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Abstract

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1 Introduction

One way to judge the quality of an institution is to use the quality of the student body as a proxy measure. Although, there is no standard to measure student quality, there are performance measures that are used to judge the quality of a student body (also referred to as peer quality). Indeed, for institutions of higher education it is now standard practice to use performance measures of the student body as an indicator of institutional quality. For example, the average high school GPA, average SAT score, and average class rank are all common reported characteristics of an institutions student body. The underlying idea of using the quality of the student body as a measure for the quality of the institution, is that the quality of one's peers matter. Using this idea as our foundation, this paper seeks to answer the question, how does the quality of one's classmates impact a student's grade? If the quality of one's peers has a strong impact on one's educational experience, than one of the most obvious places for an effect to exist is in the classroom.

2 Literature Review

There has been a fair amount of recent literature on peer effects in educational institutions. Specifically, roommate peer effects research has been a trending topic due to the natural quasi-random roommate assignments made by many institutions of higher education. Quasi-random roommate assignments, such as those used in Griffith and Rask (2014) and Zimmerman (2003), allow researchers to avoid the perils of selection bias and lead to theoretically more accurate results. However, most of the literature is divided on whether or not roommate peer effects exist (Griffith and Rask, 2014; Zimmerman, 2003; Sacerdote, 2000; Foster, 2006; McEwan and Soderberg, 2006). This is a testament to the difficulty of finding peer effects and the difficulty of solving all the econometric problems to ensure that they actually exist.

Much of the literature on peer effects in the classroom exploits quasi-random classroom assignments, in a similar vain to the roommate peer effects literature. For instance, researchers in Kang (2007) exploit the quasi-random classroom assignments in South Korean middle schools, and Carman and Zhang (2012) utilize the fact that students are assigned to Chinese middle schools either randomly or through an admissions test. Both studies focused on determining the significance of peer effects on classroom grades, and find evidence of peer effects. Kang (2007) finds that strong students have a positive impact on the academic performance other students, while weak students have a negative effect on the performance of other students. Carman and Zhang (2012) find somewhat mixed results, but in general they find evidence of positive and significant peer effects on the impact of classmate quality on the academic performance of other students. Other studies use econometric techniques, such as fixed effects modeling, to correct for any selection bias.[1] For example, Schlosser et al. (2008) and Lavy et al. (2012) control for fixed effects when studying the peer effects of underachievers and overachievers on other students in secondary schools. Both studies find evidence of peer effects where a larger proportion of lower achieving students in a high school class has a negative impact on the achievement of "regular" students in the class. Lavy et al. (2012) in particular also find a positive peer effect from high achieving peers on girls. In general, the majority of the literature finds a larger proportion of

[1] See Burke and Sass (2013) as an additional example.

higher achievers in a class has a positive impact on the academic performance of other students, and a larger proportion of low achievers in a class has a negative impact on the academic performance of other students.[2]

We seek to add to the literature by analyzing the peer effects (if any) in higher education, whereas the majority of other studies focus on K-12 education. It is possible that the peer dynamics change in the transition from secondary education to higher education, and our data set gives us a unique opportunity to analyze these peer dynamics. Our data set comes from a small liberal arts institution which should make it an excellent environment to see magnified peer effects.[3]

3 Data

Our data set comes from a selective medium sized liberal arts college in the midwest, henceforth referred to as the institution, for which we have data on 5 cohorts (2011-2015). We use classroom level data in our regressions as it has been shown to generate stronger results than other group level measures (Burke and Sass, 2013).

In total we have 1,412 observations and use 18 variables. Additionally, we use two different types of data in this study. The first type is classroom data, that consists of individual student level characteristics as well as classroom characteristics. We use data from the first class taken by first year students in order to mitigate selection bias[4]. The second type of data we use is point data, which consists of the number of points students bid on classes and their preferences for certain classes.

[2] See the Results section for the reasoning.
[3] For more details see section 3.3 (Summary Statistics).
[4] Discussed in the Empirical Methodology section.

