ONLINE VERSUS FACE-TO-FACE: DOES DELIVERY METHOD MATTER FOR UNDERGRADUATE BUSINESS SCHOOL LEARNING?

Cassandra DiRienzo, Elon University
Gregory Lilly, Elon University

ABSTRACT

Considering the significant growth in online and distance learning, the question arises as to how this different delivery method can affect student learning. Specifically, this study compares the student learning outcomes on both a "basic" and "complex" assignment given in the same course, but using two different delivery methods of traditional face-to-face and online, across five undergraduate business courses taught at Elon University during the summer 2007 session. This study includes data from over 120 students and, after controlling for other factors known to affect student performance, the results indicate that delivery method has no significant difference in student learning.

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INTRODUCTION

The breadth of online coursework has grown substantially over the past decade. According to Allen and Seaman (2011) who collaborated with the College Board to survey over 2,500 colleges and universities, 65 percent of all reporting institutions indicated that online learning was a critical piece of their long-term strategy. Further, Allen and Seaman (2011) report that over 6.1 million students took at least one online course during the fall 2010 term, an increase of approximately ten percent over the previous year, and 31 percent of all higher education students now take at least one of their courses online. The recent introduction of 'massive open online courses' (MOOCs) offers additional evidence that online learning is growing, massively. Due to their low delivery costs, MOOCs can have exceptionally high enrollments. As Herman (2012) describes, in 2008, George Siemens and Stephen Downes administered an online course for 25 paying students at the University of Manitoba; however an additional 2,300 students enrolled in the course at no charge. According to Hyman (2012), Peter Norvig, Google's director of research, and Sebastian Thrun, a Google vice president, offered one of the most successful MOOCs, "Introduction to Artificial Intelligence", in the fall of 2011. They enrolled over 160,000 students and more than 23,000 completed the course.

The reasons for the growth in online learning are likely multifaceted; however, it can arguably be explained in terms of student demand for online coursework and the cost-saving incentives institutions have to meet this demand. As Howell et al. (2003) discusses, more and more students require flexibility in their programs to meet work or family needs and thus 'shop' for courses and programs that meet their schedules and circumstances; and online learning can be designed such that the marginal cost of enrolling and instructing one more student is essentially zero.

If the online delivery method is here to stay, how does student learning and performance vary relative to the traditional brick and mortar classrooms? While Allen and Seaman (2011) report that the majority of academic leaders perceive that the learning outcomes achieved through these two delivery methods are the same, this study empirically tests this hypothesis. Specifically, this study compares the student learning outcomes on both a "basic" and a "complex" assignment given in the same course, but with the two different delivery methods of traditional face-to-face and online, across five undergraduate business courses taught at Elon University during the summer 2007 session.

Note that the design of our study was influenced by two previous studies that have found statistically significant evidence that online students learn less. First of all, student learning outcomes on 'basic' and 'complex' assignments are considered as Brown and Liedholm (2002) have found that student performance can differ on these two types on assignments given the course delivery method. Secondly, using performance on the Test of Understanding College Economics (TUCE) as their measure of learning, Coates et al. (2004) found that "students in the online sections correctly answered about two fewer questions on TUCE than students in the face-to-face sections." However, this result may not be due to deficient online instruction and learning, but rather an outcome of self-selection. According to the Coates et al. (2004) paper, all three colleges that provided the student data for their study have noteworthy part-time student enrollments (from a low of 26% to a high of 37%) and their online and face-to-face samples have several statistically significant differences. Specifically, the online sample includes older students with less financial aid and greater work commitments relative to the face-to-face students. Thus, it is possible that the results presented in Coates et al. (2004) have more to do with the characteristics of the online students than the nature of online instruction and learning. In contrast, the Elon undergraduates included in this study are full-time, traditional students, and the online courses all occurred during the summer; eliminating possible problems related to self-section.

The remainder of the document is organized as follows. The next section provides an overview of the experiment conducted in this analysis in addition to a discussion of the relevant literature and findings. The Data and Methodology summarizes the data and provides a table with the descriptive statistics. The following section, Results and Discussion, presents the analysis results and discusses the empirical findings with an emphasis on the hypothesis test results. Finally, the section Concluding Comments provides a brief summary of the study and discusses avenues for future research in addition to the limitations of the study.

