LOGGED IN OR LOGGED OUT? A STATISTICAL ANALYSIS OF ABSENCES AND VIRTUAL PRESENCE IN BUSINESS STATISTICS

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Abstract

The COVID-19 pandemic forced faculty and students to adapt to a culture of virtual learning. The transition back to normalcy was immediately positive for some, while others maintained preferences towards the virtual classroom. We elaborate on the importance of classroom attendance in business statistics courses with an online learning component by estimating the impact of virtual learning on performance. We use a sample of six sections of business statistics across three semesters. Each semester employed the same instructor, text, lecture format, and algorithmic assignments, but differed in delivery. One semester was completely virtual, one was mixed in-person and virtual, and one was completely in-person. We find that students who attended class virtually scored significantly lower on exams than their classmates who attended lectures in person. Additionally, students who attended virtually and were absent for one or more classes performed worse on exams when compared to students attending in person. Online assignment performance is a strong predictor of exam success, but less so for students who attend class virtually.

Key Words: Statistics, Attendance, Virtual Learning, In-Person Classroom

JEL Classification: A22

Introduction

The correlation between class attendance and academic performance has been a subject of scholarly inquiry for nearly a century, dating to Turner's (1927) seminal investigation establishing an inverse relationship between class absences and grade point average. The contemporary educational landscape, however, presents novel considerations through the integration of technological delivery methods. Read (2005) documents the implementation of audio-based lecture delivery systems at multiple institutions of higher education, including American, Purdue, Drexel, and Duke University. Young (2008) similarly examines video lecture implementation at the University of Minnesota-Twin Cities. These technological adaptations facilitate asynchronous content consumption according to student preference. The COVID-19 timeframe showcased vast increases in technology adoption within the classroom with the mass migration to virtual learning. Granted, this was a necessity during lockdowns, but is it a delivery method worth continuing? We feel, at least within the confines of quantitative courses like business statistics, that it is not a proper substitute.

Empirical evidence suggests the particular efficacy of in-person instruction for quantitative disciplines. Conners et al. (1998) and Perkins and Saris (2001) present compelling arguments for maintaining traditional classroom-based statistics instruction, citing enhanced retention through active learning methodologies, anxiety mitigation through cooperative learning opportunities, and

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the value of immediate instructor feedback. Cohn et al. (1995) demonstrate that the physical act of note-taking during economics lectures produces superior learning outcomes compared to passive content consumption.

This investigation seeks to analyze attendance impacts on business statistics performance within a hybrid instructional environment incorporating both traditional lectures and digital learning components. Primarily, we focus on two hypotheses: Does attending class virtually affect performance, and how does absenteeism affect grades? As Generation Z becomes the predominant undergraduate demographic, characterized by technological sophistication, the optimal integration of traditional and digital pedagogical methods warrants careful examination. Previous research by Velleman and Moore (1996) and Basturk (2005) suggests technology's optimal role as complementary rather than substitutive. Weaknesses that technology cannot overcome are the benefits students receive from working alongside peers and the instructor's ability to identify and assist struggling students. The present study incorporates data from business statistics courses conducted over three semesters (2021-2022), featuring synchronous instruction and a mixture of in-person and virtual attendance. We find that virtual attendance is inferior based on assignments and exam scores. Absences negatively impact performance scores, and the impact increases with the number of absences. This effect is worsened for students who attend virtually.

Background

The empirical literature examining the relationship between attendance and academic performance spans multiple disciplines, yielding consistently robust correlations that determine class attendance as the predominant predictor of academic achievement (Credé et al., 2010). Initial quantitative analysis by Anikeef (1954) showed that approximately 83% of grade variance in business education could be attributed to attendance-related factors, while subsequent investigations have reinforced these findings across diverse contexts: Day (1994) established attendance as a stronger predictor of sociology outcomes than cumulative GPA; Gump (2005) documented significant negative correlations in general education courses with consistency across major disciplines; and Newman-Ford et al. (2008) demonstrated strong correlations using electronic monitoring across multiple degree programs. The psychological sciences have produced rigorous investigations with multiple longitudinal studies (Gunn, 1993; Van Blerkom, 1992, 1996; Clump et al., 2003) demonstrating consistent negative correlations between absence frequency and performance, while Buckalew et al. (1986) identified specific reductions associated with initial session absence and positive correlations between classroom attendance and achievement. These findings were further corroborated by Launius (1997), who established that attendance correlates with both examination performance and external assignment completion rates. Within the natural sciences, Moore (2006) and Moore et al. (2003) established attendance as a significant predictor in biology and introductory science coursework, demonstrating increased attendance rates following presentation of attendance-grade correlations to students. Jenne (1973) identified strong attendance-learning correlations in health sciences, conceptualizing attendance as "distributed practice." Murphy and Stewart's (2015) research in physics education presents a counterpoint, revealing minimal attendance impact when traditional lectures were replaced with digital alternatives, despite lower-achieving students who opted for recordings failing to achieve parity with class averages.

The economics literature presents extensive empirical evidence regarding attendance impacts. Multiple investigations (Brocato, 1989; Park & Kerr, 1990; Durden & Ellis, 1995; Cohn et al., 1995; Devadoss & Foltz, 1996; Maloney & Lally, 1998; Marburger, 2001; Chen & Lin, 2008) consistently demonstrate negative correlations between absenteeism and academic performance. Romer's (1993) analysis of intermediate macroeconomics data, incorporating motivational controls including GPA and assignment completion rates, established attendance as a significant predictor of examination performance, with motivational controls demonstrating only moderate mediating effects.

