Remote but Influential:
Peer Effects and Reflection in Online Higher Education Classrooms

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Abstract: Peer effects influence productivity in many settings. We examine the case of online learning where all peer effects occur virtually and asynchronously. Using data from one of the largest online universities in the United States, we estimate how the nature of peer interactions affects students' performance in specific courses and their subsequent outcomes at the university. In the courses we examine, students are quasi-randomly assigned to peers conditional on when they enroll in the course. Thus our analysis can overcome the standard selection biases that arise in peer grouping. We also address potential reflection bias by exploiting unusually detailed data on student interactions. In the courses we study, we observe timing and content every communication between students—nearly two million discussion board comments over the course of one year. We find evidence of congestion effects in which more peer participation hurts student course completion and performance. On the other hand, we find that short, "bursty" interactions between students improve these outcomes. We also find some evidence that balanced discussions improve outcomes. Peer effects persist over the next year in students' persistence at the university. Since peer interactions occur asynchronously and we observe all interactions, we can track the evolution of peer effects and separate those peer interactions that arise from reflection and those which arise genuinely from unique peer interactions.

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The decisions and productivity of individual workers often are influenced by peers—colleagues whom the individual works with or among, and who are similarly situated with respect to the stakes of production (e.g. Guryan, Kroft, and Notowidigdo, 2009; Battu, Belfield, and Sloane, 2003; Bruegmann and Jackson, 2009). This peer influence can arise in settings where production is explicitly collaborative, such as decisions by a corporate board or a performance by an orchestra; or in settings where social norms and observed peer behavior pressure the individual toward expected choices, such as when productivity is openly comparable across individuals (Kandel and Lazear 1992, Mas and Morretti 2009).

Educational environments provide opportunities for understanding peer effects because of the availability of measures of individual productivity such as test performance and improvement that are often not available in other sectors. The grouping of students based both on their achievement levels and on their potential for achievement gains often makes convincing estimation of peer effects difficult, even when productivity measures are available, though researchers have often taken-up the task (see for examples Figlio and Page, 2002; Hoxby, 2000; Kulik and Kulik, 1982; Slavin, 1987).

In this paper we use data from a large higher education institution to estimate peer effects in online courses. Particularly in higher education, students and professors jointly produce the quality of a course. Students help establish expectations for class participation and the quality of course work. A growing literature documents how peers affect performance, friendships, and attitudes of college students (Zimmerman 2003; Sacerdote 2001; Kremer and Levy 2008). Most of this literature has focused on variation in residential peers at highly selective schools. However, peer effects could occur in many other classroom and social settings (e.g. Carrell, Fullerton, and West 2009). In this paper we study peer interactions that occur virtually through online discussion boards. These discussion boards are analogues to the classroom discussions and group project meetings found in traditional classrooms.

We study two freshman level online courses at DeVry University. DeVry is one of the largest for-profit universities in the nation which, in 2010, enrolled over 130,000 undergraduates or about 5 percent of the for-profit college market. DeVry provided detailed data for all online sections of two courses during 2010 covering 26,911 students and 246 professors in 1,424 sections. We focus our analysis on "College Skills", a mandatory, introductory course that covers general college skills including critical reading and writing, library research, and planning. DeVry requires all undergraduates to complete the course, and four out of five take the course during their first term. We also present evidence from DeVry's "Introduction to Psychology" course.

Identifying peer effects is difficult in most settings. Three issues, in particular, arise in trying to estimate peer effects (Manski, 1993). The first is the non-random assignment of individuals to peers based on unmeasured characteristics. For example, if individuals who have been less productive in the past but are likely to be more productive in the future because of some unobserved characteristic are assigned to more productive peers, observers might attribute higher productivity to the new peers when this higher productivity was caused by an outside factor correlated with the matching to higher productivity peers. The second issue potentially confounding the estimation of peer effects is that a common outside factor – for example, in classrooms, a common teacher – may simultaneously affect both individuals and their peers. The final issue is that even if individuals are randomly assigned to peers and there is no shared outside influence, if the peers are observed at the same time as the individual, then the peers' characteristics are partially a result of the individual, as the effects are reciprocal. This reflection problem, as described by Manski (1993), leads to difficulty in the estimation of the effects of peers. To overcome the reflection problem, researchers have to be careful about the timing of information and choose empirical specifications that adequately control for the simultaneity of many peer interactions.

Random assignment of peers can resolve selection biases, and using pre-existing peer characteristics can provide instruments for contemporaneous peer interactions and behaviors. A few studies of peer effects have made use of data with both prior information on peers and random assignment (Sacerdote, 2001; Zimmerman, 2003; Carrell, Fullerton and West, 2009). However, these studies address a narrow sample of individuals (e.g. Dartmouth and Williams College roommates). Moreover, the reflection process itself is substantively interesting and prior studies are not well positioned to model the process.

In this study, we use modifications of both strategies. First, we use quasi-random variation in peer assignment, which we isolate using DeVry's known section assignment rules. Second, while we do not consistently observe peers before they enter the classroom, we construct instruments that capture variation in peer behaviors that is, by construction, orthogonal to the behavior of the focal student. These instruments are possible because we observe the timing and content of all students' participation in the course. We obtain student fixed effect estimates—our instruments— from a panel data model where each discussion board post is an observation, and we control for the characteristics of all prior peer posts. Moreover, these detailed panel data allow us to provide richer detail than previously estimated on the saliency of the reflection problem and its evolution throughout students' relationships in the course.

The mechanisms by which peers are influential may be different in online interactions than they are in face-to-face interactions. Technology may alter the nature of peer influence as it improves in some ways and constrains in other ways the behaviors and choices that are observable to peers. To date there is little evidence on whether peer interactions in virtual settings affect productivity in the same or different ways compared to in-person peer interactions.[1]

While virtual peer effects may not be the same as face-to-face peer effects, online interactions are important both because of their growing importance in productivity generally and because they provide opportunities for understanding peer effect mechanisms that are unlikely to be available using current data and analytical techniques from face-to-face interactions. Computer networks and related technologies have first order relevance for team production and peer monitoring. Many old peer interactions have become virtual and new peer interactions are made possible. An understanding of virtual peer effects may improve productivity in sectors relying on such networking technologies. Moreover, the availability of full information on peer interactions allows researchers to view the effects not only of individuals with

[1] By contrast, employer and employee relationships that occur online have been studied by a range of researchers including, for examples, Stanton and Thomas (2012) and Casio (2000). There is also a large body of research on virtual workers, more generally (e.g. Wiesenfeld, Raghuram, and Garud, (2001) and Wellman et. al. (1996)).

particular characteristics but of the specific behaviors or actions that those individuals take that affects their peers either positively or negatively.

This understanding of the mechanisms of peer effects is potentially beneficial. If an individual has an equal effect on all of his or her peers then the implications of understanding peer effects is, to some extent, a zero-sum-gain. That is either that positive peer will be assigned to one group or another. However, if we understand how the actions of peers affect productivity, policies can be designed to alter peer behaviors, potentially achieving more than zero gains (although gains are not guaranteed, as shown by Carrell, Sacerdote, and West (2011)). Moreover, peer effects are unlikely to be the same across settings and understanding the mechanisms can help explain differences in peer effects observed in prior studies (e.g. Hoxby and Weingarth, 2005).

We examine the content and nature of peer effects. Peer effects can take many different forms (Hoxby and Weingarth, 2005), and to date, most studies of peer effects in the classroom focus on the effects of the mean contribution of peers. A key feature of the data for this study, not previously available to researchers, makes deeper analysis possible: we observe (nearly) all interactions among students and between students and professors. These interactions are observable because classes “meet” online; all communication is via typewritten comments, questions, and responses posted to the class discussion board. The discussion board transcripts detail everything that students said to each other, everything that students said to faculty members, and everything that faculty members said to students. We decompose this communication into a series of metrics, which capture variation in the volume, the frequency, and timing of peer communication across sections. Thus the discussion board transcripts allow us to examine not only whether peer effects occur, but also to measure how peer effects depend on the scope, scale, and timing of students’ dialogues.

Our findings suggest that peer effects matter, even in online settings. In particular, we find evidence both of congestion and of benefits of the “burstiness” of dialogue. That is, we find that students do better when peers post shorter comments and when they post less often; and we find that students do better when their peers' posts come rapidly one-after the other. We also find weak evidence that students do better when posts are spread more evenly across peers, not concentrated in one or two students. The results are quite consistent across the two courses that we study.

The paper is organized as follows. Next we provide additional background on peer effects and then describe the setting and the data. We then review the methodology and report the results for estimating peer effects and modeling the reflection process. We conclude with a discussion of the implications of the results for future research.

BACKGROUND

As described above there is a rich literature on peer effects in research on education. These studies often ask whether having higher-performing peers increases student performance and whether this relationship is constant across students with different levels of prior performance.

Some early studies of peer effects – particularly studies from the large education literature on tracking or ability grouping in schools – do not convincingly separate the effects of peers from unobserved influences of the individual him or herself (e.g. Oakes, 1985). More recent studies have used random assignment of students to peers and pre-assignment peer characteristics to more convincingly estimate peer effects.[2] Carrell, Fullerton and West (2009), for example, using the random assignment of students at the United States Air Force Academy, find substantial peer effects stemming from verbal SAT scores as well as non-academic measures such as athletic and leadership abilities. On average, higher performing peers have more positive effects: a one standard deviation increase in peer SATs led to a 0.083 standard deviation increase in performance. The magnitude of the estimated effect is larger for students in the bottom third of the academic ability distribution although not statistically different from that estimated for other students.

[2] Sacerdote (2001) finds that college roommates affect academic effort, though not major choice; Zimmerman (2003) finds small peer effects in which individuals with low verbal SAT scores negatively impact the academic performance of their roommates.

These prior studies estimate the effects of peer characteristics on student outcomes. They do not focus on peer behaviors that affect student outcomes. For example, they do not tell us what higher achieving students do to support peer outcomes. Numerous possible mechanisms could drive peer effects. In this paper we consider three types, hypothesized in existing literature: congestion, concentration and burstiness.

Lazear (2001) proposes a model of learning in which students affect their classmates through congestion. That is, in a one person class the student has the full attention of the teacher. As class size grows, the teacher has to divide his or her attention across more students so the amount given to each student drops. Similarly, if students are disruptive or otherwise demand more of the teacher's attention, attention to other students falls. In studies of face-to-face peer effects, estimating the effects of class size on student achievement is one way to test the congestion hypothesis. In online environments we can test the hypothesis more directly, asking whether students do worse, on average when their peers post more – either more often or with longer posts. If this result is negative, then congestion is likely the cause. However, it is not clear a priori whether higher peer posting will be negative, as they may create norms of behavior that encourage the student to participate and in turn improves his or her educational outcomes.

Other factors than congestion or quantity of peer posts may dominate the effects of peers. For example, peers themselves may provide information that is useful for other students or they may ask questions that the student would benefit from but would not ask. Understanding some of these peer effect mechanisms requires assessment of the content of the text, which is beyond the scope of this current paper. However, features of the concentration and timing of peer's participation, in addition to the quantity of participation, may affect students.

Peers may establish norms of behavior through the timing and concentration of their posts. If only one or two other students in the class post a lot and others are crowded out or for some other reason post less, then a norm may be established that does not encourage students to participate. On the other hand, if the same total number of posts come from a more equal distribution of posting, than a norm of participation may be created that pulls students into the course, increasing their participation and their future outcomes.

