



# Negative Impacts From the Shift to Online Learning During the COVID-19 Crisis: Evidence from a Statewide Community College System

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VERSION: September 2020

Suggested citation: Bird, Kelli A., Benjamin L. Castleman, and Gabrielle Lohner. (2020). Negative Impacts From the Shift to Online Learning During the COVID-19 Crisis: Evidence from a Statewide Community College System. (EdWorkingPaper: 20-299). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/gx68-rq13>

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**Abstract**

The COVID-19 pandemic led to an abrupt shift from in-person to virtual instruction in Spring 2020. Using a difference-in-differences framework that leverages within-course variation on whether students started their Spring 2020 courses in person or online, we estimate the impact of this shift on the academic performance of Virginia's community college students. We find that the shift to virtual instruction resulted in a 6.7 percentage point decrease in course completion, driven by increases in both course withdrawal and failure. Faculty experience teaching a course online did not mitigate the negative effects of moving to virtual instruction.

**Acknowledgements**

We are grateful for our partnership with the Virginia Community College System and in particular Dr. Catherine Finnegan. We thank Alex Smith for valuable conversations and feedback. Any errors are our own.

## **Introduction**

The COVID-19 health crisis has led to one of the largest disruptions in the history of American higher education. Beginning in March 2020, tens of millions of college students who were enrolled in in-person courses abruptly had to shift to online learning. While some course instructors had experience teaching online, many faculty had to pivot into online teaching for the first time, often using relatively rudimentary technology (e.g. Zoom conferencing) to deliver instruction and engage students.

Prior research demonstrates that health and economic disruptions can have substantial effects on students' achievement and educational attainment. For instance, children born during the 1918 Influenza Pandemic received significantly fewer years of education as compared to their older siblings (Parman, 2015). More recently, students exposed to hotter learning environments through a combination of extreme temperatures and insufficient air conditioning in schools, perform worse academically (Park et al, 2020). The economic downturn from the Great Recession reduced the math and English Language Arts achievement of elementary and middle-aged students (Shores and Steinberg, 2017), and negative economic shocks arising from local area job losses during adolescence can have long-term educational and mental health implications, particularly among lower-income populations (Ananat et al, 2017).

While several papers demonstrate that economic downturns affect college enrollments, institutional expenditures, and students' choice of college majors (Barr and Turner, 2013; Barr and Turner, 2015; Betts and McFarland, 1995; Ersoy, 2020; Long, 2014), there has been less research on how downturns affect student success in higher education. Descriptively, students who initially enrolled in college during the Great Recession were less likely to graduate

compared to earlier and more recent cohorts (Shapiro et al, 2016); however, this trend is likely driven in large part by compositional changes in the student population during this time.

There are various reasons why the broader COVID-19 crisis and the ensuing abrupt shift to online learning may have led to worse negative outcomes for students. Based on a survey administered to college students in April 2020, Aucejo et al (2020) report that 13% of students report delaying graduation and 40% lost a job, job offer or internship due to the pandemic. Low-income students were much more likely to report having delayed graduation. Additionally, students may have been dealing directly with health challenges associated with COVID-19 infection, or have had family members who became sick. Many students were among the tens of millions of Americans who lost their jobs during Spring 2020, or may have had family members lose employment; the stress of these job losses may have reduced the cognitive bandwidth and attention students could devote to class (Shah, Shafir, and Mullainathan, 2015). Increased child care responsibilities may have detracted from time adult students could invest in their college course work.

Research to date on the efficacy of online versus in-person learning suggests that students tend to fare worse in online classes. Randomized studies which assigned students to either in-person or online learning have shown online learning to have negative impacts on course performance (Figlio, Rush and Yin 2013; Alpert, Couch and Harmon 2016). Additional studies which employ quasi-experimental methods find that online learning decreases course completion, final grade and enrollment persistence, and increases in course repetition (Xu and Jaggars 2011; Xu and Jaggars 2013; Hart, Friedman, and Hill 2016; Bettinger et al. 2017).

At the same time, there are several reasons why the sudden shift to online learning may not have negatively affected student outcomes, or why the magnitude of this effect may have been not as profound as some might expect. For instance, the combined shift to online learning, remote work, and even job loss may have substantially increased the time available to students to invest in their courses. Forward-thinking students who anticipate the importance of additional training or education in a potentially transformed post-COVID economy may have renewed their efforts toward earning a credential. Students may have had additional access to asynchronous course materials to support their learning and exam preparation. Many colleges implemented emergency grading policies which could have reduced the effort required from students to pass their courses and make further progress towards their degree. Since the shift to online courses happened well into the Spring 2020 semester, negative impacts on student learning could also be mitigated by the opportunity to create relationships in-person prior to the switch and therefore had a higher degree of “social presence”, which is associated with better outcomes in online learning (Liu, Gomez, and Yen, 2009). Finally, most of the prior research on the efficacy of online learning has estimated local treatment effects or average treatment effects (from RCTs) that may not generalize beyond the experimental setting. These studies may not capture the relative impact of online versus in-person education in the COVID-19 context, which induced an effectively population-level shift to online education.

Isolating the effect of the abrupt shift to online learning on student outcomes is challenging, given the lack of variation in the timing over which most colleges and universities shifted to online, and because of the parallel health, economic, and child care challenges that could have also affected students’ academic success. In this paper, we use a

difference-in-differences estimation strategy, exploiting variation in whether students were enrolled in in-person or online classes at the start of the Spring 2020 semester, to produce the first causal estimates we know of on the impact of the sudden shift to online learning as a result of COVID-19. More specifically, we compare changes in course completion rates along two dimensions: (1) in-person versus online courses; (2) Spring 2020 versus recent comparison terms. We classify students enrolled in in-person courses at the start of the Spring 2020 as “treated”, i.e. they experienced the sudden shift to virtual instruction. We estimate our models with course fixed effects to respectively control for differences in student outcomes occurring across courses.

