# The Other Side of the Coin: A Multivariate Analysis of the Impact of Covid-19 For Face-to-Face Instruction in Post-Secondary Business Education

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*Face-to-face instruction has been studied for decades and yet is ever-changing and still has many challenges that need to be studied. The current work seeks to emphasize the need for study in two areas: 1) comparison of factors that impact face-to-face instruction and 2) impact of major disruptions on face-to-face instruction. Specifically, the current work looks at face-to-face instruction before, during, and after the COVID-19 pandemic to measure the presence of instructional quality gaps. The results significantly impact important metrics measuring student performance based on several factors during this timeframe. Results and future research are discussed.*

*Keywords: scholarship of teaching and learning, face-to-face instruction, Covid-19 impact, instructional quality*

## INTRODUCTION

Research has focused on studying instruction and the relevant factors influencing instruction for many years (citation). Recent research has focused more on modality of instruction (i.e., online/hybrid) and significant events like the recent pandemic (citation). Within the last five years, research has begun studying the interaction's effects between the last two factors, i.e., how the push to online instruction due to pandemic protocols influenced instruction and important instructional metrics (citation, perhaps ours). When the focus of scholarly research shifts, it is important that pertinent and traditional scholarship continues. Specifically, the ability to observe the impact of the recent pandemic on traditional, face-to-face instruction.

Much research has focused on instructional effectiveness for online instruction (e.g., Borup & Evmenova, 2019; Crawford-Ferre &Wiest, 2012; Fish & Gill, 2009) and traditional (face-to-face instruction (citations, particular focus on 2020 or newer). This research has shown that a myriad of factors that impact instruction. Research in online instruction focuses on factors such as competency with tools required for online learning (Osika, Johnson, and Buteau, 2009), prior experience teaching (Fish & Gill, 2009); whereas research in face-to-face instruction has historically focused on teaching style (e.g., Doyle & Rutherford, 1984; Giles, Ryan, Belliveau, De Freitas, & Casey, 2006; Opdenakker & Van Damme, 2006). The crux of both streams of research is the need to study the many important factors that influence effective and efficient instruction. Research illustrates the need for instructors to be organized (e.g., Lang et al., 1993; Sheridan & Kelly, 2010), flexible (e.g., Dowling et al., 2003; Lang et al., 1993; Miller, Risser, & Griffiths, 2013), acknowledgment of differing needs of students by different learning styles (e.g., Rischin, 2002; see Pashler, McDaniel, Rohrer, and Bjork, 2008 for an extensive review), continuous learners themselves, i.e., professional development (e.g., Gulbahar & Kaleioglu, 2015), foster student's interest in the material (e.g., Kalender, 2017), and develop their presence (Reupert, Maybery, Patrick, & Chittleborough, 2009).

The importance of studying these factors is becoming more prevalent as the needs of newer generations of students are changing. While this may be a concerning phenomenon for some instructors, research shows that the increased exposure/interaction to learning needs and the subsequent learning styles leads to increased teaching proficiency (e.g., Fish & Gill, 2009). A component of this is acknowledging that much of increased proficiency in teaching is a result of removing barriers to learning such as easy to follow learning materials (e.g., Godsk, 2006; Rivera and Rice, 2002), instructions that are both clear and specific (e.g., Eiriksdottir & Catrambone, 2011; Hewson et al., 2001; Wright, 1981), and minimization of learning gaps or disruptions (e.g., Spond, Ussery, Warr, & Dickinson, 2022 [authors discuss the topic]; Webster and Hackley, 1997; see Bozkurt et al., 2020 for a thorough review).

It is now five years since the pandemic began and instruction was revolutionized. As such, it is important to ascertain the pandemic's impact on instruction. The current work seeks to help scholars and practitioners better understand this impact on face-to-face instruction in an attempt to better help provide insights for how instructors and institutions of higher education can be better prepared for any future disruptions to traditional teaching practices.

