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Connections Matter! How Interactive Peers Affect Students in Online College Courses

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ABSTRACT

Peers affect individual's productivity in the workforce, in education, and in other team-based tasks. Using large-scale language data from an online college course, we measure the impacts of peer interactions on student learning outcomes and persistence. In our setting, students are quasi-randomly assigned to peers, and as such, we are able to overcome selection biases stemming from endogenous peer grouping. We also mitigate reflection bias by utilizing rich student interaction data. We find that females and older students are more likely to engage in student interactions. Students are also more likely to interact with peers of same gender and with peers from roughly the same geographic region. For students who are relatively less likely to be engaged in online discussion, exposure to more interactive peers increases their probabilities of passing the course, improves their grade in the course, and increases their likelihood of enrolling in the following academic term. This study demonstrates how the use of large-scale, text-based data can provide insights into students' learning processes.

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Connections Matter:

How Interactive Peers Affect Students in Online College Courses

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Abstract

Peers affect individual's productivity in the workforce, in education, and in other team-based tasks. Using large-scale language data from an online college course, we measure the impacts of peer interactions on student learning outcomes and persistence. In our setting, students are quasi-randomly assigned to peers, and as such, we are able to overcome selection biases stemming from endogenous peer grouping. We also mitigate reflection bias by utilizing rich student interaction data. We find that females and older students are more likely to engage in student interactions. Students are also more likely to interact with peers of the same gender and with peers from roughly the same geographic region. For students who are relatively less likely to be engaged in online discussion, exposure to more interactive peers increases their probabilities of passing the course, improves their grade in the course, and increases their likelihood of enrolling in the following academic term. This study demonstrates how the use of large-scale, text-based data can provide insights into students' learning processes.

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Key Words: peer effects; online learning; higher education; peer interaction

INTRODUCTION

Peer interactions are an integral part of higher education (Winston, 1999). Peers can influence the quality of instruction (Anderson et al., 2001; Smith, 1977), recruitment of students (Pascarella et al., 2001), retention (Pascarella & Terenzini, 1980; Stinebrickner & Stinebrickner, 2000; Skahill, 2003), and students' social and academic integration into the institution (Tinto, 1994). Multiple researchers have demonstrated that college peers can influence students' academic performance, students' attitudes toward social and cultural policies, and the likelihood that students develop friendships with a racially and socioeconomically diverse set of peers (Carrell, Fullerton, & West, 2009; Duncan et al., 2005; Kremer & Levy, 2008; Marmaros & Sacerdote, 2006; Sacerdote, 2011 & 2001; Winston & Zimmerman, 2004; Zimmerman, 2003).

Most peer interaction in higher education occurs in traditional classroom settings, during group discussions or assignments, or in residential or other social settings. However, higher education is changing. Over the past decade, the use of online courses has dramatically increased (Allen & Seaman, 2013), even excluding the recent fascination with and growth of massive open online courses (MOOCs). Approximately one-third of all undergraduates now take at least one course online (not including MOOCs), and most universities have increased the number of online courses and programs available to students. In these online courses, peer interactions are fundamentally different. Student in the same class often participate at different times and the lack of in-person meeting has been hypothesized to cause the negative effects that have been documented in the literature of online courses relative to traditional in-person courses (Bettinger et al., 2015; Hart & Friedmann, 2014; Xu & Jaggars, 2014 & 2013). However, peers do interact in online courses. They interact in different ways. In place of traditional face-to-face interactions, online discussion boards are now primary arenas for peer interaction.

Our paper addresses peer-to-peer interactions in virtual classrooms. Our study is one of the few studies of peers in these settings. We characterize peers by the nature of their direct contributions to the class, instead of by their background characteristics. Traditional studies of peers in face-to-face settings rarely have access to measures of interactions and instead use measures of background characteristics, such as prior test scores, to proxy for the inputs that peers make to the student in question. In online settings, peer interactions are recorded on discussion boards and through other digital media. These peer interactions are transcribed creating large-scale data sets that afford new opportunities to researchers. These new "big data" allow researchers to move beyond peer characteristics and to focus on the content of peer interactions. Our particular focus in this paper is peer outreach to each other. Specifically, we examine how peer-to-peer outreach and dialogue impact student learning.

We use data from DeVry University, one of the largest for-profit universities in the United States. DeVry provided us with comprehensive data including the text from all communications among students and between students and professors for their two largest undergraduate courses, "College Skills" (COLL148) and "Introduction to Psychology" (PSYC110). Our data covers nearly 29,000 students who took one of 1,421 online sections of these courses offered in Spring, Summer, or Fall session of 2010. We focus on the 10,811 in 471 sections of PSYC110 because, as described more fully below, this course is more representative of typical higher education courses and is a better forum for testing peer interaction effects. These data include unusually detailed information on students' online behaviors, including word-by-word content on students' postings and the timestamps of each post. We identify the cases in which a specific student responds to a peer's comment. We examine how peers' characteristics and actions are related to their propensity for peer interaction and how students choose peers to interact with based on the similarities and dissimilarities between peers and themselves. We then estimate the causal impacts of peers' interpersonal interaction on student academic achievement and persistence in college.

Our analysis shows that students vary systematically in their interpersonal interactions. For example, females are more likely to initiate interaction and are also more likely to be recognized by peers. When students post longer posts and post more frequently, they are more likely to engage in interactions both as recognizing peers and as being recognized by others. We also find evidence that peer engagement practices can affect student outcomes. In particular, for students who tend to be less engaged in interpersonal interactions, having peers who reach out to engage classmates benefits their class performance, improving the likelihood of completion and their grade in the course. These results are far stronger for PSYC110 where peer interactions are less common than they are in COLL148, a course that intentionally cultivates such interaction.

PRIOR RESEARCH

Our research builds on two separate literatures: the large body of research in education, sociology, and economics on peer interactions and the emerging body of research on the impacts of online courses.

Peer effects have long been of interest to education scholars, sociologists, and economists. Many early studies (e.g. Webb, 1989) linked the patterns and characteristics of small group interaction to student motivation, critical thinking, problem solving, and a wide range of learning outcomes (Webb, 1989; Smith, 1977). Students' interactions with the larger academic and social systems of their college – how well they are integrated into their institution – strongly predict their attrition at the end of their freshman year (Pascarella & Terenzini, 1980). Learning communities and other efforts to create small peer networks aim at improving students' outcomes through peer interactions (Tinto, 1994). Much of the extant literature has tried to identify the evolution and development of "social networks," and the sociology literature has examined the role of race, ethnicity, and propinquity in network formation (Biancani & McFarland, 2013). In recent years, economists and sociologists have attempted to identify the impact of peer networks on students' academic achievement and attitudes toward race and cultural awareness (e.g. Duncan, et. al 2005; Biancani & McFarland 2013).

While it is well accepted that "peer effects" can mean many things (Hoxby & Weingarth, 2000), the existing empirical studies of peers generally examine "who peers are" rather than "what peers do." For example, these studies may ask whether having higher achieving classmates increases student learning. By contrast, theoretical models of peer effects are more likely to focus on peer behaviors than on peer characteristics. For example, Lazear's model of disruption and congestion provides a theory for why class size matters (Lazear, 2001). The model focuses not on peers' characteristics but on the probability that peers disrupt the course as the operative measure. In this oft-cited model, peer effects are the vehicle by which class size might impact outcomes.

Empirically, measuring the causal impact of peer interactions is difficult, particularly in higher education. One problem is that students self-select into specific courses. Students choose their courses, their professors, and their peers. Typically, for example, students with high prior achievement tend to choose courses that attract other students with high prior achievement. These courses are often taught by accomplished professors. A study of peer effects which does not account for such student and professor sorting may be biased. Hence, many of the prominent studies on peer effects rely on random assignment (Carrell et al., 2009; Sacerdote, 2001; Zimmerman, 2003). As we explain below, we use a quasi-random student assignment process that allows us to identify exogenous shifts in students' peer groups.