We estimate the impact of abruptly shifting to online using student-level data from the Virginia Community College System, which enrolls approximately 250,000 students per year, on numerous dimensions is broadly representative of open access institutions across the country, and which had a broad slate of online course offerings prior to COVID-19.

Our analyses yield several primary results. The move from in-person to virtual instruction resulted in a 6.7 percentage point decrease in course completion. This translates to a 8.5 percent decrease when compared to the pre-COVID course completion rate for in-person students of 79.4 percent. This decrease in course completion was due to a relative increase in both course withdrawal (5.2 pp) and course failure (1.4 pp). We find very similar point estimates when we estimate models separately for instructors teaching both modalities versus only one modality, suggesting that faculty experience teaching a given course online does not mitigate the negative effects of students abruptly switching to online instruction. The negative impacts are largest for students with lower GPAs or no prior credit accumulation.

Our paper makes several contributions. First, our analyses are the first we are aware of that estimate the causal effect of the abrupt shift to online instruction stemming from the COVID-19 crisis on students' academic performance in the Spring 2020 semester. Our results make concrete the tradeoff in terms of student performance from abruptly shifting from in-person to online instruction that may arise if, during future semesters, higher education administrators need to cancel in-person classes because of COVID-19 resurgences or other future disruptions. The diminished performance in online courses that we estimate could be weighed alongside the costs of continuing in person, such as increased health risks to students, faculty, or staff, or the cost of investments in personal protective equipment. Our results moreover indicate that educators may need to invest additional resources to structure online learning environments that more closely resemble in-person instruction, such as having synchronous class meeting times, and building in additional opportunities for faculty and student engagement.

Second, we make the novel contribution of demonstrating that declines in student performance stemming from disruptions are not solely a function of economic, health, or familial challenges that students experience outside of the classroom, or a function in overall shifts in institutional resources, and are also influenced by changes in course delivery and pedagogy induced by large-scale disruptions. Finally, our paper builds on a growing body of research demonstrating mixed and often negative impacts of online education compared with similar programs of study offered in-person, and extends prior research by demonstrating the negative effects of online education in the context of a much broader shift to virtual learning.

## **Background**

### *Virginia Community College System*

The Virginia Community College System (VCCS) is comprised of 23 colleges across the Commonwealth, and in the 2018-19 academic year enrolled 228,135 students.<sup>1</sup> The population that VCCS serves is similar to other community colleges and broad access institutions nationwide. For example, the demographic characteristics of VCCS students is similar to the broader community college landscape; at similar institutions, 49% of students are White or Asian and 37% are underrepresented minorities (URM). VCCS serves a slightly higher percentage of White and Asian students (58%) with 33% URM. Thirty-three percent of students at similar institutions receive Pell grants, compared to 29% at VCCS. The graduation rate in 150% of expected time to completion is 29% at similar institutions and 32% at VCCS.

### *VCCS online course offerings*

Online courses are a well established practice at VCCS, dating back to 1996. Online instruction can take different forms, from “interactive classroom video” which consists of synchronous two-way video sessions between instructors and students, to fully asynchronous administered through a learning management system -- with the majority of VCCS online courses being offered through the latter.

In the 2008-2009 academic year, 38.5% of the student population was enrolled in online learning, either exclusively or coupled with in-person courses.<sup>2</sup> By the 2018-2019 academic year, this increased to 55.9%, with 4,235 unique courses and 12,122 individual course sections offered

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<sup>1</sup> Source: <https://www.vccs.edu/about/#statistics>

<sup>2</sup> Source: <https://www.vccs.edu/about/#statistics>

online. VCCS offers a wide range of courses online. In the 2018-2019 academic year, 64% of courses offered online were 100-level or lower (introductory courses) and 36% of courses were 200-level courses. 110 unique subjects were taught online in 2018-2019.

### *Changes within VCCS due to COVID*

In response to the COVID-19 crisis and the Governor's declaration of a state of emergency on March 12, 2020, VCCS courses which started the Spring 2020 semester in-person were moved to virtual instruction. The switch to virtual happened on March 18, 2020 and courses remained virtual through the end of the Spring semester on May 11, 2020. On March 24, the chancellor of VCCS announced the system would switch to a Pass/No Pass emergency grading system for Spring 2020. The emergency grading system consisted of four grading options: P+, indicating the course credit is transferable and counts towards VCCS degree requirements; P-, indicating the course credit is not transferable but still counts towards VCCS degree requirements; incomplete; and withdrawal. While the emergency grading system was the default, students had the option of opting-in to receiving a traditional letter grade (A-F). In practice, 71% of students opted-in to the traditional grading scale for at least one of their courses.

## **Empirical Strategy**

### *Data*

Data for this study come from systemwide administrative records for students enrolled in credit-bearing coursework at a VCCS college, beginning in Fall 2000. For each term in which a particular student was enrolled, these records contain detailed academic information including

the program of study the student was pursuing (e.g. an Associate of Arts & Sciences in Liberal Arts); which courses and course sections the students were enrolled in (e.g. ENG 111 taught by Instructor X, MWF 9-10am), the grades they earned, and any VCCS credentials awarded. The data also contain information about each course and course section, including the modality of instruction (online, in-person), an instructor-specific identifier, and basic instructor characteristics (sex, gender, full-time versus adjunct status). We also observe basic demographic information about each student, as well as National Student Clearinghouse matches starting in 2005.

### *Analytic Samples*

Our analytic sample consists of student x course level observations from the five most recent Spring terms (2016 through 2020). When we refer to a course, we treat the same general course taught at different colleges as separate courses; for example, we treat ENG 111 at Piedmont Virginia Community College as a distinct course from ENG 111 taught at Northern Virginia Community College. We focus on Spring terms because the population of VCCS students varies meaningfully between Spring, Summer, and Fall terms due to differential student attrition. We exclude observations (in both Spring 2020 and the prior comparison terms) corresponding to:<sup>3</sup>

- Dual enrollment students. We expect that the transition from in-person to virtual instruction may have been operationalized in a significantly different manner for dual

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<sup>3</sup> We also exclude hybrid courses, which are a small share of VCCS course offerings and are defined as “the combination of face-to-face and electronic delivery where 50-99% of the course content is electronically delivered”. When we instead classify hybrid courses as online and include those observations in our sample, our results are similar. We also exclude observations representing a student auditing a course, although these are very rare.

enrollment classes, as many of these courses are taught in high schools by high school faculty. In addition, the vast majority of dual enrollment courses are offered in-person.