When the pandemic occurred, much focus was placed on moving instruction online and providing resources to faculty and students to make this productive and effective. However, as the pandemic ended, less focus seemed to have been placed on the shift back to face-to-face instruction and its impact on it. In other words, it seems the shift back to face-to-face instruction may have been overlooked or assumed to be a simple process.

The current research measures the success rate of undergraduate business students at a regional, southeastern US university before, during, and after the pandemic. This timeframe is used to better understand the impact of the pandemic on face-to-face instruction as it relates to instructional quality. This work gathered data relating to incongruities in student performance based on the key variables discussed below. This work was exploratory and did not attempt to formulate any hypotheses to not limit the researcher's interpretation of findings as a result of bias (i.e., preconceived notions). As such, the current research follows these Research Questions.

***Research Question 1:*** *Will grades earned by face-to-face students be significantly impacted during the timeframe observed?*

***Research Question 2:*** *Will the available factors (e.g., race, gender, etc.) have a significant impact on instructional quality during the timeframe observed?*

## METHODOLOGY

### Sample

Undergraduate business students in a medium-sized university in the mid-south of the United States were used in the current study. Twenty thousand, two hundred and eleven students were included in the analysis. This sample represents all grades earned on a face-to-face business course between Fall 2018 and Fall 2022.

## Analysis

The focus of the current research was to measure whether the pandemic had a significant impact on face-to-face instruction. Specifically, were the grades received by students significantly different before (Fall 2018-Fall 2019), during (Fall 2020, Spring 2021, and Fall 2021), and after (Fall 2022) the pandemic protocols. Additionally, it was decided to parse out two other *conditions* as these time periods may present a significant difference in grades earned, and not for the reasons we were attempting to measure (Spring 2020 and Summer terms). Spring 2020 presented nuances to the instruction (and grading) since many schools shifted on-campus courses to online before the semester was complete. Summer terms were comprised of mainly courses taught by instructors who had previously taught (and designed) summer courses as well as students who typically *opt-in* to take online courses during that term. This suggests that there may be fruitful differences by not including these periods in the other conditions. Furthermore, these conditions are consistent with other research that focused on the effects that Covid had on online instruction during the same time period (e.g., Authors, 2024)

## Variables

The data utilized in the study came from the institution's unit of *Institutional Research* and, as secondhand data, was mined as such. The independent variables for the analysis were TermCoded (Block 1), SubjectCoded (Block 2), DepartmentCoded (Block 3), Race (Block 4), and Gender (Block 5). The dependent variables for the analysis were A count, B count, C count, D count, F count, I count, W count, P count, Passed count, DWFI count, Final Grade, and GPA. Each variable labeled *count* was determined by the number of students who either earned or did not earn the respective grade/category. GPA was calculated as the gpa for each respective course section included in the analysis. It is important to note two distinctions between variables listed above. First, P count refers to those students earning a grade of P (Pass) while Passed count refers to those students who successfully passed the class. Second, Passed is not the opposite of DWFI as some classes have different grade minimums in order to successfully pass the class (e.g., a D may be a passing grade in some courses whereas a B is in others). This means the inclusion of both DWFI and Passed count will likely provide useful lenses for the impact of the included independent variables.

# RESULTS

All available demographics (i.e., race, gender, etc.) were included in the initial analysis for each dependent variable. All demographics except Race and Gender were insignificant and therefore removed from further analysis.

## A Count

Logistic regression analyzed the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with A count. There was a statistically significant effect for all five predictor variables entered into the model as shown in Table 1.

**TABLE 1**
**A COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | .123 | .012 | 112.883 | 1 | <.001 | 1.131 |
| SubjectCoded | .102 | .006 | 298.575 | 1 | <.001 | 1.108 |
| DepartmentCoded | .062 | .031 | 3.878 | 1 | .049 | 1.064 |
| Race | -.094 | .011 | 71.066 | 1 | <.001 | .910 |
| Gender | .441 | .029 | 232.586 | 1 | <.001 | 1.555 |

### B Count

Logistic regression was used to analyze the TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with B count. There was a statistically significant effect for four of the five predictor variables as shown in Table 2.