Students may also be drawn into the course by students or student interactions that grab their attention. Barabasi (2005) pointed out that human interaction tends to happen in bursts, not at random. While Poisson processes have been used widely to model the timing of human behavior – essentially assuming that timing occurs at random – in fact, in many cases the distribution of time between events has a much heavier tail than the Poisson distribution so that there are bursts of activity and the periods of little activity. Barabasi (2005) analyzes email traffic and finds evidence of burstiness, as others have found using other types of data on virtual activity (e.g. internet chats (Dewes, Wichman, and Feldman, 2003) and network traffic (Paxon and Floyd, 1995)). Barabasi (2005) provides evidence burstiness stems from prioritizing tasks – high priority tasks get done quickly while low priority tasks create the thick tails. While virtual participation tends to bursty in nature, it is also the combination of some highly active participation and some passive or less active participation. Recent research using data on Wikipedia has found that active participants can substantially increase the participation of otherwise passive participants (Olson, Howison, and Carley, 2010). They posit that this increase is driven by active participants catching the attention of less active participants. We build on this work by testing the extent to which burstiness in peer activity – clumps of quickly following posts – affects student participation and later outcomes.

The discussion above leads to our four research questions:

1. To what extent does the quantity of peer participation affect students educational outcomes?
2. To what extent does the concentration of peer participation affect students educational outcomes?
3. To what extent does the burstiness of peer participation affect students educational outcomes?
4. How much of naively estimated peer effects can be attributed to the reflection of individuals' own characteristics (in an online setting with full adjustment for selection into the peer group)?

SETTING AND DATA

In this paper we study undergraduate students and their professors in two freshman level online courses at DeVry University. In 2010 DeVry enrolled over 130,000 undergraduates, or about 5 percent of the for-profit college market, placing it among the 8-10 largest for-profit institutions that combined represent about 50 percent of the market. Most of DeVry's students major in business management, technology, health, or some combination; and 80 percent are seeking a bachelor's degree. Two-thirds of undergraduate courses occur online, the other third occur at nearly 100 physical campuses throughout the United States.

DeVry provided us detailed data for all online sections of two courses during 2010. First, "College Skills" (COLL148) a general college skills course covering topics like critical reading and writing, library research, and planning. DeVry requires all undergraduates to complete the course, and four out of five take the course during their first term. The data include 21,017 students and 176 professors in nearly 952 sections. Second, "Introduction to Psychology" (PSYC110), which covers a typical introduction to psychology syllabus. For this course the data include 12,615 students and 93 professors in 472 sections.

The content and structure of both courses is centrally determined by the University administrators. Students use the same textbook, the same syllabus, have the same assignments, and complete the same quizzes and exams. Professors grade using the same rubrics and use the same material in many of their posts. Courses run eight weeks. The mechanism assigning students and professors to sections is also centralized and permits a quasi-experimental design as we discuss further in the next section. In short, students are assigned to sections in the order in which they enroll in the course.

Each course section, with an average of 24 students in College Skills and 29 students in Intro Psych, "meets" in a section-specific, password-protected website. A "discussion board" serves as the analog to traditional classroom discussion. Each week the section professor initiates a series of "discussion threads" each corresponding to lecture topics for that week. The professor contributes explanations, examples, questions, and instructions. Some content traditionally delivered via a classroom lecture is available to students in videos and written materials; these do not vary from section to section. Students are required, as part of their course grade, to contribute comments and questions to each topic thread. As students join the conversation, professors respond with follow-up questions, re-direction, encouragement, and clarifications. Unlike traditional classroom discussions, however, discussion board conversations are asynchronous. The discussion boards also are used for communication between students and the professor about general course matters and among students for group assignments.

The data include all of this written communication with person identifiers plus the date and time of each post—effectively transcripts of class discussions. These transcripts in our data cover more than two million posts. Course quizzes, exams, and written assignments are also submitted and returned through the website. The data include assignment-specific scores as well as overall course grade. Additional administrative data provided by DeVry track student enrollment for one year after the focus course ends, with details about current major and degree goal, and credits attempted and earned.

Table 1 describes the sample. Just under the half of the students are female and while they average approximately 31 years of age, there is substantial variability. Geographically, the largest proportion comes from the South, approximately 42 percent, but all regions are represented. Eighty-three percent of the students in the College Skills class are in their first semester as compared with 42 percent of students in Introductory Psychology.

We estimate the effects of peers on a variety of student outcomes including whether they completed the course, whether they passed the course, their course grade, the number of points they received in the course, whether they enrolled in the following semester, the number of credits they enrolled in the following semester, whether they were still enrolled at DeVry one year later and the number of credits they were enrolled in at that time. Table 1 shows that, on average, approximately 80 percent of students pass each of the two the courses. Average grades are a bit higher in COLL148, 2.7 or approximately a B-, than in PSYC110, 2.2 or approximately a C+. Approximately three quarters of students enroll in the next semester and just over 40 percent are still enrolled one year later. They take just over nine units of credit per semester, on average, when they do enroll.

Table 1 also describes our measures of student participation in the course. For each post we measure the post length in words, the elapsed time since the author's last post (in hours), and whether the post is within 10 minutes of another student's post. We see that, on average, posts average 78 words in length, though the posts are longer in PSYC110 (91) than in COLL148 (73). On average, students wait about 20 hours between posts, with longer waits for PSYC110 (26) than for COLL148 (18). The posts appear quite dense with 41 percent within 10 minutes of other students, with similar density across classes.

We use the post level data and measures to construct several summary measures of student and peer participation behavior during the course: (i) student-level measures averaging across posts, (ii) peer measures averaging (jackknife) across peers, and (iii) a Herfindahl index based on the differences in average post length of students. The latter measures how distributed (or concentrated) peer participation is in the class, which we contrast with the peer average characteristics that might be driven by a minority of talkative classmates.

EMPIRICAL STRATEGY AND RESULTS

Estimating Peer Effects

Our first objective is to identify the effect of peer characteristics and behavior on student academic success in online college classes and student persistence in college after the course. For each student outcome measure, y_{ict}, we estimate the following equation

$$y_{ict} = W_{ict}\delta + X_{ict}\beta + \theta_{b(s)} + \varepsilon_{ict} \,, \qquad \text{(equation 1)}$$

where *i* indexes students, *c* indexes courses, and *t* indexes eight-week-long terms. W_{ict} represents peer characteristics and behaviors of interest – in some specifications a single variable, in others a vector. X_{ict} includes measures of student *i*'s own characteristics and behaviors, generally measures paralleling those in W_{ict}. $\theta_{b(s)}$, which we discuss in more detail shortly, is a set of fixed effects to account for secular trends, and the assignment of students and professors to sections. We estimate equation 1 by least squares with standard errors that account for the correlation of ε_{ict} within sections, s.

We investigate four categories of peer measures and interactions among them: (i) *Quantity* of peer participation in class discussions. We first calculate each student's average post length in words, and standardize the measure (mean zero, standard deviation one) within course-by-term cells.[3] Quantity of peer participation enters W_{ict} as the jackknife median of this post length measure. (ii) *Frequency* of peer participation. Here we calculate the average elapsed time between each student's posts, standardize within course-by-term, and use the jackknife median in W_{ict}. Since a course lasts a fixed eight weeks, average time between posts measures the *number* of posts a student writes, and in discussing the results we prefer this interpretation. However, time between posts is a more tractable metric for our approach to creating instruments discussed shortly. (iii) *Dispersion* of student participation, to measure concentration, a jackknife Herfindahl index on post length measure. (iv) *Density* of peer participation in time to measure burstiness. We calculate the proportion of each student's posts that occur within 10 minutes of another student's post, and use the jackknife median in W_{ict}.

A causal interpretation of $\hat{\delta}$ requires the assumption that the error is not correlated with the peer characteristic measures:

$$\mathbb{E}[\varepsilon_{ict}|W_{ict}] = \mathbb{E}[\varepsilon_{ict}], \qquad \text{(assumption 1)}$$

which, as first explained by Manski (1993) and as described earlier, is difficult to maintain for several reasons: selection into peer groups, circumstances common to the group that influence outcomes, and endogenously determined peer interactions. The reminder of this section explains our approach to these identification challenges in turn.

[3] We censor post length at 500 words. While affects only a fraction of one percent of posts, very long posts generally represent student's quoting long passages from some outside source.

First, since peers are assigned to student i in bundles called sections, the plausibility of assumption 1 is strengthened to the extent our empirical approach accounts for DeVry's section assignment (and thus peer assignment) mechanism, i.e., to the extent $\mathbb{E}[\varepsilon_{ict}|s] = \mathbb{E}[\varepsilon_{ict}]$.

In contrast to most educational settings, DeVry uses a known observable set of rules to assign sections. DeVry assigns students to sections in the order they enrolled for the course: the first N students to enroll form section $s = 1$, students $N + 1$ through $2N$ form section $s = 2$, and so on. DeVry continues to create new sections until all demand is met. Thus, any differences in student and peer characteristics, observable or unobservable, between sequentially numbered sections arise because students complete the task of enrolling at different times. As the difference in section numbers grows the potential for unobserved differences grows; in the extreme students who register on the first possible day are likely quite a bit different from students who register after the term has already begun.[4]

DeVry assigns professors to sections based primarily on past performance evaluation: the highest-performing professor (among those scheduled to teach) is assigned to teach section $s = 1$, the second-highest to section $s = 2$, and so on. If all available professors have been assigned in a given term, assignment to teach a second section again follows evaluation rank among professors available to teach two sections. These rules likely give rise to assortative matching overall, but for sequentially numbered sections differences between professors will arise by measurement error in the performance evaluation measure.[5]

Our strategy in this case is to limit identifying variation to differences between sections within small groups or blocks, b, of sequentially numbered sections. Practically, equation 1 includes section block fixed effects, $\theta_{b(s)}$. Each section block, b, includes M sequentially formed sections from the same term for the same course; sections 1 through M are block $b = 1$, sections $M + 1$ through $2M$ are block

[4] In the appendix we show how observable student characteristics and outcomes vary with section number.
[5] In some terms newly hired professors are assigned to sections before continuing employees. This ensures that new professors are engaged in teaching soon after being hired.

$b = 2$, and so on. Choosing M is in part a trade-off between bias and power. We present results with $M = 3$, and find the results robust to $M \in 5\ or\ 7$.

We test the effectiveness of this strategy by assessing the extent to which section number predicts various student and professor characteristics with and without the section block fixed effects. Given the assignment mechanism just described, we expect section number to be predictive of (some) characteristics. Table 2 shows, for example, the sections formed earliest in College Skills, and thus have low section numbers, have students who are taking more credits and are less likely to be new students. The same early sections also have professors who are more experienced in teaching the course. By contrast the second and fourth columns of table 2 show results after including block fixed effects of $M = 3$. Here we see little relationship between section number and student or professor characteristics. The joint tests provide evidence that our approach addresses (observable) selection.

Next consider the common experiences of peers within the same class. Various determinants of y_{ict} are omitted in specification 1, some of which are inputs common to all students assigned to the same course section. Focusing identification on the within section block variation also reduces, but does not eliminate, the potential bias from this common inputs concern. The most important residual common influence is likely the section professor, and so we present estimates of equation 1 both as written and with professor fixed effects added. Each professor taught an average of just over five sections (5.38 for COLL148 and 5.03 for PSYC110, with standard deviations of 2.53 and 2.24 respectively). In many, but not all, cases the results with professor fixed effects are similar. This similarity may not be surprising given the highly scripted nature of professors teaching in these courses. In related work, we find smaller variation in professor effectiveness online than in live classes (Bettinger, Fox, Loeb, and Taylor, 2014).

The final identification concern arises because unobserved characteristics of student *i* may change the observed behavior of her class peers, W_{ict}, over the course of the term, inducing a form of the reflection problem.[6] To address this endogeneity of a student's own behavior and peer behaviors we take advantage of the sequential and recursive nature of student interactions, and the level of detail that we observe for each student and each post.[7] We use this structure and detail to isolate variation in student behavior that is orthogonal to reflection-induced variation, and use that variation to construct instruments for W_{ict} and X_{ict} in estimating specification 1.