- Courses offered outside the full session. While the majority of VCCS courses are offered within the full session, which lasts 15 or 16 weeks and spans January through May (with exact start and end dates depending on the college), some courses are offered during shorter sessions. The shorter sessions during the first half Spring 2020 were largely or entirely unaffected by COVID because they ended during March 2020, while the shorter sessions during the second half of Spring 2020 were fully online, and some students may have decided not to attempt these courses due to COVID.
- Developmental courses. The vast majority of developmental courses, which are not credit-bearing, are offered during the abbreviated sessions. Additionally, many VCCS colleges have made meaningful changes to their developmental course policies in recent years, resulting in significant decreases in the share of students required to take developmental courses.

After these restrictions, our overall sample contains 1,100,087 student x course observations, corresponding to 295,515 unique students.

We further restrict the sample to include courses that were taught both online and in-person during Spring 2020 and were taught both online and in-person during at least one of the pre-COVID comparison terms. Given that online course offerings changed within our sample (i.e. some courses were newly offered online during the 2019-20 academic year which had previously only been offered in-person), our results would be biased if student outcomes differed

meaningfully in the newly offered courses compared to those that have been offered for longer periods. This restriction also removes all courses that could not move to virtual instruction during Spring 2020 (e.g. clinical courses as part of Nursing rotations); no students enrolled in Spring 2020 received credit for such courses. We refer to the analytic sample with this restriction imposed as the “within-course” sample.<sup>4</sup> Within Spring 2020, 37% of student x course observations and 46% of unique students from the overall sample are present in the within-course sample.

In supplementary analyses, we further limit the sample to either: (1) courses taught by the same instructor, both online and in-person, during both Spring 2020 and at least one earlier term, which we refer to as the “within-instructor” model; and (2) courses taught by instructors who have only ever taught that course via one modality, online or in-person, during both Spring 2020 and at least one earlier term, which we refer to as the “across-instructor” model. Both the within-instructor and across-instructor samples are subsets of the within-course sample, so that we are still focused on courses that are offered both online and in-person during Spring 2020 and at least one comparison term.

### *Difference-in-differences models*

Our primary empirical specification is a difference-in-differences model with course fixed effects, represented in the following regression equation:

$$y_{scit} = \beta_0 + \beta_1 InPerson_{scit} + \beta_2 COVID_t + \beta_3 COVID_t * InPerson_{scit} +$$

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<sup>4</sup> We also attempted a student-level model where the main outcome of interest was the share of attempted credits the student completed within a particular term. However, this student-level model violated the parallel trends assumption of the difference-in-differences model.

$$+ \beta_4 X_{sct} + \beta_5 W_{it} + \beta_6 Z_i + CourseFE_c + \varepsilon_{sict} \quad (1)$$

where  $y_{sict}$  is the course outcome for student (s) in course (c) taught by instructor (i) in term (t).

Our primary outcome of interest is course completion; we set this binary outcome to one if the student received a grade of A, B, C, D, P+, or P- and to zero if otherwise. We also estimate the model separately for the outcomes of whether the student withdrew from or failed the course.

We are unable to use the outcome of grade points (e.g. A = 4.0), because there are no grade points assigned to the P+ or P- grades as part of VCCS's emergency grading policy.  $InPerson_{sct}$

is an indicator equal one for if the student was enrolled in an in-person section of the course, and zero for online;  $COVID_t$  is an indicator equal to one for Spring 2020 and zero for the

comparison terms.  $X_{sct}$  is a set of student-level covariates to control for basic demographics, program of study fixed effects, academic experiences at VCCS prior to term  $t$  (number of credits accumulated prior, cumulative GPA, etc), prior academic experiences at non-VCCS colleges prior to term  $t$ , and enrollment count of the section of course  $c$  in which the student was enrolled.

$W_{it}$  is a set of time-variant instructor-level covariates that includes tenure at VCCS (measured in

number of terms as a VCCS instructor since Spring 2008, which is the first term during which

we reliably observe the instructor-specific identifier), and full-time versus adjunct status;  $Z_i$  is a

set of time-invariant instructor-level covariates that includes sex and race. While we treat the

data as a repeated cross section, students can appear in multiple terms in the data. Therefore, we

cluster the standard errors at the student level. The difference-in-differences estimate ( $\beta_3$ )

measures the impact of the move from in-person to virtual instruction on course completion.

We also estimate a within-instructor model with instructor x course fixed effects, restricting the sample to instructors who taught course  $c$  both online and in-person during Spring 2020 and at least one comparison term:

$$y_{scit} = \beta_0 + \beta_1 InPerson_{sct} + \beta_2 COVID_t + \beta_3 COVID_t * InPerson_{scit} + \beta_4 X_{it} + \beta_5 W_{st} + Instructor \times Course FE_{sc} + \varepsilon_{scit} \quad (2)$$

Finally, we estimate an across-instructor model, which uses the same equation (1) shown above, but restricts the sample to instructors who taught course  $c$  during Spring 2020 and at least one comparison term, but who only taught the course via one modality, in-person or online.

## Results

### *Summary statistics*

In Table 1, we present summary statistics for select student-, course-, and instructor-level characteristics. We compare this information for the overall sample (students who meet the initial restrictions outlined above) and within-course sample to demonstrate how our main analytic sample differs from the wider population of VCCS students in full-session, college-level, credit-bearing courses. All the information shown in Table 1 is measured as of Spring 2020; the patterns are very similar when considering the four earlier comparison terms.<sup>5</sup>

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<sup>5</sup> We focus on Spring 2020 for two reasons: (1) students may appear across multiple terms within the sample; since some of the student-level characteristics are time dependent, we need to choose one term; (2) the samples are restricted to courses which were definitely offered in Spring 2020, but not necessarily in each of the comparison terms.