Cohn and Johnson (2006) extended this research through comprehensive hypothesis testing derived from Jones (1984), Durden and Ellis (1995), and Romer (1993). Their findings indicate positive attendance-test score correlations, disproportionate negative impacts from substantial absences, the absence of reverse causality from low test scores to increased absences, and greater explanatory power of SAT and GPA controls than previously documented. Their methodological innovation included categorical analysis through attendance-percentage dummy variables.

Recent research by Boyle and Goffe (2018) employed evidence-based teaching methods in large-scale macroeconomics sections, demonstrating significant learning gains through the Test of Understanding of College Economics. Their research identified four critical pedagogical elements: comprehensive feedback provision, learning spacing optimization, conceptual understanding assessment through electronic response systems, and structured quiz reflection protocols. They note that online formats of course delivery lack in instructor and peer engagement, which are deemed critical for complex subjects like economics.

Contemporary statistics education literature reveals a consistent pattern: while technological tools offer valuable pedagogical enhancements, they function most effectively as supplements to, rather than replacements for, traditional classroom instruction. Velleman and Moore's (1996) nuanced analysis of multimedia integration established this foundational principle, emphasizing technology's supplementary role in statistical education. Their findings align with subsequent research by Conners et al. (1998) and Perkins and Saris (2001) regarding the fundamental importance of active learning engagement. Though these researchers acknowledge technology's potential to replace traditional instruction for highly motivated and disciplined learners, they importantly note this approach's limitations in introductory statistics contexts.

The evidence supporting attendance's continued importance in technology-enhanced environments has grown increasingly robust. Basturk's (2005) investigation of Computer Assisted Instruction (CAI) implementation at Carnegie I Research University provides compelling evidence for integrated pedagogical approaches: among 205 graduate students, those enrolled in the "lecture-plus-CAI" section demonstrated significantly higher performance on both midterm and final assessments compared to the traditional lecture cohort, suggesting optimal outcomes emerge when technology augments rather than replaces classroom presence. This supplementary role of technology receives further empirical support from Haase (2021), whose analysis of attendance's impact on performance in statistics classes demonstrated that technology-based educational support did not replace the learning experiences occurring in physical classrooms. The pandemic era has provided additional confirmation of attendance's enduring importance, as Kofoed et al. (2024) found that online instruction negatively impacted exam and assignment scores in introductory macroeconomics classes, revealing the limitations of purely technological approaches to education delivery.

Data Collection and Variable Summary

This study was conducted at a public AACSB-accredited 4-year college located in New Jersey. The statistics class we observe is a core course for all majors in the business school and requires a prerequisite math course. The student population is typically sophomores and juniors, and the class capacity is 35 students per section. The student data we use comes from six different course sections of a hybrid business statistics course from spring 2021 through spring 2022. Hybrid courses at this institution meet synchronously once per week for 100 minutes, coupled with asynchronous online instruction. Two sections per semester were selected. The two sections in the spring 2021 semester were taught virtually where students and instructor all logged into a WebEx classroom; the two sections from the fall 2021 semester were taught in-person in the classroom but students could log in virtually and observe class from the installed WebEx room kit (large television, microphone, webcam combination); and the two sections of the spring 2022 semester were taught live in the classroom with no option for virtual observation. Each section had the same instructor, textbook, lecture format, number of assignments and exams, and assignment/exam format; the key difference is the semester delivery modality. Technology is incorporated into the lectures using Microsoft Excel and Pearson's MyStatLab. MyStatLab is an online "digital learning environment" for assignments, tutorials, study material, and spreadsheet applications.

Lectures are focused on new formulas and theories as well as how the material builds on previous lectures. Within each lecture, time is allotted for students to work through a question focusing on that class's topic. This immediately presents a key difference between delivery types. If the class is in-person, and the students are physically present in the classroom, they benefit from two opportunities: they are able to assist each other, and the instructor is able to better address students who are struggling. The frequent amount of interaction also provides opportunities to connect statistical methods to practical, real-world examples. Most importantly, the rapport built in a small classroom allows the instructor to more easily familiarize themselves with their students and thus better identify confusion in the classroom. Attendance is also taken during this time. There is no formal attendance policy, and a grade is not assigned for attendance. Students are warned at the beginning of the semester that missing class will result in the student missing substantial content. Notes are not provided; should someone miss class, they must rely on classmates. Since attendance is not for a grade, there is no need to distinguish between excused and unexcused. The focus is solely on who is present for the lecture. After accounting for exam periods and weather-related cancellations, there are 12 face-to-face lectures for each of the sections.

The performance data we explore are exam and assignment scores retrieved from MyStatLab. The homework assignments and exams are designed using algorithm-built questions, such that no two students receive the same exact question. Each student receives the same type of question and calculates the same type of statistics, but the sample data randomly changes between individuals in an effort to minimize cheating. At the end of the semester, a spreadsheet is exported detailing student performance and time spent on each assignment. We adjust homework settings so students have unlimited attempts per assignment, and the best performance is kept for their grade. This provides students the opportunity to put forth effort working through problem sets without worrying about making mistakes. It also allows for the motivated student to try again to increase their score. Anecdotally, we have seen class exam score averages increase from using this program. Exams are timed, do not get multiple attempts, and utilize Lockdown Browser as a proctoring tool to minimize cheating. Additionally, there are numerous learning tools within the program. There are video tutorials and presentations, self-assessment quizzes, an online text that links homework questions to textbook chapters and sections, step-by-step walkthroughs for calculating complicated formulas, and more.