Consider the sequence of students' participation and interactions from the perspective of a single student i. We observe a student's participation when she posts a question, answer, or other comment on the class discussion board; each student is required to post at a minimum of three times per week. Let C_{ipm} be measureable characteristics of post p made at time m: (i) the length in words, (ii) the elapsed time between the prior post $(p-1)$ and the current post p, and (iii) whether the post occurs within 10 minutes of a peer's post, etc. And let B_{ip} represent the measurable characteristics of posts made <u>by her peers</u> in the time between post $(p-1)$ and post p.

Student i's behavior in a given post, C_{ipm}, is (potentially) a function of her own prior behavior and the prior behavior of her peers, but it cannot be separately influenced by future behavior. We also assume C_{ipm} is partly a function of student abilities and preferences, μ_i, that exist before the course begins. Thus, assuming linear separability, we can take advantage of the recursive nature and write C_{ipm} in the dynamic panel data form

$$C_{ipm} = \gamma B_{ip} + \alpha C_{i,(p-1)} + \mu_i + \nu_{ipm}. \qquad \text{(equation 2)}$$

In the language of equation 2, reflection arises because B_{ip} is a function of $C_{i,(p-1)}$, similarly $C_{i,(p-1)}$ is a function of $B_{i,(p-1)}$, and so on. By contrast, if equation 2 is correctly specified, the μ_i terms capture variation in student behavior that is not influenced by peers' behavior. Consider, for example, the student's second post. The characteristic of this post would be a function of an underlying characteristic,

[6] In other settings this concern might be addressed by constructing W_{ict} using observations of peers' behavior in different courses taken before course c, but we only have detailed data for College Skills and Introductory Psychology. We also considered a strategy of using student and peer behavior during the first week or few days of the term to construct instruments. However, our analysis suggests reflection is already occurring in the first week, even the first discussion board post.

[7] Our strategy is similar in spirit to Conly and Udry's (2010) study of peer effects among farmers.

μ_i, the recent effect of peers, γB_{ip}, and the prior effects of both peers and his or her own experiences in the class, captured by $\alpha C_{i,(p-1)}$.

Equation 2 provides estimates for all students' underlying characteristics, μ_i, which we combine to create measures of peers. That is, we use estimates of μ_i to construct straightforward instruments for W_{ict} and X_{ict}. For example, if W_{ict} includes jackknife median post length (not including the reference students' μ_i) and a jackknife Herfindahl in post length, we use jackknife median $\hat{\mu}$ and a jackknife Herfindahl in $\hat{\mu}$ as instruments.

Estimating models of the form in 2 is a well-known task in econometrics. Many estimators are consistent if both the number of panel members (students) and the number of observation periods (posts) is large. Often, however, the number of periods is fixed and small; ours is just such a case. We observe many students (tens of thousands) but only tens of posts by any given student. Several methods have been proposed for consistent estimation of γ and α when the number of posts is fixed and short relative to the number of students. We adopt the common first-differences lagged-instruments approach associated with Anderson and Hsaio (1981, 1982), and use as our sample posts $p \leq 10$. Though we have tested the sensitivity of our ultimate results to alternative approaches and larger numbers of posts. We estimate the individual fixed effects by:

$$\hat{\mu}_i = \frac{1}{9}\sum_{p=2}^{10}\left\{C_{ipt} - \left(\hat{\gamma}B_{ip} + \hat{\alpha}C_{i,(p-1)}\right)\right\}$$

The quantity in braces is an estimate of $v_{ipm}$from equation 2, and thus $\hat{\mu}_i$ is the average residual. Note that this residual is not the typical predicted residual provided by standard software after the first-differenced lagged-instrument routine; instead we take the estimates $\hat{\gamma}$ and $\hat{\alpha}$ and apply them in equation 2.

We adopt the simple specification where B_{ip} and $C_{i,(p-1)}$ are scalars, and B_{ip} is the average value of C for peers' posts in the time between post $(p-1)$ and post p, specifically:

$$B_{ip} \equiv \frac{1}{JQ}\sum_{j\neq i}\sum_{q\in\{t(p-1)<t(q)<t(p)\}} C_{jq}.$$

Empirical Results – Peer Effects

Tables 3a and 3b summarize the estimates of congestion peer effects for COLL148, first for current year performance and then for future attainment. The tables provide the OLS estimates, the reduced form estimates and the 2SLS estimates in which peer posting characteristics are instrumented with our estimate for their underlying characteristics without reflection. We find consistent evidence of congestion effects. Congestion in our setting comes from two sources. First, the longer the posts of an individual's peers, the more congestion. Longer posts are more difficult to read and may crowd out short, informative discussion. They discourage interaction rather than encourage it. Thus, congestion effects should manifest themselves as a negative coefficient on the length of posts. Second, congestion arises from the overall number of posts. If peers are posting excessively often, then their posting may crowd out some discussion and makes it more difficult for other students to find and cultivate productive discussion. In our model, we use time between posts to measure the extent of posting. As the time between posts declines, the number of posts increases, since the total time in the term is fixed. Hence, a positive coefficient on time between posts is consistent with negative congestion effects.

Our results are mixed in terms of congestion. In Table 3a, we find consistent evidence of congestion effects working through the number of peer posts (time between posts). As peer posting behavior increases and hence time between posts decreases, we find that outcomes worsen for students. This negative effect is statistically significant in all of our OLS and 2SLS specifications for predicting completion, passing, overall grade, and overall points. Peers' post length presents a more mixed story. Some of the coefficients do not statistically differ from zero and those that do, some indicate a positive relationship with outcomes while the others suggest negative effects.

The relationship between peers' participation and a student's performance is, not surprisingly, different from the relationship between a student's own participation and his or her performance. Students with longer and more frequent posts often have more positive outcomes.

Table 3b shows similar effects of the number of posts on students' future attainment. Students in classes with peers who post less often are more likely to enroll both in the following semester and one year later and take more credits in the following semester. Posting less often on average suggests that time between posts increases and congestion decreases. The coefficients on peers' post lengths continue to suggest that congestion through post length has an insignificant relationship or one that appears to be inconsistent across specifications and outcomes. Students' own participation, again, displays the opposite relationship. Students who post more often have greater future participation.

The results for PSYC110 are even stronger in suggesting congestion effects. As shown in Appendix Table 1a, when peers posts are longer or more frequently, students' grades are lower and they are less likely to pass the course. This is true in both our OLS and 2SLS specifications. Congestion effects coming through peers' post length now are consistently negative and significant throughout all of our OLS and 2SLS specifications. Time between peers' posts translates to fewer posts and is associated with better outcomes while higher number of posts leads to greater congestion, shorter time between posts, and worsening outcomes. As in COLL148, when students, themselves, post more or more frequently, they do better.

In Appendix Table 1b, we continue to find that congestion effects in PSYC110 lead to negative outcomes for students. For peers' post length, we find consistent negative relationships. The coefficients are only significant in the OLS and 2SLS models for credits accumulated after one year. Our point estimates are similar in the case of peers' time between posts although only about half of the OLS and 2SLS estimates are statistically significant in these models. For post frequency, there are significant impacts on the likelihood of being enrolled and the credits enrolled in during the following term. As before, students' own post length and frequency consistently predict better outcomes.

Tables 4a and 4b give similar results focusing on the burstiness and concentration of the interactions. We measure burstiness as the average proportion of each student's posts that occur within 10 minutes of another student's post. If burstiness is productive, we should see positive coefficients on peers' posting behavior within 10 minutes. We measure concentration using the Herfindahl index in overall peer contribution. The Herfindahl increases as there is less concentration among peers' contributions while a very balanced peer discussion leads to more dispersion and hence a lower Herfindahl value.

Our results provide evidence that denser interactions – those that are burstier – lead to greater performance in the class and greater attainment in future terms. The greater the burstiness, the greater the probability of completing and passing and the higher the grade. Similarly, the greater the peer burstiness, the more likely the student is to enroll in the following term and one year later, though, given enrollment, students do not enroll for more credits. Interestingly, a student's own burstiness is negatively related to these outcomes. A possible explanation for these results is that the burstiness of peers draws students into participation in the course, but that more consistent students participate in a less bursty manner.

The results for the concentration of posts across students in the class are not nearly as consistent. While the OLS regressions show a relationship between the concentration of peer activity and student outcomes, these estimates do not hold up to the adjustments for reflection. The results for PSYC110 are somewhat similar though not nearly as strong. Peer burstiness is associated with higher grades and (marginally) higher passing (see Appendix Table 2a). Peer concentration is positively related to credits enrolled in in future years.

Describing the Evolution of Reflection

We also leverage the sequential structure of participation and detailed data to describe reflection. We examine how much of the variation in student *i*'s behavior is explained by her peer's observed prior behavior, how much of that explanatory power is attributable to student *i*'s own prior behavior reflected back through her peer's behavior, and how these parameters evolve over time.

In the analysis we begin with a variant on the model in equation 2 which is saturated with all possible lags of the dependent variable and the peer behavior terms:

$$C_{ipm} = \sum_{q \leq p} \gamma_q B_{iq} + \sum_{q<p} \alpha_q C_{iq} + \epsilon_{ipm}. \qquad \text{(equation 3)}$$

To summarize how reflection biases the estimated influence of peers, we contrast three R-squared-style parameters: (i) the R-squared when both the B_{iq} terms and the C_{iq} are included; (ii) the R-squared when the B_{iq} terms are omitted, but the C_{iq} are included; and (iii) the R-squared when the B_{iq} terms are included, but the C_{iq} are omitted. The third gives an upper bound estimate of the variance explained by peers in that includes both the effects of peers and reflection. The first minus the second, on the other hand, gives a lower bound estimate for the peer effect because it has eliminated all variance explained by the individuals' prior posts, part of which was affected by the peers. We follow these estimation steps separately for each $p \in \{1,2, \ldots P\}$ one at time. We then plot the upper and lower bounds for the peer effects, as well as the upper bound for the proportion of the estimated peer effect due to reflection. This last statistic is the difference between the upper and lower bound peer effect estimates divided by the upper bound peer effect estimate (times 100). The lower bound for the proportion of the peer effect attributable to reflection is zero.

In practice, the proportion of the peer effect attributable to reflection is likely to be less than the upper bound, and, in fact, even less than half of the upper bound. If half of the shared variance between peers' posts and the individual's posts were attributable to reflection then the individual would be influencing the peers' prior posts as much as the peers were influencing the individual's prior posts. Yet there are many peers and each peer is likely to effect the average peer posts. Thus, peer posts are likely to reflect other students' posts approximately as much as they do this individual's posts. As a result the reflection should be less than half of the shared variation – perhaps closer to the inverse of class size.

Our estimation process uses one cross-section of posts at a time. Our ability to include all interactions among classmates is the unusual benefit of the available data. To account for student sorting, before estimating equation 3 we add section block fixed effects, $\theta_{b(s)}$. Thus the R-squared-style parameters are interpreted as explaining the within block variance.

Empirical Results – Reflection

The models above adjust for reflection but do not provide an analysis of the reflection itself. The unusually detailed data available for this study make it possible to focus on the reflection itself as the object of analysis. Overall, peer behaviors explain only a small amount of the variation in students' posts, though these effects grow as the course progresses, particular over approximately the first 20 posts.

Figures 1-3 present results of the *R*-squared exercise described above in relation to equation 3. Each figure takes up a different characteristic of a student post—length, elapsed time, occurring within 10 minutes of a peer. The dashed lines are the upper and lower bounds for the peer effects. The top dotted line gives the lowess fit of a series of *R*-squared estimates, one for each post from a student's first post to their 40th, regressing the student post characteristic on all lags of peers' posts measured in the same characteristic. The lower dashed line similarly fits the difference in *R*-squared between models that include all prior peer and individual posts and models that include all prior individual posts. The solid lines then represent the percent of the peer effect due to reflection which, as described above, is some fraction of the upper dotted line. This fraction is bounded below by zero and above by shared variance between the prior posts of peers and the individual. In practice, we argue the true reflection is less than half of the maximum and closer to the inverse of class size. Imagine a case in which each student i wants to copy the behavior of her peers j=1…J. We would expect student i's behavior to look like a weighted average of the behavior of all her peers. If she treats all peers equally then the weights would be 1/J. Some students may have greater than average influence in any i j pairing, but the average weight should be 1/J (i.e. the inverse of class size minus one).