Comparing the first two columns of Panel A, we see that students in the within-course sample are slightly younger, more female, more White and Black and less Hispanic and Asian than students in the overall sample. Within-course sample students have similar academic histories as students in the overall sample, with slightly lower cumulative GPAs and fewer accumulated credits, and slightly more likely to have previous experience taking online courses at VCCS. The most notable student-level differences are that within-course students are more likely to be pursuing a Liberal Arts or other transfer-oriented associate degree program, and less likely to be pursuing applied or vocational/technical programs of study. This pattern is indicative of differences across programs of study in availability of online programming. As mentioned above, the within-course sample includes 46% all unique students from the overall sample, meaning nearly half of all students in the overall sample enrolled in at least one course that was offered both online and in-person in Spring 2020 and during at least one comparison term.

The last two columns of Panel A compare the characteristics of students in the within-course sample who were enrolled in in-person versus online courses. Online students are older, are more likely to be female or White, and have higher GPAs and more credits accumulated. Not surprisingly, online students are 50% more likely to have previously taken an online course at VCCS, and have attempted a higher share of previous credits online. Finally, online students are slightly more likely to be pursuing applied degree and certificate programs.

Panel B of Table 1 compares the characteristics of the courses represented in the overall versus within-course sample. Out of 4,722 courses offered in Spring 2020 meeting our overall sample criteria, only 663 courses (14%) meet the within-course sample criteria, though as we note above the sample accounts for 47% of students in the overall sample. The within-course

sample contains a larger share of 100-level courses (versus 200-level), and are courses with significantly higher levels of enrollment. The within-course sample also includes a larger share of courses of “general education” courses: Math, English, History, and Biology courses make up 40% of the within-course sample, compared to 15% of the overall sample. Because each course in the within-course sample must be offered both in-person and online, the only differences in the last two columns in Panel B are for in-person versus online enrollment. We see that in the average course more students enroll in the in-person version, although in-person sections tend to be slightly smaller.

Panel C compares the instructor-level characteristics across the two samples. Other than instructors in the within-course sample having a slightly longer tenure, the two samples are very similar in terms of sex, race/ethnicity, and full-time (versus adjunct) status. Over one-third of unique instructors in the overall sample (n=4,610) are represented in the within-course sample (n=1,689). The last two columns compare the characteristics of instructors in the within-course sample who taught in-person versus online courses; note that 381 instructors taught both in-person and online courses and are thus represented in both columns. Online instructors are more likely to be female, are less racially diverse, are more likely to be full-time, and have longer tenures, compared to in-person instructors.

Overall, the summary statistics for the within-instructor and across-instructor samples look quite similar to the within-course samples, with two notable exceptions. First, compared to the within-course sample, instructors in the within-instructor sample are twice as likely to be full-time (81.5% versus 40.6%) and have longer tenures at VCCS (29 versus 23 terms). However, the across-instructor sample looks quite similar to the within-course sample. Second,

the number of students, courses, and instructors represented in the within-instructor model is significantly lower: within Spring 2020, there are 12,343 unique students, 238 unique courses, and 232 unique instructors represented in the within-instructor model. The sample reduction is less stark for the across-instructor sample, which contains 26,913 unique students, 525 unique courses, and 1,099 unique instructors from Spring 2020.

### *Grade distribution*

Figure 1 shows the distribution of grades for student x course observations in the within-course sample across two dimensions: (1) online versus in-person courses; and (2) Spring 2020 (the COVID impacted term) versus Spring 2019 (the most recent pre-COVID comparison term).<sup>6</sup> The pre-COVID distribution of grades for online students is more concentrated at the tails, with a larger share of online students earning either As or Fs compared to in-person. Online students were more likely to withdraw from a course pre-COVID. Both of these patterns translate to a lower pre-COVID course completion for online versus in-person observations. There is a significant reduction in failing grades and a significant increase in withdrawals for both online and in-person students in Spring 2020. The decrease in failing grades is likely due to a combination of positive selection into the A-F scale, as well as more lenient grading practices by VCCS instructors. The grades P+ and P- are only populated during Spring 2020 as part of VCCS's emergency grading policy. The higher share of P+/P- grades among in-person observations indicate that a slightly lower share of in-person opted out of the emergency grading policy and into the A-F scale. Overall, when comparing Spring 2019 to Spring 2020 the

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<sup>6</sup> This plot looks very similar when using earlier Spring comparison terms and for the within-instructor and across-instructor samples.

relatively larger reduction in failing grades and the relatively smaller increase in course withdrawals for online students compared to in-person students suggest that the shift from in-person to virtual instruction led to lower rates of course completion; we show this explicitly within our difference-in-differences regression framework below.

### *Event studies*

The key identifying assumption for our difference-in-differences model is parallel trends in the pre-COVID outcomes for the in-person and online observations. In this context, the parallel trends assumption is that the differences in outcomes between online and in-person students were stable in all the pre-COVID periods and would have remained consistent in the Spring 2020 term were it not for the shock of COVID. We show that our approach satisfies the parallel trends assumption by presenting an event study, based on a slightly adjusted version of equation (1):

$$\begin{aligned}
 Outcome_{sict} = & \gamma_0 + \gamma_1 Spring2016_t + \gamma_2 Spring2017_t + \gamma_3 Spring2018_t + \gamma_4 Spring2020_t + \gamma_5 InPerson_{sct} \\
 & + \gamma_6 Spring2016_t * InPerson_{sct} + \gamma_7 Spring2017_t * InPerson_{sct} + \gamma_8 Spring2018_t * InPerson_{sct} + \\
 & + \gamma_9 Spring2020_t * InPerson_{sct} + \gamma_{10} X_{it} + \gamma_{11} W_{st} + \gamma_{12} Z_s + CourseFE_c + \varepsilon_{sict} \quad (3)
 \end{aligned}$$

Note that we exclude the terms  $Spring2019_t$  and  $Spring2019_t * InPerson_{sct}$  from the regression model so that Spring 2019 serves as the reference term. Therefore, in order for the

parallel trends assumption to be satisfied, the estimates of  $\gamma_6$ ,  $\gamma_7$ , and  $\gamma_8$  should all be statistically indistinguishable from zero. Figure 2 shows this to be the case for our main outcome of course completion for the within-course model (Panel A), the within-instructor model (Panel B), and the across-instructor model (Panel C). We observe very similar pre-COVID differential trend estimates for our alternative outcomes of course failure or course withdrawal.