Another common empirical problem in peer interaction studies is the "reflection problem" (Manski, 1993). The "reflection problem" describes the simultaneous nature of peer interactions in which peer behaviors are influenced by the target student's behavior as the target student's behavior is influenced by his or her peers. For example, a high achieving peer might influence a peer to perform better. The improved performance by the peer might influence (or "reflect" back on) the first student, leading to improved outcomes for the already high-achieving student. Empirically, it becomes difficult for the researcher to separate out what performance would be in the absence of any peer impacts and how strong the initial peer impact is relative to any subsequent "reflection." One of the strengths of using online data is that we see the full evolution of peer impacts and use a strategy similar to Bettinger, Loeb, and Taylor (2015) to create instruments measuring peer behaviors prior to their influence by the target student which allow us to estimate the impact of peer effects in a way which is free from reflection.

The second strand of literature upon which we build is the emerging literature on the impact of online courses. Emerging research attempts to identify whether student learning is better in online or in-person classrooms (Bowen et al., 2014; Bettinger et al., 2015; Figlio, Rush, & Yin, 2013; Joyce et al., 2015; Xu & Jaggars, 2013). These studies consistently find that students who take online courses perform worse on course completion and course grades at community colleges (Hart, Friedmann, & Hill 2014, Xu & Jaggars 2014 & 2013, Streich 2014b, a) and receive lower exam scores at four-year institutions (Figlio, Rush, & Yin 2013, Bowen et al., 2014) compared with their counterparts in in-person settings. One recent study by Bettinger et al. (2015), also using data from DeVry, finds that online courses not only reduce students' grades in the current course, but also their performance in future courses and their persistence in college. A potential factor distinguishing online and in-person settings in these studies is the peer-to-peer interaction. While we do not have data to directly compare the differences of peer interaction in online versus in-person settings, we provide some of the first evidence on how peers affect student performance in online college courses.

One paradigm for understanding peer effects is to separate students' online behavior into two categories: action and interaction. Action, like the frequency and length of student postings, is relatively easy to measure (see Bettinger, Loeb, & Taylor, 2015). By contrast, interaction is more difficult to detect because the information is hidden in the content of posts.[1] One example of interaction is course content that is introduced or queried by the professor and responded to or discussed by students. However, this content-focus aspect of interaction is only one feature of interaction. Interpersonal interaction is another. Interpersonal interaction has been recognized as one of the most critical behaviors in students' learning experiences, and is also one of the most common themes of research in distance education (Holmberg, 1987; Moore, 1993; Vygotsky, 1971).

Anderson (2003) points out two main benefits of peer interaction in both in-person and distance education. First, the act of engaging in student-to-student interaction forces students to develop ideas more deeply. Second, the communication of an idea to peers also raises students' interest and motivation due to the psychological commitment and risk taking involved in publicly espousing one's views. The nature of peer interaction frequently decides the success of online courses (Picciano, 2002). To date, there are few papers which extend these peer effect studies into online settings. Shin (2003) provides some evidence that a stronger sense of peer "presence" is

[1] In this paper, interpersonal interaction, student interaction, and peer interaction are interchangeable. They all refer to the social dimension of student interaction. In the large "distance education" literature, interaction, as a more general concept, is first clarified by Moore (1993). Interaction includes learner-instructor interaction, learner-content interaction, and learner-learner interaction. Our definition is very close to Moore's learner-learner interaction, but more specific.

related to student's satisfaction and intent-to-persist in online learning (Shin, 2003). Perhaps the most related paper is the work by Bettinger, Loeb, and Taylor (2015). They find that students in college online courses are hurt by peers who post often or who post long posts.

Our research builds on this prior research by examining social ties in online courses. When students directly respond to each other, they form a link. Since students in online courses likely hold relatively less information about peers, the factors that affect interaction formation in online courses can be different from in-person settings. For example, students may not even know the appearance or ethnicity of their peers in an online course. Thus, the nature of interactive ties may differ in online courses, as may the effects of these ties on students' motivation and participation in the course. Following the discussion above, this paper considers both the interaction formation process and the effects of peers' interpersonal interaction. Specifically, we answer two research questions:

(1) How do students' roles in interpersonal interaction in college online courses vary systematically by their characteristics and actions?

(2) How do peer's interpersonal interactions affect student course performance and persistence in the following semester, especially for those who are less likely to be engaged in classroom interactions?

DATA AND KEY METRICS

The data for our study come from DeVry University, one of the largest for-profit higher-education institutions in the United States. In the fall of 2013, DeVry enrolled about 65,000 students, 75 percent of whom pursued a Baccalaureate degree. Most students major in business management, technology, health, or some combination of these. Two-thirds of all DeVry enrollments occur in virtual classrooms, while most students take at least one in-person course at one of DeVry's nearly 100 campus locations in the United States. DeVry students are geographically and racially more diverse than most US colleges.[2]

Our data contain detailed information about the two most popular courses at DeVry – PSYC110, an introductory level psychology class, and COLL148, an introductory course covering skills useful for college including critical reading and writing, library research, and college planning. Our data include comprehensive data on the nearly 27,000 students who took PSYC110 or COLL148 during 2010. For this paper, we focus extensively on PSYC110 because of its similarity to psychology courses in most universities. COLL148 is a unique course designed to foster peer interaction. Specifically, students in this course are assigned to small groups to work on teamwork. As a result, peer interaction in COLL148 is built-in and unlikely to mirror naturally occurring peer interaction. In contrast, PSYC110 does not have such required teamwork or other features designed to strongly motivate peer interaction, which makes it more typical of most of DeVry's online courses and of online courses offered elsewhere. Thus PSYC110 provides a more representative setting to study peer interaction. We replicate our analysis for COLL148 and include them in the appendix.[3]

DeVry organizes each online course into small sections. Students participate in the course by "meeting" asynchronously in a section-specific discussion board in a password-protected website. Each week the section professor leads the discussion by posting a series of "discussion

[2] DeVry Annual Academic Report (2012-2013), http://viewer.zmags.com/publication/e1c69ab9#/e1c69ab9/1. Note that DeVry had nearly 100 campuses at the time of our data. Since 2010, they have closed roughly 15 campuses.

[3] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgibin/jhome/34787.

threads" on the board. Students are required to contribute comments on each topic thread a minimum of three days each week with their first post no latter than Wednesday. Our analysis of the data shows that students' first posts tend to concentrate on Wednesdays. The quality of posts is also considered in the grading rubrics. Quality posts should provide additional information, elaborate on previous comments, present explanations of concepts or methods, present reasoning for or against a topic, and share personal experience, etc. Post quantity as well as quality together count for 28 percent of the final grades. Besides containing information on student demographics and course outcomes, the data contain full transcripts of all the online writing communications between students. We create our measures of peer interaction from these transcripts. One weakness of this data set is that we do not observe the hierarchy of students' statements directly although the content and timing of students' statements allow us to infer much of this hierarchy. DeVry has given us separate data for a subset of students in March 2015. These data do include markers for the hierarchy of the discussion boards, which allow us to calibrate the potential measurement error that might exist in our inferred measures of student interactions. We do not use the more recent data because it would not allow us to look at outcomes for students as we can use the earlier data.

Student Demographics and Outcomes

Table 1 describes the sample. PSYC110 enrolled 11,142 students in this period, slightly over half of whom are male. Students in the three largest majors of DeVry – business, technology, and health – represent over 54 percent of the sample. Forty-one percent of students are in their first semester. We use six measures of student outcomes: whether a student passed the course, students' course grades, the number of points received (a combination of all the assignment, quiz, and exam scores), and enrollment status and enrolled credits in the following semester. These measures enable us to estimate both short-term and longer-term effects of interpersonal interaction of peers.