OVERVIEW OF EXPERIMENT AND LITERATURE REVIEW

As noted above, most academic leaders would not expect to see learning differences arise due to the course delivery method. Likewise, there is evidence that the majority of students who participated in our 2007 study believe that the two delivery methods are essentially equivalent. Specifically, each student enrolled in one of the five online courses was asked to take an online, anonymous survey at the conclusion of the course. The survey included two questions regarding student perceptions of the difficulty of online courses. The first question asked,

Q1: "*Prior to taking this online course, did you perceive online courses to be easier than traditional, 'face to face' courses?*"

The second question asked,

Q2: "*Having taken an online course was your perception correct? In other words, if you perceived online courses to be easier / harder than traditional courses, do you still have the same opinion?"*

A total of 89 students across the five online courses responded to both questions, representing a near 100 percent response rate of all students who completed one of the online courses. Table 1 contains the survey results. Of the four possible responses, two ("Yes" to Q1, "Yes" to Q2 and "No" to Q1, "No" to Q2) could be interpreted as a claim that online is easier than face-to-face. The remaining two responses ("Yes" to Q1, "No" to Q2 and "No" to Q1, "Yes" to Q2) could be interpreted as a claim that online and face-to-face are equally difficult. As summarized in Table 1, the overwhelming majority (75.6%) perceive no difference between delivery methods in terms of difficulty.

Table 1: Student Perceptions of Difficulty

		% responding
"Yes" to Q1 and "Yes" to Q2		7
"No" to Q1 and "No" to Q2		17.4
	Online is easier than face-to-face.	**24.4**
"Yes" to Q1 and "No" to Q2		32.6
"No" to Q1 and "Yes" to Q2		43
	Online and face to face are equally difficult.	**75.6**

Table 1 Summarizes two of the survey questions regarding student perceptions of the difficulty of online versus face-to-face courses.

Of course, beliefs are not always accurate and, while student perceptions about online course delivery are important, it is arguably more important to understand if the learning outcomes are dependent on the course delivery method. Our primary research question therefore is:

Do college students, on average, learn more with a traditional face-to-face delivery method?

There are arguably other meaningful differences in both the students' and instructors' experiences and attitudes toward these two different delivery methods; however, if the answer to the above question is "no;" then, as far as student learning is concerned, there is no downside to the online delivery method. We can have it all; lower costs and convenience, plus learning. If the answer is "yes;" then there is a nasty trade-off. We can only have the lower costs and convenience if we give up some student learning. Nonetheless, in order to answer the question above with some degree of confidence, we need two pieces of information: valid data on learning and a model of learning to account for other factors that can significantly affect learning besides the delivery method. A discussion of each follows.

<u>The Teaching Experiment</u>

In the summer session of 2007, instructors of the same course, but different delivery methods, were paired and asked to prepare a 'basic' assignment and a 'complex' assignment. These assignments became part of their courses, as well as the source for this study's dependent variables. For example, the instructor teaching the business statistics online was paired with the instructor teaching business statistics in the traditional classroom setting. The basic questions were designed to test students' knowledge of definitions, formulas, or concepts, and their ability to make the appropriate calculations. The complex application assignments were to be more open-ended and asked students to apply the course material beyond straightforward mechanics. An example of a 'basic' question for the business statistics course is to ask the students to calculate and interpret a correlation coefficient. Alternatively, an assignment that required students to prepare a research paper in which they collected their own data, estimated a multiple regression, and interpreted their results on a topic of their choosing, would be an example of a complex application problem for the same course.

Each student's grade on the 'basic' questions was simply collected and used to measure (on a standard 100 point scale) learning of the basics. Recording the relevant data for the complex application was a bit more involved. The faculty who were paired (teaching the same course, but using different delivery methods), were first asked to calibrate their grading and then grade the complex assignments from both of the courses. Given the nature of writing, there is inherent subjectivity when grading complex assignments (Nelson and Hayes 1988), even with a prior calibration. Thus, following rule was imposed: the complex grades could vary by less than 10 points on a 100-point scale. The final step was to take the average of the two complex grades, which served as the learning measure on the complex assignment.

