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Changing Distributions: How Online College Classes Alter Student and Professor Performance

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ABSTRACT

Online college courses are a rapidly expanding feature of higher education, yet little research identifies their effects. Using an instrumental variables approach and data from DeVry University, this study finds that, on average, online course-taking reduces student learning by one-third to one-quarter of a standard deviation compared to conventional in-person classes. Taking a course online also reduces student learning in future courses and persistence in college. Additionally, we find that student performance is more variable online than in traditional classrooms but that individual professors explain less of the variation in student performance in online settings than in traditional classrooms.

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CHANGING DISTRIBUTIONS: HOW ONLINE COLLEGE CLASSES ALTER STUDENT AND PROFESSOR PERFORMANCE*

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Abstract: Online college courses are a rapidly expanding feature of higher education, yet little research identifies their effects. Using an instrumental variables approach and data from DeVry University, this study finds that, on average, online course-taking reduces student learning by one-third to one-quarter of a standard deviation compared to conventional in-person classes. Taking a course online also reduces student learning in future courses and persistence in college. Additionally, we find that student performance is more variable online than in traditional classrooms but that individual professors explain less of the variation in student performance in online settings than in traditional classrooms.

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Online college courses are a rapidly growing feature of higher education. One out of three students now takes at least one course online during their college career, and that share has increased threefold over the past decade (Allen and Seaman 2013). The promise of cost savings, partly though economies of scale, fuels ongoing investments in online education by both public and private institutions (Deming et al. 2015). Non-selective and for-profit institutions, in particular, have aggressively used online courses. Yet there is little systematic evidence about how online classes affect student outcomes. Some studies have investigated the effects of online course-taking using distance-to-school instruments or fixed effects (e.g. Hart, Friedmann, and Hill 2014, Xu and Jaggars 2013), but in those studies, it is not clear if other aspects of the class changed between the in-person and online settings. We provide a clean counterfactual whereby we can isolate just the difference in course delivery format. In this paper we estimate the effects of online course-taking on student achievement in the course and persistence and achievement in college after the course. We examine both the mean difference in student achievement between online and in-person courses and how online courses change the variance of student achievement. We give specific attention to professors' contributions to student outcomes, and how teaching online changes those contributions.

Our empirical setting has three salient, advantageous features: an intuitive, straightforward counterfactual for each online course; plausibly-exogenous variation in whether students take a given course online or in-person; and both at a substantial operating scale. The combination of these three features has not been possible in prior work. We study students and professors at DeVry University, a for-profit college with an undergraduate enrollment of more than 100,000 students, 80 percent of whom are seeking a bachelor's degree. The average DeVry student takes two-thirds of his or her courses online. The remaining one-third of courses are conventional in-person classes held at one of DeVry's 102 physical campuses.[1] The data for this paper cover more than four years of DeVry operations, including 230,000 students observed in an average of 10 courses each.

DeVry University's approach to online education creates an intuitive, clear counterfactual. Each DeVry course is offered both online and in-person, and each student enrolls in either an online section or an in-person section. Online and in-person sections are identical in most ways:

[1] Our data include 102 campuses. DeVry opens and closes campuses each year, and hence, our number may differ from the current number of active campuses.

both follow the same syllabus and use the same textbook; class sizes are the same; both use the same assignments, quizzes, tests, and grading rubrics. The contrast between online and in-person sections is primarily the mode of communication. In online sections all interaction—lecturing, class discussion, group projects—occurs in online discussion boards, and much of the professor's "lecturing" role is replaced with standardized videos. In online sections participation is often asynchronous while in-person sections meet on campus at scheduled times.

While DeVry students self-sort across online and in-person sections, we use an instrumental variables strategy which limits identification to variation arising from where (physical campus) and when (academic term) the university offers a course in-person. In a given term, a student can choose to take a course in-person, instead of online, if the course is offered at her local campus.[2] Courses are always offered online, but each local campus' offerings vary from term to term. This temporal and spatial variation in in-person offerings is the basis for our instruments.

Specifically, our first instrument is a simple indicator if the course was offered in-person at the student's nearest campus in any of the current, prior, or following term.[3] The identifying assumption (exclusion restriction) is that the local campus' decision to offer an in-person section only affects student outcomes by inducing more (fewer) students to take the course in-person. Our estimates would be biased, for example, if higher-skilled students demand more in-person offerings, and the university's decisions respond to that demand. Our second and preferred instrument, partly in response to this threat, is the *interaction* between the first instrument and the distance between the student's home and nearest campus. Only this interaction is excluded in the second stage; we include the main effects of in-person availability (the first instrument) and distance to campus.[4] The pattern of results is similar for either instrument.

Our estimates provide evidence that online courses do less to promote student learning and progression than do in-person courses for students at the margin. Taking a course online reduces student achievement by about one-quarter to one-third of a standard deviation, as measured by course grades, and reduces the probability of remaining enrolled by three to ten percentage points (over a base of 68 percent). Taking a course online also reduces student grade point average in the next term by more than one-tenth of a standard deviation. Additionally, we find that student

[2] DeVry divides its academic calendar into six eight-week terms.
[3] As described in Section I, we further limit variation to within-course, -local-campus, and –term; and control for prior student academic achievement among other things.
[4] This interaction-instrument approach was first suggested by Card (1995).

achievement outcomes are more variable in online classes. The variation of course grades increases by as much as one-fifth in online sections, and the variance in student grade point average in the next term increases by more than one-tenth. By contrast, we find that the variation in professors' contributions to student achievement and persistence are smaller in online classes than in-person classes.

Several plausible mechanisms could lead students to perform differently in online college classes. Online courses substantially change the nature of communication between students, their peers, and their professors. First, on a practical dimension, students in online courses can participate at any hour of the day from any place. That flexibility could allow for better allocation of students' time and effort. That same flexibility could, however, create a challenge for students who have not yet learned to manage their own time. Second, online asynchronous interactions change the implicit constraints and expectations on academic conversations. For example, a student does not need to respond immediately to a question her professor asks, as she would in a traditional classroom, instead she can take the time she needs or wants to consider her response. More generally, students may feel less oversight from their professors and less concern about their responsibilities to their professors or classmates in the online setting.[5] In the standard principal-agent problem, effort by the agent falls as it becomes less visible to the principal, and where it becomes more difficult for professors to observe student engagement and effort, student outcomes may worsen (Jensen and Meckling 1976). Third, the role of the professor is quite different in online classes. Notably, eliminating differences in professors' lectures through standardized video lectures should reduce the between-professor variation in student outcomes. Indeed such standardization is a necessary condition for the economies of scale promised by online education. However, how professors choose to use the time saved by not lecturing could expand that between-professor variation. Evidence from K-12 schools consistently shows large and important between-teacher variation in student outcomes (Jackson, Rockoff, and Staiger 2014, Rivkin, Hanushek, and Kain 2005), yet the academic literature largely ignores such variation in higher education (see exceptions by Carrell and West 2010, Bettinger and Long 2010).

All of these potential mechanisms suggest heterogeneous effects of online classes from student to student. Students' skills, motivations, and work- and home-life contexts may be better or worse served by the features of online classes. While some existing work estimates average

[5] In a separate paper, we study peer effects in DeVry's online college classes Bettinger, Loeb, and Taylor (2015) .

effects, few studies have assessed differences across students, and none that we know of systematically assesses differential effects due to different course characteristics (e.g. different professors).