The last four rows in Table 1 summarize the characteristics of student action and interaction. On average students generate 42 posts in the entire span of the class, approximately 5 each week. To describe action, we use measures of posting frequency and posting length. For posting frequency we use the average time between posts for every student. Since every section has a fixed 8-week duration, the longer the average time, the fewer posts a student generates. For posting length, we use number of words. The average time between posts is about 33 hours, and the average length of posts is 90 words.

While we assess five different outcome variables: whether the student passed the course, her course grade, course points, whether she enrolled the next semester, and credits she enrolled in next semester, these variables clearly overlap. Passing the course is simply a dummy variable for having a passing grade in a course. Course points are accumulated score on course requirements, which are converted to a letter grade at the end of the course. Here we use the portion least likely to be influenced by professors' subjective judgment such as points earned on quizzes and final exam. We create standardized course points within course-by-term. The correlation between course grade and course points is 0.86. Similarly, for the longer-run outcomes, course credits are only available for students who are enrolled. Students pass their classes about 80 percent of the time. Their average grade is 2.2, approximately a C+. A large share, 82 percent enroll in the following term, with an average credit load of 9.5.

[Table 1 here]

Identifying Interpersonal Interaction

Our research questions focus on peer interactions. Measuring *peer action* is relatively easy, because we directly observe posting frequency and time elapsed between posts. Measuring *interaction* is more difficult because evidence of interaction is embedded in the content of the dialogue. To develop measures of interaction, we randomly selected a sample of 300 posts. We categorized these interactions into three groups. In the first group, students show evidence of having read peers' comments, and specifically refer to peers' ideas and names. In the second group, students show some evidence of having read peers' comments, but do not embed peers' names in the language. In the last group, students do not relate their own comments to peers' posts. Sample posts of these three situations are below:

> *Type 1. "Agreeing with* ***Peer-A***[4] *we would have to go with theory number one the restoration sleep. Like she said the body like any other piece of machinery needs down time to rest, restore, or reincorporate. …"*

> *Type 2. "huh? Well we think you're talking about how one relaxes themselves and tries to fall asleep. …"*

> *Type 3. "Stress play's a big role in my physical, mental, and emotional. When we are stressed most of the time my blood pressure goes up, we are not function the way we should be and that gets in the way of home and work. Me myself don't wont to be bother with nobody or anything at the time."*

[4] We anonymize the name here.

In the first post, the student mentions a specific peer's name, and repeats part of the peer's idea. The author then builds on the initial peers' comment. In the second sample, the student does not mention the peer's name, but the phrase "you're talking" makes the interaction evident. This post has some interpersonal interaction embedded in it, but the interaction is not as clear as it is in the first post. In the third post, the student focuses on her own experience. She may be responding to a post about the role of stress in personal life, but her post gives no indication of whether she has read or is responding to other posts.

In theory, students could initiate an interaction by referring to a specific prior peer but not name the writer. In our analysis of the 300 posts, 15 percent show evidence of interaction. Eleven percent of the posts include a specific peer's name (Type 1), while another 4 percent show evidence of interaction without using peers' names (Type 2). The majority of posts show no interaction (Type 3). Our metric focuses on Type 1, because we can use the presence of peer names to identify peer interaction across a large number of posts.

Extracting Peer Names from Post Data

To create a measure based on including peer names in a post, we need to use natural language processing techniques to extract peers' names from each post. Our algorithm starts with student name rosters from the administrative data provided by DeVry and creates a section-specific name dictionary. We then loop through every post and identify whether there is an overlapping name from the name dictionary included in the language. With this algorithm it is possible to extract a student's own name when students name themselves, so we compare the extracted name with the post author's name and nullify those self-named cases. We then build an algorithm that reads through each post to check whether there is an overlapping name between the corpus and the post. If a student mentions other students, we say that the student "nominates" others. We say that those mentioned by the students were "nominated."

The threats to the validity of our measure come from two sources. First, our name extraction might be imprecise. For example, when students use nicknames to interact with peers, we might not be able to identify those interactions given we use name rosters from administrative data. Similarly, a student may use a name when discussing their family or course material but not be referring to students in the class. We test the precision of our algorithm by taking 300 random posts and hand coding them. When we compare the results with the export from our algorithm, 96 percent of the hand-coded posts match the algorithm results.

Another concern is whether nomination of peers truly reveals the behavior of peer interaction. One possibility is that students nominate peers as a reference rather than as part of an interaction. For example, a student could mention a peer while actually talking to the professor. To determine whether peer naming accurately reflects interaction, we requested additional data from DeVry. They provided us with transcripts from a selection of DeVry online courses offered in March 2015. They did not provide us with outcomes for these students (hence we do not use them in the main analysis); however, these data do include the complete hierarchy of the discussion posts, which allows us to directly observe whether a peer's comment is in response to another students' post. We use these data to validate our measure of peer interaction. To do this, we create an alternative measure of interaction based on the new data that uses the hierarchal nature of the discussion board. This measure classifies each post as responding to a peer, to a professor, or to the public (i.e. posts that initiate a new thread without targeting a specific person). When we compare this new measure to our primary measure, we find that 92.6 percent of the naming posts appear in the discussion board hierarchy to be direct responses to peers. This similarity provides support for using our peer nomination measures to characterize peer interaction.[5]

[Table 2 here]

We include descriptions of peer nominating behavior in Table 1. Our main measure of student interaction is captured by the nomination volume of each student. Based on this measure, on average, only 4 out of 42 posts for a student have peer interaction, a ratio of less than 10 percent. To benchmark this number, in COLL148 students nominate their peers in about 11 posts, or about 17.5 percent of their total posts. This comparison reinforces our assertion that peer interaction is sparse in PSYC110.

Pairwise Description

The identification of peer names in each post enables us to match students who mention a peer's name (nominators) to the peers whom the student mentions (nominees). This exercise is useful because it can shed light on which peers are nominated and how nominators choose nominees. We generate a pairwise dataset by first matching every student to all other students in the same section. Given the identified nominees for each student, we label each student as to whether she is nominated and the frequency of nomination by the focal student. In a few sections, two students share the same first name. We label both as nominees if a student nominate their name.

[5] Unfortunately, assuming that the "responses" without names are indeed responses to the person before them, we only pick up about half of the total number of texts that follow other students. This generates measurement error in our primary measure. We compared the indirect and naming measures of interaction and found that differences in the metrics cannot be explained by student characteristics. While not a perfect test, this suggests the measurement error is unrelated to unobservable characteristics, suggesting that the error may be classical measurement error which attenuates the estimated effects.

EMPIRICAL STRATEGY

As mentioned above, there are two key problems in empirically identifying causal impacts of peer effects: student sorting and reflection. DeVry has a clear rule for assigning students to online sections. Specifically, DeVry assigns students in the order of their registration. Since there is a cap for each section, after a section is full, a new section is created to meet the demand. This process continues until all students are assigned to a course. Students who register early likely differ from those who register late. On average, early registrants may be better prepared for college and more motivated than late ones. This sorting could lead to bias in estimation for both of our research questions due to unobserved factors that affect student behavior and outcomes and correlate with peer characteristics. By contrast, students who register at the same time are likely similar in these unobserved characteristics. To exploit this information, we create blocks that contain 3 sequentially formed sections and identify our effects using only variation across sections within blocks. The underlying assumption is that if the time when students register is sufficiently close, students in those blocks are similar on average in both observed and unobserved characteristics. This similarity is especially likely to hold in the days leading up to a semester when dozens of sections are formed in a matter of hours.