A separate identifying assumption of the difference-in-difference approach is that there was no differential sorting of students due to the onset of “treatment”. However, given the sudden and unanticipated nature of the COVID crisis during March 2020, when the full session courses were nearing the mid-term mark and well past the date when students could unregister for courses without receiving a “W” grade, differential sorting would be very unlikely. Still, we confirm this by estimating equation (3) using student characteristics in place of the outcome variable. Overall, these results confirm that there was no differential sorting of students. We do see some differential trends -- specifically, a growing age gap between in-person and online students, and a differential trend in whether students were previously enrolled online -- but these differences are small in magnitude and most likely represent overall trends in which types of students were choosing to enroll online. We control for these and other student characteristics in the regression model.

#### *Impact estimates of the shift to online learning*

We present our main results for the within-course model in Table 2, Panel A. Column (1) shows an estimated 6.7 percentage point decrease in course completion due to the shift from in-person to online instruction. Relative to the course completion rate among in-person

observations in the pre-COVID comparison terms of 79.4%, this point estimate translates to a 8.5% decrease. Columns (2) and (3) show that this reduction in course completion is primarily driven by a large increase in course withdrawals (5.1 pp, 62% increase relative to pre-COVID mean), but also by a modest increase in course failure (1.4 pp / 11.6% increase). Particularly given that students had to opt-in to the traditional grading scale in order to receive an “F”, this impact on course failure suggests that the shift to virtual instruction had a meaningful negative impact even on those students who were confident enough in their ability to navigate online coursework that they actively opted out of the emergency grading policy.

Panels B and C of Table 2 present the same results for the within-instructor and across-instructor models, respectively. Despite the differences in these two samples in instructors’ experience teaching the same course across modalities, we find very similar impact estimates. We even find a slightly larger impact when the sample is restricted to instructors who taught both online and in-person (7.1 pp / 8.8% decrease) compared to those who taught only one modality (6.3 pp / 7.9% decrease). The consistency of the impact estimates across our three models suggest that instructor familiarity with online teaching was not able to mitigate the negative impact for in-person students. Instead, the negative impacts on student outcome appear to be driven by struggles students had shifting to the online learning environment.

We also estimate a number of alternative specifications. First, we limit the sample to students who were either enrolled fully online or fully in-person. We find very similar results (7.2 pp / 9.3% decrease) which are not statistically distinguishable from the main results in Table 2, suggesting that in-person students still struggled with the transition to online even if they had concurrent experience with online coursework. Second, when we classify hybrid courses as

online and include the corresponding observations in the sample, we find a smaller impact estimate (4.5 pp / 5.6% decrease; statistically distinguishable from the main results); this is intuitive, as hybrid courses also experienced some disruption from the shift to all virtual instruction, although not at the same level as the fully in-person courses. Third, when we include Fall terms in the pre-COVID comparison group, and have the pre-COVID comparison window start at Spring 2018, we again find a smaller impact estimate (4.9 pp / 6.1% decrease; statistically distinguishable from the main results). We hypothesize that this difference is driven by variability in the student population between Fall and Spring terms. Due to the traditional academic calendar year and relatively low rates of Fall-to-Spring retention at community colleges, students enrolled in Spring terms are on average higher performing and have higher baseline rates of course completion.

Finally, we test for differential impacts across student subgroups according to prior academic history and basic demographic characteristics. Table 3 shows the impact estimates on course completion for the within-course model, with each column showing the results from a separate regression with the sample limited to students in the particular subgroup listed in the column heading. We observe the largest impacts for students with a baseline GPA in the bottom third (9.8 pp / 15.4%), compared to students with GPAs in the top third (3.3 pp / 3.6%). Similarly, we observe significantly larger impacts for students with no credit accumulation (8.8 pp / 12.6%) compared to students who had previously earned at least 30 credits (5.4 pp / 6.2%). These first two comparisons show that higher performing and more experienced students were less impacted by the switch to virtual instruction, compared to lower performing and less experienced students. This result is in line with prior research that found random assignment to a

hybrid course with an online component led to worse outcomes for lower-performing students but had no negative impact among higher-performing students (Joyce et al, 2015). One explanation is that higher performing students typically have better self-regulatory behaviors, which are thought to be particularly important for success in an online learning environment (see Li et al, 2020 for a thorough review). We also observe more negative impacts for male students, though do not find differential effects by age or race/ethnicity.. These subgroup patterns are similar for the within-instructor and across-instructor models (results not shown).

## **Discussion**

Using a well-identified estimation strategy, we demonstrate that the abrupt shift to online learning as a result of the COVID-19 crisis led to a meaningful decrease in course completion among community college students in Virginia. Our results contribute to the growing strand of literature on online learning in higher education, and show that students struggled with the shift to virtual instruction despite any increased flexibility that accompanied the shift. This negative effect was particularly pronounced for lower-performing and less experienced students. The subgroup-specific patterns suggest that facing a similar situation in the future, institutions could target outreach efforts to students who are most likely to struggle with virtual learning.

The consistency of the impact estimates across our three models suggest that instructor familiarity with online teaching was not able to mitigate the negative impact for in-person students. Instead, the impacts appear to be driven by student struggles with online learning. Faced with a similar need to abruptly shift students to online in the future, our results suggest that it would be important to target support services toward students, particularly those who do

not have experience with online learning. In addition, it may be beneficial to provide guidance to instructors on how to create virtual environments that more closely resemble in-person settings instead of defaulting to a “typical” online course structure.