Our research contributes to three strands of literature. First, the study provides significant evidence of the impact of online courses in the for-profit sector across hundreds of courses. Existing evidence with much smaller samples shows negative effects on course completion and course grades at community colleges (Xu and Jaggars 2013, Hart, Friedmann, and Hill 2014, Xu and Jaggars 2014, Streich 2014b, a) and student exam scores at public four-year institutions (Figlio, Rush, and Yin 2013, Bowen et al. 2014).[6] Students who attend for-profit colleges are distinct from other student populations in higher education, and our estimates are the first to focus on the impact of online courses in this population. Furthermore, it is possible that the comparison between online and in-person courses in the previous studies is confounded by differences in syllabi or textbooks, whereas our study presents a clean comparison in which the only difference in the courses is the mode of communication.

Second, our paper contributes to the small literature on professor contributions to student outcomes. Work by Carrell and West (2010) examines between-professor variation at the Air Force Academy, and finds somewhat less variation than similar estimates in primary and secondary schools. We build on this finding demonstrating that at a much less selective institution, the between-professor variance is higher than what has previously been found in K-12 and higher education settings. We also compare the between-professor variation across online and in-person settings and show that the variance is lower in online settings.

Third, our paper adds to the new and growing literature on private for-profit colleges and universities. Research on DeVry University and its peers is increasingly important to

[6] Xu and Jaggars (2013) use a distance-to-school instrument for Washington state community colleges and find online courses cause a 7 percentage point drop in completion as well as reduction in grades. Their subsequent work in 2014 finds that these effects are strongest among young males. Streich (2014b), using an instrument of the percent of seats for a course offered online, finds negative effects on the probability of passing of 8.3 percentage points. Hart, Friedman and Hill (2014) study California community colleges using individual and course fixed effects and also find negative effects of approximately the same size (8.4 percentage points) on course completion. The only indication of positive effects comes from Streich (2014a) that finds some evidence of positive employment effects though largely in years immediately following initial enrollment when student may still be enrolled. Online courses may provide greater opportunities for students to work.

Working at a public four-year institution, Figlio et al. (2013) randomly assigned students in an economics course to take the course either online or in-person and found negative effects of the online version on exam scores especially for male, Hispanic and lower-achieving students. Bowen et al. (2014) also study students at four-year public institutions, comparing online and hybrid courses. They find no differences in student outcomes.

understanding American higher education broadly. The for-profit share of college enrollment and degrees is large: nearly 2.4 million undergraduate students (full-time equivalent) enrolled at for-profit institutions during the 2011-12 academic year, and the sector granted approximately 18 percent of all associate degrees (Deming, Goldin, and Katz 2012). Additionally, the sector serves many non-traditional students who might be a particularly important focus for policy. Thirty percent of for-profit college students have previously attended college and 25 percent having attended at least two other institutions before coming to the for-profit sector. Approximately 40 percent of all for-profit college students transfer to another college (Swail 2009). DeVry University is one of the largest and most nationally representative for-profit colleges, making it an ideal setting to study this distinct and important group of students.

While the results suggest that students taking a course online do not perform as well as they would have taking the same course in a conventional in-person class, our results have limitations. First, a full welfare analysis of online college courses is not possible. Notably, online offerings make college courses available to individuals who otherwise would not have access. Our estimates are based on students who could take a course in-person or online, and we cannot quantify the extent of this access expansion in our setting. Second, we study an approach to online courses that is common today, but online approaches are developing rapidly. Further development and innovation could alter the results.

The remainder of the paper is organized as follows. Section I describes the setting, data, and approach to estimation. Section II presents our results, and Section III discusses the paper including making some conclusions based on our analysis.

I. Empirical Setting and Methods

We address three empirical research questions in this paper:

1. How does taking a course online, instead of in a conventional in-person class, affect average student academic outcomes: course completion, course grades, persistence in college, and later grades?

2. How does taking a course online affect the variance of student outcomes?

3. How does teaching a course online affect the variance of professor performance, as measured by professors' contributions to student outcomes?

In this section we first describe the specific students, professors, and courses on which we have data, and second describe our econometric approach.

A. Data and Setting

We study undergraduate students and their professors at DeVry University. While DeVry began primarily as a technical school in the 1930s, today 80 percent of the University's students are seeking a bachelor's degree, and most students major in business management, technology, health, or some combination. Two-thirds of undergraduate courses occur online, and the other third occur at one of over 100 physical campuses throughout the United States. In 2010 DeVry enrolled over 130,000 undergraduates, or about 5 percent of the for-profit college market, placing it among the largest for-profit colleges in the United States.

DeVry provided us with data linking students to their courses for all online and in-person sections of all undergraduate courses from Spring 2009 through Fall 2013. These data include information on over 230,000 students in more than 168,000 sections of 750 different courses. About one-third of the students in our data took courses both online and in-person. Only the data from Spring 2012 through Fall 2013 contain information on professors, so part of our analysis is limited to this group of approximately 78,000 students and 5,000 professors. In this sub-sample 12 percent of professors taught both online and in-person classes. Table I describes the sample. Just under half of the students are female and average approximately 31 years of age, though there is substantial variability in age. Students in online courses are more likely to be female (54 percent vs. 35 percent) and older (33.0 years vs. 28.4 years).

[Table I here]

The focus of this paper is on the levels and variance of student outcomes. The data provide a number of student outcomes including course grades, whether the student withdrew from the course, whether the student was enrolled during the following semester and how many units he or she attempted, whether the student was enrolled one year later and the number of units attempted in that semester. Ideally, we would like to know how much students learn in each course the take (whether online or in-person); our imperfect measure of learning is course grade. In many higher education institutions course grades are subject to professor discretion, and professors may exercise that discretion differently in online and in-person classes. That discretion is a consideration in this paper, but DeVry's grading process permits less discretion than the typical selective college or university. For each course, DeVry's professors are asked to follow a common rubric for evaluating individual assignments and assigning grades. In many cases quizzes and tests are standardized across sections, whether online or in-person. Additionally, alongside course grades both for the target course and in future courses, we present results for persistence—a consequential outcome for students seeking a degree and one not influenced by professor subjectivity.

As shown in Table I, the average grade was 2.8 (approximately B-), on the traditional zero (F) to four (A) scale. There is substantial variation in grades: the standard deviation is 1.3 (more than a full letter grade). Approximately 23 percent of students failed any given course, while 41 percent receive an A- or higher in the courses we observe. Over 88 percent were still enrolled at DeVry University in the following semester or had completed their degree. Over 69 percent were enrolled one year later or had completed their degree. These outcome means are consistently higher in the in-person classes than in the online setting.[7] These differences could be the result of selection bias, and in the next section we discuss our strategies for overcoming the selection bias in estimating causal effects of online courses.

[Table II here]

While we focus on one large university in the for-profit sector, our results are likely generalizable beyond DeVry University. Table II shows average characteristics of students from various sectors of education. The first four columns use data from the National Postsecondary Student Aid Study from 2012. The final column uses the DeVry data. DeVry has a similar profile to other for-profit colleges, though collectively for-profit colleges differ from traditional sectors, including two-year colleges, given their focus on non-traditional students and African-American students.

[7] This difference remains true when we limit the sample to students who take both online and in-person classes.

