Characteristics and Evaluation of Ten Mathematics Tutoring Centers

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Quantitative and qualitative evaluation of math tutoring centers is a critical step to identify characteristics of effective centers. A group of ten math tutoring centers gathered quantitative and qualitative measures of effectiveness as part of an ongoing project to identify characteristics of effective centers. This report summarizes the data collected. We will use this data in a future paper to generate testable hypotheses about characteristics of effective math tutoring centers.

Keywords: mathematics tutoring centers, evaluation, characteristics of effective centers

College-level math support programs are common throughout the United States and globally (Bressoud, Mesa, & Rasmussen, 2015; Matthews, 2013). While these programs have many forms, peer tutoring is a common one, with 89.5% percent of universities surveyed in the US reporting the use of peer tutoring (Johnson & Hanson, 2015). The math tutoring environment has the potential to engage students in a more active way compared to a typical classroom (i.e., Topping, 1996; Topping & Watson, 1996). Tutoring has been shown to impact student self-efficacy (Maxwell, 1994), confidence (Topping, 1996), and have the most impact on at-risk students (Mac an Bhiard, Morgan, & O'Shea, 2009; Rickard & Mills, 2018; Xu, Hartman, Uribe & Mencke, 2001). We study math tutoring centers that serve all students enrolled in eligible mathematics courses. Our long-term goal is to identify characteristics of successful math tutoring centers because there is no research on the characteristics of such centers that contribute to student success (Byerley et. al, 2019).

Literature Review

Although tutoring centers are common, there is little published statistical evidence of the effectiveness of math tutoring centers. One possible reason is the difficulty in measuring the impact of centers on student success (Matthews, 2013). The number of visits to the center is commonly used as a measure of the center's effectiveness, but this measure does not show that visiting the center is correlated with higher grades. In Berkopes and Abshire's (2016) study, the high number of visits by students, particularly by first-generation college students, was evidence of success. In contrast, Marr (2010) interpreted the high number of repeat tutor appointments as a weakness on the part of the tutor to assist the student effectively in their difficulties.

It is hard to imagine a study that would demonstrate that math tutor center visits cause increases in student grades because of self-selection bias (Byerley, Rickard & Campbell, 2018). Students cannot be randomly assigned to a tutoring center treatment. Large numbers of highachieving students may not seek out tutoring services or, alternatively, more motivated students might be more likely to earn high grades and also more likely to visit the center. Several studies found positive statistical correlations between student visits to tutoring centers and student success (Cuthbert & MacGillivray, 2007; Dowling & Nolan, 2006; Mac an Bhaird, Morgan & O'Shea, 2009). However, these studies do not mitigate the self-selection bias because they do not include control variables in their linear models. In contrast, Cooper (2010) did not find a correlation between tutor center visits and course grades.

Several studies have employed more advanced regression techniques to help account for the biasing self-selection. For example, Xu and colleagues (2001) performed a regression analysis and found that, at Arizona State, visiting the tutoring center predicted higher final exam scores in College Algebra when controlling for well-known predictive variables (gender, SAT, math placement, and high school GPA). Tutoring also had a larger impact on students in the bottom quartile of SAT scores compared to the students in the top quartile (Xu et al., 2001). Byerley, Rickard, and Campbell (2018) found a statistically significant positive correlation between students' tutor center attendance at Colorado State University and Calculus II course grades when controlling for prior student aptitude, same-semester achievement, and motivation (measured by variables such as high school GPA, early test grades, and lecture attendance). Similarly, Rickard and Mills (2018) used a multiple regression model and found that when controlling from prior aptitude, each visit to the tutoring center at Oklahoma State University corresponded with an increase in students' Calculus I final course grades by 0.33%. They found that students with the lowest high school GPAs had the largest benefit from visiting the center.

