Peer Mechanism: How Interactive Peers Affect Students in College Online Courses

#### Eric Bettinger, Jing Liu, and Susanna Loeb Nov. 11, 2015



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#### Peer Effects

- Peers often influence decisions and productivity of individual workers, especially when production is explicitly collaborative (Guryan, Kroft, and Notowidigdo, 2009; Battu, Belfield, and Sloane, 2003; Bruegmann and Jackson, 2009).
- In higher education, student learning is jointly produced by professors, peers and student themselves.
- A growing literature focus on how peers affect performance, friendships, and attitudes of college students (Sacerdote, 2001&2011; Marmaros & Sacerdote, 2006; Zimmerman, 2003; Carrell, Fullerton, & West, 2009; Kremer & Levy, 2008).
- To date little research studies the mechanism of peer effects.
- How peers affect students might be different in online interactions relative to face-to-face.

#### Mechanisms of Peer Effects

- Peers have to influence individuals through actions
  - Group work
  - Engagement
- It is very hard to measure because we rarely observe peers in action
- College online courses and the associated data allow us to examine peers actions
  - Not all online courses entail peer interaction (Florida Virtual Courses)

#### Our Context

- Different from MOOCs
- These are virtual classrooms where the only difference is that the course is being conducted online
- Same materials, syllabus, class sizes, etc. as the in-person courses
- Promise of reduced cost and easier access, but research generally shows negative effects of online courses compared with in-person ones.

#### Peer Effects in Virtual Courses

- Peer actions
  - Length of postings
  - Frequency of postings
- Peer interactions
  - Course Content

-Interpersonal

- Peer outreach to classmates
- The social dimension of peer interaction

## Research Questions (1)

- How do interpersonal interactions in college online courses differ across students with different background characteristics and different levels of engagement in the course.
- Students vary systematically in their interpersonal interactions.

### Research Questions (2)

How do peer's interpersonal interactions affect student course performance, especially for those who are less likely to be engaged in classroom interactions?

 More peer engagement practices improve short-term student outcomes, especially for students on the margin.

#### Data

• Two online courses delivered in 2010 by DeVry University

Course	Sections	Students	Professors
COLL148	177	21,017	176
PSYC110	99	12,615	99

- Class organization:
  - Students are assigned to sections based on their registration order.
  - Students meet in a password-protected website.
  - Section professor leads the lecture by posting discussion threads on the discussion board.
  - Student must comment each thread 3+ times each week to earn grades.
- Full transcripts of all the online writing communications by students > 2 million posts

#### Types of Posts

#### • Type 1: Direct mention of peer names

"Agreeing with Peer-A I would have to go with theory number one the restoration sleep. Like she said the body like any other piece of machinery needs down time to rest, restore, or reincorporate....."

#### • Type 2: Interaction without direct mention of peer names

- "huh? Well I think you're talking about how one relaxes themselves and tries to fall asleep. But if I'm wrong I'll have to re post. After I call it a night and I'm trying to fall asleep I clear my mind and think of black velvet so close to my face that it fills my line of vision....."