B. *Empirical Methodology*

Effects on the Mean of Student Outcomes—We first estimate the effect of taking a course online, instead of a traditional in-person classroom, on the average student's success in the course and persistence in college after the course. We measure student success using course grades. We measure student persistence in the subsequent semester and the semester one year later. Calculating the difference in means is straightforward, but the decision to take a course in an online section or traditional section is likely endogenous—driven by unobservable information that could also influence each student's chances of success in the online versus traditional options. Our identification strategy is to use only variation in online versus traditional course taking that arises because of idiosyncratic changes over time in each local campus's in-person course offerings.

Our first student outcome is the grade, y_{ict}, received by student i in course c during term t. Each professor assigns traditional A-F letter grades, which we convert to the standard 0-4 point equivalents.[8] To estimate δ—the mean difference in course grades, y_{ict}, between students in online and traditional classes—we first specify the following statistical model:

$$(1) \qquad y_{ict} = \delta Online_{ict} + \alpha \bar{y}_{i,\tau<t} + X_{it}\beta + \pi_c + \phi_t + \psi_{b(it)} + \varepsilon_{ict}$$

In addition to the variable of interest, the $Online_{ict}$ indicator, specification 1 includes several relevant controls: students' prior grade point average (GPA), $\bar{y}_{i,\tau<t}$, measured in all terms before term t, observable student characteristics, X_{it} (gender and age), course fixed effects, π_c, for each of the 800+ courses, and a non-parametric time trend, ϕ_t, over the 27 terms (4.5 years, May 2009 through the end of 2013) in our data. Specification 1 also includes fixed effects for each student's "home campus" represented by $\psi_{b(it)}$. DeVry University operates over 100 local campuses throughout the United States. We assign each student to a home campus, b, based on the physical distance between the student's home address and the local campus addresses; selecting as "home"

[8] An A is 4 points, A- is 3.7, B+ is 3.3, B is 3, etc.

the campus with the minimum distance.[9] By limiting estimation to the within-campus over-time variation, we account for fixed differences between local campuses in the scope of course offerings.

Fitting specification 1 by least squares will provide an unbiased estimate of δ under the assumption:

$$(2) \qquad \mathbb{E}\left[\varepsilon_{ict} \mid Online_{s(ict)}\right] = \mathbb{E}[\varepsilon_{ict}]$$

In words, students taking online classes are no more likely to score higher (lower) than students taking traditional in-person classes, conditional on included controls. While the available controls, especially prior GPA and home campus, are helpful, we remain concerned about unobserved student-level determinants of the online versus in-person decision that would bias our estimates.

In response to these concerns we propose an instrumental variables strategy. Specifically, we instrument for $Online_{s(ict)}$ in specification 1 with an indicator variable $= 1$ if student i's home campus b offered course c on campus in a traditional class setting during term t. Combined with the home campus fixed effects, $\psi_{b(it)}$, this limits the identifying variation to between-term variation within-campuses in the availability of an in-person option for a given course. This strategy produces a local average treatment effect (LATE) estimate, where $\hat{\delta}$ is interpreted as the effect of taking a course online for compliers: students who would take a course in-person if it was offered at the nearest DeVry campus but otherwise take the course online.

With this setting "never takers" deserve special consideration. A never taker is a student who would always take the given course in-person. Notably, if the course is not offered at their home campus in the term they would prefer to take the course, these never takers may wait until next term to take the course or take the course earlier than they would prefer in order to find an in-person section. This potential inter-temporal behavior motivates a modification to our instrument. Specifically, we instrument for $Online_{s(ict)}$ in specification 1 with an indicator variable $= 1$ if

[9] In addition to students with missing address data, we exclude all students with international addresses and students whose addresses are not within the continental United States. The resulting sample contains 78 percent of the universe of undergraduate DeVry students over the time frame.

student i's home campus b offered course c on campus in a traditional class setting during term any of terms t, $t - 1$, or $t + 1$.[10]

In this instrumental variables framework, the identifying assumption (exclusion restriction) is: The local campus' decision to offer an in-person section only affects student outcomes by inducing more (fewer) students to take the course in-person. Our estimates would be biased, for example, if higher-skilled students demand more in-person offerings, and the university's decisions respond to that demand. This assumption seems plausible but is untestable. As a robustness check, we report results using two alternative instruments.

Our second and preferred instrument is the *interaction* between the first instrument and the distance between the student's home and nearest campus. The logic here is that a student's local campus offerings should be more influential for students who live learner their local campus. Only the interaction is excluded in the second stage; we include the main effects of in-person availability (the first instrument) and distance to campus in the second stage. This kind of interaction instrument was first proposed by Card (1995). While further limiting the identifying variation, the advantage of this instrument is that it allows us to control directly for in-person availability and distance from campus.

For completeness, and comparison to prior papers, we also report results using a third instrument: the simple distance between the student's home and nearest campus, without regard to course offerings at that campus. The advantages and disadvantages of such distance instruments have been long discussed (e.g. Card 2001). We focus in this paper on results from the first and second instruments.

In addition to student grade points, we use the same specification and strategy to estimate δ for other student outcomes. First, we examine whether the effect on grade points is concentrated in a particular part of the grade distribution. We replace grade points with binary outcome variables: receiving an A- or higher, a B- or higher, a C- or higher, and simply passing the course. These results are provided in the appendix. Second, we turn to student persistence outcomes. We estimate the difference in the probability of enrolling at DeVry in the very next semester, and the difference in the number of units a student attempts the next semester. We repeat the same analysis

[10] This instrument assumes that "never taker" students do not shift their course taking by more than one term before or after their preferred term. In results not presented we find that expanding the instrument to include $t \pm 2$ or $t \pm 3$ does not change the pattern of results.

for enrollment during the semester one year after term t.[11] Results for the extensive margin of persistence are presented here; the intensive margin results are provided in the appendix. Lastly, we repeat the analysis using a student's GPA in the next term as the outcome.

Effects on the Variance of Student Outcomes—Our second objective is to estimate the effect of taking a course online, instead of a traditional in-person classroom, on the *variance* of student outcomes. If students were randomly assigned to take a course online or in-person, the parameter of interest could be estimated straightforwardly by

$$\hat{\gamma} = var(y_{ict} \mid Online_{ict} = 1) - var(y_{ict} \mid Online_{ict} = 0).$$

We estimate the variance effect, γ, using an instrumental variables approach that builds on our approach for estimating the mean effect. First, we obtain the fitted residuals, $\hat{\varepsilon}_{ict}$, after two-stage least squares estimation of specification 1. Second, we repeat the identical two-stage least squares regression used to estimation specification 1, except that the dependent variable, y_{ict}, is replaced with the squared residuals $\hat{\varepsilon}^2_{ict}$. This is analogous to the familiar steps in FGLS or tests for heteroskdasticity. Unbiased estimates of γ require the same assumptions as the IV estimate for mean effects.