3.1 Classroom Data

The classroom level data on first year students in their first class at the institution is primarily used in the second stage (primary) regression.[5] There are five key variables in our primary regression, Grade, AcadRating (Academic Rating), PctTopX, PctBotX, and PctMidY. Grade is the primary outcome of interest, and is the grade received by a student after taking the course. Courses are graded on a four point scale, and there are eleven possible grades ranging from an "A" (4.0) to "F" (0.0).[6] As a measure for student ability we follow the literature and use a proxy measure developed on data prior to college enrollment, Academic Rating (Griffith and Rask, 2014). The Academic Rating is a number assigned to all students at the institution. It is a number that represents the culmination of a student's high school GPA, their test scores, the difficulty of the high school curriculum, the quality of their high school, and their writing ability. As suggested by the literature these variables are all common (and "good") indicators of college academic performance (Betts and Morell, 2003; Dooley et al., 2012). The Academic Rating variable ranges from a low of 1 (representing a low ability student) to a high of 65 (representing a high ability student).

We used the Academic Rating variable to create our peer measure variables PctTopX, PctBotX, and PctMidY. PctTopX represents the proportion of students in the class that are in the top X percent of the sample based on Academic Rating. For instance, PctTop5 represents the proportion of students in the class that are in the top five percent of the sample based on Academic Rating. PctBotX

[5] Some classroom level data was also used in the first stage regression. See section 3.2 (Points Data) for details.

[6] The possible grades are A = 4.0, A- = 3.7, B+ = 3.3, B = 3.0, B- = 2.7, C+ = 2.3, C = 2.0, C- = 1.7, D+ = 1.3, D = 1.0, F = 0.0

is defined similarly for the bottom X percentage in terms of Academic Rating. PctMidY is the proportion of students in a class that are not in the top X percent or bottom X percent of the sample in terms of Academic Rating. The remaining variables, Minority, Female, InState, Intl (International), Needy, ClassSize, URM (Underrepresented Minority), Year, Division, and Professor, were used as control variables in the regression. Refer to Table 3.1 below for the definitions of all the class level variables used.

Table 3.1: Classroom Variable Definitions

Variable	Definition
Grade	The grade received by a student after taking the course.
AcadRating	Referred to as Academic Rating, a number that represents the culmination of a student's high school GPA, their test scores, the difficulty of the high school curriculum, the quality of their high school, and their writing ability.
PctTopX	The proportion of students in the class in the top X percent of the sample based on Academic Rating
PctBotX	The proportion of students in the class in the bottom X percent of the sample based on Academic Rating
PctMidY	The proportion of students in a class that are not in the top X percent or bottom X percent of the sample in terms of Academic Rating.
Minority	A dummy variable representing whether or not the student is non-Caucasian. 1 = non-Caucasian & 0 = Caucasian
Female	A dummy variable representing whether or not the student identifies as a female. 1 = female & 0 = male
InState	A dummy variable indicating whether or not the student is an in-state student. 1 = in-state & 0 = out of state
Intl	A dummy variable indicating whether or not the student is an international student. 1 = international & 0 = not international
Needy	Whether or not a student qualified for need based financial aid. 1 = financial aid & 0 = no financial aid
ClassSize	An integer the represents the total number of students in a class.
URM	Under Represented Minority, a dummy variable indicating whether or not the student is non-Caucasian or Asian. 1 = Asian or Caucasian & 0 = other ethnicity
Year	The year the class took place.
Division	The subject area of the class, either Natural Science, Social Sciences, or Humanities.
Professor	An identifier for the professor teaching the class.

3.2 Points Data

At this institution a bidding system is used to ration classes. From 2011-2014 the bidding system was as follows: students are allotted 20 points and must rank eight classes in terms of their preferences, after classes are ranked students then must bid a number between 0 and 20 (inclusive) points per class on their list, students with the highest number of points bid per class are allotted seats, and ties are broken randomly. If a student does not make it into any class on his or her preference list, then a class is chosen for the student at random.

In the year 2015, the bidding system was changed in an effort to allow more students to select into a class higher on their preference list. The system was changed in the following ways: students are allotted 100 points and must rank eight classes in terms of their preferences, after classes are ranked students then must bid a number between 1 and 20 (inclusive) points per class on their list. The remaining rules from the original system are the same. This new system effectively forces students to spread their points into multiple classes (whereas in the original system all points could be placed into one class) and therefore decreases the standard deviation.