A total of 203 students completed the course. Withdrawals and incompletes are not considered due to the student not completing the course, having missing grade observations, and potentially tainting the data as an outlier. In addition to performance data, descriptive measures were collected via a survey. This project did receive IRB approval.[2]

Table 1a

Absence-Grade Summary (Whole Sample)

Grade Range	# Students	Absences			
		Average	Std. Dev	Min	Max
A	35	1.257	2.105	0	8
B	63	1.524	2.395	0	12
C	47	2.957	3.683	0	12
D	36	2.472	3.533	0	12
F	22	3.318	3.386	0	10
Whole Sample	203	2.172	3.087	0	12

Table 1b

Absence-Grade Summary (In-person)

Grade Range	# Students	Absences			
		Average	Std. Dev	Min	Max
A	23	1.130	2.437	0	8
B	39	1.308	2.364	0	12
C	22	3.000	4.024	0	12
D	21	2.190	3.868	0	12
F	8	4.375	4.502	0	10
Whole Sample	113	1.982	3.311	0	12

Tables 1a-c show a simple summary of absences by average exam score. The letter grades represent the grade range that matches the student's performance. Comparisons of the extremes suggest a distinct pattern between students earning either an A or an F. In fact, the group of students that scored in the A-range had a lower average number of absences across all other grade ranges. This is true for both in-person and virtual attendees. Except for the C-range and the F's, the average number of absences is lower for in-person attendance than virtual.

[2] This project was approved by the Ramapo College Institutional Review Board (IRB Approval #611).

Table 1c

Absence-Grade Summary (Virtual)

Grade Range	# Students	Absences			
		Average	Std. Dev	Min	Max
A	12	1.500	1.314	0	4
B	24	1.875	2.455	0	11
C	25	2.920	3.439	0	12
D	15	2.867	3.091	0	9
F	14	2.714	2.555	0	8
Whole Sample	90	2.411	2.779	0	12

Test averages and homework assignment averages are the two performance measures of concern that will be tested. The included indicator variables follow the specification mechanism outlined by Haase (2021), which builds off the premise outlined by Cohn and Johnson (2006). They incorporate discrete dummy variables indicating different levels of absences with their students to test the conclusion of Durden and Ellis (1995) that substantial absences have a detrimental impact on performance. This relationship is further expanded to incorporate virtual attendance. Attendance dummy variables were selected based on the sample's frequency distribution, which appears in Table 2.

The attendance dummy variables used by Cohn and Johnson (2006) are based on different percentages of attendance. For example, their sample had 8% of students who attended all classes, 28% attended 92% or more but less than 100%, and 23% attended less than 68% of classes. Our sample frequency distribution shows 44.8% of students attended all classes, 18.7% had one absence (corresponds to 91.7% or more but less than 100% classes attended), and 24.1% were absent four or more classes (corresponds to 66.7% or less classes attended). Since our sample has a different pattern, applying these types of percentages does not represent well, hence we follow the specification outlined by Haase (2021). The selected number of absences for each dummy variable was chosen in an attempt to group absences into the closest resemblance of quartiles.

Further dissection of the frequency distribution yields some interesting preliminary findings. Students who missed one class have a higher test average than the group with full attendance and a slightly higher maximum score. The small cluster of students who missed two classes has a lower average than the full attendance group, but presents a higher maximum and minimum. Some groups have only one observation. One student missed seven classes, and another missed ten classes; both have a failing test average. However, the one student who missed 11 classes has the highest average across all groups, at 81.8%. It is worth reiterating that attendance does not count toward their grade, so it is entirely possible to only attend class for exams. Romer (1993) describes attendance as an exogenous choice. If the student is a self-motivated, high-performing outlier, this choice may have been favorably exercised. For instance, the highest exam score belongs to a student who missed two classes, and the group with three absences has the highest exam average across all groups composed of more than one student.

Table 2

Frequency Distribution: Absences and Test Average

Absences	Freq.	Rel. Frequency	Cum. Rel. Frequency	Test Average	Std. Dev	Min	Max
0	91	44.8%	44.8%	0.782	0.127	0.409	0.961
1	38	18.7%	63.6%	0.790	0.126	0.358	0.978
2	10	4.9%	68.5%	0.778	0.182	0.462	0.984
3	15	7.4%	75.9%	0.796	0.110	0.530	0.939
4	11	5.4%	81.3%	0.764	0.160	0.430	0.919
5	9	4.4%	85.7%	0.753	0.109	0.600	0.911
6	7	3.5%	89.2%	0.641	0.135	0.403	0.828
7	1	0.5%	89.7%	0.500	.	0.500	0.500
8	10	4.9%	94.6%	0.744	0.131	0.565	0.949
9	3	1.5%	96.1%	0.648	0.065	0.576	0.703
10	1	0.5%	96.6%	0.489	.	0.489	0.489
11	1	0.5%	97.1%	0.818	.	0.818	0.818
12	6	3.0%	100.0%	0.751	0.078	0.639	0.848
Total	203	100%					

To investigate the role virtual attendance and absences have on student performance, we gathered or calculated the following variables:

- ***Test***: weighted average of all exams. Each student has two midterms and a final exam. Each exam covers the same course material and contains objective questions. It is a percentage with a range from 0 - 1.
- ***Hwscore***: assignment score from MyStatLab. It is the average of the highest-scoring attempts from all chapter assignments turned in. It is a percentage with a range from 0-1.
- ***Absences:*** count variable for the number of absences recorded for a student.
- ***Abs0***: indicator variable for students with no absences. 44.83% of students are represented.
- ***Abs1***: indicator variable for students with one absence. 18.72% of students are represented.
- ***Abs23***: indicator variable for students with two or three absences. 12.32% of students are represented.
- ***Abs4plus***: indicator variable for students with four or more absences. 24.14% of students are represented.