As an alternative approach we estimate γ using a linear mixed model extension of specification 1:

$$(3) \qquad y_{ict} = \delta Online_{ict} + \alpha \bar{y}_{i,\tau<t} + X_{it}\beta + \pi_c + \phi_t + \psi_{b(it)} + \alpha_i^O Online_{ict} + \alpha_i^T (1 - Online_{ict}) + \epsilon_{ict},$$

$$\text{with the assumption} \begin{bmatrix} \alpha_i^O \\ \alpha_i^T \end{bmatrix} \sim N\left(\begin{bmatrix} \bar{\alpha}^O \\ \bar{\alpha}^T \end{bmatrix}, \begin{bmatrix} \sigma^2_{\alpha^O} & \\ \sigma_{\alpha^O,\alpha^T} & \sigma^2_{\alpha^T} \end{bmatrix}\right).$$

The new terms α_i^O and α_i^T are student random effects, specific to online and traditional class settings respectively. We estimate 3 by maximum likelihood and obtain $\hat{\gamma} = \left(\hat{\sigma}^2_{\alpha^O} - \hat{\sigma}^2_{\alpha^T}\right)$. We limit the estimation sample to students who have taken at least one course online and one course

[11] DeVry's academic calendar divides the year into six terms, with two consecutive terms equivalent to a semester in a more traditional calendar. Following the University's approach, we define "enrollment the next semester" as enrollment during either term $t + 1$ or $t + 2$ or both. We define "enrollment one year later" as enrollment during either term $t + 6$ or $t + 7$ or both.

in-person. This approach does not directly address student selection, but it has the benefit of estimating the variance of student outcomes in online and traditional classes directly rather than just estimating the difference in variance (as in the first approach). Furthermore, to partly address selection we replace the dependent variable, y_{ict}, in specification 3 with the residual from 2SLS estimation of specification 1, $\hat{\varepsilon}_{ict}$.

Effects on the Variance of Professor Contributions to Student Outcomes—Finally, we estimate the effect of teaching a course online on the variance of professors' contributions to student outcomes. These estimates provide important context for understanding potential mechanisms behind the other effects we estimate. The estimates are also of interest because they provide information on how professor job performance varies, and how that variability is affected by moving a class online.

We estimate the difference in the variance of professor effects using a linear mixed model approach analogous to the specification in 3. In this case we replace the student random effects with random effects for professors, $\mu_{j(ict)}$, and for course sections, $\theta_{s(ict)}$.

$$
\begin{aligned}
(4) \qquad y_{ict} = \delta Online_{ict} + f\left(\bar{y}_{i,\tau<t}\right) + X_{it}\beta + \pi_c + \phi_t + \psi_{b(it)} \\
+\mu^{O}_{j(ict)} Online_{ict} + \mu^{T}_{i(ict)}(1 - Online_{ict}) \\
+\theta^{O}_{s(ict)} Online_{ict} + \theta^{T}_{s(ict)}(1 - Online_{ict}) + \epsilon_{ict},
\end{aligned}
$$

$$
\text{with the assumption} \begin{bmatrix} \mu^{O}_{j} \\ \mu^{T}_{j} \\ \theta^{O}_{s} \\ \theta^{T}_{s} \end{bmatrix} \sim N\left(\begin{bmatrix} \bar{\mu}^{O} \\ \bar{\mu}^{T} \\ \bar{\theta}^{O} \\ \bar{\theta}^{T} \end{bmatrix}, \begin{bmatrix} \sigma^2_{\mu^O} & & & \\ \sigma_{\mu^O,\mu^T} & \sigma^2_{\mu^T} & & \\ 0 \quad 0 & & \sigma^2_{\theta^O} & \\ 0 \quad 0 & & \sigma_{\theta^O,\theta^T} & \sigma^2_{\theta^T} \end{bmatrix} \right).
$$

The section random effects, $\theta_{s(ict)}$, capture shocks common to all students in student i's class, s, but not common to all classes taught by professor j. We estimate 4 by maximum likelihood and obtain $\hat{\lambda} = \left(\hat{\sigma}^2_{\mu^O} - \hat{\sigma}^2_{\mu^T}\right)$.

Though we do not have an instrument for whether a professor teaches online or in-person, we can use the instrumental variables approach to help address student selection. Specifically, we replace the dependent variable, y_{ict}, in specification 4 with the residual from 2SLS estimation of specification 1, $\hat{\varepsilon}_{ict}$. In both approaches, we show results (i) for all professors and (ii) limiting the estimation sample to professors who have taught at least one course online and one course in-person. Additionally, the estimation sample is limited to nine terms from May 2012 forward; the data system used before May 2012 did not record the professor for each course section.

II. Results

A. Effects on Average Student Outcomes

For the average student, taking a course online, instead of in a traditional in-person classroom setting, reduces student learning, as measured by course grades, and lowers the probability of persistence in college. Table III reports our instrumental variables estimates. (The ordinary least squares estimates shown in Panel A of Appendix Table A.1 are similar.) These estimates are consistent with the negative effects reported in other settings and papers. Nevertheless, our estimates provide new information on an important but unstudied population – students at private for-profit colleges and universities – and they are based on more convincingly exogenous variation.

[Table III here]

Panel A of Table III identifies the effect of taking a course online instead of in-person by instrumenting for taking a course online with an indicator $= 1$ if the student's local campus offered the course in-person either during the term the student took the course or the term just before or after. The coefficient on the excluded instrument in the first stage is highly statistically significant, indicating that when the course is offered in-person, students are 17.5 percentage points less likely to take the class online. The local average treatment effect of taking a course online versus in-person on achievement is a 0.38 grade point drop in course grade, approximately a 0.28 standard deviation decline. Put differently, complier students taking the course in-person earned roughly a B- grade (2.8) on average while their peers in online classes earned a C (2.4). Results presented in the appendix suggest this effect is true across the grade distribution, not simply at the top or bottom. The estimates for persistence show a 3 percentage point drop in the probability of remaining enrolled (or graduating within) one year later. The complier students taking the course in-person had a 69 percent probability of remaining enrolled while their peers in online courses had a 66 percent probability. Finally, the effect of taking a course online versus in-person on students' GPA next term is a 0.13 grade point drop.

Panel B shows local average treatment effects using the distance from a student's home address to the nearest DeVry campus as the instrument. The results are larger in magnitude and all highly statistically significant, though the source of variation is less convincingly causal. Panel C uses our alternative instrument which is an interaction between the indicator for whether the student's local campus offered the course in-person and the distance between the student's home and the local campus. The first stage on this instrument is positive and highly significant, indicating that if the course is offered in-person, the probability of taking the course online increases as distance from the campus increases. With this strategy, the effect of taking a course online instead of in-person is statistically significantly negative. The LATE estimate is a drop of 0.44 grade points, or a 0.33 standard deviation decline. The results for persistence indicate an 11 percent drop in the probability of being enrolled one year later, and the results for GPA in the next term show a drop of 0.17 grade points.

While our setting is quite different, it is useful to consider other effects in the higher education literature. For example, the literature on financial aid often finds that $1000 in financial aid increases persistence rates by about three percentage points (Bettinger 2004) and college mentorship increases persistence rates by five percentage points (Bettinger and Baker 2013).

[Table IV here]

The estimates in Table III are estimates of effects among compliers; in this case compliers are students who, for a given course, take the course in-person if it is offered in-person at the nearest DeVry campus but otherwise take the course online. The remaining students—the non-compliers—include "always online" students who would take the course in question online no matter the local in-person offerings, and similarly "always in-person" students. (We assume there are no defiers). To get a sense of how the complier students differ from their always online and always in-person peers, we can estimate the average observable characteristics of these three groups.[12] Table IV provides these results. Compared to other DeVry undergraduates, compliers are older, less likely to be female, and have higher prior GPAs on average.