The changes to the bidding system affect one of our key variables in the first stage regression, Demand. The Demand variable represents the total number of points bid on a course divided by the number of bidders. In an attempt to correct for the changes in the bidding system, the 2015 Demand calculations were divided by five, because students received five times the number of points compared to the original system. This corrected the mean of Demand in 2015, however the affect on standard deviation still remains. Due to the nature of the bidding system changes, we are unable to correct the affect on the standard deviation, but fortunately this does not affect the overall results.[7]

Another key variable in our first stage regression is Ranking. Ranking is our dependent variable in the first stage regression, and is a number between one and eight that specifies the student's preference for the course, where one is a high preference, eight is a low preference, and preferences are not repeated. We used the remaining variables in the first stage regression, Minority, Female, InState, Intl (International), Needy, AcadRating, URM (Underrepresented Minority), and Subject as control variables. Refer to Table 3.2 below for the definitions of the unique variables used in the first stage regression.

Table 3.2: Points Data Variable Definitions

Variable	Definition
Ranking	A number between one and eight specifying the student's preference for the course, where one is a high preference and eight is a low preference.
Demand	The total number of points bid on a course divided by the number of bidders. For the year 2015, this variable was divided by five to correct for the bidding system changes.
Subject	The specific subject of the course, such as mathematics, anthropology, chemistry, psychology, etc. For a full list of subjects see Appendix A.

3.3 Summary Statistics

The descriptive statistics for the non-dummy variables are given below in Table 3.3.[8] The outcome of interest, Grade, has a mean that changes slightly over time, while the standard deviation remains fairly constant. From 2011-2012 the

[7] See the Results section for more details.
[8] Control variables, such as Year, Professor, Division, and Subject where not summarized.

mean Grade was 3.115, then from 2013-2015 the mean grade increased to 3.15. This suggests that their might have been some grade inflation over the years as the mean Academic Rating, a measure of student ability, remained fairly consistent from 2011-2014 (jumping by about 2 points in 2015). The variables PctTopX, PctBotX, and PctMidY all vary slightly from their expected values, indicating that the distribution of abilities is not uniform every year. That is, one would expect the mean of PctTop5 to always be about 0.05, however this is not the case since the Academic Rating cutoffs are not exact[9] and the distribution of abilities is not uniform. In fact, the distribution of abilities seems to be bias towards recent years as the higher mean Academic Rating, PctTop5, and PctTop10 in 2015 indicate. The ClassSize variable jumps from a mean of 11 in 2011-2014 to 14.27 in 2015 because fewer classes were offered and more students were in the incoming class. The average number of classes offered fell from 29 in 2012-2014 to 25 in 2015.[10] As expected, the Demand variable has a lower standard deviation in 2015 compared to 2011-2014 because the bidding system changes.

It may be valuable to note that several studies suggest that smaller class sizes have a positive impact on average student achievement (measured by grades and test scores) (Diette and Raghav, 2015; Kokkelenberg et al., 2008). The primary reasoning for the inverse relationship between achievement and class size is that students have more quality time to interact with teachers and peers as class size decreases. As this institution has relatively small class sizes, we may expect to find magnified peer effects.

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[9] Exactly 5% of students do not have an Academic Rating higher than our cutoff. Instead the number is about 0.048% and this is true for all of our defined cutoffs.

[10] In 2011 the mean class size was also 25, however there were fewer students in the incoming class.