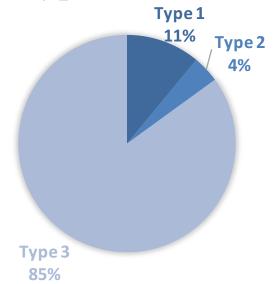
#### • Type 3: No interaction

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



## Frequency of Post Type

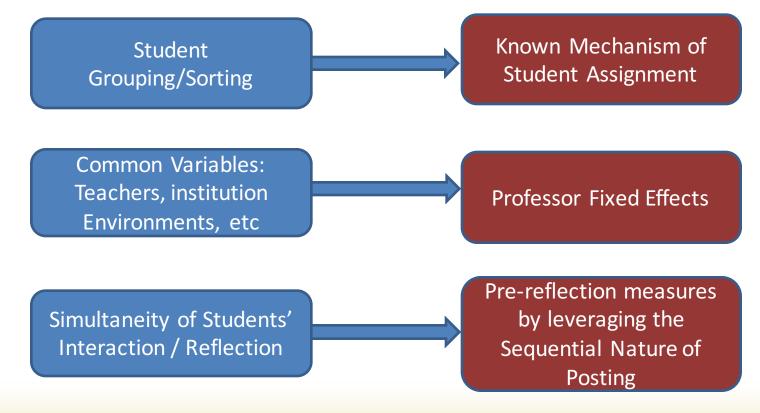
• We take a random sample of 300 posts and classify them into the three types



• Because the large majority of interaction posts mention names (73.3%), we use name mentioning to identify posts with interpersonal interaction.

#### Identification Strategy

• Peer/Social interaction effects (Manski, 1993&2000)



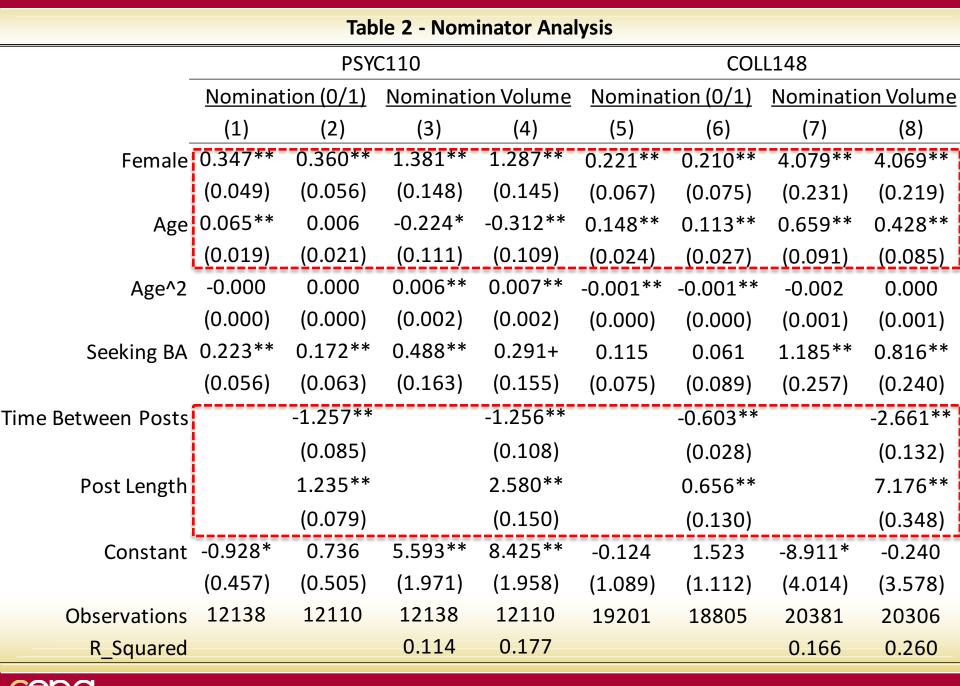
## RQ1: How do interpersonal interactions differ across students?

$$y_{ict} = C_{ict}\beta_0 + E_{ict}\beta_1 + \theta_b + \nu_p + \varepsilon_{ict}$$