To test whether sequential blocks can successfully eliminate selection bias, we run a set of validation tests. First, we regress each student characteristics on the sequential number of sections. If students who register late are different from those who register early, we expect to see significant differences in the outcomes related to registration time. We then rerun the regressions with block fixed effects as described above. If our assumption is correct, we should expect few differences across students related to registration time once we include the block fixed effects. The results are presented in Table 3. As the first column shows, early and late registrants significantly differ on age, status at the university, number of credits enrolled, and major. The joint test is significant over a 99 percent confidence interval. By contrast, after controlling block fixed effects, the joint test is no significant at traditional levels. We cannot measure whether students are balanced in unobservable characteristics, but given that the observable characteristics are balanced, our assumption is justifiable.

Sorting occurs not only by students, but also by professors. For example, DeVry allocates professors primarily based on their prior performance evaluation. The professor who has the highest ranking in the evaluation is assigned to teach section 1; the professor with the second place ranking is assigned to section 2; and so on. Once all available professors have one section to teach, the assignment starts again the professor who ranked first. To adjust for the systematic sorting of professors to classes, we include professor fixed effects in the analyses. We observe six terms and have adequate variation within professors. While not reported, we conducted analyses similar to Table 3; and find no evidence that the assignment of professors creates bias.

In keeping with this discussion, we employ block fixed effects and professor fixed effects[6] to alleviate selection bias in the analysis of both research questions. As the reflection problem is not central to our descriptive analysis (Research Question 1), we discuss it below when we outline our methods for measuring causal estimates.

Research Question 1

How do students' roles in interpersonal interaction in college online courses vary systematically by their characteristics and actions? To answer this question, we first examine the characteristics that predict the likelihood of being a nominator and a nominee. Then, using the pairwise dataset

[6] In some specifications we estimate models with and without professor fixed effects to test the robustness of results.

described in the previous section, we investigate the interaction between nominators and nominees, asking whether nominators are more likely to nominate peers with characteristics similar to their own.

In the analysis of both nominators and nominees, we run simple ordinary least square regressions.

$$y_{ict} = \beta_0 + \beta_1 Gender_{ict} + \beta_2 Age_{ict} + \beta_3 BA_{ict} + \theta_b + \nu_p + \varepsilon_{ict} \quad (1)$$

where y_{ict} indexes the outcomes of interest for student i in course c in term t. For addressing who initiates interpersonal interaction, the dependent variables include an indicator variable for whether a person is a nominator and a continuous variable for the total volume of nomination. Two similar outcome variables measure interaction receipt: an indicator for whether the student is nominated and a continuous measure for the number of nominations received.

We test whether students who differ in the following characteristics are differentially likely to nominate and be nominated: gender, age and whether they are seeking a baccalaureate degree. In these models, we control for block fixed effects and professor fixed effects, indexed by θ_b and ν_p, to mitigate the potential bias. In some models, we also include a measure of the individual's average time that elapses between posts, which measures the number of posts that students make, and we include a measure of the individual's average post length. We include these measures in order to test whether students who nominate and are nominated also post differently along other dimensions. Controlling for the frequency of posts also turns out to be important for answering research question 2.

To address the second part of this question, whether student nominate peers who are observably similar, we use the matched pairwise dataset to build new variables indicating whether two students share characteristics. We again use gender, age, and whether they are seeking a BA.

We also add a variable indicating whether the students live closest to the same DeVry campus. We control for block fixed effects and professor fixed effects and include nominator-level individual fixed effects to control for individual time-invariant factors. The coefficients are straightforward to interpret. For example, the reference group for "same gender" naturally includes male to female and female to male combinations.

Research Question 2

How do peer's interpersonal interactions affect student course performance and persistence in the following semester, especially for those who are less likely to be engaged in classroom interactions? In addition to the problems of bias arising from student and professor sorting, a difficulty in measuring peer effects comes from the "reflection problem." The reflection problem occurs because of the simultaneity of peer interaction. Peers interact with each other and "reflect" onto each other. Our strategy for overcoming this simultaneity is the same as that employed by Bettinger, Loeb and Taylor (2015), who utilize the "big data" nature of transcript data to generate instrumental variables. Their method relies on the sequential nature of student posting behavior to isolate variation in student behavior that is free from the influence of reflection-induced variation. This variation can then be used to instrument both peers' behavior and students' own behavior.

To understand this strategy, we start by modeling student outcomes in equation (2):

$$y_{ict} = W_{ict}\beta_0 + X_{ict}\beta_1 + \theta_b + \nu_p + \varepsilon_{ict} \quad (2)$$

In this model, y_{ict} indexes academic outcomes of student i in course c in term t. W_{ict} indicates i's peer interpersonal interaction, measured by the volume of peer nominating behavior. X_{ict} indicates measures of student i's own behavior paralleling those in W_{ict}. θ_b is a set of fixed effects to account for block fixed effects, and ν_p indicates professor fixed effect. β_0 – in particular, the coefficient on the measure of peer's intensity of interpersonal interaction within W_{ict} – is the parameter of interest in this paper. To create this measure, we use the jackknife median of peers' nomination volume within section-by-course-by-term. We similarly use jackknife medians to create the other measures of peer action in W_{ict}.

The reflection problem arises because student i's behavior (e.g. whether they nominate a peer) in a given post p, indexed as C_{ip}, is (potentially) a function of her own prior behavior and the prior behavior of her peers, $B_{i(p-1)}$. For example, whether a student initiates an interaction depends on her behavior in her last post and whether peers responded to it. It is also plausible that C_{ip} is partly a function of student time-invariant abilities and preferences, μ_i. Thus, assuming linear separability, we can take advantage of the recursive nature of the data and write C_{ip} in the dynamic panel data form:

$$C_{ip} = \gamma B_{ip} + \alpha C_{i,(p-1)} + \mu_i + \upsilon_{ip} \quad (3)$$

Reflection arises because peer behavior, B_{ip}, is a function of the student's prior behavior, $C_{i(p-1)}$. Similarly, $C_{i(p-1)}$ is a function of $B_{i(p-1)}$, and so on.

By contrast, if equation (3) is correctly specified, the μ_i terms capture variation in student behavior, say ability and preferences, which are not influenced by peers' behavior. Thus, estimation of μ_i can provide exogenous student behavior measures that can be used to instrument W_{ict} and X_{ict} in equation (2). For example, for the jackknife median (i.e. the median excluding the student whose observation is in question) of peers' interpersonal interaction volume, we use jackknife median $\hat{\mu}_i$ as instruments.

To estimate equation (3), we adopt the common first-differences lagged-instruments approach proposed by Anderson & Hsiao (1982). Specifically, we use students' first 10 posts

($p \leq 10$) to estimate equation (3), and then apply the estimated coefficients $\hat{\gamma}$ and $\hat{\alpha}$ to estimate each student's underlying propensity to interact, $\widehat{\mu_i}$, as given in equation (4):

$$\widehat{\mu_i} = \frac{1}{9}\sum_{p=2}^{10}\{ C_{ip} - \left(\hat{\gamma}B_{ip} + \hat{\alpha}C_{i,(p-1)}\right)\} \quad (4)$$

We adopt a simple specification where B_{ip} is the average value of C for peers' posts between posts of the student in question. Intuitively, estimating Equation (3) helps us understand the relationship between a student's posts and her peer and prior self-posts. From there, we can compute a naïve estimate of an individual student's latent willingness to participate μ_i. Equation (4) is simply the average of the naïve estimates of μ_i over nine of the first ten posts. We exclude the first post as we need the first observation to compute the $C_{i(p-1)}$ in the first period. Once we get an estimate for each student, we can then compute the jackknife median of peers' latent willingness to participate. This median is our instrument for the peer contribution.

One of our goals is to examine how the estimates vary with students' propensity to be nominated. To do this, we first predict the probability of being nominated using the student's gender, age, and major.[7] Figure 1 plots the distribution of the predicted possibilities. The distribution is approximately normal. We use the predicted variable as an interaction term in equation (2) to identify how impacts vary with students' probabilities of being nominated.