The top panel of Figure 1 considers the extent to which peers' choices about post length in the past influence a given student's decision about post length. This analysis suggests the influence of peer behavior grows noticeably over the first 20 posts, but then stabilizes or perhaps begins to decline. Consistent with the underlying mechanisms, reflection is small at the beginning of the term and also grows most during the early posts. In other words, during the early part of the term the posts of students in the same class are becoming more homogeneous as measured by their length in words. This occurs as a given student follows the behavior of her peers, but, of course, her peers are themselves partly following her prior lead. Thus the well-known difficulty of separating peer behavior from the behavior of an individual—the reflection problem. The results suggest meaningful reflection bias, but reflection that stabilizes over time. Reflection stabilize at a maximum of 80 percent of the total naïve peer *R*-squared. Our estimate for the reflection is, then, approximately 3.8 percent of the naïve peer estimate (the max divided by average class size of 22 minus 1).

In Psychology (bottom panel Figure 1), by contrast, the influence of peer behavior grows throughout the term. The percent estimated to be reflection stabilizes at a maximum of about 80 percent just as in the College Skills setting. Our estimate for the percent of reflection is 3.1 percent since class size is slightly larger in this course.

Figure 2 shows results for the time elapsed between a student's current and previous post. In this case, peer influence starts relatively strong and declines as the term progresses. Perhaps peers initial posts garner immediate responses from classmates but classmates own tendencies outweigh these initial responses as the class goes on. Reflection grows to a maximum about 50 percent of the naïve peer *R*-squared and then moves somewhat down and then up. Our best guess for the reflection is approximately 2.4 percent of full peer effect. Figure 3 shows results for whether a student's post is made within 10 minutes of a peer post. Peer influence grows throughout the term, though at a steeper rate early in the term. The percentage of naïve *R*-squared attributed to reflection stabilizes after about 20 posts at a lower maximum of approximately 18 percent – for a best-guess estimate less than one percent.

DISCUSSION AND CONCLUSION

Table 5 provides a summary table of our key results. Here we focus on the 2SLS specification which includes professor fixed effects. We only report the sign and significance level of the respective coefficients. We find that congestion effects lead to worse outcomes and that bursty peer discussion improves outcomes. Our congestion finding comes from the fact that as the length between posts decreases and hence the overall number of posts increases students outcomes get worse. This estimate is significant for current term outcomes (passing, completion, grades, and points accumulated) and for most long-term outcomes (enrollment and credits next term and one year later). In terms of burstiness, the concentration of discussion within ten minute periods improves outcomes in both COLL148 and PSYC110. As peers engage in rapid dialogue, individuals benefit.

Our findings are consistent with the broader literature on online discourse. That literature finds that bursty discussions lead to increased involvement (e.g. Barabasi (2005) and Olson, Howison, and Carley, (2010)). In our case, we can relate these bursty exchanges to the future outcomes of students. Our finding extends the prior literature by showing that the increased involvement leads to changes in current *and* future educational outcomes. Prior literature had only related to persistence in discussion forums, and the fact that persistence in DeVry forums leads to better educational outcomes shows that burstiness can improve outcomes.

The congestion effects are also important in extending the academic discussions of peer effects. Since Lazear (2001) posited a model of peer effects which relied on congestion and disruption, economists have both been searching for peer effects and also trying to characterize the nature of them. In our case, we find that congestion effects stemming from the overall volume that students need to review and examine lead to worse outcomes. Our finding is significant in that it goes beyond simply identifying a peer effect and shows that the peer effect takes specific forms in affecting students' outcomes. As in the case of burstiness, the presence of congestion effects leads to both short- and long-run changes in outcomes. Our results on reflection provide the first estimate on the magnitude of the reflection problem. Manski's (1993) seminal contribution has guided the research on peer effects, but to date, no one has been able to characterize the exact nature or magnitude of reflection. Given the sequential nature of interactions, we can provide a crude estimate of reflection, and our results suggest that peer effects increase over the first part of the course. Our best guess is that reflection accounts for only a small part of peer interactions but we cannot rule out larger effects.

While our results do not have direct policy implications, they suggest practices to actively promote and monitor the evolution of peer to peer, online discussion forums can affect student outcomes. Peer effects can either be productive (e.g. burstiness) or unproductive (e.g. congestion). Creating rules in terms of the length of post, the frequency of posting, and encouraging rapid, bursty discussion may improve student engagement and consequently better student outcomes. Further research may demonstrate how the actual content of these posts generates peer effects as well.

Finally, prior peer literature has largely focused on the exposure to peers and peers' average characteristics as the measure and mechanism of peer effects. Our results show that the nature of the interaction makes a difference. We find both positive and negative peer effects within the same sample of students. The average characteristics may capture a real peer effect, but in our case, the average characteristics did not change from one sample to the next. What changed was the nature and characteristics of the interaction between the students, and the varied interactions led in some cases to bursty, productive conversations and in other cases to negative, congestion-filled conversations. As the cost of gathering data on peer interactions falls (as our opportunities and capabilities of observing peer interactions increase), our paper provides a first look at how the simple concept of peer effects is truly deeper and more nuanced set of complex interactions which can have both positive and negative elements.

References

Albert-László Barabási (2005). The origin of bursts and heavy tails in human dynamics *Nature 435*, 207-211

Anderson, Theodore Wilbur, and Cheng Hsiao. 1981. "Estimation of dynamic models with error components." *Journal of the American Statistical Association 76* (375): 598-606.

Anderson, Theodore Wilbur, and Cheng Hsiao. 1982. "Formulation and estimation of dynamic models using panel data." *Journal of Econometrics 18* (1): 47-82.

Battu, Harminder, Clive R. Belfield, and Peter J. Sloane. (2003). "Human Capital Spillovers within the Workplace: Evidence for Great Britain." *Oxford Bulletin of Economics and Statistics, 65*(5), 575–94.

Bettinger, Eric, Lindsay Fox, Susanna Loeb, and Eric Taylor (2014). "Changing Distributions: How Online College Classes Alter Student and Professor Performance." Working Paper.

Bruegmann, Elias and Kirabo Jackson. (2009). "Teaching Students and Teaching Each Other: The Importance of Peer Learning for Teachers." *American Economic Journal: Applied Economics. 1.4*: 85–108.

Carrell, Scott, Richard Fullerton, and James West. (2009). "Does Your Cohort Matter? Measuring Peer Effects in College Achievement," *Journal of Labor Economics*, 27(3), 439-464.

Carrell, Scott E., Bruce I. Sacerdote, and James E. West (2011). "From Natural Variation to Optimal Policy? The Lucas Critique Meets Peer Effects" NBER Working Paper Number 16865.

Cascio, Wayne F. (2000). "Managing a virtual workplace." *Academy of Management Perspectives, 14*(3), 81-90

Conley, Timothy G., and Christopher R. Udry. (2010). "Learning about a new technology: Pineapple in Ghana." *The American Economic Review 100* (1): 35-69.

Dewes, C., Wichmann, A., & Feldman, A. (2003) "An Analysis of Internet Chat Systems," Proc. 2003 ACM SIGCOMM Conf. on Internet Measurement (IMC-03), ACM Press, New York.

Figlio, David N. and Marianne E. Page. (2002). "School Choice And The Distributional Effects Of Ability Tracking: Does Separation Increase Inequality?," *Journal of Urban Economics, 51*(3,May), 497-514.

Guryan, Jonathan E., Kory Kroft, and Matthew J. Notowidigdo. (2009). “Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments.” *American Economic Journal: Applied Economics, 1*(4): 34–68.

Hoxby, C. (2000). “Peer Effects in the Classroom: Learning from Gender and Race Variation.” NBER Working Paper 7867.

Hoxby, Caroline and Gretchen Weingarth Salyer, (2005). "School Reassignment and the Structure of Peer Effects," Working Paper.

Kandel, Eugene, and Edward P. Lazear. (1992). “Peer Pressure and Partnerships.” *Journal of Political Economy, 100*(4): 801–17.

Kremer, Michael, and Dan Levy. (2008). Peer Effects and Alcohol Use among College Students. *Journal of Economic Perspectives 22*(3), 189 - 206.

Kulik, C. C. and J. A. Kulik. (1982). “Effects of Ability Grouping on Secondary School Students: A Meta-analysis of Evaluation Findings.” *American Educational Research Journal, 19*, pp. 415-428.

Lazear, E. (2001). “Educational Production.” *The Quarterly Journal of Economics, 16*(3), 777-803.

Manski, C. F. (1993). “Identification of Endogenous Social effects: The Reflection Problem.” *Review of Economic Studies, 60*, pp. 531-542.

Mas, Alexandre, and Enrico Moretti. (2009). “Peers at Work.” *American Economic review, 99*(1): 112–45.

Oakes, J. (1985). Keeping Track: How Schools Structure Inequality. New Haven, CT: Yale University Press.

Olson, J.F., Howison, J. ; Carley, K.M. (2010). “Paying Attention to Each Other in Visible Work Communities: Modeling Bursty Systems of Multiple Activity Streams,” *Social Computing* 276-281.

Paxson, V. & Floyd, S., (1995). “Wide-Area Traffic: The Failure of Poisson Modeling,” IEEE/ACM Tansactions in *Networking 3*, 226.

Sacerdote, Bruce. (2001). "Peer Effects With Random Assignment: Results For Dartmouth Roommates," *Quarterly Journal of Economics, 116*(2,May), 681-704.

Shorrocks, Anthony F. 1982. "Inequality decomposition by factor components."Econometrica 50 (1): 193-211.

Slavin, R. E. (1987). "Ability Grouping and Student Achievement in Elementary Schools: A Best-Evidence Synthesis." *Review of Educational Research, 57*, pp. 293-336.

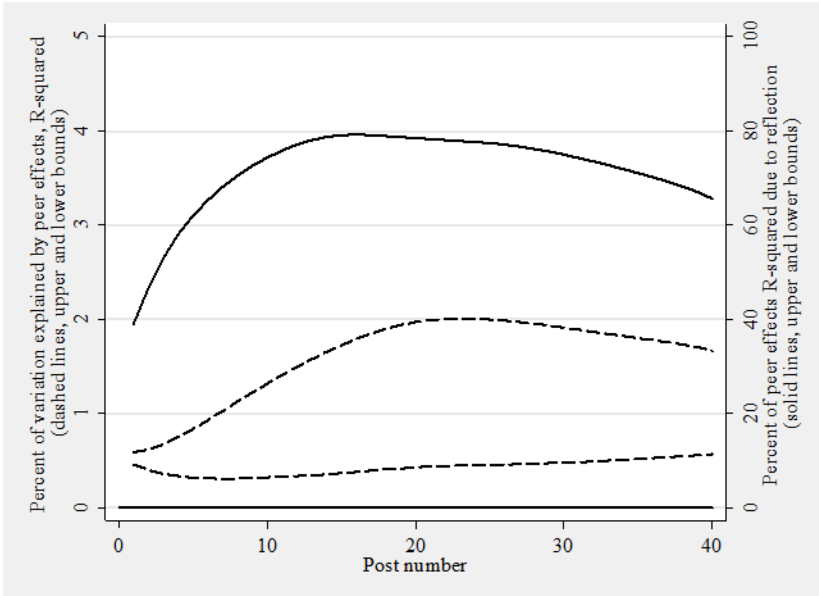
Stanton, Christopher & Catherine Thomas. (2011) "Landing the First Job: The Value of Intermediaries in Online Hiring." Working Paper.