Table 2 provides the layout of the experiment. Five different courses, ACC = Principles of Financial Accounting, OPS = Operations & Supply Chain Management, STAT = Business Statistics, ECON = Principles of Economics and BLaw = Business Law; and eight different teachers: T1, T2, T3, T4, T5, T6, T7, and T8, were part of the project. As shown in Table 2, teacher T4 taught OPS with both delivery methods, as did T3 with BLaw. While the teacher and delivery method differed in the other three courses (ACC, STAT, and ECON), all participating teachers were tenured, full-time Elon professors with similar amounts of teaching experience.

Table 2: Courses, Students, and Faculty Data Summary

Online										**Number of Students Enrolled**
		T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	
	ACC		T2							12
	OPS				T4	T5				27
	STAT								T8	13
	ECON							T7		10
	BLaw			T3						17
Face to Face										
	ACC	T1								7
	OPS				T4					9
	STAT							T7		10
	ECON						T6			8
	BLaw			T3						8
Total										121

Table 2 summarizes the courses, faculty instructors, and the number of students enrolled in each course. This data is used in the analyses.

<u>The Learning Model: Carroll</u>

The learning model used in this analysis originates from Carroll's (1963, 1989) seminal work. According to Carroll, learning is a function of time. While students vary in the amount of time they *need* in order to achieve a certain degree of learning, any student can achieve that certain degree of learning by *spending* the necessary amount of time. Carroll equates the *degree of learning* (*D of L*) achieved by a student to a comparison of the time that student actually *spent* on learning against the time that student *needed* to have spent. Equation *(1)* captures the idea.

D of L = f (*Time Spent / Time Needed*) (1)

When the ratio: (*Time Spent / Time Needed*) is large, a high degree of learning occurs; when this ratio is small, not much learning occurs.
In the Carroll Model there are two factors driving *Time Spent*, described in *(2)*:

Time Spent = g_1 *(Motivation (+), Opportunity to Learn (+))* (2)

If the student is highly motivated to learn, then the student spends more time on the learning task; hence, the plus sign after *"Motivation"* in *(2)*. The other factor determining *Time Spent* is *Opportunity to Learn.* Think of this factor as the time that has been explicitly set aside for the learning assignment. For example, if the teacher devotes three hours of class time to learning task A, and one hour of class time to learning task B, then the *Opportunity to Learn* associated with task A is greater than the *Opportunity to Learn* associated with task B. Following Carroll, we assume that if more time is invested by a teacher on a task, more time will be spent by the student on that task, perhaps in the form of homework.

To measure a student's academic motivation (*Motivation*), student cumulative GPAs are used and the following assumption is made:

(Student *x* is *more motivated* than Student *y*) if, and only if (the GPA of *x* > the GPA of *y*) (3)

There are challenges to this assumption. Chiefly, it is possible for an unmotivated student with a high IQ to generate higher grades than a highly motivated student with a lower IQ; after all an extensive body of literature has found a significant positive correlation between IQ scores and measures of school learning (Jensen (1998) and Geary (2005)). Given that Frey and Detterman (2004) find that SAT scores are essentially a measure of IQ, the counterexample to (3) is unlikely to occur in our sample as Elon's business students have a relatively narrow SAT range. The other *Time Spent* variable in Carroll's model is the *Opportunity to Learn.* To capture this factor, we consider the number of courses each student was enrolled in during this assessment period. The majority of the students enrolled in either one or two courses during the summer session, but a small percentage enrolled in three courses. While obviously not a perfect measure for *Opportunity to Learn*, the more courses a student takes within a period of time, the less time and opportunity they have for learning a given subject. Thus, we assume:

(Student x has *more opportunity to learn* than Student y) if, and only if, (x takes fewer courses in this summer session than y) (4)

We now consider the other side of the Carroll Model; there are two factors driving *Time Needed*, as described in equation *(5)*.