- ***Vatt***: indicator variable for students who are virtual attendees.
- ***Vabsences***: interaction between ***Vatt*** and ***Absences.***
- ***Vabs# (multiple variables)***: interaction variables for ***Vatt*** and the ***Abs*** indicator variables.
- ***Spring21/Fall21***: indicator variables to capture semester fixed effects. The spring 2022 semester is the reference group.

An IRB-approved survey was administered at the end of the semester in order to gather more details on the students. A total of 179 students completed the survey. The variables created from the survey are as follows:

- ***GPA***: Midpoint of the student's selected GPA 'bucket.'
- ***Prereq***: indicator variable representing 1 if the student chose the lower-level statistics course as their prerequisite; 0 if they chose precalculus or calculus.
- ***Credit# (multiple variables)***: indicator variables identifying if the student was enrolled in credit amounts equal to full-time enrollment, part-time enrollment, or overload.
- ***Work***: indicator variable representing 1 if the student has a job outside of class; 0 otherwise.
- ***Enjoy***: indicator variable taking a value of 1 if the student indicated that they enjoy math-based courses; 0 otherwise.

These selected variables, motivated by Romer (1993), were gathered to capture general student differences. Romer (1993) only included GPA as a control; we expanded with additional measures. The information collected is intended to capture student-specific traits that may inform us on ability, prior knowledge, affinity, and the ability to dedicate time to learning. For accuracy in reporting and to provide a degree of comfort that would induce honest completion of the survey, some questions were asked using group selection. For example, students could select that their GPA was between 3.0 and less than 3.25. There is still an opportunity for dishonesty in reporting, which we can do little about. A summary of all variables used is located in Table A1 in the appendix.

Methodology and Empirical Results

We begin our analysis by considering two broad comparisons: virtual performance versus in-person performance and semester performance comparisons. We conduct a one-way ANOVA and two t-tests for differences in means, tables for which can be found in the appendix. Table A2 presents the results from a One-Way ANOVA, testing for the difference in mean ***Test*** score across the three semesters studied. Table A3 presents the results for a two-sample t-test of means comparing absences between virtual attendees and in-person students. Similarly, Table A4 presents the results for a two-sample t-test of means comparing ***Test*** scores between virtual attendees and in-person students.

According to the ANOVA results in Table A2, we cannot determine that any semester test average is uniquely different. Dismissing the semester effects as not having a significant impact on performance is helpful, as it helps build the story toward looking at the student's class delivery and attendance patterns as further indicators of success. Comparing absences across virtual attendees and in-person students yields insignificant results, as shown in Table A3. There appears to be no unique difference in absences for these two modalities. The comparison of test scores in Table A4 indicates a weakly significant (10%) difference in favor of the in-person classroom delivery for higher exam performance. At the onset, all three considered semesters produced similar exam score averages, and attendance patterns are similar between in-person and virtual attending students, but in-person attendance appears to correlate with improved performance on exams versus virtual attendance. This does not account for individual performance and absences, which is the impetus for this analysis.

Table 3

Baseline Regression Results

Variable	(1) Test Average
Intercept	0.462***
	(0.051)
Absences	0.006*
	(0.003)
Vatt	-0.052*
	(0.029)
Vabsences	-0.010**
	(0.005)
Hwscore	0.363***
	(0.050)
Spring2021	0.088***
	(0.033)
Fall2021	0.016
	(0.022)
Observations	203
R-squared	0.350
F-statistic	17.81
RMSE	0.108

Note.*,**,*** indicates significance at the 10%, 5%, and 1% levels. Standard errors are robust and in parentheses.

Preliminary Regression Specifications

We begin by establishing a baseline relationship between absence and exam performance:

$$(1)\ Test_i = \beta_0 + \beta_1 Absences_i + \beta_2 Vatt_i + \beta_3 Vabsences_i + \beta_4 Hwscore_i + \beta_5 Spring2021_i + \beta_6 Fall2021_i + \varepsilon_i$$

Equation 1 regresses the student's test average on the number of marked absences, includes an indicator for virtual attendance, an interaction term for virtual absence, the student's homework average, and dummy variables to account for semester effects. Standard errors are robust. Results are presented in Table 3. Oddly, the coefficient on ***Absences*** is positive and marginally significant. Although the coefficient is small at 0.006, this would indicate someone who misses all twelve class meetings would score on average 7.2% points higher than someone in full attendance. Reflecting back to the frequency distribution in Table 2 points out that the average score for zero absences is higher than that for 12 absences; however, the minimum test score at twelve absences is 23% points higher. We suspect some outlier performances may be affecting this simple relationship.