In addition to assessing the outcomes in Table III, we also estimate the effects of online course taking on a range of other outcomes which are reported in Appendix Table A.1. We find that online students are less likely to pass the course (a reduction of 8.4 percentage points), and less likely to receive an A minus or above by (a reduction of 12.3 percentage points). After taking an online course, the students are 8.9 percentage points less likely to enroll in the following semester and, if they do, take fewer credits.[13]

[Table V here]

We also explore whether the negative impact of taking a course online is heterogeneous by student ability, measured by prior grade point average. Table V shows results for course grades and persistence from a model in which taking a course online is interacted with prior GPA. The results indicate that the effect of taking a course online is less negative for students with higher prior GPAs. For example, the point estimates from Panel C imply that a one point increase in prior GPA increases the impact of taking an online course instead of an in-person course by 0.12 grade points. The effect on GPA next term is slightly smaller with a magnitude of 0.11. This pattern holds across the full set of outcomes (see Appendix Table A.2).

B. Effects on the Variance of Student Grades

In addition to reducing average achievement, online courses also increase the variance of student academic performance as measured by course grades both in the target course and during the next term. Table VI reports estimates using our three instruments (Rows A-C) as well as the maximum-likelihood student-random-effects approach (Rows D-E). When students take a course online, instead of in a conventional in-person class, the between-student standard deviation of

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[12] The average value of X among compliers is given by: $\hat{\bar{X}}_C = \frac{\hat{\bar{X}} - \hat{\pi}_N \hat{\bar{X}}_N - \hat{\pi}_A \hat{\bar{X}}_A}{\hat{\pi}_C}$ where C, N, A denote compliers, never-takers, and always-takers, respectively, and π is the proportion of the sample in a particular group. For these calculations, we use the first (binary) instrument based on availability.

[13] The results are unchanged when we limit the sample to students who are taking the course for the first time. When we code withdrawals as a failing grade, the results are consistently larger in magnitude.

grades is one-eighth to one-fifth larger. This increase in variance is large but perhaps not surprising given our discussion in the introduction of differences between online and in-person practices and technologies, and the results on heterogeneity by prior GPA.

[Table VI here]

C. Professor Effects on Student Outcomes

Difference in professor job performance between online and in-person settings is a potential mechanism that could generate differences in student performance. Yet while the variance of student achievement increases in online classes, we find the opposite for professor performance, as measured by professor contributions to student achievement. Table VII provides these results: Panel A reports the estimates from the simple estimation of equation 4, and panels B-D show estimates of equation 4 where the dependent variable is the residual from the student IV model.

When estimated using the full sample of professors (Columns 1-2) we find large, statistically-significant differences in the variance of professor contributions to student achievement. In online classes, between-professor variation in student grades is significantly smaller (a standard deviation of 0.24 grade points) than between-professor variation in in-person classes (0.32 grade points). Much smaller but still statistically significant differences exist when the outcome is GPA next term (0.03 and 0.09 points, respectively). However, these results remain subject to selection bias from professors sorting across online and in-person settings. As a first-order response to professor selection concerns, we limit the estimation sample to only those professors we observe teaching both online and in-person. In this limited sample (Columns 3-4), the differences between the variance in professor contributions to student grades in online and in-person settings persists and is only slightly smaller in magnitude (0.27 grades points in in-person versus 0.23 grade points in online). There is no statistical difference in the variance of professor contributions between online and in-person settings in terms of student GPA in the next term.

Across the different models, the estimate of the standard deviation of professor contributions ranges from 0.24 to 0.32 when the outcome is course grade. In student standard deviation terms, these are roughly 0.18 and 0.24. That places these estimates at the upper end of similar estimates from K-12 teachers, measured with student test scores. And both the online and in-person professor differences are noticeably larger than estimates from the more-selective, in-person Air Force Academy (Carrell and West 2010).

[Table VII here]

III. Discussion and Conclusion

This study is the first, of which we are aware, to not only estimate the effects of at-scale online courses but to also understand the distributional consequences of online courses at non-selective 4-year institutions of higher education or at for-profit institutions, both of which serve a substantial proportion of students. In addition, this study uses an instrumental variables strategy for addressing selection and estimating causal effects that is arguably more convincing than prior approaches to estimating effects of online course taking at scale. Furthermore, in contrast to previous studies of online courses, our setting provides a clean counterfactual in which the only difference between online and in-person courses is the medium of instructional delivery. All other aspects of the course – professor assignment, class size, syllabus, textbooks, etc. – are identical across online and in-person courses.

Our analyses provide evidence that students in online courses perform substantially worse than students in traditional in-person courses, and these findings are robust across a number of specifications. We also find that the variance of student outcomes increases, driven at least in part, by differentially larger negative effects of online course taking for students with lower prior GPA. The results are in line with prior studies of online education in showing that in-person courses yield better mean outcomes than online courses (e.g. Figlio, Rush, and Yin 2013, Streich 2014b). Our estimates of lower grades and lower persistence in online courses are similar to those in Xu and Jaggars (2013, 2014) and Hart, Friedman, and Hill (2014).

While we find that online courses lead to poorer student outcomes, we cannot provide a full welfare analysis. Most notably, the existence of an online course option might have enabled some students to take college courses that otherwise would not have done so. First, our estimates are most appropriately generalized to students who could take a course online or in-person. Second, we cannot estimate the extent of this expansion in college course access in our setting.

Our estimates are, nevertheless, a critical input to a more complete welfare analysis.

There are several potential explanations for the increase in student variance. Figlio et al. (2013) argues that procrastination in online settings was much more prevalent and led to the worsening of outcomes. While we have no measure of procrastination, we find the worsening of outcomes is especially large at the bottom of the distribution – students who either withdraw or fail the course. These students generally fail to complete the course requirements and may have procrastinated in their course responsibilities. We find fewer differences in outcomes at the top of the grade distribution suggesting that online courses may not be worse for high achieving students. If indeed procrastination is driving many of the results, courses could be redesigned to improve student participation.

As for the change in the variance attributable to professors, the decrease in variance in online classes would be both good and bad. It might eliminate extreme outcomes from bad instructions, yet it might also stifle good teaching. A number of potential reasons for these differences exists. In the online courses, professors use the same syllabus, lectures, and materials, and in some cases, even the same scripts. The greater adherence to a script among professors surely contributes to a more similar and less varied experience across professors. It may also be the case that online interactions are more limited than in-person so there are fewer opportunities for professors to influence students.

Overall, the results – lower student performance, greater student variation, and lower professor variation – while not necessarily surprising, provide evidence that online courses are not yet as effective as in-person courses. This current state, however, is clearly not a necessary end state. The greater homogeneity of online courses points to the potential to scale good courses and reduce the variability in experiences that students have within the same course taught by different professors in traditional classrooms. Lastly, our results provide a rationale and jumping off point for exploring the potential mechanisms that could be driving the results such as student effort, procrastination, and professor behavior.

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Table I—Student Characteristics and Outcomes

	All	Online	In-person
	(1)	(2)	(3)
Observations			
Student-course-session	2,323,023	1,373,521	949,502
Students	230,484	184,799	118,041
Professors	5,290	2,590	3,370
Courses	750	559	653
Sections	168,223	63,443	104,780
Student characteristics			
Female	0.467	0.545	0.354
Age	31.107	32.986	28.390
Online	0.591	1	0
Student prior academics			
Cumulative GPA	3.027	3.057	2.983
	(0.866)	(0.873)	(0.853)
Failed any course	0.234	0.229	0.241
Withdrew from any course	0.214	0.214	0.212
Student course outcomes			
Grade (0-4)	2.821	2.798	2.856
	(1.329)	(1.357)	(1.285)
A- or higher	0.410	0.413	0.406
B- or higher	0.696	0.688	0.707
C- or higher	0.831	0.821	0.845
Passed	0.884	0.875	0.898
Student persistence outcomes			
Enrolled next semester	0.882	0.874	0.893
Credits attempted	9.764	9.126	10.652
next semester	(4.657)	(4.555)	(4.651)
Enrolled semester one year later	0.686	0.681	0.693
Credits attempted	7.737	6.899	8.906
semester one year later	(5.642)	(5.392)	(5.774)

Note. Authors' calculations. Means (standard deviations) for DeVry University undergraduate course enrollments from May 2009 to November 2013.