Table 3.3: Summary Statistics

	2011 Data		2012 Data		2013 Data		2014 Data		2015 Data	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Grade	3.12	0.96	3.11	0.87	3.17	0.78	3.15	0.81	3.16	0.87
AcadRa~g	50.72	6.09	50.89	5.9	49.98	6.25	50.95	6.44	52.80	6.19
PctTopQ	0.30	0.13	0.28	0.17	0.22	0.17	0.27	0.15	0.41	0.14
PctTop5	0.08	0.10	0.06	0.10	0.06	0.07	0.04	0.07	0.14	0.10
PctTop10	0.16	0.12	0.14	0.13	0.14	0.11	0.16	0.13	0.26	0.13
PctBotQ	0.23	0.11	0.19	0.11	0.28	0.17	0.18	0.10	0.13	0.10
PctBot5	0.04	0.06	0.05	0.08	0.06	0.12	0.06	0.08	0.04	0.06
PctBot10	0.08	0.08	0.07	0.08	0.10	0.14	0.08	0.08	0.06	0.08
PctMid50	0.47	0.16	0.54	0.16	0.50	0.17	0.54	0.14	0.46	0.14
PctMid90	0.87	0.11	0.89	0.12	0.87	0.14	0.90	0.12	0.82	0.10
PctMid80	0.77	0.14	0.78	0.14	0.76	0.16	0.76	0.16	0.68	0.13
Minority	0.21	0.41	0.37	0.48	0.46	0.50	0.35	0.48	0.39	0.49
Female	0.47	0.50	0.55	0.50	0.53	0.50	0.51	0.50	0.54	0.50
InState	0.15	0.35	0.13	0.33	0.15	0.36	0.12	0.33	0.15	0.36
Intl	0.02	0.15	0.01	0.08	0.06	0.23	0.05	0.22	0.07	0.25
Needy	0.39	0.49	0.36	0.48	0.36	0.48	0.32	0.47	0.43	0.50
ClassS~e	10.85	3.09	11.91	3.05	11.11	2.48	11.39	2.62	14.27	2.47
URM	0.11	0.31	0.29	0.45	0.36	0.48	0.27	0.44	0.30	0.46
Ranking	1.77	1.54	1.70	1.44	1.79	1.41	1.91	1.79	2.14	1.41
Demand	2.81	0.83	2.62	0.75	2.28	0.86	2.37	0.86	2.44	0.22
N	226		292		290		285		319	

4 Empirical Methodology

Our foundational peer effects model is as follows:

$$G_i = \beta_0 + \beta_1 Ability_i + \beta_2 Ability_i^{CM1} + \beta_3 Ability_i^{CM2} + \overrightarrow{\beta}\,\overrightarrow{z} + \varepsilon_i \qquad (1)$$

This is an OLS model, where G_i is the grade received by student i in their first course at the institution, $Ability_i$ is a proxy for the student's academic ability (Academic Rating)[11], $Ability_i^{CM1}$ and $Ability_i^{CM2}$ are classmate ability measures, $\overrightarrow{z}$ is a vector of control variables[12], and ε_i is the error term. $Ability_i^{CM1}$ and $Ability_i^{CM2}$ are our peer measures and are defined as one of the following, the proportion of high achieving, middle achieving, or low achieving students in a class[13](as defined by cutoffs in academic rating), and $Ability_i^{CM1}$ is not the same measure as $Ability_i^{CM2}$. Thus β_2 and β_3 are the primary coefficients of interest, as they estimate the impact of the classmate abilities variables (our peer measures) on a student's grade. The OLS regression is run on the subset of students that are not part of the peer measures. For example, if $Ability_i^{CM1}$ and $Ability_i^{CM2}$ were defined as the proportion of high achievers in a class and the proportion of low achievers in a class respectively, then the model would be run on the middle achievers.

However, because our sample is nonrandom[14] the calculated coefficients of model (1) are at risk of being bias (Heckman, 1979).[15] This bias, known as selec-

[11] For more information see section 3 (Data).
[12] Control variables included Minority, Female, InState, International, Needy, Class Size, URM, Year, Division, and Professor. See Table 3.1 and Table 3.2 for definitions.
[13] Unfortunately due to data limitations only the proportion of high achievers and low achievers in a class was used for our peer measures, for more details see section 5 (Results).
[14] Unfortunately students are not assigned to classes and institutions randomly, instead the institution selects specific students, students next select the institution, and students then select into classes.
[15] For more details see section 4.2 (Controlling Selection Bias)

tion bias, is a serious threat to this type of peer effects model because self selection often exists and leads to a nonrandom sample (Carman and Zhang, 2012; Betts and Morell, 2003; Ding and Lehrer, 2007). Therefore, we must update our model in order to correct for any selection bias that may exist.