These studies offer evidence that math tutor center visits can have positive impact on student success. However, these studies were conducted at single institutions and offer few clues about what characteristics of the tutoring center contributed to the effectiveness. These studies do not show if a center was effective compared to other institutions. The tutor centers themselves are likely not representative of tutor centers at a national scale: for example, Rickard and Mills (2018) report a 61% attendance rate at their tutoring center, while the national average is 40% (Johnson & Hanson, 2015). We are interested in more than whether a tutoring center is effective; we are also interested in the attributes that characterize effective tutoring centers. By comparing qualitative and quantitative data from multiple centers we will be able to generate hypotheses about common features of more effective centers.

A group of math tutor center administrators proposed a set of six dimensions that characterize centers (Byerley et al., 2019): (a) specialist vs. generalist math tutor models, (b) strength of relationship between center and math instructors, (c) type and extent of tutor training, (d) types of tutoring services, (e) physical layout and location, and (f) tutoring capacity. The current study extends this work by offering both statistical analysis of the effectiveness of ten different math tutoring centers with qualitative descriptions of the centers in terms of these previously identified dimensions. Due to space limitation, the dimensions are not redefined in this paper; understanding the tables reported in this study depends on being familiar with the six dimensions defined in previous research (Byerley et al., 2019).

Research Questions

This paper answers the following research questions for the ten mathematics tutoring centers that contributed data.

1. What percent of eligible students use the center and how often do they use it?
2. What are the characteristics of each center on each of the six dimensions proposed by Byerley and colleagues (2019)?

3. What is the correlation between visiting a center and students' grades after controlling for students' high school G.P.A. and standardized test scores?

Theoretical Perspective

This paper privileges the questions of practitioners who lead tutoring centers. We understand typical requirements of that job because we oversee or have overseen tutoring centers. Privileging the needs of center leaders often requires conducting research at odds with research guided by constructivist theoretical perspectives. For example, it is well known that passing calculus does not mean a student has constructed productive meanings for calculus. Despite this, we use students' grades in math courses as a measure of success because grades are important to students' academic progression and those in administration who monitor this. For details on the perspective we adopt, refer to the editorials on bringing research closer to practice and reducing isolation between practitioners (Cai, et. al., 2018a, 2018b).

Methods

Data collected from a convenience sample of ten universities includes characteristics of the tutoring centers as well as student academic and visit data. The data on characteristics of the tutoring centers were based on dimensions identified by Byerley and colleagues (2019). They include: the number of students eligible to use the center by virtue of being enrolled in a course served by the center, the percentage of those students who visited the center, the average number of visits to the center per eligible student, tutor hours per student visit, tutor hours per eligible student per week, and the type of tutors the center employs. Tutor hours is the total sum of all hours worked by all tutors in a given semester. In order to standardize analyses across universities, participating center leaders were surveyed to determine what student data were available to them. Initial factors considered were number of student visits to the tutoring center, duration of student visits to the tutoring center, course letter grade, course percentage grade, math placement score, standardized test scores, standardized test math subscores, high school grade point average, high school math grade point average, ethnicity, first generation status, Pell grant status, and number of math course repetitions. Many factors were excluded as not all contributors were able to obtain access to the data needed. The factors that essentially all contributors were able to procure data for were: (a) student visits to the tutoring center, (b) high school grade point average, (c) standardized test scores, and (d) course letter grade converted to grade points. These factors represent only a small portion of factors that might influence student grades in a course. It was nevertheless decided that, in order to ensure similar analyses for each institution, the research team needed to analyze data that all members could access.

Quantitative data from each institution were collected for the fall semester of 2017 and/or 2018 depending on the year data were available. For many tutoring centers, students from any course are allowed to use the tutoring center, including courses the tutoring center may not have tutors for. It was therefore decided that data would only be analyzed for students enrolled in mathematics courses for which the tutoring center purposefully serves. This includes any mathematics course for which the math center specifically provides tutors. Data for all students in a course served by the tutoring center were collected, including those who did not visit the tutoring center. Students with missing data and students who withdrew from the course were removed from the analyses, but these counts are shared in the data tables that follow. Students enrolled in multiple mathematics courses were treated as separate data points, with the number of visits to the tutoring center split equally between the courses taken.