Table II—Student Characteristics, Institution Types, and DeVry University

	Public 4-year	Private not-for-profit 4-year	Public 2-year	Private for-profit	DeVry University
	(1)	(2)	(3)	(4)	(5)
Age					
23 or younger	69.6	71.2	49.1	31.6	28.1
24-39	24.8	19.0	36.4	50.7	52.5
40+	5.6	9.9	14.4	17.7	19.4
Female	53.9	56.6	55.7	64.1	44.5
Race/Ethnicity					
African-American or Black	12.8	13.4	16.4	25.6	25.5
Asian	6.9	6.9	5.0	2.9	4.9
Hispanic or Latino	13.8	10.1	18.6	18.5	18.7
Other, More than one	4.4	4.5	4.3	4.6	4.8
White	62.2	65.1	55.8	48.5	46.1

Note. Columns 1-4 come from the 2011-12 National Postsecondary Student Aid Study (NPSAS:12) as reported by NCES QuickStats. Column 5 is from DeVry administrative data. Race/ethnicity is imputed for 16.9 percent of students assuming missing at random.

Table III—Effect of Taking a Course Online, Instead of In-person, on Student Achievement and Persistence (Local Average Treatment Effects)

	Dependent variable			
	Course grade (A = 4 ... F = 0)	Enrolled Next Semester	Enrolled One Year Later	GPA next term
	(1)	(2)	(3)	(4)
A. Instrument = Course available in person at home campus				
Online	-0.380***	-0.016**	-0.025**	-0.134***
	(0.017)	(0.005)	(0.009)	(0.014)
First stage coefficient on instrument	-0.175	-0.167	-0.167	-0.181
First stage F-statistic	161.99	115.41	115.41	181.46
B. Instrument = Distance to home campus				
Online	-0.572***	-0.081***	-0.183***	-0.554***
	(0.071)	(0.020)	(0.052)	(0.120)
First stage coefficient on instrument	0.001	0.001	0.001	0.001
First stage F-statistic	19.40	17.13	17.13	18.76
C. Instrument = Course availability interacted with distance to home campus				
Online	-0.442***	-0.089***	-0.106***	-0.173***
	(0.023)	(0.010)	(0.014)	(0.027)
First stage coefficient on instrument	0.001	0.001	0.001	0.001
First stage F-statistic	193.02	139.20	139.20	205.32
Sample mean (st. dev.) for dep. var.	2.821	0.882	0.686	2.817
	(1.329)			(1.234)
Number of observations	2,323,023	2,360,645	2,360,645	1,974,831

Note. The first row of each panel reports the estimated local average treatment effect from a separate two-stage least squares regression. Row two reports the coefficient on the excluded instrument from the first stage. The rows at the bottom of the table report the sample mean (standard deviation) of the dependent variable. Dependent variables described in column headers. The specification includes one endogenous treatment variable, an indicator = 1 if the student took the course online. In panel A, the excluded instrument is a binary variable = 1 if the course was offered in-person at the student's home campus (defined as the nearest campus) in any of the current term, the previous term, or the following term. In panel B, the excluded instrument is the distance in miles from the student's home address to her home campus. In panel C, the excluded instrument is the interaction between availability in the current, previous or following term and distance to home campus. All specifications also included controls for (i) prior cumulative grade point average, (ii) an indicator for student gender, (iii) student age, and (iv) separate fixed effects for course, term, and home campus. The estimation sample is limited to students who have address information. Standard errors allow for clustering within sections. *p<.05, **p<.01, ***p<.001

Table IV—Observable Characteristics of Compliers

Characteristic	Compliers (1)	Always Online (2)	Always In-Person (3)
Female	0.45	0.54	0.34
Age	31.67	32.39	28.01
Prior GPA	3.10	2.97	3.05
Prior GPA in online courses	3.06	2.92	2.78
Prior GPA in in-person courses	2.99	3.14	3.10
Proportion of courses taken online	0.43	0.82	0.14
Proportion repeating a course	0.03	0.06	0.03
Number of courses taken in first session	1.75	1.77	1.95
Proportion of courses taken online in first session	0.36	0.82	0.12
Number of units taken in first session	5.90	5.70	6.32
Proportion of units taken online in first session	0.36	0.82	0.12
Proportion taking all online courses in first session	0.31	0.77	0.06
Proportion taking all in-person courses in first session	0.58	0.14	0.81
Proportion taking a mix of courses in first session	0.11	0.10	0.13
Proportion taking a course within their major	0.55	0.28	0.56
Initial Business major	0.46	0.53	0.25
Initial Computers major	0.36	0.32	0.54
Initial Health major	0.16	0.14	0.21
Initial Criminal Justice Major	0.02	0.01	0.01

Note. Assuming no "defiers", compliers make up 27.4 percent of the sample, always-takers 47.8 percent, and never-takers 24.8 percent. The treatment indicator is = 1 if the student took the course online. The excluded instrument is a binary variable = 1 if the course was offered in-person at the student's home campus (defined as the nearest campus) in any of the current term, the previous term, or the following term. The estimation sample is limited to students who have address information: 2,323,023 student-course observations.

Table V—Heterogeneity of Effect of Taking a Course Online, Instead of In-person, by Prior Achievement

	Dependent variable			
	Course grade (A = 4 ... F = 0)	Enrolled Next Semester	Enrolled One Year Later	GPA next term
	(1)	(2)	(3)	(4)
A. Instrument = Course available in person at home campus				
Online	-0.913***	-0.252***	-0.365***	-0.506***
	(0.069)	(0.025)	(0.038)	(0.047)
Online * prior grade point avg.	0.192***	0.086***	0.124***	0.133***
	(0.025)	(0.009)	(0.015)	(0.016)
First stage F-statistic: online	191.299	131.694	131.694	198.406
First stage F-statistic: interaction	105.053	80.627	80.627	121.073
B. Instrument = distance to home campus				
Online	-0.769***	-0.150***	-0.258***	-0.675***
	(0.051)	(0.015)	(0.039)	(0.087)
Online * prior grade point avg.	0.134***	0.050***	0.054***	0.076**
	(0.016)	(0.003)	(0.009)	(0.023)
First stage F-statistic: online	571.447	372.624	372.624	454.259
First stage F-statistic: interaction	163.017	130.111	130.111	163.866
C. Instrument = interaction between availability and distance				
Online	-0.621***	-0.173***	-0.211***	-0.339***
	(0.023)	(0.008)	(0.010)	(0.023)
Online * prior grade point avg.	0.123***	0.062***	0.079***	0.107***
	(0.009)	(0.004)	(0.005)	(0.007)
First stage F-statistic: online	873.301	669.444	669.444	555.450
First stage F-statistic: interaction	98.329	88.627	88.627	114.106
Number of observations	2,323,023	2,360,645	2,360,645	1,974,831