Wellman, Barry, Janet Salaff, Dimitrina Dimitrova, Laura Garton, Milena Gulia and Caroline Haythornthwaite (1996). "Computer Networks as Social Networks: Collaborative Work, Telework, and Virtual Community." *Annual Review of Sociology, 22*, 213-238.

Wiesenfeld,Batia M., Sumita Raghuram, and Raghu Garud (2001). Organizational identification among virtual workers: the role of need for affiliation and perceived work-based social support. *Journal of Management*, *27*(2). 213-229.

Zimmerman, D. J. (2003). "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment." *Review of Economics and Statistics, 85*(1), 9-23.

A: COLLEGE SKILLS



B: PSYCHOLOGY

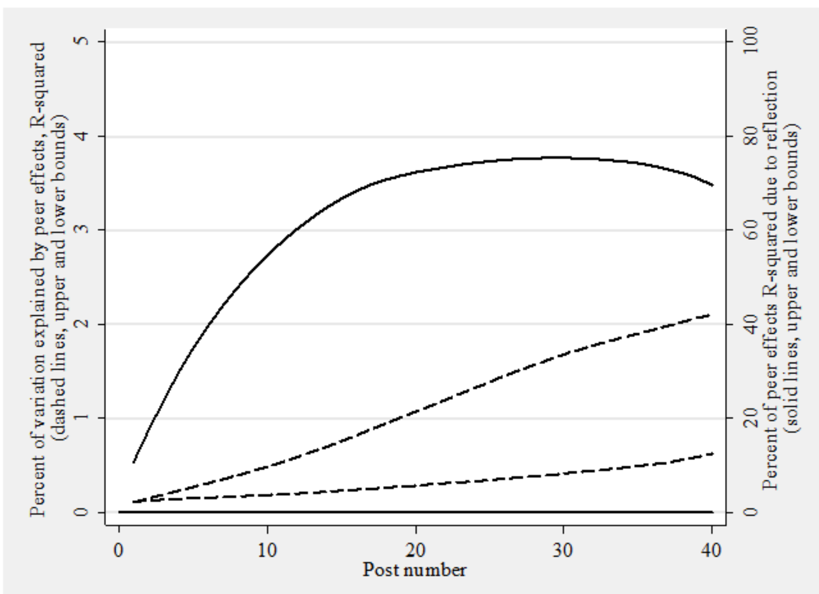
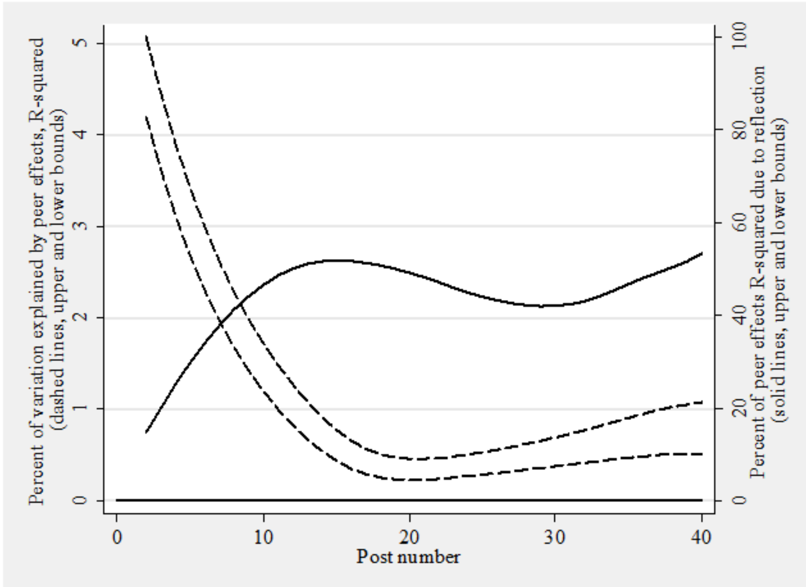


FIGURE 1— REFLECTION IN STUDENT POST LENGTH
OVER THE COURSE OF THE TERM

NOTE: Dashed lines are lowess fits through a series of R-squared estimates. The upper dashed line fits R-squared values from a regression where the length in words of the given post $p \in \{1,2,\ldots,40\}$, shown on the x-axis, is the outcome variable; and the control variables are a vector of peer average post lengths for each preceding post $q < p$. Call this model (a). The lower dashed line fits values which are the difference between two R-squared values (b) minus (c). Model (c) is identical to model (a) except that instead of peer average controls it includes a vector of post lengths for the student's own preceding posts $q < p$. Model (b) includes both peer average controls and own controls. The upper solid line is a lowess fit through the percentage difference between the two dashed lines, specifically, (a) – [(b) – (c)] / (a). The lower solid line is zero by definition.

A: COLLEGE SKILLS



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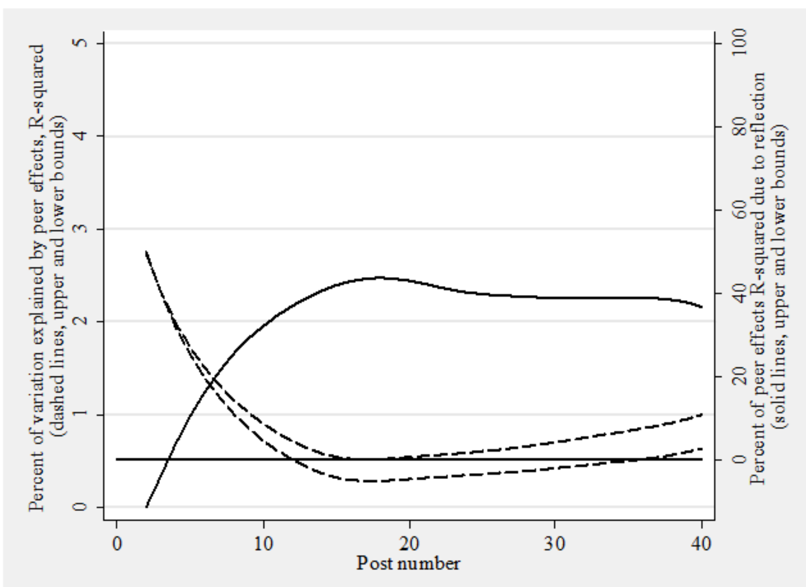
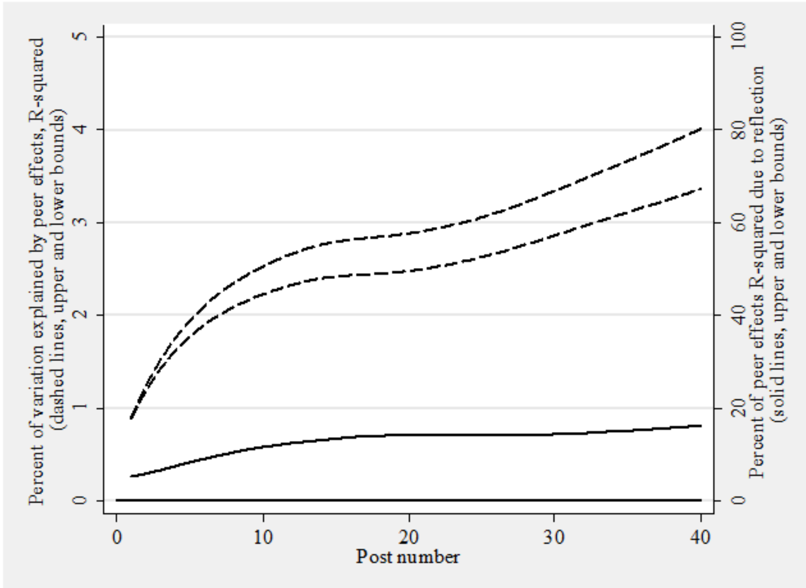


FIGURE 2— REFLECTION IN ELAPSED TIME SINCE STUDENT'S PREVIOUS POST OVER THE COURSE OF THE TERM

NOTE: Dashed lines are lowess fits through a series of R-squared estimates. The upper dashed line fits R-squared values from a regression where for the given post $p \in \{1,2,\ldots,40\}$, shown on the x-axis, the outcome variable is the time elapsed since the student's previous post $p-1$; and the control variables are a vector of peer averages for the outcome variable for each preceding post $q < p$. Call this model (a). The lower dashed line fits values which are the difference between two R-squared values (b) minus (c). Model (c) is identical to model (a) except that instead of peer average controls it includes a vector of the outcome variable for the student's own preceding posts $q < p$. Model (b) includes both peer average controls and own controls. The upper solid line is a lowess fit through the percentage difference between the two dashed lines, specifically, (a) – [(b) – (c)] / (a). The lower solid line is zero by definition.

A: College Skills



B: Psychology

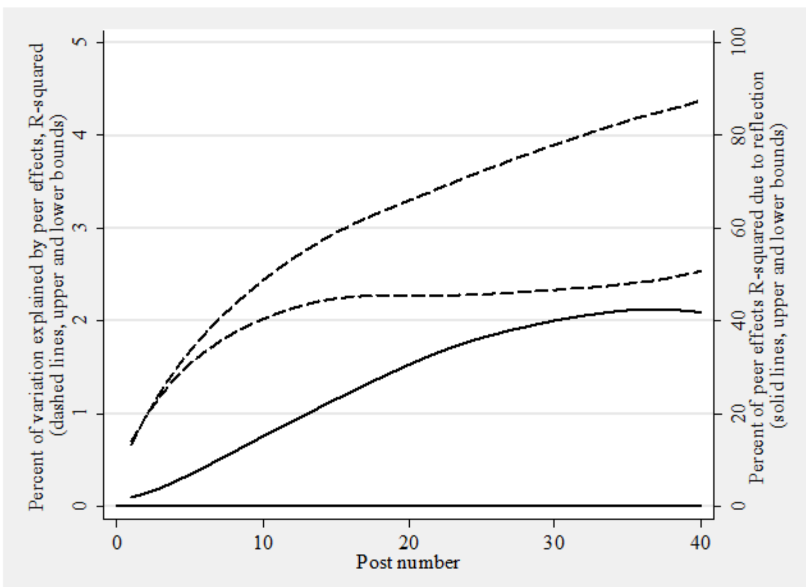


Figure 3— Reflection in Whether Student Post Made within 10 Minutes of a Peer Post Over the Course of the Term

Note: Dashed lines are lowess fits through a series of R-squared estimates. The upper dashed line fits R-squared values from a regression where an indicator for whether the given post $p \in \{1,2,\ldots,40\}$, shown on the x-axis, occurred within 10 minutes of another student post is the outcome variable; and the control variables are a vector of peer averages of the outcome variable for each preceding post $q < p$. Call this model (a). The lower dashed line fits values which are the difference between two R-squared values (b) minus (c). Model (c) is identical to model (a) except that instead of peer average controls it includes a vector of indicators for the student's own preceding posts $q < p$. Model (b) includes both peer average controls and own controls. The upper solid line is a lowess fit through the percentage difference between the two dashed lines, specifically, (a) – [(b) – (c)] / (a). The lower solid line is zero by definition.