Multiple regression analyses were conducted on the data from each tutoring center using course grades as the dependent variable and student visits to the tutoring center, high school grade point average, and standardized test scores as the independent variables. Due to many smaller enrollment courses, analyses combined all courses within each university.

In addition to collecting data and conducting statistical analysis on it, each tutor center leader wrote a qualitative description of his or her respective math center using the six dimensions from Byerley and colleagues' (2019) framework. The leaders included both positive and negative information about their centers in their descriptions, submitting information to the lead author who blinded it prior to making it available to the rest of the research team. In the future, our team and other experts will analyze blinded qualitative and quantitative features of centers to hypothesize characteristics of effective centers.

Results

While common aspects, such as hiring tutors from pool of students who made high grades in course are not included in Table 1, it describes other less obvious aspects of each center. Some aspects differ widely among center for reasons that are not evident in the table. For example, Bird U has limited physical center space; so, no professors hold office hours in the center, and students enter the center to ask questions but not stay to study. Gorilla U has a number of computers that all students on campus can use, even if not working on mathematics assignments. Dolphin U has high tutor hours per student visit because they offer appointment-based tutoring. Instructors at Dog U offer students tiny amounts of extra credit to correct their tests at the center.

Table 2 displays the statistical results from each center. The R^2 of the model represents the proportion of course grades that can be accounted for by the predictor variables. For five centers the model suggests that a higher number of center visits is predictive of higher grades. The model for Whale U, for example, predicts that if students visit the tutor center 10 times in a semester, their course grade point would be 0.16 higher. Unsurprisingly, high school GPA and standardized test scores are significant predictors of grades at all universities. Dolphin U's model suggests that a higher number of tutoring visits is predictive of lower grades. The data from Dolphin U is from the first semester the center was open, and it was known as a place for struggling students to get help despite the efforts of the director to welcome all students.

Table 3 provides information about tutor training at each center. In addition to considering the number of hours of formal training we also considered if the center had a *generalist* or *specialist* tutor model (Byerley et. al., 2019). *Specialist tutors* must meet some criteria (e.g. being an LA or grader) or complete some event (e.g., training or exam) successfully before they are allowed to tutor a particular course. For example, learning assistants attend the course they tutor to help instructors with group work. Specialists often tutor one course per semester and the tutoring center groups students by course. Cat U and Dog U use specialist tutors. Fish U, Gorilla U, Hamster U and Horse U use a mix of generalist and specialist tutors. A benefit of specialist tutors is that they know the content, the instructors, and the expectations for the course. *Generalist tutors* are allowed to tutor multiple courses without having to meet specific criteria. Dolphin U, Bird U, and Whale U use generalist tutors. Undergraduates usually tutor classes they did well in; however, in some generalist settings undergraduate tutors tutor for classes they have not taken (e.g., Business Calculus). The generalist model allows quick access to a tutor because students do not have to wait for the tutor assigned to their course to be free. However, generalist tutors face difficulties when they tutor more advanced non-coordinated courses that have different concepts, texts, and expectations.

Table 1. This table provides counts and other basic quantitative information about students and tutors at each center.

School	# of eligible students	% of students who visited	Visits/eligible student	Tutor hours/visit	Tutor hours/eligible student/week	Square footage	Drop in or appointment
Bird	1209	9.30%	1.3	0.66	0.04	450	Drop in
Cat	4304	48.40%	6.1	0.32	0.12	4700	Drop in
Dog	1335	67.80%	5.2	0.19	0.07	1738	Drop in
Dolphin	1158	11.50%	0.5	1.00	0.05	1000	Appointment
Goat	1300	16.10%	0.61	0.84	0.03	470	Drop in
Gorilla	4,217	54.40%	7.3	0.20	0.09	8000	Drop in
Fish	8292	8.61%	0.36	1.36	0.03	1607	Drop in
Hamster	6,576	26.20%	1.2	0.29	0.03	2700	Mostly drop in
Horse	2154	28.60%	1.2	1.2	0.10	960	Mostly drop in
Whale	4543	34.30%	2.1	0.48	0.07	1875	Drop in

Table 2. We used linear regression to predict math course letter grade point with number of visits, high school GPA, and SAT or ACT.