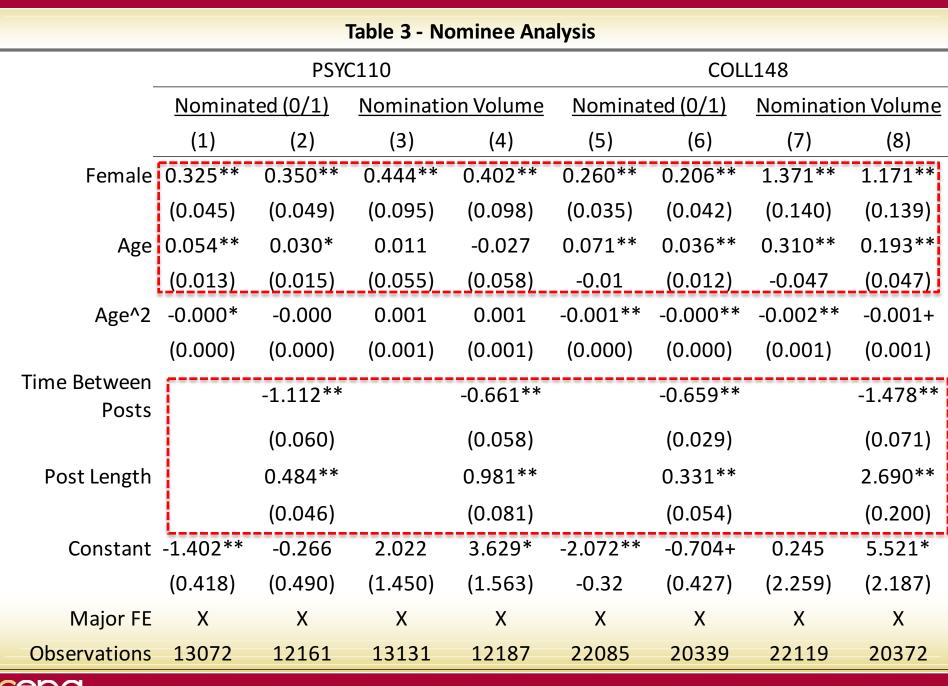
- $y_{ict}$  indicates a student's role as a nominator or nominee in the interaction
- $C_{ict}$  refers to student gender, age, and whether the person is pursing a BA degree
- $-E_{ict}$  refers to the length and frequency of their posts
- $\theta_b$  indicates block fixed effects, and  $\nu_p$  indicates professor fixed effects.

#### Results – RQ1

- Female and older students engage more in interactions.
- Students who post more frequently and generate lengthier posts also interact more with other students.
- Students choose to interact with peers who share gender and location, but farther away in age.



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RQ 2:How do peer's interpersonal interaction affect student course performance?

 $y_{ict} = W_{ict}\beta_0 + X_{ict}\beta_1 + \theta_b + \nu_p + \varepsilon_{ict}$ 

IV: Students time-invariant abilities and preferences estimated using dynamic panel data methods.

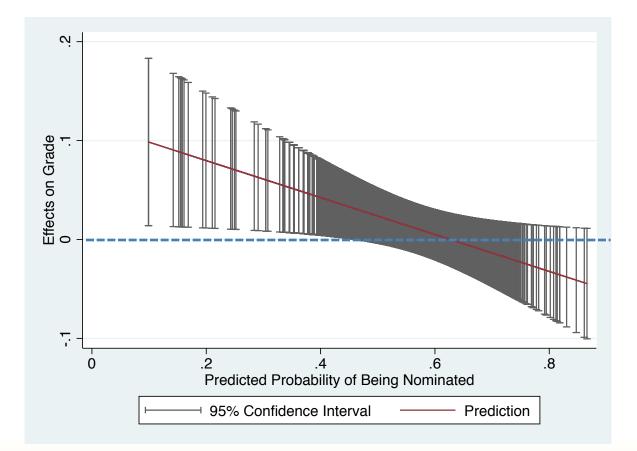
- $y_{ict}$  indexes academic outcomes of student i in course c in term t, including grade, whether passing the course, and course points.
- $W_{ict}$  indicates i's peer interpersonal interaction and other actions, while  $X_{ict}$  indicates measures of student i's own behavior.
- Construct instruments that capture variation in peer behaviors that are orthogonal to the behavior of the focal student