RESULTS

Research Question 1

[7] We estimate a Logistic regression model in which the dependent variable is whether a student is a nominee, and the independent variables include gender, age, and major.

How do students' roles in interpersonal interaction in college online courses vary systematically by their characteristics and actions? We begin by examining student characteristics that predict being a nominator and the volume of nominations an individual generates. Table 4 summarizes the results. Across specifications, female students are more likely to nominate peers and generate a larger volume of nomination than do male students. Both students who enter more posts and those who write lengthier posts have higher probabilities of nominating their peers. The negative coefficients on time between posts indicate a positive relation between posting frequency and nomination behavior, because the shorter the average time elapses between posts for a student, the more frequently she posts. The results are mixed in terms of other student characteristics. While older people are more engaged in initiating interactions, there are nonlinearities when using nomination volume as the dependent variable. BA seekers do not appear more engaged than those seeking other degrees (i.e. AS).

Similar to the analysis addressing nominators, we examine the characteristics of nominees. Table 5 reports the results. Although females are more like to nominate peers, they are not more likely to be nominated compared with their male classmates. The role of age non-linear with older students tending to be nominated more but at a decreasing rate. Students who post more frequently and who post longer messages receive more nominations.

Tables 4 and 5 describe nominators and nominees but not the interactions between them. Table 6 shows homophily between students of the same gender and between students who live in the same geographic area. We performed additional analyses (available upon request) and found that both males and females nominate more same-gender classmates. Students do not appear to nominate other students with the same major any more than students with other majors. There is also weak evidence that the absolute difference in age between students and their peers positively correlates with the nomination behavior. Further analysis shows that younger students nominate older students more but not vice versa.

In sum, the results for the first research question show differential interpersonal interactions across students in college online courses. Students' behaviors are more consistently correlated with their role as nominators and nominees in online discussion than they are with their background characteristics. That is, more active students in terms of number of posts and length of posts also nominate other students more. Female students engage more in initiating interactions. Homophily is evident in interaction formation process. In particular, students choose to interact with peers who share gender and location. Given researchers find homophily on propinquity in many in-person settings, our results show students engage more with those who live close with them even in an online environment. These results taken together provide evidence of systematic differences in interpersonal engagement across students and suggest that course sections likely vary in the extent to which peers initiate interactions. These peer differences in initiating behavior could affect student engagement and student learning. We explore these potential effects in our second research question.

Research Question 2

How do peer's interpersonal interactions affect student course performance and persistence in the following semester, especially for those who are less likely to be engaged in classroom interactions? Table 7 shows the 2SLS estimates of peer's interpersonal interaction on student outcomes. In all the specifications, we control for the average time that elapses between posts and average post length for both students themselves and their peers, in order to distinguish interaction from action quantity. Since these action measures are also endogenous, we use a similar instrumental variables strategy to avoid bias. The method of generating these instruments follows equation (4), which is identical to how we construct instruments for peer nomination. The first three dependent variables, including whether a student passed the course, her letter grade, and course points, are short-term outcomes. Enrollment status and enrolled credits in the following semester are two longer-term outcomes.

When we control for professor fixed effects, the main effects of peers' nomination volume are positive and statistically significant for final grade and total points received. Students assigned to classrooms with more peer nominations have higher academic outcomes. The coefficients on the interaction term between peers' nomination volume and the probability of being nominated are generally negative and statistically significant. This interaction effect provides evidence that students who are less likely to be nominated in a typical class benefit more from being in a class where the nomination volume is high. These students benefit differentially from being in a classroom where peers are referring to each other's ideas. The results are similar for both of our longer-term outcomes. With and without professor fixed effects, the main effects of peers' nomination volume are positive. Students are more likely to enroll and take more credits when they are exposed to more interactive peers. As before, these effects are strongest for students who are the least likely to be nominated.

To make the heterogeneous effects more intuitive, Figures 2A, 2B, 2C, and 2D plot the marginal effects of peers' nomination volume – on students' letter grade, the points they earned, and whether a student enrolled in the following semester – over the predicted probabilities of being nominated. In all three graphs, the marginal effects are positive for students with a probability smaller than approximately 0.6. Since all the confidence intervals are above zero, these positive effects are statistically different from zero. As the predicted probabilities increase, the marginal effects decline, and become statistically indistinguishable from zero.[8]

The magnitudes of the effects are not statistically different from zero for those most likely to be nominated but they small to moderate in magnitude for the least engaged students. Consider a male student, age 20, and who is majoring in business network communication. We estimate that he has about a 47 percent chance of being nominated. For such a student, the estimated effect on grades is approximately 0.19 grade points or about 13 percent of a standard deviation. Similarly, for this student, the effect on enrollment next semester would be about 6.3 percentage points (on a base of 82 percent) and on credits would be about 0.65 (18 percent of a standard deviation).

DISCUSSION AND CONCLUSION

The rapid increase in online courses and the accompanying data creates opportunities to investigate peer effects from new perspectives. Because it is possible to observe student behaviors online, researchers can examine student interactions directly and assess how peer behaviors, not just peer background characteristics, affect student learning and educational attainment. Beyond measuring student actions – such as posting length and frequency – we look into the content of student language, capturing an element of student interaction. Using data from all online student postings, we use natural language processing techniques to create measures of student interaction, an approach that could be used easily on an even larger scale. While clearly a first step in measuring peer interactions and classroom processes, more generally, our study is the first that we know of

[8] The estimates for COLL148 though directionally somewhat similar to PSYC110 show no statistically significant effects for both short-run and long-run outcomes. As shown in table 6, neither the main-effect terms nor the interaction terms are significant.

to examine large-scale language data generated in online courses to assess the effects of peers using a rigorous causal framework.

Using data from a large undergraduate psychology course delivered by DeVry University online, we create variables for the extent to which students refer to each other in their postings. These variables are our measures of student interactions. We find that females and older students are more likely to engage in student interactions. In addition, students do not choose which peers to interact with randomly. Students are more likely to interact with peers who share the same gender and residential areas. They also are likely to exhibit other forms of homophily, but the student characteristic measures in this study are limited. In contrast, not all patterns reflect homophily; for example, younger students tend to nominate older peers.

Given that students have varying engagement levels in student interactions, we examine the heterogeneous effects of peers' interpersonal interaction on student learning outcomes. We find that for students who are relatively less likely to be engaged in online discussion, exposure to more active peers increases their probabilities of passing the course, earned grade and course points. These effects are not large, but they are meaningful. With engaging peers, students with a 50 percent chance of being referred to by peers perform 13 percent of a standard deviation higher in grades and increase their probability of enrollment in the following term by more than 6 percentage points.

This paper provides evidence that peers can affect students by engaging them more in class discussions and this engagement can benefit their course performance. This result has direct implications for policies and practices that aim to improve student learning in online settings. An increasing research literature indicates that students on the margin of taking online courses instead of face-to-face courses perform substantially worse in the online setting (Bettinger et al., 2015;

Hart & Friedmann, 2014). A possible explanation for these negative effects, especially among lower performing students, is that the online setting does not engage them as well. Peer (and professor) actions that engage students hold promise for improving these students' educational outcomes, especially in these online settings. While these settings may, on average, be less effective for students today, with improvements in engagement practices they may be able to equal in-person in engagement while maintaining the benefits of online courses, such as reduced travel time and flexible scheduling.

As college online courses grow at an accelerating speed, policymakers and education administrators are searching to find effective policy instruments to enhance student experiences, and improve their learning outcomes. Online courses provide richer data because interactions are captured and can be used for analysis. They also are easier to manipulate than in-person courses, and, thus, can allow for research to assess the effectiveness of different approaches. Some of these approaches are likely to be specific to online settings, but others likely are generalizable to teaching and learning in higher education more generally. This paper finds positive causal effects of peers' interpersonal interaction on less engaged students; and, thus, both provides an indication of the barrier that lack of engagement presents in online learning and some of the first evidence on productive interventions to engage students online. As one of the first studies in this area, our measure of peer interaction has clear short-comings, and it is possible that we understate the power of peer interaction due to the limitation of our measure. Future research should build on the current work to develop constructs that can better capture the richness of peer interactions.