Table 1: Descriptive Statistics

	Both Courses		COLL148		PSYC110	
Student Characteristics						
Female	0.483		0.491		0.469	
Age	31.140	(8.898)	31.179	(8.952)	31.075	(8.807)
Northeast	0.123		0.124		0.122	
South	0.425		0.427		0.422	
Midwest	0.259		0.261		0.254	
West	0.175		0.171		0.181	
Outside US	0.018		0.017		0.021	
First Semester at University	0.677		0.831		0.418	
Continuing Student	0.271		0.123		0.521	
Enrolled Credits Current Semester	8.527	(3.220)	8.160	(3.075)	9.146	(3.362)
Seeking BA	0.722		0.713		0.738	
Business Management Major	0.363		0.366		0.358	
Technology Major	0.096		0.102		0.086	
Health Major	0.125		0.134		0.111	
Student Outcomes						
Completed Course	0.855		0.846		0.870	
Passed Course	0.800		0.804		0.794	
Course Grade (A-F > 4-0)	2.481	(1.528)	2.668	(1.562)	2.178	(1.418)
Course Points	0.423	(0.696)	0.334	(0.720)	0.569	(0.629)
Enrolled Next Semester	0.738		0.730		0.751	
Enrolled Credits Next Semester	9.296	(3.487)	9.225	(3.448)	9.412	(3.548)
Enrolled One Year Later	0.429		0.410		0.460	
Enrolled Credits One Year Later	9.280	(3.501)	9.178	(3.483)	9.432	(3.522)
Post Characteristics						
Length (words)	78.38	(66.86)	72.98	(66.50)	91.33	(65.93)
Time Between Posts for Student (hours)	20.42	(34.79)	17.65	(31.65)	26.33	(40.82)
Posts within 10 min Other Students	0.41		0.42		0.38	
Student-by-section Observations	35,354		22,125		13229	
Students	26,911		21,017		12615	
Course Sections	1,424		952		472	
Professors	246		176		93	

Table 2: Testing Selection With and Without Block Fixed Effects

	COLL148		PSYC110	
Student Characteristics	No Block FE	With Block FE	No Block FE	With Block FE
Female	-0.0001+	-0.0049	-0.0005**	0.0054
	(0.0001)	(0.0041)	(0.0002)	(0.0053)
Age	-0.0032*	-0.0833	-0.0332**	-0.0483
	(0.0013)	(0.0731)	(0.0030)	(0.0936)
Northeast	-0.0000	-0.0037	-0.0001	0.0027
	(0.0000)	(0.0027)	(0.0001)	(0.0035)
South	0.0003**	0.0024	0.0001	0.0010
	(0.0001)	(0.0041)	(0.0002)	(0.0053)
Midwest	-0.0003**	0.0030	-0.0002	-0.0023
	(0.0001)	(0.0036)	(0.0001)	(0.0046)
West	0.0001	-0.0021	0.0002	-0.0006
	(0.0001)	(0.0031)	(0.0001)	(0.0041)
Outside US	0.0000	0.0004	-0.0000	-0.0008
	(0.0000)	(0.0011)	(0.0000)	(0.0015)
First Term at University	0.0014**	0.0061*	0.0062**	-0.0031
	(0.0001)	(0.0030)	(0.0002)	(0.0049)
Continuing Student	-0.0013**	-0.0047+	-0.0067**	-0.0003
	(0.0000)	(0.0026)	(0.0002)	(0.0049)
Enrolled Credits Current Semester	-0.0069**	-0.0303	-0.0227**	0.0152
	(0.0005)	(0.0230)	(0.0011)	(0.0349)
Seeking BA	0.0002**	0.0001	0.0001	-0.0052
	(0.0001)	(0.0037)	(0.0002)	(0.0047)
Business Management Major	0.0001+	-0.0003	-0.0009**	-0.0046
	(0.0001)	(0.0040)	(0.0002)	(0.0051)
Technology Major	-0.0000	-0.0008	-0.0001	0.0018
	(0.0000)	(0.0025)	(0.0001)	(0.0030)
Health Major	0.0000	0.0004	0.0003**	0.0022
	(0.0000)	(0.0028)	(0.0001)	(0.0033)
Joint Test $\chi 2$	977.337	11.820	2315.801	7.532
p-value	0.000	0.542	0.000	0.873
Observations	22125	22125	13229	13229
Professor Characteristics				
Female	0.0003	-0.0041	0.0009	0.0036
	(0.0003)	(0.0146)	(0.0007)	(0.0170)
Doctoral Degree	0.0009**	0.0059	0.0011	0.0103
	(0.0003)	(0.0141)	(0.0009)	(0.0233)
# Times Taught Course Past Year	-0.0064*	0.1355	0.0058	-0.0533
	(0.0030)	(0.0918)	(0.0046)	(0.1026)
Joint Test $\chi 2$	14.954	2.280	6.465	0.430
p-value	0.002	0.516	0.091	0.934
Observations	22058	22058	13173	13173

Table 3a--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Least squares estimates (College Skills course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.045*	0.095**	0.128**	0.234**	0.666**	1.178**	0.277**	0.491**
	(0.019)	(0.023)	(0.032)	(0.035)	(0.149)	(0.156)	(0.062)	(0.065)
Average post length[b]	0.053**	0.072**	-0.055*	0.000	-0.527**	-0.070	-0.217**	-0.019
	(0.016)	(0.020)	(0.024)	(0.026)	(0.101)	(0.110)	(0.045)	(0.047)
Proportion posts within	0.165**	0.239**	0.347**	0.467**	1.975**	2.646**	0.815**	1.066**
10 min of another post[c]	(0.051)	(0.054)	(0.075)	(0.078)	(0.332)	(0.336)	(0.137)	(0.139)
Herfindahl of average	0.960*	1.435**	1.576**	1.225*	5.892*	5.868*	2.585*	2.409*
post lengths[d]	(0.398)	(0.430)	(0.553)	(0.538)	(2.608)	(2.420)	(1.092)	(1.027)
Own Behaviors								
Time between posts[a]	-0.066**	-0.066**	-0.159**	-0.158**	-0.595**	-0.591**	-0.332**	-0.330**
	(0.003)	(0.003)	(0.011)	(0.011)	(0.041)	(0.041)	(0.021)	(0.021)
Average post length[b]	-0.042**	-0.041**	0.058**	0.062**	0.546**	0.570**	0.180**	0.188**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.033)	(0.033)	(0.014)	(0.015)
Proportion posts within	-0.012	-0.009	-0.121**	-0.114**	-0.699**	-0.661**	-0.331**	-0.317**
10 min of another post[c]	(0.021)	(0.021)	(0.026)	(0.026)	(0.097)	(0.097)	(0.047)	(0.047)
Professor fixed effects		Y		Y		Y		Y
Student observations	20375	20375	18366	18366	18366	18366	18252	18252

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

+ indicates p < 0.10, * 0.05, ** 0.01

Table 3a (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Least squares estimates (College Skills course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.056+	0.146**	0.930**	1.217**	0.087*	0.206**	0.905*	0.690
	(0.030)	(0.033)	(0.295)	(0.307)	(0.042)	(0.045)	(0.391)	(0.436)
Average post length[b]	0.011	0.025	0.209	0.336	0.012	0.054	-0.203	0.273
	(0.023)	(0.027)	(0.215)	(0.277)	(0.027)	(0.034)	(0.306)	(0.379)
Proportion posts within	0.186*	0.237**	1.713*	1.685*	0.404**	0.460**	-0.195	0.127
10 min of another post[c]	(0.079)	(0.083)	(0.720)	(0.712)	(0.096)	(0.098)	(1.015)	(1.070)
Herfindahl of average	0.729	0.984+	13.098*	14.511*	1.537*	1.486+	4.284	5.445
post lengths[d]	(0.559)	(0.585)	(5.680)	(5.848)	(0.774)	(0.813)	(7.334)	(7.547)
Own Behaviors								
Time between posts[a]	-0.062**	-0.061**	-0.330**	-0.324**	-0.069**	-0.068**	-0.276**	-0.280**
	(0.003)	(0.003)	(0.029)	(0.028)	(0.003)	(0.003)	(0.067)	(0.067)
Average post length[b]	-0.006	-0.005	0.393**	0.396**	0.059**	0.063**	0.589**	0.600**
	(0.008)	(0.008)	(0.075)	(0.076)	(0.009)	(0.009)	(0.102)	(0.104)
Proportion posts within	-0.023	-0.020	0.043	0.043	-0.077**	-0.075**	0.281	0.335
10 min of another post[c]	(0.024)	(0.024)	(0.212)	(0.214)	(0.022)	(0.022)	(0.311)	(0.317)
Professor fixed effects		Y		Y		Y		Y
Student observations	20373	20373	15638	15638	20373	20373	8888	8888

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

+ indicates p < 0.10, * 0.05, ** 0.01

Table 4a--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--2SLS (College Skills course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.075**	0.113**	0.253**	0.368**	1.573**	2.163**	0.576**	0.780**
	(0.029)	(0.032)	(0.048)	(0.055)	(0.231)	(0.259)	(0.094)	(0.106)
Average post length[b]	0.065**	0.071**	-0.035	0.035	-0.383**	0.103	-0.164**	0.047
	(0.017)	(0.022)	(0.029)	(0.031)	(0.128)	(0.139)	(0.053)	(0.056)
Proportion posts within	0.269**	0.305**	0.419**	0.544**	2.959**	3.585**	1.031**	1.192**
10 min of another post[c]	(0.080)	(0.084)	(0.127)	(0.132)	(0.585)	(0.615)	(0.238)	(0.247)
Herfindahl of average	1.008+	1.484**	0.872	0.463	4.487	2.528	1.494	0.419
post lengths[d]	(0.524)	(0.520)	(0.792)	(0.733)	(3.727)	(3.544)	(1.492)	(1.360)
Own Behaviors								
Time between posts[a]	-0.071**	-0.071**	-0.204**	-0.203**	-0.781**	-0.776**	-0.423**	-0.421**
	(0.005)	(0.005)	(0.017)	(0.017)	(0.067)	(0.067)	(0.033)	(0.033)
Average post length[b]	-0.065**	-0.065**	0.042**	0.045**	0.516**	0.539**	0.155**	0.163**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.033)	(0.033)	(0.014)	(0.014)
Proportion posts within	-0.130**	-0.128**	-0.226**	-0.217**	-0.976**	-0.930**	-0.506**	-0.494**
10 min of another post[c]	(0.024)	(0.024)	(0.029)	(0.029)	(0.113)	(0.113)	(0.051)	(0.051)
Professor fixed effects		Y		Y		Y		Y
Student observations	20230	20230	18326	18326	18326	18326	18208	18208
F-statistic excluded instruments								
Peer measures								
Number of posts	595.8	766.6	634.9	731.7	634.9	731.7	631.8	730.9
Average post length	6730.7	5687.6	6688.6	5599.6	6688.6	5599.6	6608.2	5601.6
Prpn. within 10 min	780.7	912.7	785.2	911.0	785.2	911.0	789.6	912.4
Herfindahl of lengths	243.2	388.8	220.0	377.8	220.0	377.8	217.1	374.9
Own measures								
Number of posts	1881.0	1853.6	1022.8	1005.4	1022.8	1005.4	1041.0	1023.3
Average post length	29566.8	28526.4	63012.6	59694.5	63012.6	59694.5	62402.2	59071.1
Prpn. within 10 min	15962.4	15960.4	28651.9	28724.4	28651.9	28724.4	27972.3	27977.8

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single two-stage least squares regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

All excluded instruments are based on the estimated μ terms described in the text (see text for important details). Excluded instruments are: the student's own estimated μ for hours between posts, total words in a post, and proportion of posts that occur within ten minutes of another post; jackknife meadians of the same three student μ measures; and the jackknife Herfindahl index. *F*-statistics for excluded instruments in the various first stages are as suggested by Angrist and Pishke (2009).

