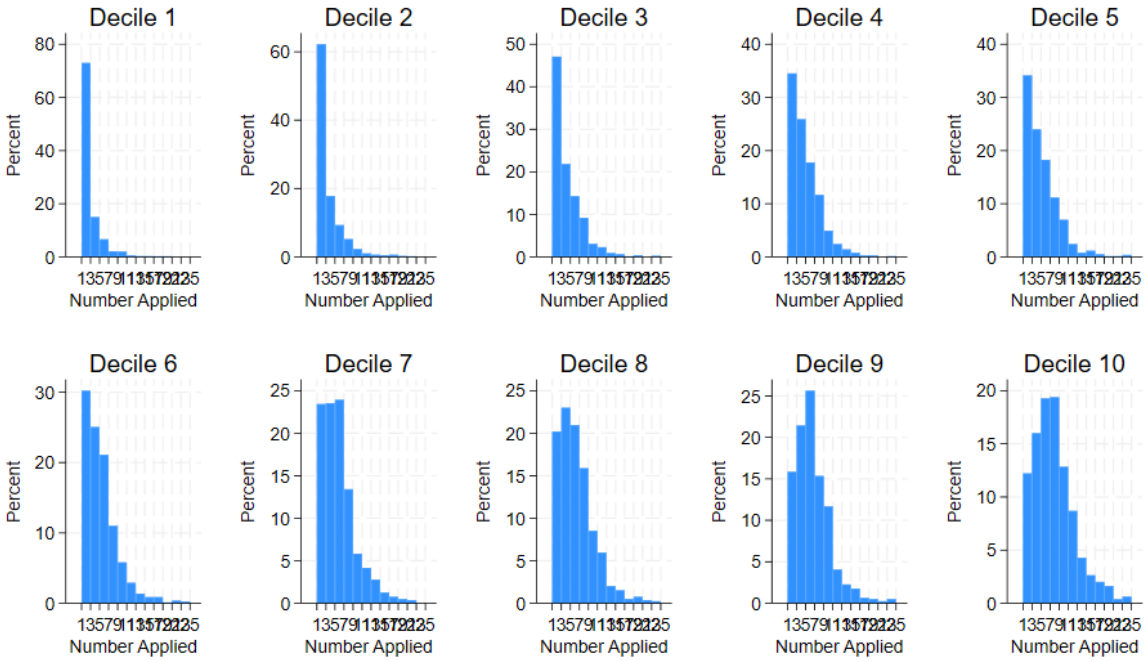


Figure A4: Number of Applications by GPA Decile (Among Applicants)