The remaining significant coefficients have signs that meet expectations. ***Vatt*** is negative and significant at the 10% level with a value of -0.052 suggesting a performance penalty to virtual attendance. ***Vabsences*** is significant at the 5% level with a coefficient of -0.010, indicating worsening performance for those who miss class while attending virtually. ***Hwscore*** is positive and significant at the 1% level with a value of 0.363. Students who perform well on their assignments will, on average, perform better on exams independent of attendance modality

The two regression equations that form the basis of our analysis follows the specification established by Haase (2021). We use these as a benchmark to check the relationship between attendance and performance by grouping students into clusters outlined in the variable listing. This is to capture isolated portions of the distribution. The specification is as follows:

$$(2)\ Test_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs23_i + \beta_3 Abs4plus_i + \beta_4 Vatt_i + \beta_5 Vabs1_i + \beta_6 Vabs23_i + \beta_7 Vabs4plus_i + \beta_8 Hwscore_i + \beta_9 Spring2021_i + \beta_{10} Fall2021_i + \varepsilon_i$$

$$(3)\ Hwscore_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs23_i + \beta_3 Abs4plus_i + \beta_4 Vatt_i + \beta_5 Vabs1_i + \beta_6 Vabs23_i + \beta_7 Vabs4plus_i + \beta_8 Spring2021_i + \beta_9 Fall2021_i + \varepsilon_i$$

Equation 2 tests the impact of attendance and delivery on exam scores for each student; equation 3 tests the same impact on assignment performance. Each equation contains the indicator variables for absences (zero absences is our reference), an indicator for whether or not the student attended virtually, and interactions for virtual attendance and absences. Semester effects are included with the spring 2022 semester acting as our reference. Robust standard errors are used in both regressions. Table 4 displays the results for equations 2 and 3.

The results from equations 2 and 3 produce evidence suggesting virtual attendance in class is inferior to in-person attendance. The coefficient on ***Vatt*** for both equations is negative and significant at the 5% level. In equation 2, the coefficient -0.072 suggests that students attending virtually score 7.2% lower on exams than their in-person counterparts. The coefficient -0.120 in equation 3 indicates the virtual student's homework score is 12% lower than the in-person class attendees. Beyond this, the interpretations on other coefficients become unique to its individual equation.

Table 4
Regression Results

Variable	(2) Test Average	(3) Homework Score
Intercept	0.449***	0.937***
	(0.051)	(0.021)
Abs1	0.043	-0.089
	(0.027)	(0.056)
Abs23	0.087**	-0.087
	(0.034)	(0.065)
Abs4plus	0.046	-0.263***
	(0.030)	(0.055)
Vatt	-0.072**	-0.120**
	(0.032)	(0.055)
Vabs1	0.019	0.022
	(0.041)	(0.082)
Vabs23	-0.098**	0.093
	(0.048)	(0.083)
Vabs4plus	-0.066*	0.118
	(0.038)	(0.077)
Hwscore	0.361***	-
	(0.047)	-
Spring2021	0.110***	0.048
	(0.034)	(0.059)
Fall2021	0.026	-0.061*
	(0.023)	(0.034)
Observations	203	203
R-squared	0.378	0.222
F-statistic	13.08	6.32
RMSE	0.107	0.185

Note. (2) estimates the impact of the listed variables on a student's overall average test score across three exams. (3) estimates the impact of the listed variables on a student's overall average homework score. *,**,*** indicates significance at the 10%, 5%, and 1% levels. Standard errors are robust, and in parentheses.

Equation 2 has significant coefficients for ***Abs23***, ***Vatt***, ***Vabs23***, ***Vabs4plus***, ***Hwscore***, and ***Spring2021***. The coefficient for ***Abs23*** is positive. Though this is contrary to what we expect, it is not entirely surprising considering the potential outlier patterns noted in the frequency distribution in Table 2. This may be the source of the positive coefficient on ***Absences*** in Table 3. The negative coefficients on ***Vatt, Vabs23,*** and ***Vabs4plus*** add further evidence to the inferiority of virtual attendance. The coefficient of -0.098 for ***Vabs23*** and -.066 for ***Vabs4plus*** indicates that absence from virtual class two or more times negatively impacts the student's exam score in addition to the detriment already established by attending virtually. ***Vabs23*** is significant at the 5% level while ***Vabs4plus*** is significant at the 10% level. ***Hwscore*** is positive and significant at the 1% level with the largest slope coefficient of 0.361. This is no surprise and is a useful interpretation to any student who begrudges doing their work. On average, a student who practices enough to earn a 100% on their assignments can expect an increase in their exam scores of 36.1%; a C student who earns 75% on their homework would boost their average exam score by 27.075% points. Students in the Spring 2021 semester performed significantly better than in the two following semesters. The only conjecture we can offer is that this semester was taught virtually, as was the semester before it. We consider that the students may be familiar with the virtual layout due to its widespread delivery across all courses during the pandemic. The semesters that follow all shift back to the classroom, which may have been more disruptive than once believed. However, the previous ANOVA and consistent control of the course delivery offer no evidence that this semester was uniquely different. Only when incorporating other variables does this change. This is also the only instance where a semester effect is significant.

Table 5

Example Student Outcomes

Student Description	Count	E(Homework)	E(Test)
In person, no absence	63	93.70%	78.73%
Virtual, no absence	28	81.70%	67.19%
In person, one absence	18	93.70%	78.73%
Virtual, one absence	20	81.70%	67.19%
In-person, two or three absences	6	93.70%	87.43%
Virtual, two or three absences	19	81.70%	66.09%
In-person, four or more absences	26	67.40%	69.23%
Virtual, four or more absences	23	55.40%	51.10%

Note. E(Homework) is calculated by entering the specified number of absences into regression equation (3). E(Test) is calculated by entering the specified number of absences and the E(Homework) in the regression equation (2)

Equation 3 produces similar results in interpretation but also adds further emphasis to the channels in which absence can affect performance. The coefficients on ***Abs4plus***, ***Vatt***, and ***Fall2021*** are all significant. Excessive absence from class negatively impacts the student's performance on their homework. The coefficient on ***Abs4plus*** of -0.263 indicates a drop in homework scores of 26.3% if the student misses four or more classes. This is strongly significant at the 1% level. ***Abs23*** does not have a significant coefficient, but the sign is negative, which follows the intuition similarly. ***Fall2021*** has a negative coefficient and is significant at the 10% level. This particular semester was the start of transitioning back to campus, with some students attending in person while some remained virtual. Besides this transitional period and potential pandemic burnout, any other reasons for this variable's significance are purely speculative.