#### Table 5 - The Effects of Peer's Interpersonal Interaction on Student Outcomes (PSYC110)

	Passed Course		Letter Grade		Course	Points	
	(1)	(2)	(3)	(4)	(5)	(6)	
Nomination Volume_Peer	0.025*	0.030*	0.095*	0.116*	0.044**	0.054**	
	(0.012)	(0.012)	(0.045)	(0.046)	(0.017)	(0.017)	
Nomination Probability	-0.044+	-0.047*	-0.203*	-0.216*	-0.087**	-0.094**	
X Nomination Volume_Peer	(0.023)	(0.023)	(0.088)	(0.088)	(0.033)	(0.033)	
Nomination Volume_Own	0.002**	0.002**	0.017**	0.018**	0.005**	0.005**	
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	
Predicted Nomination Probability	0.294**	0.292**	1.418**	1.398**	0.525**	0.528**	
	(0.091)	(0.091)	(0.326)	(0.324)	(0.127)	(0.125)	
Observations	11216	11216	11216	11216	11145	11145	
Professor FE		Х		Х		Х	
F-statistic in First Stage							
Nomination Volume_Peer	387.291	380.116	387.291	380.116	421.823	388.151	
Nomination Probability X							
Nomination Volume_Peer	355.733	425.644	355.733	425.644	333.362	420.040	
Nomination Volume_Own	2223.975	2131.016	2223.975	2131.016	2207.277	2113.644	
Time Between Posts_Peer	387.693	417.836	387.693	417.836	390.160	420.340	
Time Between Posts_Own	933.140	921.581	933.140	921.581	925.067	913.418	
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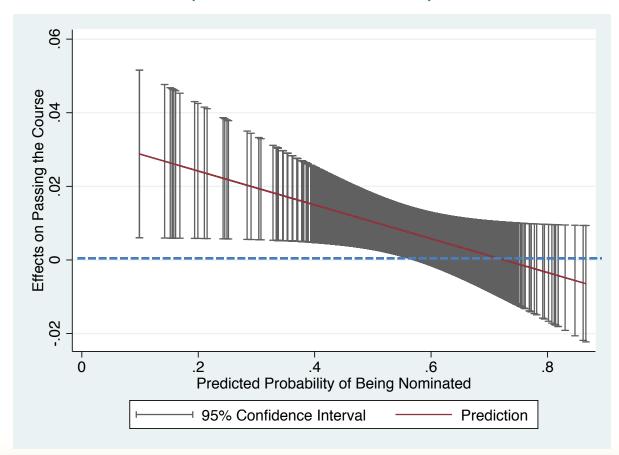
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#### Effects on Grade (PSYC110)



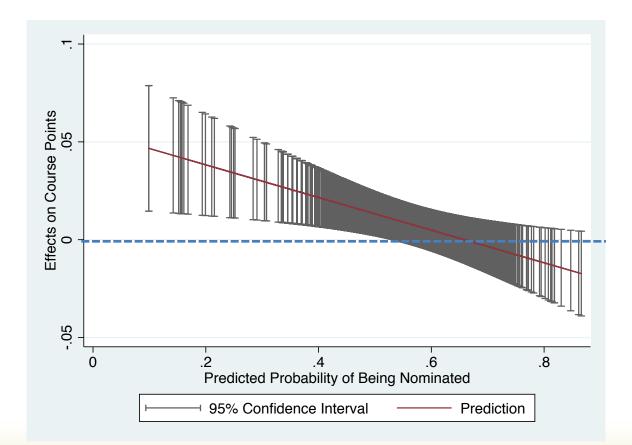
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# Effects on Passing the Course (PSYC110)



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# Effects on Course Points (PSYC110)



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#### Implications

- Peers matter not only because of who they are but because of what they do.
- This paper provides some of the first evidence on productive interventions to engage students online.
- The availability of detailed data on interactions allowed for this understanding.