4.1 Two Stage Selection Model

In an effort to correct for selection bias we use a two stage selection model, similar to the one described in Heckman (1979). Our two stage selection model uses an ordered probit model in the first stage and an OLS model in the second stage. From the first stage ordered probit model we take the calculated inverse mills ratios and use them as a control variable in the second stage regressions. The inverse mills ratios are calculated estimates, that when used in the second stage regression, help to control for selection bias (Heckman, 1979).[16]

For the first stage regression we use an ordered probit model, defined as follows:

$$R_i^* = \alpha_1 D_i + \overrightarrow{\alpha}\,\overrightarrow{\omega} + \varepsilon_i \tag{2}$$

$$R_i = \begin{cases} 1 \;\; if \;\; -\infty < R_i^* \leq \mu_1 \\ \vdots \\ j \;\; if \;\; \mu_j < R_i^* < \infty \end{cases} \tag{3}$$

Where D_i is the demand for the student's selected class, $\overrightarrow{\omega}$ is a vector of control variables[17], and ε_i is the error term. In (3) we see that the unobserved selection

[16] For more information see Greene (2002).
[17] Specifically the variables include Minority, Female, InState, Intl, Needy, AcadRating, URM

variable R_i^* corresponds to the observed R_i through μ, a vector of unknown cut-offs. The variable j represents the number of selection categories there are, where in any of our regressions j is at least two and at most four. For example, if j is equal to two, then R_i equal to one represents those students who selected into their first choice class and R_i equal to two represents those students who did not select into their first choice class (instead selecting into their second choice, third choice, etc.). The ordered probit model ultimately estimates the probability that R_i is equal to j using R_i^*, that is,

$$Pr(R_i = j) \ = \ Pr(\mu_{j-1} < R_i^* \leq \mu_j) \tag{4}$$

Once we calculate the first stage ordered probit, we use the inverse mills ratios in the second stage OLS regression.

We use an OLS regression very similar to our foundational model for our second stage model, the only difference is that the inverse mills ratios are added as a control variable to correct for selection bias. The model is as follows:

$$G_i = \beta_0 + \beta_1 Ability_i + \beta_2 Ability_i^{CM1} + \beta_3 Ability_i^{CM2} + \beta_4 \lambda_i + \overrightarrow{\beta}\,\overrightarrow{z} + \varepsilon_i \tag{5}$$

Where the variables are defined in the same manner as (1), and λ_i is the inverse mills ratios calculated in the first stage regression. Just as in (1) the OLS regression is run on the subset of students that are not part of the peer measures. However, the calculation of different inverse mills ratios for each of the possible selection categories makes it necessary for a separate regression to be run on each of the students who selected into a particular selection category.[18] As an example,

(Underrepresented Minority), and Subject. See Table 3.1 and Table 3.2 for definitions.

[18] This is why there are Grade1, Grade2, etc. categories in the regressions seen in section 5 (Results).

suppose $Ability_i^{CM1}$ and $Ability_i^{CM2}$ were defined as the proportion of high achievers in a class and the proportion of low achievers in a class respectively and the number of selection categories (j) is equal to two. The second stage OLS model will first be regressed on the middle achievers who selected into their first choice class, then on the middle achievers who did not select into their first choice class, producing two sets of regression outputs.

4.2 Controlling Selection Bias

By using the ranking and points data in the two stage selection model we are attempting to correct for selection bias, a serious problem in many peer effect models (Carman and Zhang, 2012; Betts and Morell, 2003; Ding and Lehrer, 2007). Specifically, our model is controlling for any selection bias that results from students selecting into classes high on their preference list. The idea is that there are unobservable factors that correlate with both student class preferences and the grade received in the class, which would then bias our coefficients of interest (β_2 and β_3). For instance, it may be that popular courses draw a higher proportion of high achieving students, while the majority of middle achieving students are drawn into those same courses because they enjoy the subject. In this case a higher proportion of high achievers is not causal to the increased grades of middle achievers. Instead, an unobservable variable (passion for the subject) drives middle achievers to self select into courses where they will achieve higher grades and there happen to be a higher proportion of high achievers. In such a case, the self-selection of middle achieving students would bias our coefficients of interest and our results would be inaccurate. By using the two stage regression model, we are attempting to correct for this type of selection bias.

5 Results

6 Conclusion

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