**TABLE 2**
**B COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | -.047 | .013 | 13.357 | 1 | <.001 | .955 |
| DepartmentCoded | .201 | .034 | 34.898 | 1 | <.001 | 1.223 |
| Race | -.034 | .012 | 8.153 | 1 | .004 | .966 |
| Gender | -.130 | .031 | 17.053 | 1 | <.001 | .878 |

### C Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with C count. There was a statistically significant effect for all five predictor variables as shown in Table 3.

**TABLE 3**
**C COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | -.079 | .017 | 21.216 | 1 | <.001 | .924 |
| SubjectCoded | -.094 | .009 | 113.463 | 1 | <.001 | .911 |
| DepartmentCoded | -.260 | .048 | 28.965 | 1 | <.001 | .771 |
| Race | .066 | .014 | 21.673 | 1 | <.001 | 1.068 |
| Gender | -.328 | .042 | 61.573 | 1 | <.001 | .720 |

### D Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with D count. There was a statistically significant effect for all five predictor variables as shown in Table 4.

**TABLE 4**
**D COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | -.206 | .033 | 38.323 | 1 | <.001 | .814 |
| SubjectCoded | -.134 | .017 | 66.380 | 1 | <.001 | .874 |
| DepartmentCoded | -.316 | .091 | 11.932 | 1 | <.001 | .729 |
| Race | .107 | .023 | 22.202 | 1 | <.001 | 1.113 |
| Gender | -.398 | .075 | 27.992 | 1 | <.001 | .672 |

### F Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with F count. There was a statistically significant effect for four of the five predictor variables entered into the model as shown in Table 5.

**TABLE 5**
**F COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | -.135 | .029 | 22.152 | 1 | <.001 | .874 |
| SubjectCoded | -.115 | .015 | 60.49 | 1 | <.001 | .891 |
| Race | .192 | .018 | 111.97 | 1 | <.001 | 1.212 |
| Gender | -.518 | .069 | 56.575 | 1 | <.001 | .596 |

### I Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with I count. There was a statistically significant effect for TermCoded and Gender as shown in Table 6.

**TABLE 6**
**I COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | .421 | .151 | 7.812 | 1 | <.01 | 1.523 |
| Gender | .997 | .489 | 4.154 | 1 | <.05 | 2.709 |

### W Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with W count. There was a statistically significant effect for all five predictor variables as shown in Table 7.

**TABLE 7**
**W COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | .061 | .036 | 2.848 | 1 | <.10 | 1.063 |
| SubjectCoded | -.082 | .020 | 16.554 | 1 | <.001 | .921 |
| DepartmentCoded | -.240 | .112 | 4.621 | 1 | <.04 | .786 |
| Race | .110 | .029 | 14.272 | 1 | <.001 | 1.116 |
| Gender | -.214 | .095 | 5.089 | 1 | <.03 | .807 |

### P Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with P count. There was a moderately, statistically significant effect for DepartmentCoded as shown in Table 8.

**TABLE 8**
**P COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| DepartmentCoded | -.399 | .238 | 2.812 | 1 | <.10 | .671 |

### Passed Count

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with Passed count. There was a statistically significant effect for all five predictor variables as shown in Table 9.

**TABLE 9**
**Passed COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | .057 | .023 | 6.377 | 1 | <.02 | 1.058 |
| SubjectCoded | .105 | .012 | 76.471 | 1 | <.001 | 1.111 |
| DepartmentCoded | .149 | .065 | 5.330 | 1 | <.03 | 1.161 |
| Race | -.176 | .016 | 124.149 | 1 | <.001 | .839 |
| Gender | .408 | .056 | 52.912 | 1 | <.001 | 1.504 |

### DWFI

Logistic regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with DWFI count. There was a statistically significant effect for all three predictor variables entered into the model as shown in Table 10.