## Challenges and Opportunities

- Data management
  - Humongous data (4 GB/day)
  - Need advanced management tools
- Theory driven research questions
  - An unprecedented opportunity to understand how people interact and learn
  - Endless variables we could construct with the data
- Collaboration
  - Understand institutional details
  - Mutual benefits

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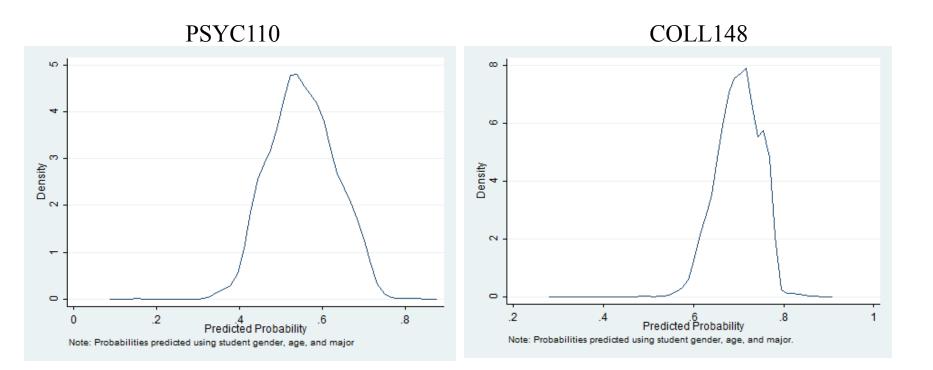
## Main Findings

- Research question 1
  - Students vary systematically in their interpersonal interactions.
  - Females are more likely to initiate interaction, and also more likely to get nominated by peers.
  - Older students also tend to be more engaged, but not consistent in both courses.
  - Students sharing the same gender and home campus are more likely to interact with each other.
  - Students tend to interact with those who are farther from themselves in age.
- Research question 2
  - More peer engagement practices improve short-term student outcomes.
  - For students who tend to be less engaged in interpersonal interactions, having peers who reach out to engage their classmates benefits their class performance, improving the likelihood of completion and their grade in the course.
  - Stronger for PSYC110 where peer interactions are less common than they are in COLL148, which is a course that directly cultivates such interaction.

Table 1 - Descriptive Statistics								
	Both Courses PSYC110					.148		
variable	mean	sd	mean	sd	mean	sd		
<u>Student Outcomes</u>								
Passed Course	0.800		0.794		0.804			
Course Grade (A-F > 4-0)	2.481	1.528	2.178	1.418	2.668	1.562		
Course Points	0.423	0.696	0.569	0.629	0.334	0.720		
Enrolled Next Semester	0.738		0.751		0.730			
Enrolled Credits Next Semester	9.296	3.487	9.412	3.548	9.225	3.448		
Student Characteristics								
Female	0.483		0.469		0.491			
Age	31.140	8.898	31.075	8.807	31.179	8.952		
Northeast	0.123		0.122		0.124			
South	0.425		0.422		0.427			
Midwest	0.259		0.254		0.261			
West	0.175		0.181		0.171			
Outside US	0.018		0.021		0.017			
First Semester at University	0.677		0.418		0.831			
Continuing Student	0.271		0.521		0.123			
Enrolled Credits Current Semester	8.527		9.146		8.160			
Seeking BA	0.722		0.738		0.713			
Business Management Major	0.363		0.358		0.366			
Technology Major	0.096		0.086		0.102			
Health Major	0.125		0.111		0.134			
Post Characteristics								
Time Between Posts for Student (hours)	20.420	34.790	26.330	40.820	17.650	31.650		
Length (words)	78.380	66.860	91.330	65.930	72.980	66.500		
Nomination Volume	10.949	14.207	5.432	7.980	14.268	15.988		

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## Predicted Probability of Being Nominated