Time Needed = g_2 *(Aptitude (-), Quality of Instruction (-))* (5)

If the student has a high aptitude for learning then the student can learn quickly, as indicated by the first negative sign in *(5)*). In Carroll's model, aptitude refers to general intelligence, which can be measured by an IQ test. As mentioned above, there is plenty of evidence that this kind of aptitude positively affects student learning, all else constant. Letting MSAT stand for the math sub-score of a student's SAT results, the following assumption is made (recall the Frey and Detterman (2004) findings):

(Student x has *more aptitude* than Student y) if, and only if (the MSAT of x > the MSAT of x) (6)

The SAT math score is used in place of the total SAT score as it is more highly correlated with the assignment scores and has historically been a stronger predictor of overall student performance in the business school at Elon. Finally, the last factor is *Quality of Instruction.* Carroll's model assumes that instruction can vary in effectiveness such that better instruction implies less time needed; hence, the second negative sign in *(5)*. Variation in instruction can be due to the effectiveness of teachers. Some teachers may be so effective that, all else held constant, the teacher can reduce the amount of time that the student needs to attain the requisite learning outcome. Perhaps certain methods of teaching are particularly effective; or perhaps the effectiveness of instruction varies by the subject matter being taught. For example, Sweller et al. (1998) have argued that due to its high "element interactivity," mathematics is more difficult to learn than a subject like history where ideas are often only weakly connected. Following Sweller at al. (1998), we assume:

(Student x has *better instruction* than Student y) if (y is in STAT and x is in one of the other four courses: ACC, OPS, ECON, or BLaw) (7)

In *(7)* we assume that teachers are equally effective across the courses, but that there is a greater instructional challenge in teaching the statistics course. Further, *(7)* also allows for the possibility that one delivery method is better than the other is.

Two More Predictions

When Carroll created his model of school learning, the theoretical construct of *working memory* (WM) was relatively unknown; however WM is now considered a central idea in cognitive science and WM could be viewed as the organizing construct for a more complete understanding of the *Time Needed*-side of Carroll's model. Consider then the following brief explanation of WM and *working memory capacity* (WMC). Our WM connects our sensory input to our Long-Term Memory (LTM), where our school knowledge is stored. If our WM is unable to process that input, it will not be added to our LTM. Correspondingly, in order for information in our LTM to affect our behavior on test taking and paper writing, this information has to pass through our WM. If our WM is unable to process that information, our test taking and paper, writing will proceed without that information. Since WM is quite limited in its capacity to store information, and the stored information in WM decays quickly, WM is known as the "bottleneck" of human cognition. Evidence is accumulating that there are important differences between the WMs of individuals; some WMs can store more information, some WMs can store information longer, some can do both. As Conway et al. (2003) discuss, while WMC and general intelligence (IQ) are different concepts, they are highly related.

We predict that two key differences between the basic and complex grades created from our teaching experiment will come from the fact that each complex application involved a writing assignment that the students could complete through successive drafts. The first predicted difference between the grade-types is described as follows. Since these drafts are essentially problem-solving aids external to WM, the complex applications are less reliant on WMC, hence the complex grades will be less related to MSAT (since both WMC and MSAT are positively correlated with IQ, general intelligence). On the other hand, the basic applications are traditional questions that require some degree of memorization; making the basic grades dependent upon WMC and highly related to MSAT. The second predicted difference between the grade-types is related to student GPA. As Flower and Hayes (1981) discuss, given the way that papers are written, more drafts implies more reviewing, evaluating and revising and this process usually leads to a better final product. The willingness to produce more drafts is a sign of high motivation. Thus, we expect our proxy for motivation, GPA, to be strongly related to the complex grades. Since basic grades should be fundamentally connected to WMC, and we are unaware of any relationship between motivation and WMC, we will not be surprised by a weak relationship between GPA and basic grades, if MSAT has already been controlled for. In an effort to consolidate the information outlined in this section, Table 3 summarizes the essential discussion points.