School	# of students	R^2	Increase in grade per 1 visit	Increase in grade point per 1 grade point HS GPA	Increase in grade per 1 std deviation SAT/ACT	# of withdraws incompletes
Bird	1096	0.17	0.003	1.00***	0.26***	40
Cat	3270	0.26	0.019***	1.09***	0.59***	540
Dog	1004	0.25	0.035***	0.77***	0.49***	105
Dolphin	1070	0.15	-0.034**	1.63***	Not available	87
Goat	443	0.19	-0.057***	0.57***	0.36***	18
Gorilla‡	2737	0.19	0.015***	0.67***	0.24***	447
Fish	6609	0.09	0.022***	0.71***	0.13***	639
Hamster	5151	0.17	-0.002	1.08***	0.13***	850
Horse	1971	0.12	-0.006	0.20***	0.38***	69
Whale	3453	0.23	0.016***	0.86***	0.26***	360

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ 1; ‡Gorilla U used HS GPA in mathematics courses rather than overall HS GPA.

Table 3. Type of Tutors and Qualifying Criteria/Events For Tutors to Tutor a Course

Institution's types of tutors*	Qualifying Criteria/Events for Undergraduate and Graduate Tutors				
	Training		Previous/Concurrent Course Experience as…		Course-Specific Tasks
	General Tutoring (first semester)	Course-Specific	Assistant	Instructor	
Bird *UGs*	10 hrs	2-3 hrs/semester	none	none	none
Cat *UGs, GTAs*	5 hrs for GTAs before first semester; weekly meetings for new GTAs in fall	10 hrs per tutoring area if no experience for UGs & GTAs	UGs as LAs or graders, GTAs as recitation leaders	GTAs as course instructors	course-specific training exam
Dog *UGs, GTAs*	9 hours for GTAs. 17 hours for UG	weekly coordination meetings	UG and GTAs as LAs in course tutored	GTAs as course instructors	none
Dolphin *UGs*	3 hrs for UGs	none	none	none	none
Gorilla *UGs*	4 hrs for UGs	integrated in general training	none	none	exams for UGs
Goat UGs, GTAs	12 hrs for all	none	none	none	none
Fish *UGs, GTAs*	6 hrs for UGs plus pedagogy course 15 hrs GTAs	6 hrs UGs	UGs as LAs	none	none
Hamster *GTAs*	brief training on software	available but voluntary	drill section leaders	GTAs as course instructors	none
Horse *UGs, GTAs*	limited and voluntary	limited and voluntary	none	none	exams for UGs
Whale *UGs, GTAs*	5 hrs for GTAs; 4 hrs for UGs	none	none	none	none

*Only GTAs (graduate Teaching Assistants), UGs (undergraduate students), and LAs (undergraduate learning assistants) are included in the table even though many institutions reported faculty holding office hours in their centers.

Table 4. Connections between math centers and math department during data collection period.

	Connections to Department
Bird	• Math center director was also calculus coordinator. • Tutors had access to common homework sets for most classes.
Cat	• Math center director and associate director were renewable term faculty members in the math department; associate director was a course coordinator. • Math center director met monthly with all course coordinators. • 3 of 5 course coordinators voluntarily held office hours in math center. • Course coordinators and math department advisor led the course-specific training.
Dog	• Math center co-directors were both math tenure-track faculty. • All instructors held office hours in center and gave extra credit to attend center.