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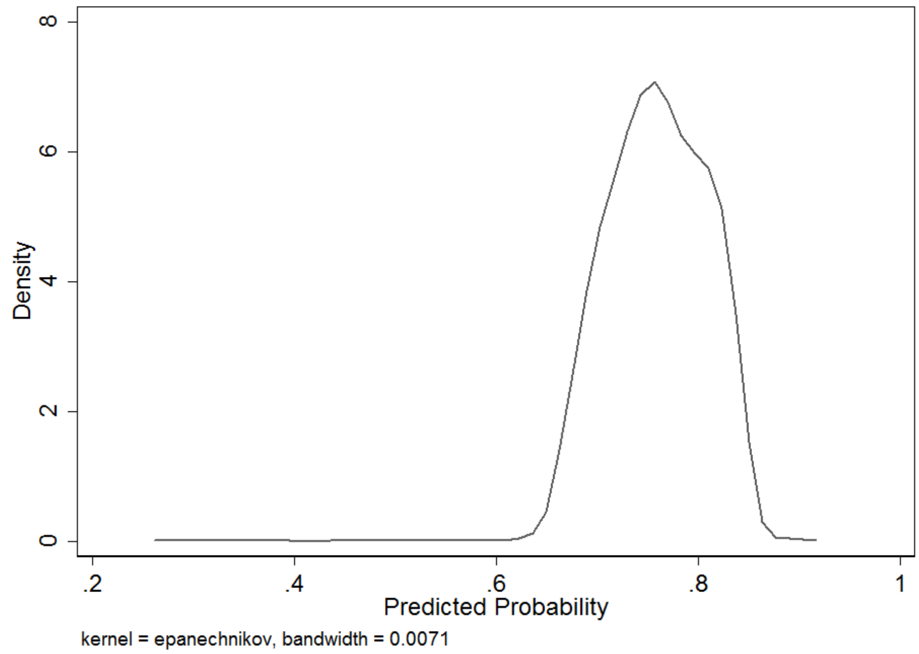

Note. Prediction of whether a student is nominated by any peer based on gender, age, age squared, and major.

Figure 1. Predicted Probability of Being Nominated

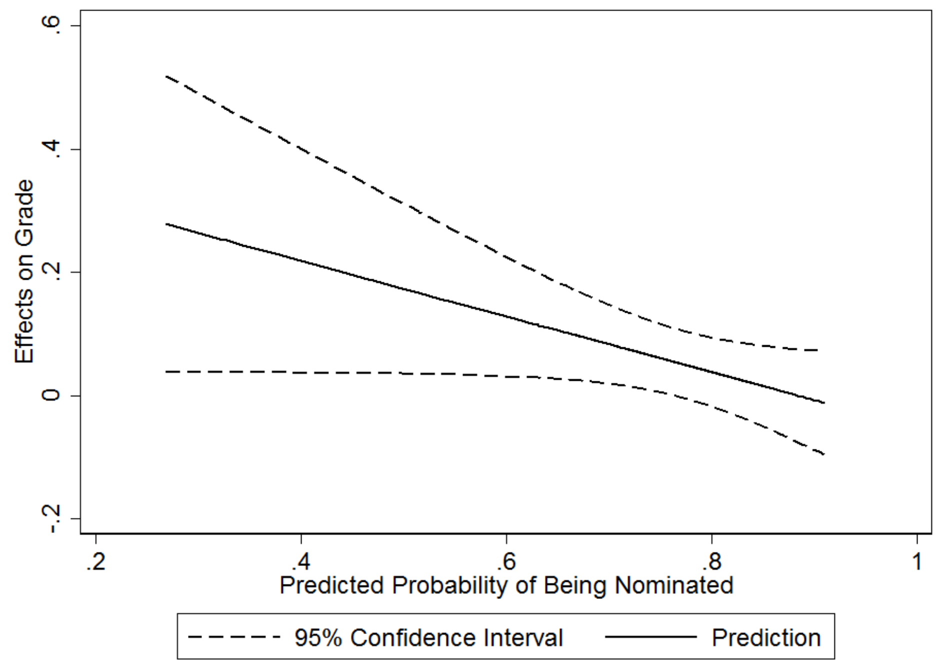

Figure 2a. Marginal Effects of Peer's Nomination on Grade

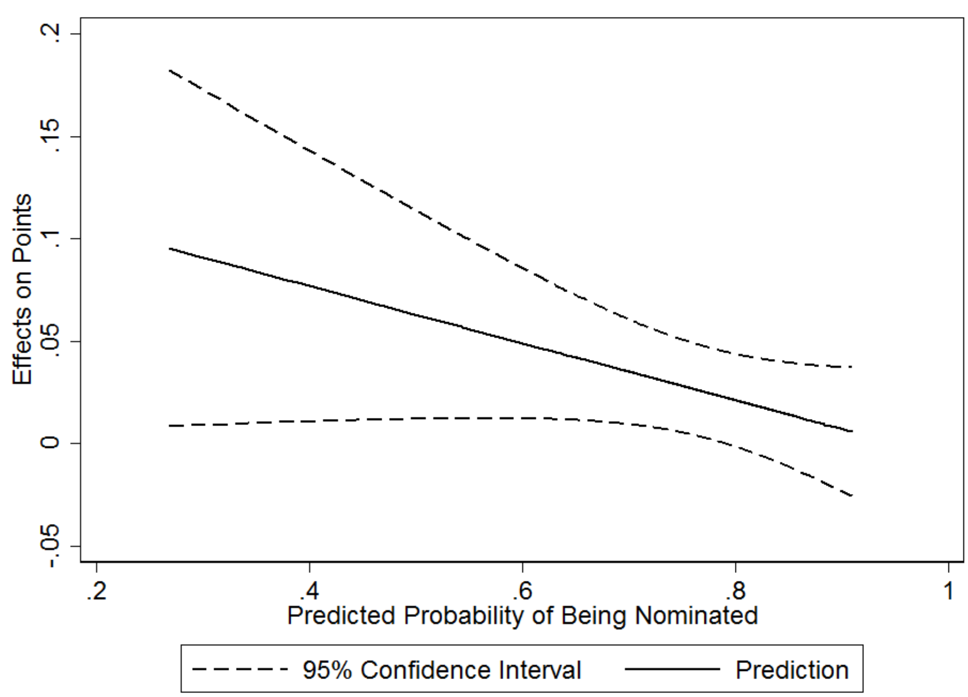

Figure 2b. Marginal Effects of Peer's Nomination on Points Received

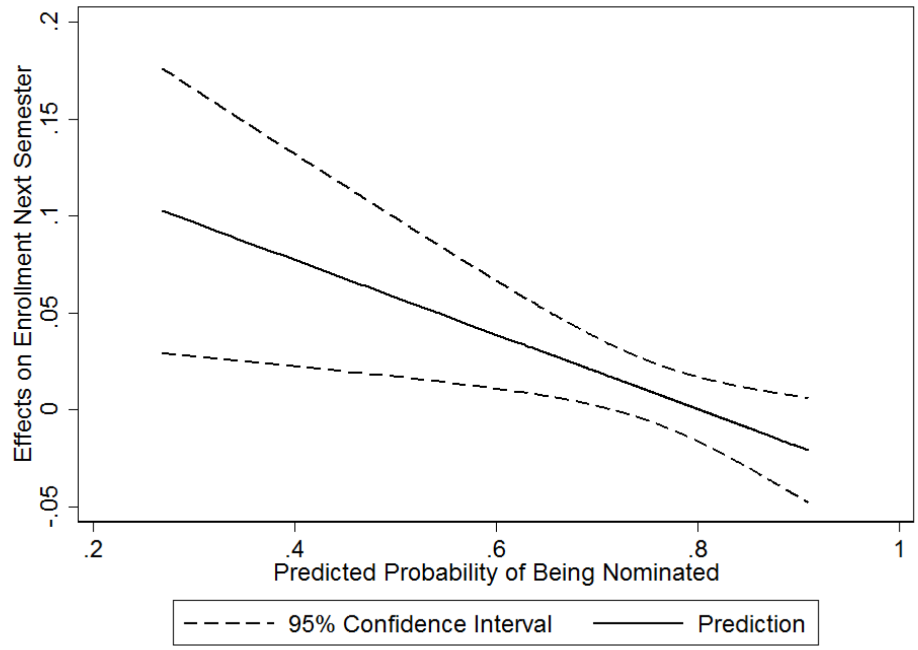

Figure 2c. Marginal Effects of Peer's Nomination on Enrollment Status Next Semester