#### Results – RQ1

Table 4 - Nominee Analysis (Pairwise Level)									
	PSYC110				COLL148				
	<u>Nominat</u>	:ed (0/1)	<u>Nominatio</u>	on Volume	<u>Nomina</u>	ted (0/1)	Nomination Volume		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Same Gender	0.008**	0.007**	0.015**	0.014**	0.007**	0.007**	0.023**	0.022**	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	
Both Seeking BA	-0.001		-0.002		-0.000		0.001		
	(0.001)		(0.002)		(0.001)		(0.004)		
Same Major		0.004**		0.007**		0.001		0.005	
		(0.001)		(0.002)		(0.001)		(0.006)	
Same Home Campus	0.004**	0.004**	0.007**	0.007**	0.005**	0.005**	0.015**	0.015**	
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.005)	
Age Abs. Diff.	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001	0.001	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Age Abs. Diff. Square	-0.000*	-0.000*	-0.000+	-0.000+	-0.000**	-0.000**	-0.000*	-0.000*	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Constant	0.064**	0.063**	0.090**	0.088**	0.131**	0.131**	0.322**	0.322**	
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.005)	
Observations	359310	359310	359310	359310	494212	494212	494212	494212	
R_squared	0.147	0.147	0.173	0.173	0.167	0.167	0.138	0.138	

*Notes:* Each column reports coefficients from an OLS regression with individual fixed effects. The analysis is based on a dataset where every student is paired with every other student in the same course-section. To identify whether a peer is nominated by a student, the frequency of nomination and peer demographics, I merge post-level data with student-level data using peer names embedded in student posts. Due to the complexity of human language, about 50.66% of peers are merged. Since BA students and non-BA students have different majors, I do not put these two variables in the same regression to avoid collinearity.



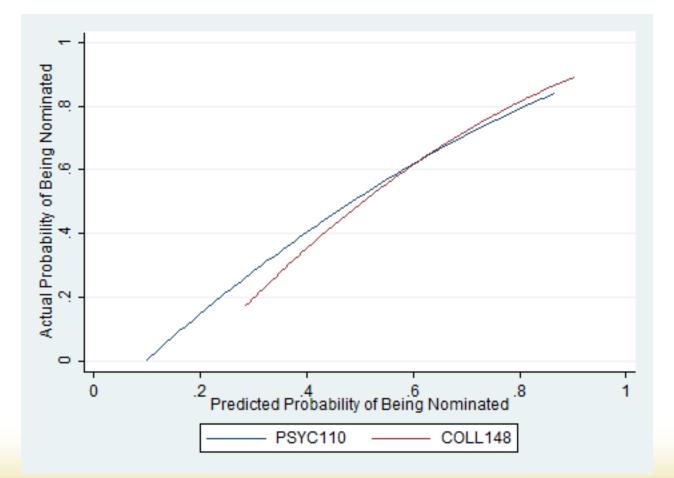
#### Results – RQ2

	Table 7 - Mediator A	nalysis		
	PSYC	2110	COLI	L148
		Nominet	ted (0/1)	
	(1)	(2)	(3)	(4)
Nomination Volume_Peer	0.052**	0.049**	0.014*	0.013+
	(0.017)	(0.017)	(0.007)	(0.007)
Nomination Probability	-0.070*	-0.063+	-0.033+	-0.034+
X Nomination Volume_Peer	(0.034)	(0.033)	(0.018)	(0.018)
Nomination Volume_Own	0.017**	0.017**	0.006**	0.006**
	(0.001)	(0.001)	(0.000)	(0.000)
Predicted Nomination Probability	0.722**	0.690**	0.435*	0.454*
	(0.125)	(0.123)	(0.196)	(0.196)
Professor FE		Х		Х
Observations	12053	12053	20203	20203
F-statistic in First Stage				
Nomination Volume_Peer	391.248	379.560	478.474	563.512
Nomination Probability X Nomination Volume_Peer	364.739	432.529	381.184	428.886
Nomination Volume_Own	1840.569	1781.597	2727.706	2719.905
Time Between Posts_Peer	407.252	427.716	596.264	583.349
Time Between Posts_Own	1145.078	1143.465	1710.400	1683.262

*Notes:* Each column reports estimates from a single two-stage least squares (2SLS) regression. Every regression controls time between posts for peers and student own, and block fixed effects. The dependent variable is a dummy indicating whether a student is nominated at least once in week 2 to 8.