Table 3: Summary of Empirical Model and Predictions

Proxies and Measures

D of L → *BG* and *CG*
Motivation → *GPA*
Opportunity to Learn → *Courses*
Aptitude → *MSAT*
Quality of Instruction → *STAT, ACC, BLaw, OPS, ECON*
Delivery Method (DM) → *Online and Face-to-Face Instruction*

Specifications

$$BG = \beta_o + \beta_1 MSAT + \beta_2 GPA + \beta_3 Courses + \beta_4 DM + \beta_5 ACC + \beta_6 BLaw + \beta_7 OPS + \beta_8 Econ + \varepsilon$$

$$CG = \gamma_o + \gamma_1 MSAT + \gamma_2 GPA + \gamma_3 Courses + \gamma_4 DM + \gamma_5 ACC + \gamma_6 BLaw + \gamma_7 OPS + \gamma_8 Econ + \varepsilon$$

Predictions

$\beta_1 > \gamma_1 > 0$
$\gamma_2 > \beta_2 > 0$
$\beta_3 < 0$ and $\gamma_3 < 0$
$\beta_5 > 0, \beta_6 > 0, \beta_7 > 0, \beta_8 > 0$
$\gamma_5 > 0, \gamma_6 > 0, \gamma_7 > 0, \gamma_8 > 0$
Research Question: What is the impact of the delivery method (DM) captured by β_4 and γ_4

Table 3 provides a summary of data measures, regression model, and predictions employed in the analysis.

DATA AND METHODOLOGY

To empirically test the primary research question if delivery method significantly affects student performance on learning outcomes, we estimate the two regression models summarized in Table 3. As a preliminary analysis, the descriptive statistics of the data used to estimate these two models are provided in Table 4. It should be noted that the sample standard deviation for the basic grades (both for the online and face-to-face subsamples) is relatively greater than the sample standard deviations for the complex grades and this will be discussed in detail below. Further, the students were given the basic assignments early in the semester and the complex assignment was due later in the semester. Some of the students did not complete the course, thus the sample size is slightly smaller for the complex versus the basic grades.

Table 4: Descriptive Statistics

Combined		Mean	Standard Deviation	*N*
	Basic Grade (BG)	82.8	19.3	121
	Complex Grade (CG)	83.3	12.7	112
	MSAT	589.3	67.8	121
	GPA	3.0	0.43	121
	Courses	1.4	0.51	121
Online				
	Basic Grade (BG)	83.9	18.1	79
	Complex Grade (CG)	83.4	13.2	73
	MSAT	595.9	64.8	79
	GPA	3.16	0.38	79
	Courses	1.4	0.52	79
Face to Face				
	Basic Grade (BG)	80.6	21.3	42
	Complex Grade (CG)	83.0	11.8	39
	MSAT	576.9	72.4	42
	GPA	2.78	0.43	42
	Courses	1.3	0.46	42

Table 4 provides a summary of the data and the descriptive statistics for the data used in the analysis discussed below.

The first regression model uses the student's score on the basic assignment as the dependent variable and uses the proxies for Carroll's aptitude (SAT math), motivation (cumulative GPA), opportunity to learn (number of courses enrolled), and quality of instruction (a dummy for online versus face to face that takes the value of one if the course is taught online.) as well as dummy variables to control for the course the student is taking (accounting, economics, etc.).

RESULTS AND DISCUSSION

The estimation results are presented in Tables 5 and 6. In regards to the estimated results for Model 1, the coefficient on *MSAT* is significant and positive, indicating the expected result that higher math SAT scores lead to higher scores on the basic assignment. Further, all of the coefficients on the dummy variables for which the student was enrolled, accounting, economics, etc., are significant, indicating that there are differences in grading or difficulty in the basic assignments across courses, as predicted by assumption *(7)*. The coefficient on *GPA* is not significant; however as discussed, this is not an entirely unexpected result. Further, all of the variance inflation factors (VIFs) are less than 5.3, the cutoff for multicollinearity suggested by Hair et al. (1992), indicating that multicollinearity does not appear to be a problem in this analysis.

In reference to the primary question posed in this study, the coefficient on *DM* is not significant. This suggests that there is no significant difference in the student performance on basic application questions either in foundational undergraduate business courses that are delivered online or in traditional, face-to-face classrooms. The estimated regression results for Model 2 are presented in Table 6. While a more detailed discussion of the regression results follows, interestingly, the coefficient on *DM* remains insignificant. Thus, student performance on both basic applications and complex assignments are found not to depend on the course delivery method.