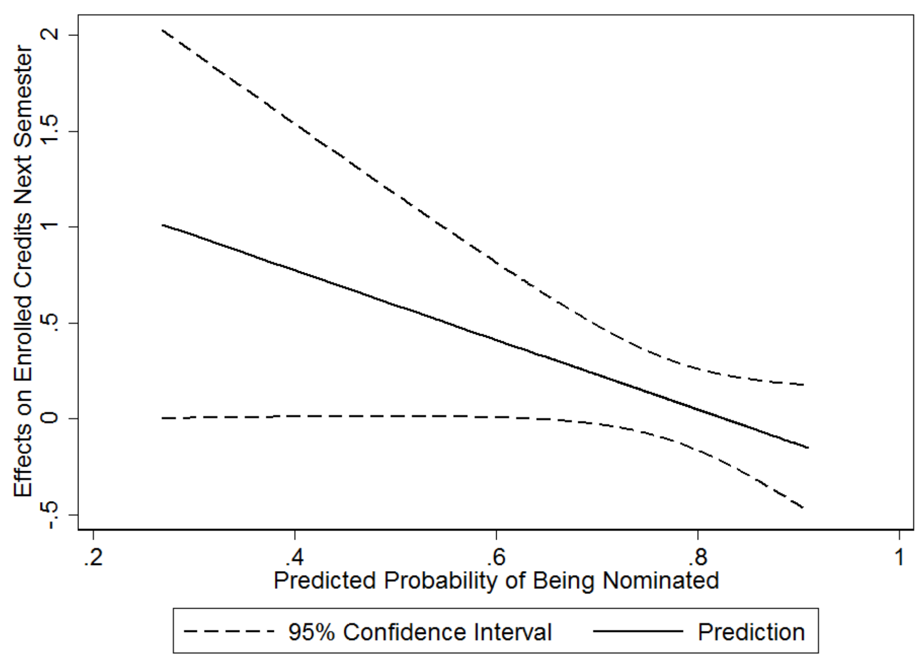

Figure 2d. Marginal Effects of Peer's Nomination on Enrolled Credits Next Semester

Table 1. Descriptive statistics.

Variables	Mean	Std. dev.
Student Outcomes		
Passed Course	0.796	
Course Grade(A-F > 4-0)	2.180	(1.414)
Course Points	0.583	(0.611)
Enrolled Next Semester	0.820	
Enrolled Credits Next Semester	9.509	(3.545)
Student Characteristics		
Female	0.469	
Age	31.343	(8.884)
Northeast	0.125	
South	0.418	
Midwest	0.251	
West	0.183	
Outside US	0.023	
Fist Semester at University	0.413	
Continuing Student	0.534	
Enrolled Credits Current Semester	9.284	(3.362)
Seeking BA	0.741	
Business Management Major	0.354	
Technology Major	0.091	
Health Major	0.109	
Post Characteristics		
Number of Posts	42.304	(20.256)
Average Word Count	89.368	(35.707)
Average Time Between Posts for Student (hours)	33.285	(32.803)
Total Volume of Peer Nomination	3.874	(6.129)
Student-by-Section Observations		11142
Students		10811
Course Sections		471
Professors		93

Note: Based on student-by-section observations in "Introduction to Psychology" (online) between March 2010 and February 2011.

Table 2. Relationship between peer nomination and responding behavior.

Naming Peers	Following the post of a …			
	Peer	Faculty	Not Specific	Total
No	201,061 (20.62)	514,570 (52.76)	259,660 (26.62)	975,291 (100)
Yes	194,120 (92.63)	10,867 (5.19)	4,570 (2.18)	209,557 (100)
Total	395,181 (33.35)	525,437 (44.35)	264,230 (22.3)	1,184,848 (100)

Note: Based on data from all online courses offered between March 1 and April 26 in 2015.

Table 3. Sorting tests with and without block fixed effects.

	No Block FE	With Block FE
Female	-0.0003	0.0060
	(0.0002)	(0.0058)
Age	-0.0334**	0.0150
	(0.0033)	(0.1026)
Northeast	-0.0001	0.0034
	(0.0001)	(0.0039)
South	0.0001	0.0001
	(0.0002)	(0.0057)
Midwest	-0.0003	-0.0016
	(0.0002)	(0.0050)
West	0.0002	-0.0016
	(0.0001)	(0.0045)
Outside US	0.0000	-0.0004
	(0.0001)	(0.0017)
First Semester at University	0.0064**	-0.0064
	(0.0002)	(0.0053)
Continuing Student	-0.0070**	0.0027
	(0.0002)	(0.0053)
Enrolled Credits Current Semester	-0.0241**	0.0307
	(0.0012)	(0.0375)
Seeking BA	0.0002	-0.0037
	(0.0002)	(0.0051)
Business Management Major	-0.0008**	-0.0048
	(0.0002)	(0.0055)
Technology Major	0.0000	0.0018
	(0.0001)	(0.0034)
Health Major	0.0003**	0.0008
	(0.0001)	(0.0035)
Observations	11142	11142
Joint χ^2	2134.866	8.298
χ^2 p-value	0.000	0.824
Female	0.0008	0.003
	-0.0007	-0.0172
Doctoral Degree	0.0012	0.0095
	-0.0009	-0.0234
# Times Taught Course Past Year	0.0058	-0.0527
	-0.0046	-0.1025
Observations	11099	11099
Joint χ^2	6.319	0.388
χ^2 p-value	0.097	0.943

Note: Every coefficient is from a separate regression using the sequential number of the section as the predictor. The second column controls for block fixed effects.

Table 4. Nominator analysis.

	Nomination (0/1)		Nomination Volume	
	(1)	(2)	(3)	(4)
Female	0.086**	0.082**	1.138**	1.110**
	(0.009)	(0.009)	(0.104)	(0.103)
Age	0.010**	0.005+	-0.161*	-0.198**
	(0.003)	(0.003)	(0.077)	(0.076)
Age^2	-0.000	-0.000	0.004**	0.004**
	(0.000)	(0.000)	(0.001)	(0.001)
Seeking BA	0.014	0.007	0.226+	0.167
	(0.010)	(0.009)	(0.118)	(0.116)
Time Between Posts[a]		-0.107**		-0.879**
		(0.011)		(0.110)
Post Length[b]		0.091**		0.698**
		(0.008)		(0.101)
Observations	10965	10965	10965	10965
R_Squared	0.087	0.144	0.130	0.158

Note: All students enrolled in "Introduction to Psychology" (online) between March 2010 and February 2011. The analytical sample here excludes posts generated in week 1. Column 1 and 2 report results from linear probability regressions using whether a student nominates any peer as the outcome, and column 3 and 4 are results from regression using nomination volume as the outcome. Standard errors are clustered to section level. All models control block fixed effects and professor fixed effects.

a. Average time (hours) elapsed between posts from week 2 to week 8 (standardized within term).

b. Average word counts of posts from week 2 to week 8 (standardized within term).