Note. Each column, within panels, reports estimates from a separate two-stage least squares regression. Dependent variables described in column headers. The specification includes two endogenous treatment variables, an indicator = 1 if the student took the course online, and the interaction of that indicator and students' cumulative prior grade point average. The excluded instruments are a binary variable = 1 if the course was offered in-person at the student’s home campus (defined as the nearest campus) in any of the current term, the previous term, or the following term (panel A), the distance in miles from the student’s home address to her home campus (panel B), the interaction of availability and distance (panel C); and the interaction of those variables, respectively, with prior GPA. All specifications also included controls for (i) prior cumulative grade point average main effect, (ii) an indicator for student gender, and (iii) student age, and (iv) separate fixed effects for course, term, and home campus. The estimation sample is limited to students who have address information. Standard errors allow for clustering within sections. *p<.05, **p<.01, ***p<.001

Table VI—Effect of Taking a Course Online, Instead of In-person, on the Variance of Student Achievement

	Sample st. dev. course grade	Online - in-person diff.	P-value test diff. = 0	Student-course observations
	(1)	(2)	(3)	(4)
A. Instrument = Course available in person at home campus				
Dep Var = Course grade	2.821	0.361	0.000	2,323,023
Dep Var = GPA next term	2.871	0.158	0.260	1,974,831
B. Instrument = Distance to home campus				
Dep Var = Course grade	2.821	0.534	0.006	2,323,023
Dep Var = GPA next term	2.871	0.608	0.020	1,974,831
C. Instrument = Course availability interacted with distance to home campus				
Dep Var = Course grade	2.821	0.566	0.000	2,323,023
Dep Var = GPA next term	2.871	0.375	0.000	1,974,831
D. Random effects estimate (all students)				
Dep Var = Course grade	2.821	0.183	0.000	2,323,023
Dep Var = GPA next term	2.871	0.049	0.000	1,974,831
E. Random effects estimate (only students who took courses both online and in-person)				
Dep Var = Course grade	2.891	0.344	0.000	1,118,736
Dep Var = GPA next term	2.844	0.078	0.000	1,050,322

Note. Column 2 reports the estimated effect of taking a course online on the standard deviation of student course grade. The dependent variable scale is 0-4, A = 4 ... F = 0. Column 1 reports the sample standard deviation of course grade.

The estimates in rows A-C are instrumental variables estimates obtained in two steps. Step 1 obtain the fitted residuals from the two-stage least squares regression used to estimate the mean effect on course grades. Step 2 repeat the identical two-stage least squares regression except that the dependent variable course grade is replaced with the squared residuals from step 1. Just as in Table III, the 2SLS specification includes one endogenous treatment variable, an indicator = 1 if the student took the course online. The excluded instrument in row A is a binary variable = 1 if the course was offered in-person at the student's home campus (defined as the nearest campus) in any of the current term, the previous term, or the following term. The excluded instrument in row B is distance in miles from the student's home address to her home campus. The excluded instrument in Row C is the interaction of availability and distance. All specifications also includes controls for (i) prior cumulative grade point average, (ii) an indicator for student gender, (iii) student age, and (iv) separate fixed effects for course, term, and home campus. The estimation sample is limited to students who have address information. The test in column 3 allows for error clustering within sections.

The estimates in rows D and E are random effects estimates from a linear mixed model. The specification includes a random student effect which is allowed to be different for online and in-person classes. The fixed portion of the model includes the same regressors (i)-(iv) as the 2SLS model. The test in column 3 is a likelihood-ratio test where the constrained model requires the online and in-person variance parameters to be equal.

Table VII—Variance of Professor Effects in Online and In-person Classes
(Random Effects Estimates)

	A. All professors		B. Professors who teach both in-person and online	
	Course grade	GPA next session	Course grade	GPA next session
	(1)	(2)	(3)	(4)
A. Dep. Var.: observed values				
Standard deviation of professor effects				
In-person classes	0.316	0.0858	0.270	0.0622
Online classes	0.243	0.0347	0.232	0.0534
In-person = online test p-value	[0.000]	[0.000]	[0.002]	[0.470]
B. Dep. Var.: residuals after 2SLS with instrument = Course available in person at home campus				
Standard deviation of professor effects				
In-person classes	0.313	0.0873	0.274	0.0640
Online classes	0.235	0.0320	0.227	0.0505
In-person = online test p-value	[0.000]	[0.000]	[0.000]	[0.265]
C. Dep. Var.: residuals after 2SLS with instrument = Distance to home campus				
Standard deviation of professor effects				
In-person classes	0.316	0.119	0.273	0.0842
Online classes	0.235	0.0616	0.226	0.0661
In-person = online test p-value	[0.000]	[0.000]	[0.000]	[0.099]
D. Dep. Var.: residuals after 2SLS with instrument = Course availability interacted with distance to home campus				
Standard deviation of professor effects				
In-person classes	0.312	0.0874	0.269	0.0649
Online classes	0.236	0.0320	0.228	0.0506
In-person = online test p-value	[0.000]	[0.000]	[0.001]	[0.239]
Student-course observations	524,172	440,948	126,734	108,478

Note. Each column reports estimates from a separate linear mixed model. In Panel A, in-person and online variances are estimated random effects parameters. The same is true for Panels B-D except that, to control for student selection, we first run an instrumental variables 2SLS regression, obtain the residuals, and replace the dependent variable in the linear mixed model with the squared residuals. Dependent variables are listed in the column headers. Additional fixed controls include (i) prior cumulative grade point average, (ii) an indicator for student gender, (iii) student age, (iv) separate fixed effects for course, term, and home campus. The estimation sample is limited to May 2012 to November 2013, the time period in which we can identify the specific sections of courses professors taught.

Appendix Table A.1—Effects of Taking a Course Online Instead of In-Person on All Outcomes

	Grade	Grade: At least A-	Grade: At least B-	Grade: At least C-	Passed	Withdrew	Credits Next Semester	Enrolled Next Semester	Credits Next Year	Enrolled Next Year
Panel A. OLS Estimates										
Online	-0.380***	-0.104***	-0.110***	-0.092***	-0.074***	0.055***	-0.801***	-0.050***	-0.839***	-0.050***
(standard error)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.056)	(0.002)	(0.053)	(0.003)
Panel B. IV using Availability (current session)										
Online	-0.349***	-0.109***	-0.102***	-0.078***	-0.060***	0.044***	-0.654***	-0.030***	-1.003***	-0.030***
(standard error)	(0.014)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)	(0.056)	(0.004)	(0.078)	(0.006)
First stage coefficient	-0.259	-0.259	-0.259	-0.259	-0.259	-0.257	-0.259	-0.251	-0.272	-0.251
First stage F-statistic	270.18	270.18	270.18	270.18	270.18	262.58	215.56	190.81	263.57	190.81
Panel C. IV using Availability (current, next, prior sessions)										
Online	-0.380***	-0.123***	-0.113***	-0.083***	-0.061***	0.031***	-0.660***	-0.016**	-1.004***	-0.025**
(standard error)	(0.017)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.086)	(0.005)	(0.110)	(0.009)
First stage coefficient	-0.175	-0.175	-0.175	-0.175	-0.175	-0.174	-0.175	-0.167	-0.185	-0.167
First stage F-statistic	161.99	161.99	161.99	161.99	161.99	160.15	128.03	115.41	152.24	115.41
Panel D. IV using Availability (current, next 1 or 2, prior 1 or 2 sessions)										
Online	-0.412***	-0.134***	-0.123***	-0.089***	-0.067***	0.030***	-0.766***	-0.023***	-1.041***	-0.036***
(standard error)	(0.022)	(0.009)	(0.008)	(0.006)	(0.005)	(0.004)	(0.111)	(0.006)	(0.116)	(0.010)
First stage coefficient	-0.146	-0.146	-0.146	-0.146	-0.146	-0.144	-0.144	-0.138	-0.154	-0.138
First stage F-statistic	118.53	118.53	118.53	118.53	118.53	117.61	93.91	85.62	111.17	85.62