One caveat is that VCCS implemented an emergency grading policy during Spring 2020 designed to minimize the negative impact of COVID on student grades; instructors may have been more lenient with their grading. As such, we view these estimates as a lower-bound of the negative impact of the shift to virtual instruction.

These results only represent the short-term impact of the COVID crisis on student outcomes. Because our empirical strategy identifies the impact of the shift to online learning based on within-course variation, we have limited ability to estimate the longer-term impacts of this shift. Yet as prior research both on the impact of health and economic disruptions and on online learning has demonstrated, the near-term negative effects we estimate may translate into longer-term reductions in students’ educational attainment. The concrete decline in academic performance we estimate could contribute to higher education administrators’ assessment of the costs of future shifts to online learning (e.g. in the face of another COVID-19 resurgence) alongside the costs of continuing in person.

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**Table 1: Summary statistics of students, courses, and instructors in overall and within-course analytic sample, Spring 2020**

Panel A: Student-level characteristics

	Overall	All	Within-Course In-person	Online
<i>Demographic characteristics</i>				
Age	24.83	24.06	22.97	25.19
Female	56.8%	59.6%	55.4%	66.8%
White	52.4%	57.7%	56.0%	61.3%
Black	18.5%	21.4%	21.4%	20.4%
Hispanic	14.3%	9.6%	10.6%	8.1%
Asian	7.5%	3.7%	4.1%	3.1%
Other Race	7.2%	7.6%	7.9%	7.1%
<i>Academic history</i>				
Prior cumulative GPA	2.82	2.77	2.74	2.85
Prior accumulated credits	29.19	25.74	23.68	29.01
Previously enrolled at VCCS?	92.7%	91.4%	91.2%	92.4%
Previous online enrollment at VCCS?	56.5%	60.8%	51.4%	78.4%
Share of previously attempted credits online	19.0%	21.9%	13.7%	34.4%
<i>Broad program of study category</i>				
Liberal Arts	38.9%	49.5%	51.6%	49.4%
Health Sciences	11.8%	10.3%	9.5%	11.2%
Applied Sciences	3.4%	1.3%	1.3%	1.1%
Vocational / Technical	45.9%	38.8%	37.6%	38.3%
<i>Degree level pursuing</i>				
Transfer-oriented associate	66.6%	75.1%	78.7%	72.1%
Applied associate	24.2%	17.3%	14.4%	20.0%
Certificate	2.6%	1.9%	1.5%	2.3%
Career Studies Certificate (short-term)	5.4%	4.4%	4.2%	4.3%
Other	1.1%	1.2%	1.2%	1.3%
N	84648	39690	27396	18193

Panel B: Course-level characteristics

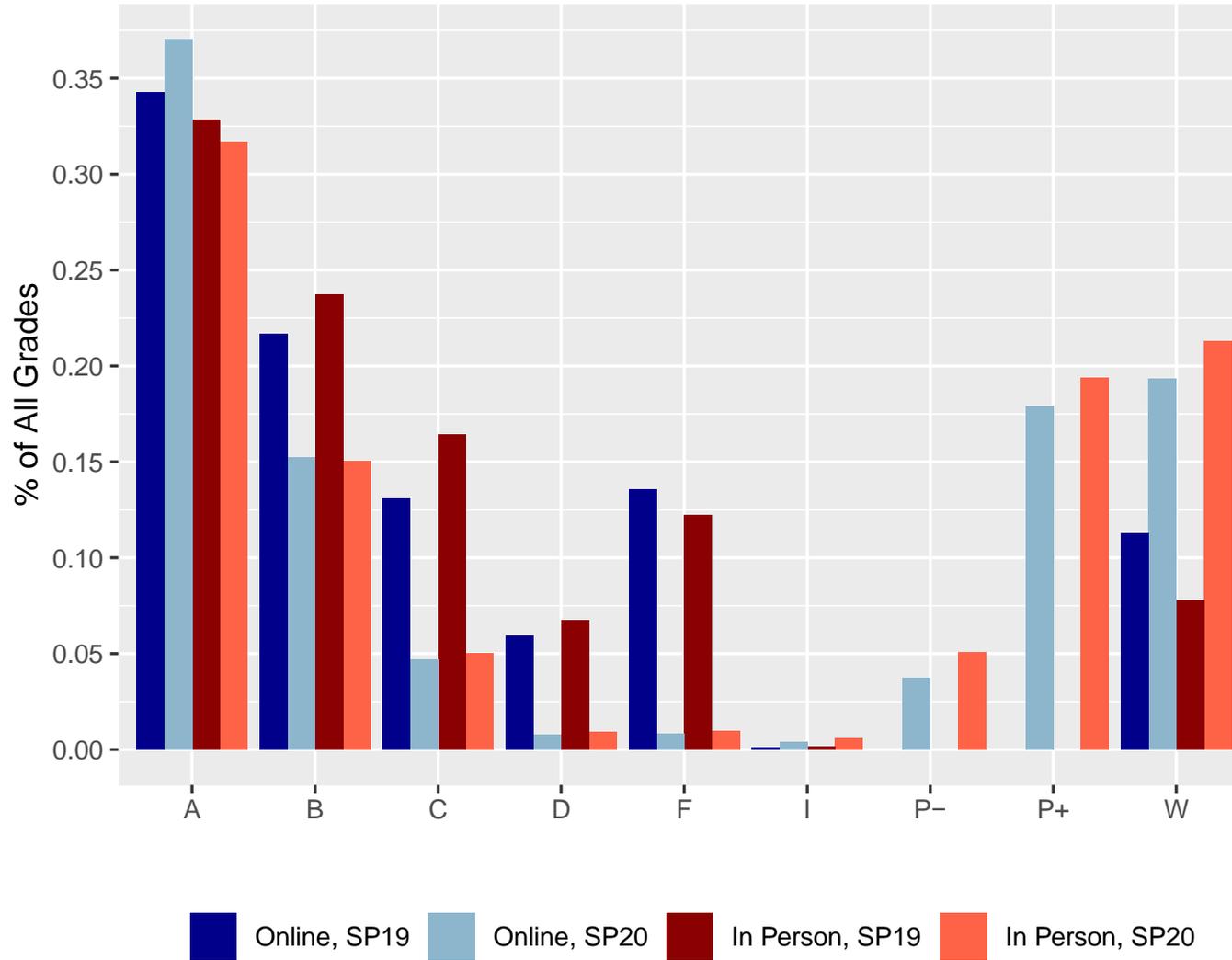
	Overall	All	Within-Course In-person	Online
100-level	53.2%	62.1%	62.1%	62.1%
Course enrollment	982	2724	1629	1022
Section (class) enrollment, overall	15	22	20	24
<i>Course Subject</i>				
Math	5.3%	13.4%	13.4%	13.4%
English	4.1%	9.8%	9.8%	9.8%
History	2.5%	8.3%	8.3%	8.3%
Biology	3.0%	8.1%	8.1%	8.1%
N	4722	663	663	663