+ indicates p < 0.10, * 0.05, ** 0.01

Table 4a (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--2SLS (College Skills course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.166**	0.248**	1.371**	1.676**	0.205**	0.335**	0.814	0.424
	(0.047)	(0.052)	(0.441)	(0.450)	(0.062)	(0.069)	(0.553)	(0.613)
Average post length[b]	0.045+	0.062*	0.212	0.289	0.043	0.118**	-0.253	0.175
	(0.026)	(0.031)	(0.249)	(0.307)	(0.032)	(0.039)	(0.347)	(0.413)
Proportion posts within	0.417**	0.399**	1.916	1.133	0.556**	0.558**	1.087	1.199
10 min of another post[c]	(0.122)	(0.130)	(1.176)	(1.145)	(0.153)	(0.167)	(1.545)	(1.580)
Herfindahl of average	0.377	0.168	15.094*	8.672	0.768	0.165	18.238+	17.300+
post lengths[d]	(0.748)	(0.787)	(7.513)	(8.261)	(0.984)	(1.036)	(9.679)	(10.186)
Own Behaviors								
Time between posts[a]	-0.077**	-0.076**	-0.393**	-0.387**	-0.094**	-0.093**	-0.333**	-0.350**
	(0.005)	(0.005)	(0.042)	(0.041)	(0.005)	(0.005)	(0.088)	(0.089)
Average post length[b]	-0.023*	-0.023*	0.417**	0.414**	0.054**	0.058**	0.606**	0.604**
	(0.009)	(0.009)	(0.078)	(0.079)	(0.009)	(0.009)	(0.104)	(0.104)
Proportion posts within	-0.100**	-0.100**	-0.098	-0.160	-0.144**	-0.142**	0.184	0.184
10 min of another post[c]	(0.030)	(0.030)	(0.257)	(0.257)	(0.030)	(0.030)	(0.365)	(0.373)
Professor fixed effects		Y		Y		Y		Y
Student observations	20228	20228	15582	15582	20228	20228	8878	8878
F-statistic excluded instruments								
Peer measures								
Number of posts	595.8	766.6	645.9	725.7	595.8	766.6	852.1	722.2
Average post length	6729.9	5686.4	6599.3	5383.8	6729.9	5686.4	6655.3	5345.9
Prpn. within 10 min	780.8	912.8	778.0	902.1	780.8	912.8	748.8	817.9
Herfindahl of lengths	243.2	388.8	215.1	369.3	243.2	388.8	182.7	331.5
Own measures								
Number of posts	1880.9	1853.5	875.1	865.3	1880.9	1853.5	254.6	246.9
Average post length	29556.2	28519.3	56295.9	52999.5	29556.2	28519.3	64497.3	62089.5
Prpn. within 10 min	15962.1	15959.9	19219.0	19460.4	15962.1	15959.9	13213.5	13018.1

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single two-stage least squares regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

All excluded instruments are based on the estimated μ terms described in the text (see text for important details). Excluded instruments are: the student's own estimated μ for hours between posts, total words in a post, and proportion of posts that occur within ten minutes of another post; jackknife meadians of the same three student μ measures; and the jackknife Herfindahl index. *F*-statistics for excluded instruments in the various first stages are as suggested by Angrist and Pishke. + indicates $p < 0.10$, * 0.05, ** 0.01

Table 3b--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Least squares estimates (Introduction to Psychology course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.107*	0.130*	0.159*	0.388**	0.903**	2.172**	0.356**	0.725**
	(0.047)	(0.050)	(0.079)	(0.079)	(0.311)	(0.285)	(0.113)	(0.116)
Average post length[b]	-0.030+	-0.003	-0.099**	-0.069*	-0.619**	-0.302**	-0.215**	-0.148**
	(0.018)	(0.019)	(0.028)	(0.027)	(0.109)	(0.093)	(0.045)	(0.039)
Proportion posts within	0.094+	0.060	0.142+	0.169+	0.720*	0.656*	0.342**	0.333*
10 min of another post[c]	(0.056)	(0.058)	(0.084)	(0.092)	(0.331)	(0.322)	(0.130)	(0.133)
Herfindahl of average	0.546	1.245**	-0.241	-0.190	-0.410	-0.948	0.795	0.754
post lengths[d]	(0.472)	(0.471)	(0.785)	(0.718)	(2.909)	(2.661)	(1.154)	(1.010)
Own Behaviors								
Time between posts[a]	-0.063**	-0.063**	-0.168**	-0.168**	-0.524**	-0.520**	-0.292**	-0.292**
	(0.006)	(0.006)	(0.018)	(0.018)	(0.059)	(0.060)	(0.033)	(0.033)
Average post length[b]	0.009+	0.011*	0.078**	0.079**	0.630**	0.645**	0.197**	0.200**
	(0.005)	(0.005)	(0.008)	(0.008)	(0.028)	(0.029)	(0.012)	(0.013)
Proportion posts within	-0.102**	-0.103**	-0.181**	-0.179**	-0.848**	-0.846**	-0.336**	-0.333**
10 min of another post[c]	(0.023)	(0.024)	(0.028)	(0.028)	(0.089)	(0.089)	(0.044)	(0.044)
Professor fixed effects		Y		Y		Y		Y
Student observations	12274	12274	11249	11249	11249	11249	11181	11181

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

+ indicates p < 0.10, * 0.05, ** 0.01

Table 3b (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Least squares estimates (Introduction to Psychology course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.138*	0.264**	0.719	1.494*	0.205*	0.357**	0.778	1.051
	(0.064)	(0.077)	(0.645)	(0.658)	(0.081)	(0.093)	(0.818)	(0.898)
Average post length[b]	-0.020	0.032	-0.087	-0.287	-0.017	0.026	-1.004**	-0.982**
	(0.024)	(0.027)	(0.229)	(0.275)	(0.027)	(0.032)	(0.282)	(0.323)
Proportion posts within	0.182*	0.006	1.297+	0.498	0.397**	0.285**	-0.355	-0.739
10 min of another post[c]	(0.081)	(0.088)	(0.784)	(0.875)	(0.096)	(0.100)	(1.032)	(1.148)
Herfindahl of average	1.292	1.468+	14.339+	18.703**	0.733	1.558+	-15.529	2.171
post lengths[d]	(0.868)	(0.811)	(7.312)	(7.146)	(0.855)	(0.890)	(9.599)	(8.857)
Own Behaviors								
Time between posts[a]	-0.066**	-0.065**	-0.252**	-0.256**	-0.080**	-0.080**	-0.235**	-0.249**
	(0.006)	(0.006)	(0.054)	(0.054)	(0.006)	(0.006)	(0.078)	(0.080)
Average post length[b]	0.034**	0.037**	0.373**	0.358**	0.086**	0.088**	0.264**	0.270**
	(0.008)	(0.008)	(0.071)	(0.072)	(0.009)	(0.009)	(0.089)	(0.092)
Proportion posts within	-0.146**	-0.154**	0.514*	0.462+	-0.196**	-0.200**	0.514	0.431
10 min of another post[c]	(0.026)	(0.027)	(0.241)	(0.243)	(0.026)	(0.027)	(0.322)	(0.328)
Professor fixed effects		Y		Y		Y		Y
Student observations	12195	12195	9535	9535	12195	12195	5911	5911

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

+ indicates p < 0.10, * 0.05, ** 0.01

Table 4b--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--2SLS (Introduction to Psychology course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.045	0.044	0.164	0.465**	0.782*	2.060**	0.367*	0.800**
	(0.062)	(0.061)	(0.104)	(0.116)	(0.391)	(0.426)	(0.156)	(0.175)
Average post length[b]	-0.032+	-0.004	-0.085**	-0.050+	-0.558**	-0.235*	-0.174**	-0.097*
	(0.019)	(0.020)	(0.031)	(0.030)	(0.117)	(0.100)	(0.048)	(0.042)
Proportion posts within	0.103	0.029	0.188	0.232+	1.158**	1.065*	0.513**	0.589**
10 min of another post[c]	(0.067)	(0.074)	(0.116)	(0.131)	(0.436)	(0.445)	(0.173)	(0.184)
Herfindahl of average	0.161	0.608	-0.158	0.226	0.719	1.231	0.663	1.283
post lengths[d]	(0.538)	(0.512)	(0.907)	(0.821)	(3.252)	(2.882)	(1.275)	(1.062)
Own Behaviors								
Time between posts[a]	-0.079**	-0.080**	-0.244**	-0.243**	-0.785**	-0.782**	-0.421**	-0.420**
	(0.007)	(0.007)	(0.021)	(0.021)	(0.069)	(0.069)	(0.035)	(0.035)
Average post length[b]	0.013**	0.015**	0.076**	0.077**	0.631**	0.645**	0.196**	0.200**
	(0.005)	(0.005)	(0.008)	(0.008)	(0.028)	(0.028)	(0.012)	(0.012)
Proportion posts within	-0.103**	-0.104**	-0.202**	-0.197**	-0.964**	-0.953**	-0.385**	-0.376**
10 min of another post[c]	(0.023)	(0.023)	(0.028)	(0.028)	(0.090)	(0.090)	(0.041)	(0.041)
Professor fixed effects		Y		Y		Y		Y
Student observations	12166	12166	11216	11216	11216	11216	11145	11145
F-statistic excluded instruments								
Peer measures								
Number of posts	355.8	447.3	341.7	436.7	341.7	436.7	343.4	439.3
Average post length	4388.6	4750.8	4331.8	4722.8	4331.8	4722.8	4339.0	4725.0
Prpn. within 10 min	778.3	711.0	751.4	701.7	751.4	701.7	753.8	701.4
Herfindahl of lengths	930.4	1072.7	880.1	1037.9	880.1	1037.9	882.3	1042.7
Own measures								
Number of posts	1222.7	1223.7	978.8	966.2	978.8	966.2	970.7	957.9
Average post length	60840.3	60393.1	100173.2	101742.9	100173.2	101742.9	99296.5	100735.3
Prpn. within 10 min	31648.0	30803.8	34546.8	33666.3	34546.8	33666.3	32560.7	31649.0

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single two-stage least squares regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

All excluded instruments are based on the estimated μ terms described in the text (see text for important details). Excluded instruments are: the student's own estimated μ for hours between posts, total words in a post, and proportion of posts that occur within ten minutes of another post; jackknife meadians of the same three student μ measures; and the jackknife Herfindahl index. *F*-statistics for excluded instruments in the various first stages are as suggested by Angrist and Pishke (2009). + indicates p < 0.10, * 0.05, ** 0.01

Table 4b (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--2SLS (Introduction to Psychology course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.092	0.194+	1.561	2.399*	0.108	0.198	-0.125	0.257
	(0.097)	(0.104)	(0.976)	(1.033)	(0.118)	(0.132)	(1.169)	(1.258)
Average post length[b]	-0.009	0.046	-0.115	-0.266	-0.017	0.029	-1.245**	-1.239**
	(0.029)	(0.029)	(0.262)	(0.310)	(0.030)	(0.034)	(0.314)	(0.342)
Proportion posts within	0.253*	0.068	1.673	1.625	0.426**	0.222	-1.861	-2.154
10 min of another post[c]	(0.120)	(0.129)	(1.107)	(1.300)	(0.126)	(0.136)	(1.272)	(1.519)
Herfindahl of average	1.325	1.557+	13.102+	16.085*	0.705	1.254	-16.861	2.069
post lengths[d]	(1.012)	(0.932)	(7.348)	(7.246)	(0.917)	(0.906)	(10.427)	(9.394)
Own Behaviors								
Time between posts[a]	-0.092**	-0.092**	-0.343**	-0.341**	-0.119**	-0.120**	-0.323**	-0.334**
	(0.009)	(0.009)	(0.069)	(0.068)	(0.009)	(0.009)	(0.085)	(0.087)
Average post length[b]	0.034**	0.036**	0.374**	0.359**	0.086**	0.087**	0.254**	0.258**
	(0.008)	(0.008)	(0.072)	(0.073)	(0.009)	(0.009)	(0.089)	(0.092)
Proportion posts within	-0.170**	-0.177**	0.383	0.345	-0.231**	-0.238**	0.375	0.253
10 min of another post[c]	(0.029)	(0.029)	(0.269)	(0.271)	(0.032)	(0.032)	(0.346)	(0.349)
Professor fixed effects		Y		Y		Y		Y
Student observations	12087	12087	9490	9490	12087	12087	5902	5902
F-statistic excluded instruments								
Peer measures								
Number of posts	353.8	445.7	330.1	436.5	353.8	445.7	314.8	415.4
Average post length	4385.2	4726.4	4317.4	4567.4	4385.2	4726.4	4240.5	4678.4
Prpn within 10 min	773.5	709.0	753.2	722.9	773.5	709.0	764.7	727.2
Herfindahl of lengths	973.5	1093.8	826.1	957.1	973.5	1093.8	873.4	922.0
Own measures								
Number of posts	1221.6	1222.5	626.9	624.4	1221.6	1222.5	192.2	186.0
Average post length	60518.6	60086.4	89617.0	88803.9	60518.6	60086.4	58743.7	59230.5
Prpn within 10 min	31657.4	30750.1	30035.9	28204.0	31657.4	30750.1	24651.1	23398.6

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single two-stage least squares regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). Standard errors, in parentheses, allow for clustering within sections.

a. Student level standard deviations (within term) of hours between posts after week one of the course. Peer measure is the jackknife median of student measures.

b. Post level standard deviations (within term) of total words in post. Student measure is the mean of all posts made after week one. Peer measure is the jackknife median of student measures.

c. Student measure is the proportion of posts, made after week one, that occur within ten minutes of another post. Peer measure is the jackknife median of student measures.

d. Jackknife Herfindahl index calculated on post length measure.