It is further worth noting that virtual attendance and absences affect both exam scores and assignment scores, which in turn also affects exam scores. Absences, in this manner, can have a more magnified effect on test performance. Consider the following examples based on these coefficients:

The examples in Table 5 illustrate six different 'students' and their potential performance based on the estimation output from equations 2 and 3 from Table 4. In all cases, the in-person class experience produces better homework and exam scores, and a large number of absences produces worse scores. As Romer (1993) explains, attending class is an exogenous choice, and it is therefore impossible to isolate the impact attendance has on exam performance. This analysis adds new evidence suggesting that virtual attendance produces subpar results and that excessive absence from class has a stronger negative impact on students.

Survey Criteria Regression Specifications

We expand the regressions to include variables collected from the self-reported survey. Benchmark equations 2 and 3 are preserved and expanded to include the following variables:

$$(4)\ Test_i = \beta_0 + \beta_{z1}Z1_i + \beta_{11}GPA_i + \beta_{12}Prereq_i + \beta_{13}CreditPT_i + \beta_{14}CreditOverload_i + \beta_{15}Work_i + \beta_{16}Enjoy_i + \varepsilon_i$$

$$(5)\ Hwscore_i = \beta_0 + \beta_{z2}Z2_i + \beta_{10}GPA_i + \beta_{11}Prereq_i + \beta_{12}CreditPT_i + \beta_{13}CreditOverload_i + \beta_{14}Work_i + \beta_{15}Enjoy_i + \varepsilon_i$$

Equation 4 expands equation 2 with selected variables that may capture student abilities. For space, we include $\beta_{z1}Z1_i$ to represent the vector of variables and estimators used in equation 2; $\beta_{z2}Z2_i$ represents the vector of variables used in equation 3 that are similarly present in equation 5. The additional variables included are: ***GPA***, which represents the midpoint of the GPA group selected by the student; ***Prereq***, which takes a value of 1 if the student previously took the elementary statistics prerequisite course; ***CreditPT***, which takes a value of 1 if the student is enrolled in 12 credits or less; ***CreditOverload***, which takes a value of 1 if the student is enrolled in over 18 credits; ***Work***, which takes a value of 1 is the student currently holds a job outside of class; and ***Enjoy***, which takes a value of 1 if the student self-reports that they enjoy math-based courses. The rationale, as motivated by Romer (1993), is to capture student abilities and motivations that may not be easily observed. Results are displayed in Table 6.

Equation 4 has significant coefficients for ***Abs23***, ***Vatt***, ***Vabs23***, ***Hwscore***, ***Spring2021, GPA,*** and ***CreditPT***. The positive signage on ***Abs23*** remains; we offer no further explanation for this. The significant negative coefficients on ***Vatt*** and ***Vabs23*** further support our idea that virtual learning and absence negatively impacts performance. The coefficient on ***Vatt*** increased in magnitude to -0.077 indicating an average exam score that is 7.7% points lower than an in-person attendee. Missing two or three classes now has a stronger impact, with the coefficient on ***Vabs23*** reporting at -0.125. This is also larger in magnitude than the benchmark equation 2. ***Hwscore*** is still significant and positive, although its effect is slightly diminished with a coefficient of 0.297. Out of all of the survey variables, the only significant coefficients are for ***GPA*** and ***CreditPT. GPA*** has a coefficient of 0.069. This positive result is in line with Romer (1993) suggesting that students with higher GPA's exhibit higher abilities in class. If we use the common GPA scale, maxing out at 4.0, we can estimate that student with a 4.0 GPA would score on average 13.8 percentage points higher than of someone with a reported GPA of 2.0. The coefficient on ***CreditPT*** indicates that students with a lower credit load perform better on their exams by 6.2 percentage points.

Table 6

Regression Results with Survey Input

Variable	(4) Test Average	(5) Homework Score	Variable	(4) (cont.) Test Average	(5) (cont.) Homework Score
Intercept	0.222**	0.066	Spring2021	0.114***	-0.004
	(0.093)	(0.133)		(0.033)	(0.044)
Abs1	0.038	-0.011	Fall2021	0.025	-0.030
	(0.033)	(0.054)		(0.025)	(0.036)
Abs23	0.109***	-0.063	GPA	0.069**	0.209***
	(0.041)	(0.046)		(0.028)	(0.035)
Abs4plus	0.057	-0.148***	Prereq	0.023	0.014
	(0.036)	(0.048)		(0.022)	(0.027)
Vatt	-0.077**	-0.032	CreditPT	0.062*	-0.059
	(0.030)	(0.039)		(0.032)	(0.080)
Vabs1	0.028	-0.016	CreditOverload	0.041	-0.065
	(0.048)	(0.069)		(0.040)	(0.065)
Vabs23	-0.125**	0.080	Work	0.012	0.014
	(0.051)	(0.059)		(0.019)	(0.024)
Vabs4plus	-0.062	0.078	Enjoy	0.006	0.042***
	(0.043)	(0.067)		(0.008)	(0.011)
Hwscore	0.297***	-			
	(0.076)	-			
Observations	176	176	*F-statistic*	8.55	8.04
R-squared	0.392	0.456	*RMSE*	0.106	0.145

Note. (4) estimates the impact on a student's overall average test score across three exams. (5) estimates the impact on a student's overall average homework score. *,**,*** indicates significance at the 10%, 5%, and 1% levels. Standard errors are robust and in parentheses.