Table 5: Estimation Results Model 1: Dependent Variable: *BG*

	Coefficient Estimate	Std Err	t Stat	p-value	VIF
Intercept	20.98	13.68	1.53	0.1280	0
MSAT	0.057***	0.021	2.68	0.0084	1.26
GPA	1.25	3.56	0.35	0.7265	1.47
Courses	2.59	2.63	0.98	0.8358	1.28
DM	-1.49	3.02	-0.50	0.6213	1.09
ACC	13.89***	4.51	3.08	0.0026	1.67
BLaw	38.60***	4.22	9.14	<0.0001	1.81
OPS	28.21***	3.92	7.18	<0.0001	2.00
Econ	23.59***	4.57	5.16	<0.0001	1.64
Adj. R^2 *= 0.4737*	*F stat = 14.50****				

Table 5 provides the estimation results for Model 1 with the dependent variable of 'Basic Grades' (BG). As shown above, the coefficient on Delivery Method (DM) is not statistically significant, indicating that online versus face-to-face does not affect student learning on basic assignments. p <0.10*; ***p* <0.05; ****p*<0.01

Table 6: Estimation Results Model 2: Dependent Variable: *CG*

	Coefficient Estimate	Std Err	*t* Stat	*p*-value	VIF
Intercept	58.63***	11.82	4.96	<0.0001	0
MSAT	0.0008	0.02	0.04	0.9672	1.36
GPA	7.31**	3.21	2.28	0.0240	1.60
Courses	1.08	2.30	0.47	0.6376	1.36
DM	-3.09	2.65	-1.17	0.2540	1.09
ACC	-0.75	3.80	-0.20	0.8443	1.66
BLaw	10.71***	3.57	3.00	0.0034	1.80
OPS	0.48	3.50	0.14	0.8900	1.82
Econ	0.007	3.86	0.001	0.9985	1.60
Adj. R^2 =0.1453	*F* stat = 3.360***				

Table 6 provides the estimation results for Model 1 with the dependent variable of 'Basic Grades' (BG). As shown above, the coefficient on Delivery Method (DM) is not statistically significant, indicating that online versus face-to-face does not affect student learning on basic assignments. p <0.10*; ***p* <0.05; ****p*<0.01

As shown in Table 5, the Adjusted R^2 for Model 1 is notably higher (0.4737) compared to the Adjusted R^2 for Model 2 (0.1453), giving Model 1 greater explanatory power. Considering that the independent variables are the same in the two regressions, the question arises as to why these variables explain a greater proportion of the variance in the basic grades compared to the complex grades. Recall the theoretical prediction that the complex assignments do not stress working memory capacity as much as basic assignments, suggesting that *MSAT* should be an insignificant predictor of complex grades. Thus, we are left with only one predictor of within course variation in complex grades, a proxy for academic motivation, the student's cumulative *GPA*. Further, since complex assignments are not as clearly defined or structured as the basic assignments, grading these assignments is more subjective. Although an effort was made to reduce the subjectivity of the complex grades by taking the average of two faculty members' grades for the same assignment, averaging must have reduced the total sum of squares by more than the reduction in the error sum of squares caused by our averaging. These changes will obviously lower the Adjusted R^2 for Model 2. Alternatively, working memory capacity is a much stronger determinant of success than motivation for basic assignments. Given that *MSAT* is a relatively clear signal of working memory capacity, there will be less measurement error associated with Model 1, hence a higher Adjusted R^2.

Consider one more difference between Model 1 and Model 2. The estimated coefficients on the courses (*ACC*, *OPS*, and *ECON*) are significant in Model 1, but are not significant in Model 2. While the estimated coefficient on *BLaw* is significant in both regressions, the *t*-stat is smaller in Model 2. To explore this result further, the sample variances for the basic and complex grades were compared across each of the courses. For example, the sample variance of the basic grades was compared to the sample variance of the complex grades for the *ACC* course and similar comparisons were made for the remaining four courses. Of the five courses considered, four of the sample variances of the basic grades were greater than the sample variances of the complex grades. Also, as shown in Table 4, the overall sample variance of the basic grades is greater than the overall sample variance of the complex grades. This indicates that there is generally less variability in the complex grades, both overall and by course. Given the algebra underlying OLS estimation, this will give less explanatory power to the course dummies in Model 2 relative to Model 1, thus increasing the likelihood that the coefficients on the course dummies will be insignificant, or at least less significant, in Model 2.