**TABLE 10**
**DWFI COUNT: SIGNIFICANT FINDINGS ONLY**

| | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|
| TermCoded | -.119 | .019 | 38.067 | 1 | <.001 | .887 |
| SubjectCoded | -.125 | .010 | 154.459 | 1 | <.001 | .882 |
| DepartmentCoded | -.218 | .054 | 16.019 | 1 | <.001 | .804 |
| Race | .162 | .014 | 136.034 | 1 | <.001 | 1.175 |
| Gender | -.429 | .047 | 84.494 | 1 | <.001 | .651 |

### Final Grade

Ordinal regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with Final Grade Earned. There was a statistically significant effect for multiple predictor variables as shown in Table 11.

**TABLE 11**
**FINAL GRADE EARNED: SIGNIFICANT FINDINGS ONLY**

| | Estimate | S.E. | Wald | df | Sig. |
|---|---|---|---|---|---|
| TermCoded 1 - Before | .498 | .047 | 112.865 | 1 | <.001 |
| TermCoded 2 – During | .295 | .047 | 38.700 | 1 | <.001 |
| TermCoded 3 - After | .282 | .052 | 29.627 | 1 | <.001 |
| TermCoded 4 - Summer | -.790 | .160 | 24.589 | 1 | <.001 |
| SubjectCoded 3 - Finance | -.835 | .093 | 81.045 | 1 | <.001 |
| SubjectCoded 4 – Information Systems | -1.035 | .096 | 117.532 | 1 | <.001 |
| SubjectCoded 5 – Marketing | -1.182 | .092 | 165.423 | 1 | <.001 |
| SubjectCoded 6 – Management | -.760 | .089 | 72.229 | 1 | <.001 |
| SubjectCoded 7 – Political Science | -1.288 | .090 | 204.011 | 1 | <.001 |
| SubjectCoded 8 – Business Administration | -1.843 | .139 | 174.608 | 1 | <.001 |
| SubjectCoded 9 – Business Law | -.726 | .107 | 46.011 | 1 | <.001 |

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|---|---|---|---|---|---|
| SubjectCoded 10 – International Studies | -1.130 | .196 | 33.235 | 1 | <.001 |
| Race 1 - White | -.495 | .076 | 42.827 | 1 | <.001 |
| Race 2 – African American | .528 | .084 | 39.244 | 1 | <.001 |
| Race 4 - Asian | -.795 | .163 | 23.898 | 1 | <.001 |

**GPA**

Ordinal regression was used to analyze the relationship between TermCoded, SubjectCoded, DepartmentCoded, Race, and Gender with Final Grade Earned. There was a statistically significant effect for multiple predictor variables as shown in Table 12.

**TABLE 12**
**GPA: SIGNIFICANT FINDINGS ONLY**

| | Estimate | S.E. | Wald | df | Sig. |
|---|---|---|---|---|---|
| TermCoded 1 - Before | -.504 | .047 | 115.490 | 1 | <.001 |
| TermCoded 2 – During | -.298 | .047 | 39.481 | 1 | <.001 |
| TermCoded 3 - After | -.283 | .052 | 29.936 | 1 | <.001 |
| TermCoded 4 - Summer | .790 | .160 | 24.485 | 1 | <.001 |
| SubjectCoded 3 - Finance | -.835 | .093 | 81.045 | 1 | <.001 |
| SubjectCoded 4 – Information Systems | -1.035 | .096 | 117.532 | 1 | <.001 |
| SubjectCoded 5 – Marketing | -1.182 | .092 | 165.423 | 1 | <.001 |
| SubjectCoded 6 – Management | -.760 | .089 | 72.229 | 1 | <.001 |
| SubjectCoded 7 – Political Science | -1.288 | .090 | 204.011 | 1 | <.001 |
| SubjectCoded 8 – Business Administration | -1.843 | .139 | 174.608 | 1 | <.001 |
| SubjectCoded 9 – Business Law | -.726 | .107 | 46.011 | 1 | <.001 |
| SubjectCoded 10 – International Studies | -1.130 | .196 | 33.235 | 1 | <.001 |
| Race 1 – White | .497 | .076 | 43.037 | 1 | <.001 |
| Race 2 – African American | -.536 | .084 | 40.341 | 1 | <.001 |
| Race 4 - Asian | .796 | .163 | 23.936 | 1 | <.001 |