## Actual Probability vs. Predicted Probability (Quadratic Fit)



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#### Appendix 1 - The Effects of Peer's Interpersonal Interaction on Student Outcomes (PSYC110)

	Passed Course		Letter	Letter Grade		Course Points	
	(1)	(2)	(3)	(4)	(5)	(6)	
Nomination Volume_Peer	0.029*	0.033*	0.091+	0.107*	0.044*	0.052**	
	(0.013)	(0.013)	(0.048)	(0.047)	(0.018)	(0.018)	
Nomination Probability	-0.040+	-0.042+	-0.142+	-0.155+	-0.064*	-0.071*	
X Nomination Volume_Peer	(0.023)	(0.023)	(0.081)	(0.080)	(0.030)	(0.030)	
Nomination Volume_Own	0.000	0.000	0.003	0.003	0.000	0.001	
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	
Time Between Posts_Peer	0.258*	0.591**	0.964*	2.384**	0.460**	0.961**	
	(0.100)	(0.123)	(0.378)	(0.448)	(0.153)	(0.185)	
Time Between Posts_Own	-0.239**	-0.238**	-0.759**	-0.757**	-0.413**	-0.412**	
	(0.020)	(0.021)	(0.067)	(0.067)	(0.034)	(0.035)	
Word Length_Peer	-0.121**	-0.092**	-0.714**	-0.378**	-0.256**	-0.182**	
	(0.026)	(0.028)	(0.101)	(0.094)	(0.040)	(0.039)	
Word Length_Own	0.088**	0.090**	0.687**	0.702**	0.221**	0.225**	
	(0.007)	(0.008)	(0.027)	(0.028)	(0.011)	(0.012)	
Predicted Nomination Probability	0.248**	0.244**	0.952**	0.939**	0.363**	0.362**	
	(0.091)	(0.090)	(0.312)	(0.309)	(0.124)	(0.123)	
Observations	11105	11105	11105	11105	11033	11033	
Professor FE		Х		Х		Х	

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#### Appendix 2 - The Effects of Peer's Interpersonal Interaction on Student Outcomes (COLL148)

	Passed Course		Letter Grade		Course Points	
	(1)	(2)	(3)	(4)	(5)	(6)
Nomination Volume_Peer	-0.006	-0.002	0.025	0.048	0.008	0.015
	(0.012)	(0.012)	(0.041)	(0.041)	(0.018)	(0.018)
Nomination Probability	0.006	0.004	-0.060	-0.069	-0.018	-0.020
X Nomination Volume_Peer	(0.017)	(0.017)	(0.058)	(0.059)	(0.025)	(0.025)
Nomination Volume_Own	0.002**	0.002**	0.015**	0.016**	0.006**	0.006**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Time Between Posts_Peer	0.170**	0.291**	0.765**	1.462**	0.351**	0.593**
	(0.046)	(0.056)	(0.209)	(0.247)	(0.085)	(0.101)
Time Between Posts_Own	-0.186**	-0.185**	-0.670**	-0.664**	-0.379**	-0.377**
	(0.017)	(0.017)	(0.062)	(0.062)	(0.032)	(0.032)
Word Length_Peer	-0.066*	-0.017	-0.585**	-0.226+	-0.240**	-0.071
	(0.027)	(0.030)	(0.116)	(0.129)	(0.049)	(0.053)
Word Length_Own	0.039**	0.040**	0.446**	0.459**	0.140**	0.145**
	(0.009)	(0.009)	(0.034)	(0.034)	(0.015)	(0.016)
Predicted Nomination Probability	0.176	0.179	2.683**	2.689**	0.876**	0.862**
	(0.181)	(0.183)	(0.637)	(0.639)	(0.266)	(0.267)
Observations	18302	18302	18302	18302	18184	18184
Professor FE		Х		Х		Х

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#### Thanks!



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