CONCLUDING COMMENTS

This study considers the potential for differences in student learning outcomes based on the delivery method (face-to-face or online). Our results indicate that delivery method does not significantly affect student-learning outcomes on either basic or complex assignments. These results contradict the conclusions found in the two studies mentioned in the introduction: Brown and Liedholm (2002) and Coates et al. (2004). We will end by using the Carroll Model to propose some hypotheses reconciling the conflicting evidence. We suspect that the online students in the Brown and Liedholm (2002) and the Coates et al. (2004) samples fared worse because of an insufficient amount of *Time Spent* compared to the corresponding face-to-face students.

In the Coates et al. (2004) sample, the online students were older and less likely to have financial aid, suggesting that they needed to work more than their fellow students did in the face-to-face sample. All else constant, this need could have reduced their *Time Spent* through the *Opportunity to Learn* factor. Now consider Brown and Liedholm (2002), they find that the students who enrolled in the online course performed significantly worse on the most complex questions on the examinations. We hypothesize that the cause of the deficient *Time Spent* in this case though is through the *Motivation* factor. Specifically, when outlining our theory, we introduced the idea of *Long-Term Memory* (LTM). LTM is the location of the stored knowledge we access when solving problems. Problem-solvers differ in their expertise; experts can solve complex problems in their field of expertise, novices cannot. Experts have this ability because their LTM has a structure quite different from a novice's LTM (Ericsson and Kintsch 1995). For an expert, the "right" information has been encoded into the "right" schemas; as a result, an expert can reliably retrieve what is relevant. This ability requires practice, time and effort, which requires high motivation in order to achieve expert status and be able to solve complex problems. In reference to Brown and Liedholm (2002), if this theory is correct, there should be indications that their online students were less motivated than their face-to-face students were, which is the case. As measured by better class attendance, Brown and Liedholm (2002) note that their face-to-face students did put more effort into the course. In addition, the Brown and Liedholm (2002) online students, when compared to the face-to-face students, have higher ACT scores, yet slightly lower GPAs. Given the relationship between standardized test scores and grades, the combination of high ACTs and low grades can signify lower academic motivation.

Brown and Liedholm (2002) conclude that their "results strongly suggest that the virtual course represents an inferior technology to the live sections" because "doing as well in an online course as in the live

alternative seems to require extra work or discipline beyond that demonstrated by our students, especially when it comes to learning the more difficult concepts." Given our theoretical model and empirical findings, we disagree. Most of our students view online and face-to-courses as equally difficult. Based on Table 4, there appears to be no difference in student motivation levels between the two delivery methods and the students in our online courses do as well on complex assignments as our face-to-face students.
It should be noted; however, that our study is not without its limitations. First, while the sample used in this analysis is not small, a larger sample size would provide results that are more robust. Further, as with all studies attempting to measure variables that are largely qualitative such as intrinsic student motivation, the proxies cannot be perfect measures and thus these results should be considered with this note of caution.

Finally, we conclude with avenues for future research in this area. Specifically, Marissa Mayer, the CEO of Yahoo, recently promoted the value of workplace interaction and communications by removing previous company policies that had allowed employees to telecommute. Many Yahoo employees expressed distress in the policy change as many stated the significant benefits of telecommuting; especially their increased productivity. While this study found no significant difference in student learning outcomes from the two different delivery methods, an avenue for future research would be to explore possible differences in other factors such as student and faculty relationships and the effectiveness and quality of communication and sharing of ideas. Such research could shed light on some of the more intangible and qualitative differences of teaching, learning, and working in the same physical location compared to online or telecommunication.

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BIOGRAPHY

Dr. Cassandra E. DiRienzo is an Associate Professor of Economics and Associate Dean at Elon University. She can be contacted at: Elon University, 2075 Campus Box, Elon, NC, 27244. Phone: 336-278-6000. Email: cdirienzo@elon.edu.

Dr. Gregory Lilly is an Associate Professor of Economics at Elon University. He can be contacted at: Elon University, 2075 Campus Box, Elon, NC, 27244. Phone: 336-278-6000. Email: lillyg@elon.edu.