All excluded instruments are based on the estimated μ terms described in the text (see text for important details). Excluded instruments are: the student's own estimated μ for hours between posts, total words in a post, and proportion of posts that occur within ten minutes of another post; jackknife meadians of the same three student μ measures; and the jackknife Herfindahl index. *F*-statistics for excluded instruments in the various first stages are as suggested by Angrist and Pishke (2009). + indicates $p < 0.10$, * 0.05, ** 0.01

Appendix Table 1a--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Reduced form (College Skills course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.046+	0.079**	0.197**	0.298**	1.231**	1.718**	0.448**	0.631**
	(0.025)	(0.027)	(0.039)	(0.045)	(0.176)	(0.199)	(0.076)	(0.087)
Average post length[b]	0.072**	0.062**	-0.043+	0.002	-0.465**	-0.088	-0.181**	-0.014
	(0.017)	(0.022)	(0.025)	(0.026)	(0.108)	(0.110)	(0.047)	(0.046)
Proportion posts within	0.261**	0.276**	0.303**	0.372**	2.119**	2.451**	0.759**	0.823**
10 min of another post[c]	(0.065)	(0.069)	(0.093)	(0.095)	(0.416)	(0.422)	(0.175)	(0.176)
Herfindahl of average	1.270**	1.802**	0.594	0.218	2.117	0.286	0.955	0.157
post lengths[d]	(0.453)	(0.455)	(0.599)	(0.541)	(2.748)	(2.506)	(1.114)	(1.003)
Own Behaviors								
Time between posts[a]	-0.067**	-0.067**	-0.198**	-0.197**	-0.762**	-0.758**	-0.411**	-0.410**
	(0.005)	(0.005)	(0.019)	(0.019)	(0.074)	(0.074)	(0.037)	(0.037)
Average post length[b]	-0.117**	-0.117**	0.027**	0.030**	0.465**	0.487**	0.122**	0.130**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.032)	(0.033)	(0.014)	(0.015)
Proportion posts within	-0.166**	-0.166**	-0.256**	-0.251**	-1.076**	-1.055**	-0.561**	-0.557**
10 min of another post[c]	(0.023)	(0.023)	(0.027)	(0.027)	(0.102)	(0.102)	(0.049)	(0.049)
Professor fixed effects		Y		Y		Y		Y
Student observations	20642	20642	18353	18353	18353	18353	18236	18236

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). All covariates, besides fixed effects, are the estimated μ terms described in the text (see text for important details). Standard errors, in parentheses, allow for clustering within sections.

a. Post level standard deviations (within term) of hours between posts. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

b. Post level standard deviations (within term) of total words in post. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

c. Student measure is the student's estimated μ for proportion of posts that occur within ten minutes of another post. Peer measure is the jackknife median of student μ's.

d. Jackknife Herfindahl index calculated on the estimated μ's for post length.

+ indicates $p < 0.10$, * 0.05, ** 0.01

Appendix Table 1a (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Reduced form (College Skills course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.126**	0.198**	1.086**	1.432**	0.151**	0.267**	0.578	0.254
	(0.038)	(0.042)	(0.348)	(0.358)	(0.049)	(0.053)	(0.438)	(0.477)
Average post length[b]	0.044+	0.039	0.191	0.263	0.041	0.089**	-0.235	0.180
	(0.023)	(0.027)	(0.220)	(0.271)	(0.028)	(0.034)	(0.313)	(0.372)
Proportion posts within	0.355**	0.319**	1.365	0.609	0.448**	0.407**	0.609	0.837
10 min of another post[c]	(0.092)	(0.100)	(0.878)	(0.883)	(0.112)	(0.123)	(1.160)	(1.215)
Herfindahl of average	0.550	0.646	12.375*	8.360	0.683	0.482	15.628+	14.356+
post lengths[d]	(0.591)	(0.599)	(6.127)	(6.666)	(0.763)	(0.788)	(8.023)	(8.561)
Own Behaviors								
Time between posts[a]	-0.075**	-0.074**	-0.388**	-0.381**	-0.093**	-0.093**	-0.362**	-0.381**
	(0.006)	(0.006)	(0.045)	(0.044)	(0.006)	(0.006)	(0.107)	(0.111)
Average post length[b]	-0.067**	-0.067**	0.366**	0.363**	0.013	0.016+	0.609**	0.609**
	(0.009)	(0.009)	(0.080)	(0.081)	(0.009)	(0.009)	(0.108)	(0.110)
Proportion posts within	-0.137**	-0.139**	-0.238	-0.309	-0.168**	-0.170**	0.103	0.114
10 min of another post[c]	(0.026)	(0.026)	(0.226)	(0.229)	(0.024)	(0.024)	(0.322)	(0.334)
Professor fixed effects		Y		Y		Y		Y
Student observations	20640	20640	15649	15649	20640	20640	8902	8902

Note: All students enrolled in "College Skills" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). All covariates, besides fixed effects, are the estimated μ terms described in the text (see text for important details). Standard errors, in parentheses, allow for clustering within sections.

a. Post level standard deviations (within term) of hours between posts. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

b. Post level standard deviations (within term) of total words in post. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

c. Student measure is the student's estimated μ for proportion of posts that occur within ten minutes of another post. Peer measure is the jackknife median of student μ's.

d. Jackknife Herfindahl index calculated on the estimated μ's for post length.

+ indicates $p < 0.10$, * 0.05, ** 0.01

Appendix Table 1b--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--
Reduced form
(Introduction to Psychology course)

	Completed Course		Passed Course		Letter Grade		Course Points (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Behaviors								
Time between posts[a]	0.075	0.077	0.119	0.312**	0.589*	1.418**	0.267*	0.537**
	(0.049)	(0.047)	(0.076)	(0.081)	(0.285)	(0.307)	(0.116)	(0.127)
Average post length[b]	-0.033+	-0.007	-0.092**	-0.039	-0.601**	-0.188+	-0.201**	-0.091*
	(0.020)	(0.021)	(0.029)	(0.028)	(0.110)	(0.097)	(0.046)	(0.042)
Proportion posts within	0.095+	0.036	0.140	0.098	0.896*	0.463	0.379**	0.291*
10 min of another post[c]	(0.057)	(0.061)	(0.092)	(0.100)	(0.351)	(0.339)	(0.139)	(0.143)
Herfindahl of average	0.583	1.204*	-0.063	0.237	0.753	1.172	0.741	1.334
post lengths[d]	(0.550)	(0.546)	(0.880)	(0.812)	(3.279)	(2.954)	(1.290)	(1.107)
Own Behaviors								
Time between posts[a]	-0.063**	-0.063**	-0.199**	-0.198**	-0.638**	-0.636**	-0.342**	-0.342**
	(0.007)	(0.007)	(0.017)	(0.017)	(0.058)	(0.058)	(0.029)	(0.029)
Average post length[b]	0.023**	0.025**	0.084**	0.087**	0.676**	0.695**	0.216**	0.222**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.028)	(0.029)	(0.012)	(0.013)
Proportion posts within	-0.077**	-0.077**	-0.189**	-0.189**	-0.877**	-0.884**	-0.359**	-0.357**
10 min of another post[c]	(0.022)	(0.023)	(0.025)	(0.025)	(0.080)	(0.080)	(0.038)	(0.037)
Professor fixed effects		Y		Y		Y		Y
Student observations	12343	12343	11244	11244	11244	11244	11178	11178

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). All covariates, besides fixed effects, are the estimated μ terms described in the text (see text for important details). Standard errors, in parentheses, allow for clustering within sections.

a. Post level standard deviations (within term) of hours between posts. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

b. Post level standard deviations (within term) of total words in post. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

c. Student measure is the student's estimated μ for proportion of posts that occur within ten minutes of another post. Peer measure is the jackknife median of student μ's.

d. Jackknife Herfindahl index calculated on the estimated μ's for post length.

+ indicates $p < 0.10$, * 0.05, ** 0.01

Appendix Table 1b (cont.)--Effects of Peer Behaviors on Student Course Outcomes and Persistence in College--Reduced form (Introduction to Psychology course)

	Enrolled Next Semester		Enrolled Credits Next Semester		Enrolled One Year Later		Enrolled Credits One Year Later	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Peer Behaviors								
Time between posts[a]	0.092	0.159*	1.051	1.612*	0.086	0.157+	0.037	0.193
	(0.069)	(0.072)	(0.701)	(0.714)	(0.085)	(0.091)	(0.852)	(0.901)
Average post length[b]	-0.024	0.039	-0.226	-0.318	-0.034	0.027	-1.214**	-1.190**
	(0.026)	(0.028)	(0.250)	(0.296)	(0.027)	(0.033)	(0.301)	(0.337)
Proportion posts within	0.161+	-0.009	1.298	1.053	0.319**	0.124	-1.138	-1.453
10 min of another post[c]	(0.095)	(0.100)	(0.904)	(1.016)	(0.103)	(0.102)	(1.068)	(1.229)
Herfindahl of average	1.253	1.748+	13.127+	16.429*	0.873	1.617+	-17.686	1.557
post lengths[d]	(0.995)	(0.957)	(7.508)	(7.505)	(0.941)	(0.975)	(11.063)	(9.978)
Own Behaviors								
Time between posts[a]	-0.077**	-0.076**	-0.283**	-0.282**	-0.100**	-0.100**	-0.245**	-0.254**
	(0.007)	(0.007)	(0.059)	(0.058)	(0.008)	(0.008)	(0.060)	(0.063)
Average post length[b]	0.040**	0.044**	0.403**	0.390**	0.095**	0.098**	0.278**	0.287**
	(0.008)	(0.009)	(0.076)	(0.076)	(0.009)	(0.009)	(0.095)	(0.098)
Proportion posts within	-0.142**	-0.149**	0.282	0.234	-0.193**	-0.201**	0.332	0.230
10 min of another post[c]	(0.025)	(0.025)	(0.232)	(0.235)	(0.027)	(0.027)	(0.308)	(0.313)
Professor fixed effects		Y		Y		Y		Y
Student observations	12261	12261	9549	9549	12261	12261	5920	5920

Note: All students enrolled in "Introduction to Psychology" between March 2010 and February 2011. Within panels each column reports estimates from a single regression. Dependent variables are listed in column headers. In addition to the listed covariates, all regressions include fixed effects for groups of sections--each group includes three sequentially created sections (see text for more discussion). All covariates, besides fixed effects, are the estimated μ terms described in the text (see text for important details). Standard errors, in parentheses, allow for clustering within sections.

a. Post level standard deviations (within term) of hours between posts. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

b. Post level standard deviations (within term) of total words in post. Student measure is the student's estimated μ. Peer measure is the jackknife median of student μ's.

c. Student measure is the student's estimated μ for proportion of posts that occur within ten minutes of another post. Peer measure is the jackknife median of student μ's.

d. Jackknife Herfindahl index calculated on the estimated μ's for post length.

+ indicates $p < 0.10$, * 0.05, ** 0.01