The regression focusing on homework performance in equation 5 loses some of the prior significance reported in equation 3. When we include the survey variables, the only significant coefficients appear for ***Abs4plus***, ***GPA***, and ***Enjoy***. ***Abs4plus*** has a significant negative coefficient of -0.148, indicating a large decrease in homework performance of nearly 15 percentage points if the student missed four or more classes. ***GPA*** has the largest coefficient at 0.209, followed by ***Enjoy,*** which is 0.042. This suggests that a student's ability to complete homework may not be affected only by excessive absence, but potentially better explained through their abilities and affinity toward the subject. Higher performing students entering the class may have stronger abilities or better work habits that influence their assignment scores. Students who enjoy the material have an added benefit by performing on average 4.2 percentage points higher on assignments.

Both equations 4 and 5 yield insignificant coefficients for the variables ***Prereq***, ***CreditOverload***, and ***Work***. These variables, intended to capture some mechanism representing the time students can dedicate to their studies, seem to have no effect. Interactions with the absence indicator variables (not reported here) do not add anything more substantial either. The driving factors behind performance are prior GPA, virtual attendance, missing multiple classes, and the student's interest in the subject.

Alternate Regression Specification with Choice

We lastly consider an alternate specification to highlight the students who chose to attend virtually when in-person learning was available. This is unique to the students from the Fall 2021 semester. We reconsider the preliminary regressions by including the following variables:

$$(6)\ Test_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs23_i + \beta_3 Abs4plus_i + \beta_4 VChoice_i + \beta_5 VNoChoice_i + \beta_6 Vabs1_i + \beta_7 Vabs23_i + \beta_8 Vabs4plus_i + \beta_9 Hwscore_i + \beta_{10} Spring2022_i + \varepsilon_i$$

$$(7)\ Hwscore_i = \beta_0 + \beta_1 Abs1_i + \beta_2 Abs23_i + \beta_3 Abs4plus_i + \beta_4 VChoice_i + \beta_5 VNoChoice_i + \beta_6 Vabs1_i + \beta_7 Vabs23_i + \beta_8 Vabs4plus_i + \beta_9 Spring2022_i + \varepsilon_i$$

The indicators used for virtual attendees and semester identifiers were replaced with the following variables:

- ***VChoice***: indicator variable where 1 represents students who choose to attend virtually when in-person learning is available; 0 otherwise.
- ***VNoChoice***: indicator variable where 1 represents students who attended virtually when the only option was virtual learning; 0 otherwise.
- ***Spring2022***: indicator variables to capture the fully in-person semester fixed effects. The Fall 2021 semester in-person students are the reference group.

Table 7 displays the estimation results for equations 6 and 7. Robust standard errors are used. Many coefficients retain the sign, magnitude, and significance found in the preliminary regressions in Table 4. There are some distinct differences worth mentioning. ***VChoice*** captures the negative and significant impact found in the original ***Vatt*** variable in both equations. ***VNoChoice*** is insignificantly different from zero. This suggests that students who choose to attend virtually perform worse than those who were forced to attend virtually.

Table 7

Regression Results: Virtual Choice

Variable	(6) Test Average	(7) Homework Score
Intercept	0.476***	0.876***
	(0.047)	(0.023)
Abs1	0.043	-0.089
	(0.027)	(0.056)
Abs23	0.087**	-0.087
	(0.034)	(0.065)
Abs4plus	0.046	-0.263***
	(0.030)	(0.055)
VChoice	-0.072**	-0.120**
	(0.032)	(0.055)
VNoChoice	0.012	-0.011
	-0.026	-0.048
Vabs1	0.019	0.022
	(0.041)	(0.082)
Vabs23	-0.098**	0.093
	(0.048)	(0.083)
Vabs4plus	-0.066*	0.118
	(0.038)	(0.077)
Hwscore	0.361***	-
	(0.047)	-
Spring2022	-0.026	0.061*
	(0.023)	(0.034)
Observations	203	203
R-squared	0.378	0.222
F-statistic	13.08	6.32
RMSE	0.107	0.185

Note. (6) estimates the impact of the listed variables on a student's overall average test score across three exams. (7) estimates the impact of the listed variables on a student's overall average homework score. *,**,*** indicates significance at the 10%, 5%, and 1% levels. Standard errors are robust, and in parentheses.

Students who choose to attend virtually perform worse on exams, on average, by 7.2% points; they score on average 12% points lower on homework. This may suggest a lower academic engagement by those who do not make the effort to arrive to attend in person. Unfortunately, we have no way to determine if this is due to external stressors (e.g., work, caregiving, health concerns) or mere disengagement. The magnitude, sign, and significance level for the variables ***Abs23, Vabs23, Vabs4plus, Hwscore*** in equation 6 and ***Abs4plus*** in equation 7 match the output from the preliminary regression results in Table 4. Excessive absence still negatively impacts homework performance for all students, and excessive absence disproportionately affects students who attend virtually.