Panel C: Instructor-level characteristics

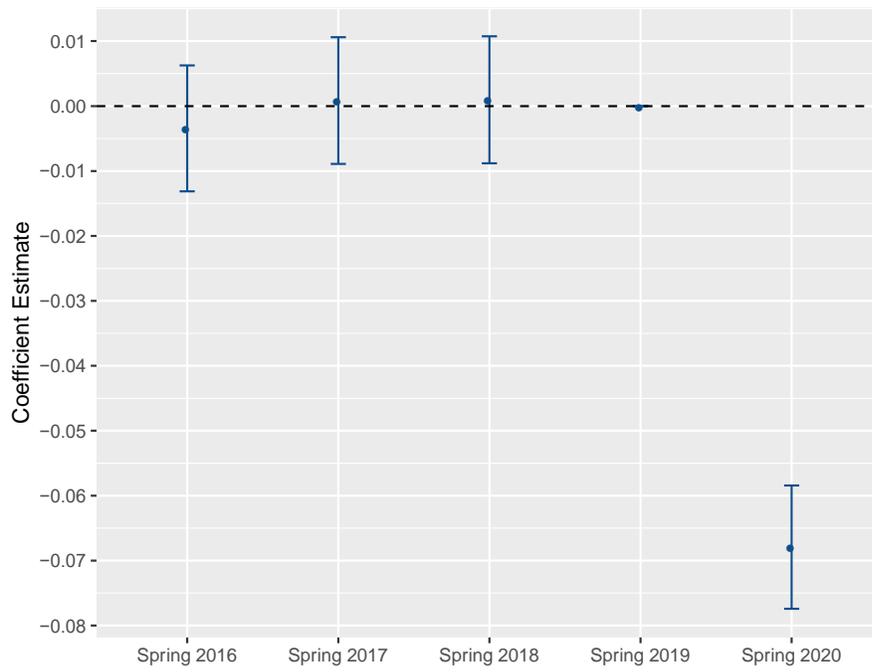
	Overall	All	Within-Course In-person	Online
Female	53.0%	54.8%	51.4%	60.9%
White	78.6%	80.2%	79.3%	84.9%
Black	12.6%	13.5%	14.0%	9.4%
Hispanic	2.5%	2.2%	2.3%	2.3%
Asian	5.5%	3.3%	3.4%	2.3%
Other Race	0.8%	0.8%	1.0%	0.8%
Tenure (terms)	20	23	22	26
Full-time	40.3%	40.6%	42.4%	54.9%
N	4610	1689	1336	734

Notes: The Overall Sample excludes all observations corresponding to dual enrollment students, developmental courses, audited courses, and courses offered outside of the full-session. The Within-Course sample includes all observations corresponding to courses that are offered both online and in-person during Spring 2020, and also offered both online and in-person during at least one of the comparison terms. All information presented is for students enrolled in, courses offered during, and instructors teaching during the Spring 2020 term. The "Other Race" category includes students who identify as American Indian or Alaskan, Hawaiian or Pacific Islander, two or more races, or whose race is missing. If a student has no prior VCCS enrollment history, their value for previous online enrollment and share of previously attempted credits online are both set to zero. Courses in both the Overall and Within-Course samples are either 100-level or 200-level. Tenure is measures in number of terms the instructor taught at least one course between Spring 2008 and Spring 2020, inclusive, with a maximum of three terms within an academic year.

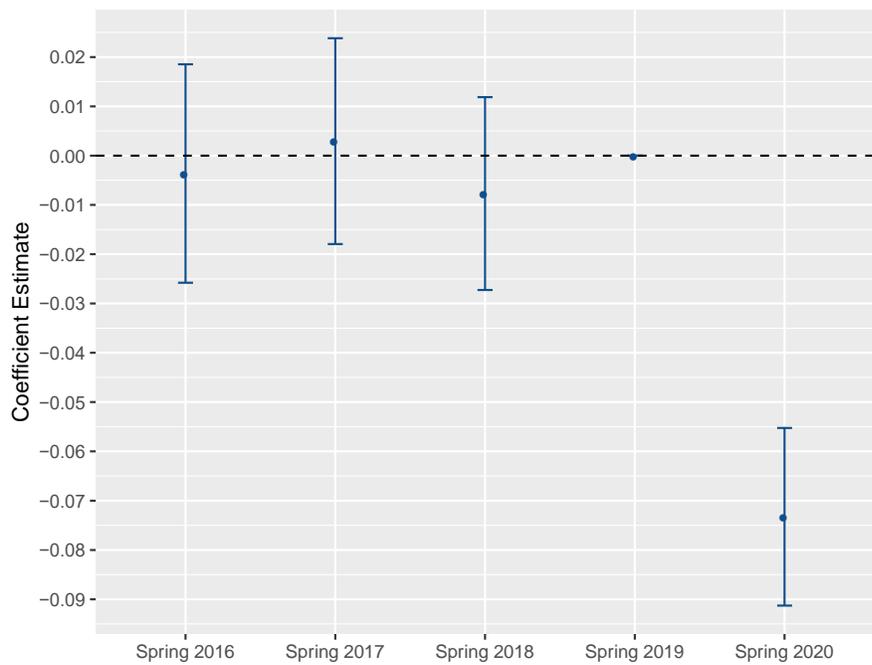
**Figure 1: Distribution of grades for observations in Within-Course in Spring 2019 and Spring 2020, by instructional modality**