	• Tutors interacted with faculty often because they were LA's in their classrooms.
Dolphin	• Math center director taught calculus for the math department.
Goat	• Math center director was a tenured associate professor of mathematics • Tutors had access to a blackboard site where resources were posted.
Gorilla	• Math center director was a renewable term math faculty member. • Math center director communicated weekly with all course coordinators. • Course coordinators shared instructional materials with the math center.
Fish	• The center is in the mathematics building. • Math center director was a renewable term math faculty member. • Undergraduate learning assistants tutor in center and help with group work in math courses.
Hamster	• Math center co-directors were both renewable term math faculty members. • Since course instructors held office hours in math center, they shared information regarding the center with their students.
Horse	• Math center director taught calculus for the math department. • Tutors visited all classes served by the math center to advertise at start of term.
Whale	• Math center director was a math faculty member. • Math center organized review sessions prior to course exams.

Table 4 includes a summary of the relationship between the math departments and the ten math centers in the study sample. A variety of features indicate a strong relationship between the tutoring centers and the math departments. One feature is having faculty tutoring at the center because this makes it easier for undergraduate tutors to discuss the course they tutor with faculty.

Conclusions, Limitations and Future Work

One limitation of the data set is the use of letter grades instead of percent grades as the outcome variable in the model. Dog U did have access to course percent grades. Students who earn $\leq$ 60% get an F; yet, a student with a grade of 59% is typically quite different than a student with a grade of 10%. To determine the effect on the model of categorizing all grades as either 0, 1, 2, 3, or 4 rather than using the percentage earned, we ran separate models for Dog U using standardized grade point and standardized percent. The coefficient for the variable "visits to the tutoring center" was the same in each model to two decimal places. In this model the effect of using grade points instead of grade percent is minimal. Note that Dog U had the strongest relationship between visits and course grade. This relationship can be visualized in Figure 1.

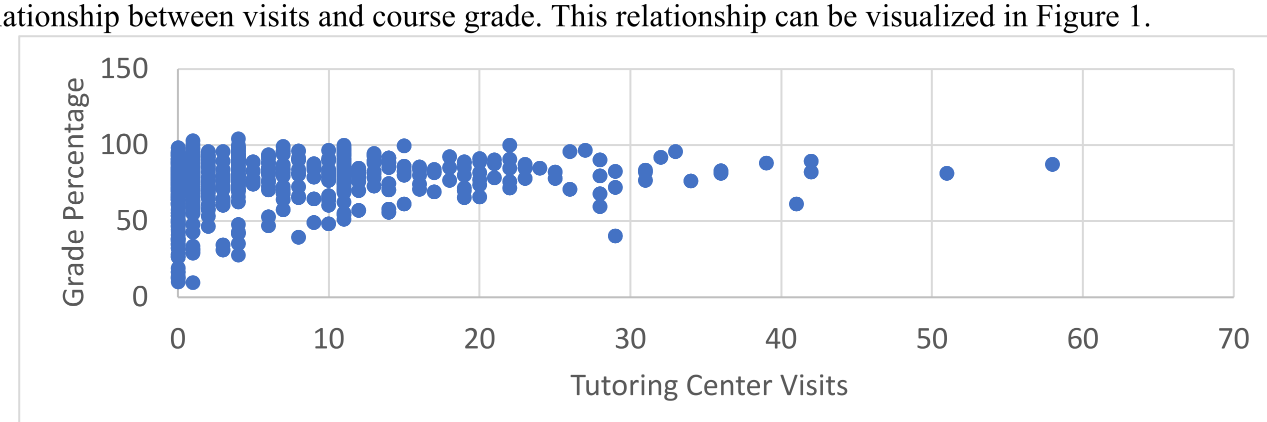

Figure 1. Relationship between grade percentage and tutor center visits at Dog U in Fall 2017.

In the future, our group will use the Delphi method to generate hypotheses about the characteristics of centers that contributed to their effectiveness (Clayton, 1997).

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