Uniquely, the indicator for ***Spring2022*** is only significant in equation 7, indicating students who were all required to attend in-person performed better on homework, yet had no direct influence on exams. This is in comparison to students who attended in-person after the pandemic restrictions began to lift in the Fall 2021 semester. The only explanation we can suggest is a matter of the environment in which the semesters were held. Instruction was held in identical fashion with regard to interaction between instructor and student, but peer engagement increased as distancing restrictions relaxed. We suspect the positive effect on homework scores is due to increased interaction outside of the classroom, providing positive externalities (e.g., use of office hours, working with peers, tutors).

Conclusion

While technological advancement continues to transform educational delivery methods, this investigation suggests that traditional attendance patterns remain significant predictors of academic success, even in technologically enhanced learning environments. In the environment of business statistics classes, virtual classrooms are not a perfect substitute for in-person learning. The efficiency gains from logging in to class from home do not outweigh the cost in performance.

This study compared the performance of six sections of an undergraduate statistics course over three semesters where nearly every component had been controlled for except for the delivery method. Roughly half of the students attended in-person, while the other half attended virtually via WebEx. Circumstances for virtual attendance differ. In the Spring 2021 semester, all students were required to attend virtually, but in the Fall 2021 semester, students had the option to choose their modality. Multiple specifications were tested. Prior GPA and assignment scores play a significant role in determining a student's exam performance, which is consistent with previous literature. Students who choose to attend virtually perform worse on assignments and exams. Excessive absence from class negatively impacts performance on assignments, which in turn impacts exam scores. Excessive absence from class negatively impacts exam scores for students who attend virtually disproportionately more than those who are in attendance in-person.

We can derive a practical and informed perspective from these results. If the student can choose their course delivery, evidence suggests that in-person attendance provides the best avenue for their best performance. The value in student effort, evidenced through assignments, is profound. Successful completion of assignments has a substantial positive impact on exam performance for both modalities. Absence from class harms students in both modalities, though it manifests in different ways. Excessive absence from in-person learning is strongly correlated to lower assignment performance, which in turn translates to lower test scores. Additionally, multiple absences in a virtual setting directly lower the expected performance on exams. In sum, this evidence simply suggests that attending your classes and completing your work does, in fact, produce better test results.

These findings contribute to the growing body of literature examining educational effectiveness in increasingly digital learning environments while suggesting promising directions for future research. Education literature across multiple disciplines maintains an overarching theme that links attendance to academic success, with cautious focus on the role of technology. Technology can assist in education delivery but has yet to adequately replace all traditional classroom experiences. We approach the use of technology in business statistics course delivery and find that it can serve as a substitute if the student remains vigilant and motivated; however, if given the choice, it is not preferred. As educational technology continues to evolve, understanding the optimal integration of traditional and digital pedagogical methods, while remaining critical of their effects, remains an area for continued investigation.

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Appendix

Table A1
Summary Statistics

Continuous Variable	Obs.	Mean	Std. Dev	Min	Max
Test	203	0.770	0.132	0.358	0.984
Hwscore	203	0.812	0.205	0.003	1
Absences	203	2.172	3.087	0	12
Vabsences	203	1.069	2.202	0	12
GPA	176	3.489	0.390	2.125	4

Indicator Variable	Obs.	Count: 1	Count: 0	Percentage (1)
Abs0	203	91	112	44.83%
Abs1	203	38	165	18.72%
Abs23	203	25	178	12.32%
Abs4plus	203	49	154	24.14%
Vatt	203	90	113	44.33%
Vabs0	203	28	175	13.79%
Vabs1	203	20	183	9.85%
Vabs23	203	19	184	9.36%
Vabs4plus	203	23	180	11.33%
Prereq	176	131	45	74.43%
CreditPT	176	7	169	3.98%
CreditOverload	176	6	170	3.41%
Work	176	130	46	73.86%
Enjoy	176	44	159	25.00%
VChoice	203	25	178	12.32%
VNoChoice	203	65	138	32.02%
Spring2021	203	65	138	32.02%
Fall2021	203	69	134	33.99%
Spring2022	203	69	134	33.99%

Table A2

ANOVA: Test for Semester Differences

Source	Sum of Squares	Df	Mean Square	F	Prob > F
SSB	0.0608	2	0.0304	1.76	0.1747
SSW	3.4567	200	0.0173		
SST	3.5176	202	0.0174		

Bartlett's Test for Equal Variances			
Chi-squared =	1.1503	Prob>Chi-squared =	0.563

Note. This table displays the output for a single-factor ANOVA. Semester is the factor (Spring 2021, Fall 2021, Spring 2022)

Table A3

Comparing Absences for Virtual vs In-person attendance

Group	Obs	Mean	Std. Error
Virtual	90	2.411	0.293
In-person	113	1.982	0.311
Difference		0.429	0.436
t= 0.983		P-val=0.327	

Note. This test for the difference between means is a two-tailed test assuming equal population variances. The variable compared is the average test score over three exams; the hypothesis test is to determine if there is a difference in attendance for students attending virtual vs. in-person.

Table A4

Comparing Test Scores for Virtual vs In-person attendance

Group	Obs	Mean	Std. Error
Virtual	90	0.754	0.014
In-person	113	0.783	0.012
Difference		-0.029	0.019
t=-1.564		P-val=0.0598	

Note. This test for the difference between means is a lower tailed test assuming equal population variances. The variable compared is the average test score over three exams; the hypothesis tested is that the mean test average for virtual attendance will be lower.