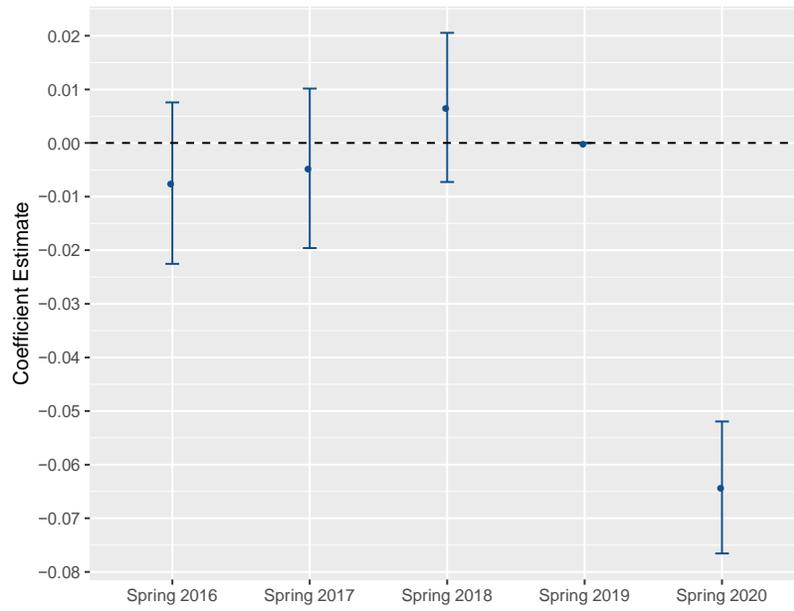
**Figure 2: Event study plots**  
*Panel A: Within-course model*



*Panel B: Within-instructor model*



*Panel C: Across-instructor model*



Notes: these plots show the coefficient estimates and 95% confidence intervals of the coefficients in the Term x In-Person indicators from equation (3) in the text, for the course completion outcome.

**Table 4: Difference-in-differences estimates of the impact of switch to virtual instruction**

	Course Completion (1)	Withdrew (2)	Failed (3)
<b>Panel A: Within-Course Model</b>			
DID Estimate	-0.0672*** (0.0038)	0.0514*** (0.0036)	0.0142*** (0.0018)
Pre-COVID in-person outcome mean	0.794	0.0832	0.122
R-squared	0.1617	0.0944	0.1023
N	385,259	385,259	385,259
<b>Panel B: Within-Instructor Model</b>			
DID Estimate	-0.0711*** (0.0074)	0.0543*** (0.0069)	0.0144*** (0.0038)
Pre-COVID in-person outcome mean	0.811	0.0719	0.117
R-squared	0.2006	0.1394	0.1247
N	52,234	52,234	52,234
<b>Panel C: Across-Instructor Model</b>			
DID Estimate	-0.0633*** (0.0051)	0.0490*** (0.0047)	0.0137*** (0.0027)
Pre-COVID in-person outcome mean	0.803	0.0796	0.117
R-squared	0.1685	0.1078	0.1113
N	149,711	149,711	149,711
Notes: within each panel, each column represents a separate regression using the model specified in equation 1 (Panels A and C) or equation 2 (Panel B) in the text, with the outcome variable as noted in the column header. The received credit outcome is equal to one if the student earned a grade of A-D, P+, or P-, and is equal to zero if the student earned a grade of F, I, or W. *** p < 0.01; ** p < 0.05; p < 0.1			

**Table 5: Subgroup-specific impacts on course completion from within-course model**

*Panel A: Subgroups by prior academic history*

	Tercile of prior cumulative GPA			Prior credits accumulated			
	Bottom (1)	Middle (2)	Third (3)	0 (4)	1 to 14 (5)	15 to 29 (6)	30+ (7)
DID Estimate	-0.0982*** (0.0087)	-0.0697*** (0.0067)	-0.0335*** (0.0048)	-0.0882*** (0.0144)	-0.0766*** (0.0077)	-0.0674*** (0.0080)	-0.0548*** (0.0055)
Comparison mean	0.639	0.846	0.928	0.702	0.743	0.825	0.875
R-squared	0.1240	0.0851	0.0705	0.1467	0.1829	0.1580	0.1503
N	115,542	115,642	115,601	42,230	130,618	86,439	125,972

*Panel B: Subgroups by student demographics*

	Age		Gender		Race/Ethnicity	
	< 25 (8)	25+ (9)	Female (10)	Male (11)	Underrep Minority (12)	White/ Asian (13)
DID Estimate	-0.0719*** (0.0046)	-0.0629*** (0.0071)	-0.0545*** (0.0048)	-0.0787*** (0.0065)	-0.0735*** (0.0068)	-0.0628*** (0.0046)
Comparison mean	0.787	0.820	0.814	0.770	0.748	0.823
R-squared	0.1778	0.1483	0.1612	0.1670	0.1664	0.1522
N	278,564	106,695	224,572	159,959	148,176	237,083

Notes: each column within each panel represents a separate regression using the model specified in equation (1) in the text, restricted to the subgroup denoted by the column headers. This table is limited to results from the within-course model, with the outcome of "received credit". Note that students with no prior cumulative GPA are not included in the first three columns. The underrepresented minority category includes Black, Hispanic, and Other Race. \*\*\* p < 0.01; \*\* p < 0.05; p < 0.1