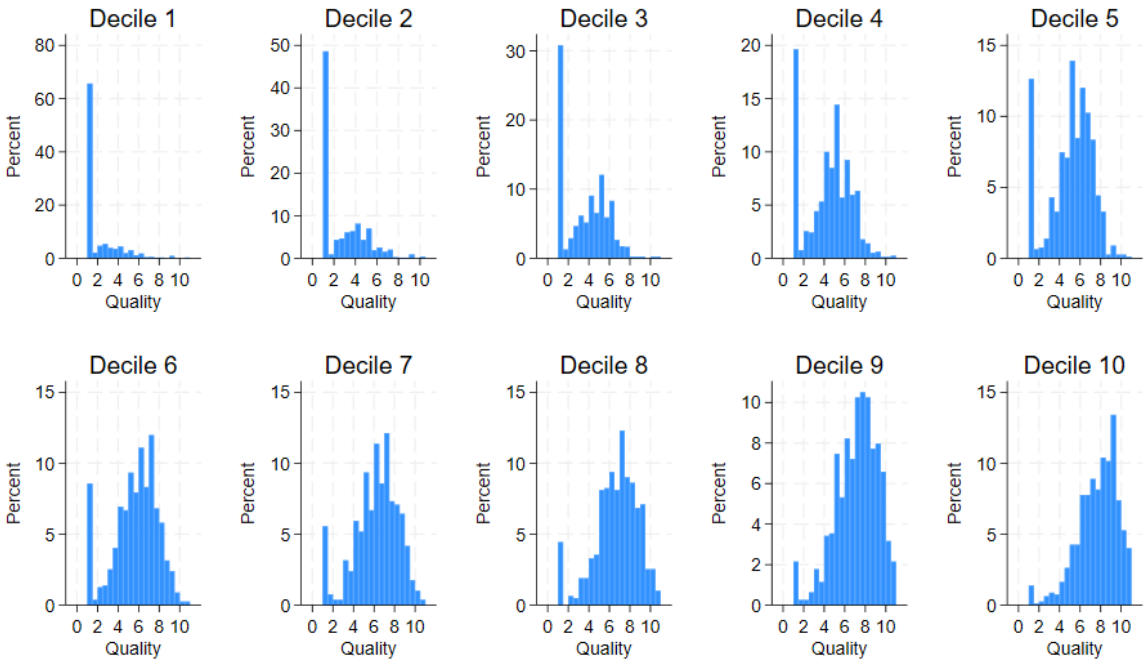


Figure A5: Application Quality by GPA Decile (Among Applicants)

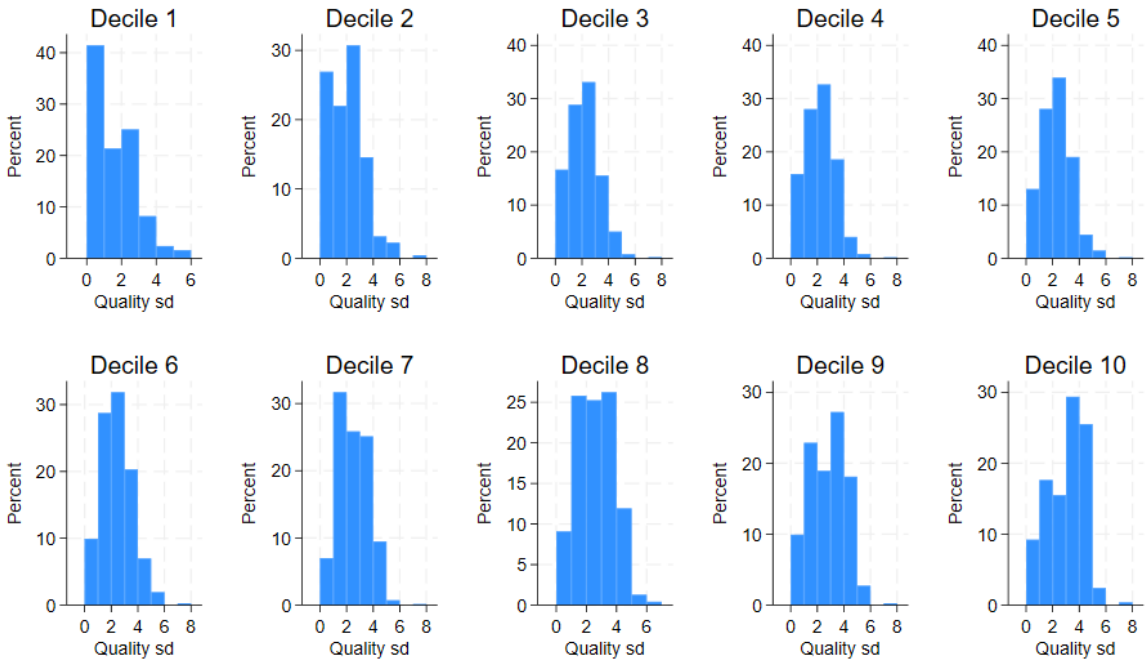


Figure A6: Within-Student Variation (SD) in Application Quality by GPA Decile (Among Applicants)

B Appendix: Senior Survey 2024

In this section we list the questions from the Senior Survey 2024 administered to student who apply to colleges. Here is the list of questions:

1. Class Year
2. Student ID
3. What are your plans for next year?
4. Please update your college admissions information below. IMPORTANT: You MUST tell us where you plan to attend college next year by checking the box in the "ATTENDING" and "SEND FINAL TRANSCRIPTS" columns for one college on your list. THIS IS WHERE YOUR FINAL TRANSCRIPTS WILL BE SENT.
    - If you plan to attend college next year: which school should we send your final high school transcript to?
5. Did you win a scholarship? Yes or No? If yes, please list the total dollar amount you were awarded, even for schools you are not attending.
6. Are you a first-generation college student? (Your parents did not complete a 4-year college degree).
7. Please let us know what counseling services you used? Check all that apply.
    - Met with my school counselor
    - Met with a college rep
    - Met with a college and career coordinator
    - Participated in (college) prep course