Table 5. Nominee analysis.

	Nominated (0/1)		Nominated Volume	
	(1)	(2)	(3)	(4)
Female	-0.008	-0.011	-0.083	-0.108
	(0.007)	(0.007)	(0.071)	(0.069)
Age	0.012**	0.008**	-0.035	-0.066
	(0.003)	(0.002)	(0.048)	(0.048)
Age^2	-0.000**	-0.000*	0.001*	0.002*
	(0.000)	(0.000)	(0.001)	(0.001)
Seeking BA	-0.001	-0.006	-0.018	-0.076
	(0.009)	(0.009)	(0.079)	(0.077)
Time Between Posts[a]		-0.095**		-0.639**
		(0.010)		(0.084)
Post Length[b]		0.043**		0.729**
		(0.007)		(0.076)
Observations	10965	10965	10965	10965
R_Squared	0.135	0.181	0.206	0.237

Note: All students enrolled in "Introduction to Psychology" (online) between March 2010 and February 2011. The analytical sample here excludes posts generated in week 1. Column 1 and 2 report results from linear probability regressions using whether a student is nominated by any peer as the outcome, and column 3 and 4 are results from regression using nominated volume as the outcome. Standard errors are clustered to section level. All models control block fixed effects and professor fixed effects.

a. Average time (hours) elapsed between posts from week 2 to week 8 (standardized within term).

b. Average word counts of posts from week 2 to week 8 (standardized within term).

Table 6. Nominee analysis (pairwise level).

	Nomination(0/1)		Nomination Volume	
	(1)	(2)	(3)	(4)
Same Gender	0.005**	0.005**	0.007**	0.007**
	(0.001)	(0.001)	(0.001)	(0.001)
Both Seeking BA	-0.001		-0.003+	
	(0.001)		(0.002)	
Same Home Campus	0.003**	0.003**	0.004*	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Age Abs. Diff	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age Abs. Diff Squared	0.000+	0.000+	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Same Major		-0.000		0.001
		(0.001)		(0.002)
Observations	330750	330750	330750	330750
R_squared	0.175	0.175	0.206	0.206

Note: All students enrolled in "Introduction to Psychology" (online) between March 2010 and February 2011. The analytical sample here excludes posts generated in week 1. The data is organized in a way that every student is paired with every other student in the same section. All models control for student fixed effects. Since BA students and non-BA students have different majors, we do not put these two variables in the same regression to avoid collinearity.

Table 7. The effects of peer's interpersonal interaction on student outcomes.

	Passed Course		Letter Grade		Course Points		Enrolled Next Semester		Enrolled Credits Next Semester	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nomination Volume_Peer[a]	0.028	0.052	0.273	0.399*	0.091	0.133*	0.138*	0.154**	1.289+	1.503+
	(0.054)	(0.054)	(0.183)	(0.185)	(0.066)	(0.066)	(0.059)	(0.057)	(0.766)	(0.779)
Nomination Probability	-0.020	-0.038	-0.331	-0.453+	-0.103	-0.140+	-0.184*	-0.193*	-1.799+	-1.819+
X Nomination Volume_Peer	(0.070)	(0.069)	(0.236)	(0.237)	(0.085)	(0.084)	(0.078)	(0.075)	(0.997)	(0.991)
Nomination Volume_Own[a]	0.000	0.000	0.002	0.002	-0.000	-0.000	0.002+	0.002+	0.010	0.011
	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.014)	(0.014)
Predicted Nomination Probability[b]	0.512**	0.526**	3.151**	3.247**	1.079**	1.102**	0.793**	0.803**	4.384*	4.443*
	(0.131)	(0.131)	(0.435)	(0.438)	(0.168)	(0.169)	(0.138)	(0.136)	(1.872)	(1.861)
Observations	10884	10884	10884	10884	10884	10884	10884	10884	10884	10884
Professor FE		X		X		X		X		X
F-statistic in First Stage										
Nomination Volume_Peer	42.014	63.644	42.014	63.644	42.014	63.644	42.014	63.644	42.014	63.644
Nomination Probability X Nomination Volume_Peer	42.140	52.019	42.140	52.019	42.140	52.019	42.140	52.019	42.140	52.019
Nomination Volume_Own	589.882	575.512	589.882	575.512	589.882	575.512	589.882	575.512	589.882	575.512

Note: All students enrolled in "Introduction to Psychology" (online) between March 2010 and February 2011. The sample excludes posts generated in week 1 of the course. Each column reports estimates from a single two-stage least squares (2SLS) regression. Every regression controls time between posts for peers and student own, average post length for peers and student own, and block fixed effects. Time between posts is the standard deviation of hours (within term) between posts. Average post length is the average number of words of posts. The peer measure is the jackknife median for the focal student's peers in the same section.

a. Nomination volume is the frequency of nominating peers in week 2 to 8 within a term. The peer measure is the jackknife median of student nomination volume for the focal student's peers.

b. Predicted nomination probability is the predicted probability of being nominated by a peer using focal student's gender, age, and major.

Appendix 1. The effects of peer's interpersonal interaction on student outcomes (COLL148).

	Passed Course		Letter Grade		Course Points		Enrolled Next Semester		Enrolled Credits Next Semester	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nomination Volume_Peer[a]	-0.022	-0.015	0.080	0.124	0.021	0.036	0.051	0.051	0.740	0.864
	(0.038)	(0.039)	(0.137)	(0.140)	(0.054)	(0.054)	(0.048)	(0.048)	(0.567)	(0.572)
Nomination Probability	0.022	0.018	-0.124	-0.143	-0.034	-0.039	-0.056	-0.055	-0.820	-0.957
X Nomination Volume_Peer	(0.043)	(0.044)	(0.157)	(0.160)	(0.062)	(0.062)	(0.055)	(0.055)	(0.647)	(0.652)
Nomination Volume_Own[a]	0.003**	0.004**	0.024**	0.025**	0.009**	0.009**	0.002**	0.002**	0.013*	0.014*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.006)	(0.006)
Predicted Nomination	0.415	0.406	4.547**	4.524**	1.535**	1.517**	1.127**	1.089**	14.700**	15.173**
Probability[b]	(0.265)	(0.270)	(0.965)	(0.976)	(0.381)	(0.384)	(0.334)	(0.334)	(3.962)	(3.977)
Observations	18009	18009	18009	18009	18009	18009	18009	18009	18009	18009
Professor FE		X		X		X		X		X
F-statistic in First Stage										
Nomination Volume_Peer	25.885	36.340	25.885	36.340	25.885	36.340	25.885	36.340	25.885	36.340
Nomination Probability X Nomination Volume_Peer	26.917	39.373	26.917	39.373	26.917	39.373	26.917	39.373	26.917	39.373
Nomination Volume_Own	1829.441	1821.011	1829.441	1821.011	1829.441	1821.011	1829.441	1821.011	1829.441	1821.011

Note: All students enrolled in "College Skills" (online) between March 2010 and February 2011. The sample excludes posts generated in week 1 of the course. Each column reports estimates from a single two-stage least squares (2SLS) regression. Every regression controls time between posts for peers and student own, average post length for peers and student own, and block fixed effects. Time between posts is the standard deviation of hours (within term) between posts. Average post length is the average number of words of posts. The peer measure is the jackknife median for the focal student's peers in the same section.

a. Nomination volume is the frequency of nominating peers in week 2 to 8 within a term. The peer measure is the jackknife median of student nomination volume for the focal student's peers.

b. Predicted nomination probability is the predicted probability of being nominated by a peer using focal student's gender, age, and major.