**Additional Analysis**

A Kruskal-Wallis test was conducted to determine whether there is an effect of department a course was housed and GPA. The results indicate a significant difference, $\chi2(1) = 139.925$, $p = <0.001$. This indicates a need to reject the null hypothesis that the distribution of GPA is the same across departments.

A Kruskal-Wallis test was conducted to determine whether there is an effect of the subject a course covered and GPA. The results indicate a significant difference, $\chi2(10) = 1394.241$, $p = <0.001$. This indicates a need to reject the null hypothesis that the distribution of GPA is the same across subjects.

A Kruskal-Wallis test was conducted to determine whether there is an effect of term a course was taught and GPA. The results indicate a significant difference, $\chi2(4) = 189.472$, $p = <0.001$. This indicates a need to reject the null hypothesis that the distribution of GPA is the same across terms a face-to-face course was taught.

A Kruskal-Wallis test was conducted to determine whether there is an effect of race and GPA. The results indicate a significant difference, $\chi2(6) = 523.701$, $p = <0.001$. This indicates a need to reject the null hypothesis that the distribution of GPA is the same across race.

A Kruskal-Wallis test was conducted to determine whether there is an effect of gender and GPA. The results indicate a significant difference, $\chi2(1) = 273.833$, $p = <0.001$. This indicates a need to reject the null hypothesis that the distribution of GPA is the same across gender.

## DISCUSSION AND CONCLUSION

Consistent with our research on the impact of the pandemic on online instruction (see Authors, 2024), the current results indicate statistically significant effects for numerous predictor variables. These findings suggest a need for continued research into the impact of significant events on instructional effectiveness. In other words, scholarship of teaching and learning should continue to assess the impact that disruptive and/or revolutionary events (e.g., pandemic) have on important instructional metrics. Most importantly, the current findings suggest an increased need to focus on the impact of instructional metrics after the events are over and instruction *resumes its normal state*.

The results provided suggest weaknesses of this study and a need for careful and thoughtful interpretation. The current results focus on answering questions surrounding *what* as opposed to *why*; therefore, any suppositions must be interpreted cautiously. Because this is one of few research projects identified by the authors that measures such an impact on instructional metrics focusing on a return to *normalcy* in instruction, further research is needed.

Additionally, it must be acknowledged that the sample of the current research may have some limited generalizability. It is possible that non-measured demographic, socio-cultural, psychosocial/psychographic, or other factors may have influenced the results. Both of these weaknesses suggest a need for additional research to ascertain the potential for impact on the stated findings.

Future areas of study that may prove beneficial center around the utilization of other predictor variables (e.g., class related [time of day, length of class], availability of support services [tutoring, supplemental instruction]), other instructional metrics aside from those studied here as dependent variables (e.g., progression, retention, graduation rates, placement), and mitigating/exacerbating factors (e.g., demographics not measured here). Additionally, measuring how long these effects occur and if there are ways to reduce them would be prudent. In other words, how long instruction is impacted due to such an event and what can be done by institutional actors (i.e., administrators, staff, and faculty) to reduce this time. Future research should focus on providing foundational knowledge dissemination to institutional actors that can be applied broadly (across student groups [e.g., demographics]) as well as narrowly (i.e., focusing on learning gaps specific to particular student groups).

The current work emphasizes the need for continued research on how to best provide high quality instruction, before, during, and after major (or minor) events in post-secondary institutions. It is the position of the authors that the way instructors conceptualize instruction is changing to accommodate students' needs and respond to significant shifts (i.e., like the pandemic). Therefore, research must continue to identify the best methods for effectively and efficiently delivering instruction to maximize learning. The authors hope that these findings will help with this needed goal.

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