Panel E. IV using Availability (current, next 1, 2 or 3, prior 1, 2, or 3 sessions)										
Online	-0.415***	-0.137***	-0.125***	-0.088***	-0.065***	0.029***	-0.802***	-0.017**	-1.099***	-0.035**
(standard error)	(0.025)	(0.010)	(0.008)	(0.007)	(0.005)	(0.004)	(0.122)	(0.007)	(0.132)	(0.011)
First stage coefficient	-0.132	-0.132	-0.132	-0.132	-0.132	-0.130	-0.130	-0.124	-0.139	-0.124
First stage F-statistic	100.70	100.70	100.70	100.70	100.70	100.28	80.51	73.93	94.19	73.93
Panel F. IV using Distance to nearest campus										
Online	-0.572***	-0.131***	-0.161***	-0.153***	-0.126***	0.043***	-2.411***	-0.081***	-3.780***	-0.183***
(standard error)	(0.071)	(0.016)	(0.020)	(0.021)	(0.018)	(0.011)	(0.519)	(0.020)	(0.892)	(0.052)
First stage coefficient	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.001
First stage F-statistic	19.40	19.40	19.40	19.40	19.40	19.93	15.75	17.13	13.45	17.13
Panel G. IV using Availability (current, next, or prior sessions) interacted with distance										
Online	-0.442***	-0.123***	-0.134***	-0.102***	-0.084***	0.065***	-0.722***	-0.089***	-1.637***	-0.106***
(standard error)	(0.023)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.100)	(0.010)	(0.169)	(0.014)
First stage coefficient	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
First stage F-statistic	193.02	193.02	193.02	193.02	193.02	187.83	147.23	139.20	146.01	139.20
N (student-by-course)	2323023	2323023	2323023	2323023	2323023	2601742	1980377	2360645	1520954	2360645

Note. The top row of each panel reports a local average treatment effect from a separate regression, estimated using OLS (panel A) and standard instrumental variables methods (Panel B-G). Dependent variables are those listed in the column headers. The specifications include one endogenous treatment variable, an indicator = 1 if the student took the course online. The excluded instrument in each of Panel B-E is a binary variable = 1 if the course was offered in-person at the student's home campus in (i) the current session, (ii) any of the current session, previous session, or following session, (iii)any of the current session, previous two sessions, or following two sessions, and (iv) any of the current session, previous three sessions, or following three sessions, respectively. Panel E uses distance from the student's home to the nearest DeVry campus as the instrument, and panel F uses in the interaction between availability in the current, previous or following term and distance. Other included regressors include: (i) prior cumulative grade point average, (ii) an indicator for student gender, (iii) student age, and (iv) separate fixed effects for course, term, and home campus. The estimation sample is limited to those students who have address information. Standard errors are clustered at the section level. *p<.05, **p<.01, ***p<.001

Appendix Table A.2—Heterogeneity of Effect of Taking a Course Online Instead of In-person, by Prior Achievement, for All Outcomes

	Grade	Grade: At least A-	Grade: At least B-	Grade: At least C-	Passed	Withdrew	Credits Next Semester	Enrolled Next Semester	Credits Next Year	Enrolled Next Year
Panel A. OLS Estimates										
Online	-0.570***	-0.145***	-0.162***	-0.142***	-0.120***	0.089***	-0.738***	-0.101***	-0.903***	-0.116***
(standard error)	(0.013)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.064)	(0.003)	(0.055)	(0.005)
Online*Prior GPA	0.093***	0.020***	0.025***	0.025***	0.023***	-0.017***	-0.030*	0.026***	0.028*	0.034***
(standard error)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.015)	(0.001)	(0.014)	(0.002)
Panel B. IV using Availability (current, next, prior sessions)										
Online	-0.913***	-0.193***	-0.245***	-0.248***	-0.227***	0.174***	0.508*	-0.252***	-0.654***	-0.365***
(standard error)	(0.069)	(0.019)	(0.021)	(0.019)	(0.018)	(0.015)	(0.206)	(0.025)	(0.135)	(0.038)
Online*Prior GPA	0.192***	0.025***	0.048***	0.060***	0.060***	-0.052***	-0.422***	0.086***	-0.123***	0.124***
(standard error)	(0.025)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.072)	(0.009)	(0.034)	(0.015)
First stage F-statistic: online	191.299	191.299	191.299	191.299	191.299	189.787	139.888	131.694	164.118	131.694
First stage F-statistic: interaction	105.053	105.053	105.053	105.053	105.053	107.678	85.884	80.627	90.765	80.627
Panel C. IV using distance										
Online	-0.769***	-0.178***	-0.217***	-0.203***	-0.170***	0.091***	-2.045***	-0.150***	-3.055***	-0.258***
(standard error)	(0.051)	(0.014)	(0.015)	(0.015)	(0.012)	(0.008)	(0.367)	(0.015)	(0.565)	(0.039)
Online*Prior GPA	0.134***	0.032***	0.038***	0.034***	0.030***	-0.034***	-0.228*	0.050***	-0.374*	0.054***
(standard error)	(0.016)	(0.004)	(0.005)	(0.005)	(0.004)	(0.002)	(0.105)	(0.003)	(0.176)	(0.009)
First stage F-statistic: online	571.447	571.447	571.447	571.447	571.447	469.757	382.398	372.624	515.331	372.624
First stage F-statistic: interaction	163.017	163.017	163.017	163.017	163.017	166.666	127.671	130.111	112.595	130.111

Panel D. IV using interaction between availability and distance										
Online	-0.621***	-0.135***	-0.173***	-0.164***	-0.150***	0.120***	-0.823***	-0.173***	-1.592***	-0.211***
(standard error)	(0.023)	(0.010)	(0.008)	(0.007)	(0.006)	(0.006)	(0.090)	(0.008)	(0.119)	(0.010)
Online*Prior GPA	0.123***	0.008	0.027***	0.043***	0.046***	-0.040***	0.066**	0.062***	-0.025	0.079***
(standard error)	(0.009)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.025)	(0.004)	(0.041)	(0.005)
First stage F-statistic: online	873.301	873.301	873.301	873.301	873.301	895.753	437.532	669.444	407.763	669.444
First stage F-statistic: interaction	98.329	98.329	98.329	98.329	98.329	107.909	90.656	88.627	92.428	88.627
N (student-by-course)	2323023	2323023	2323023	2323023	2323023	2601742	1980377	2360645	1520954	2360645

Note. Each panel reports local average treatment effects from a separate regression, estimated using OLS (panel A) and standard instrumental variables methods (Panel B-D). Dependent variables are those listed in the column headers. The specifications include two endogenous treatment variables, an indicator = 1 if the student took the course online and the indicator interacted with prior cumulative GPA. The excluded instruments are a binary variable = 1 if the course was offered in-person at the student's home campus (defined as the nearest campus) in any of the current term, the previous term, or the following term (panel A), the distance in miles from the student's home address to her home campus (panel B), the interaction of availability and distance (panel C); and the interaction of those variables, respectively, with prior cumulative GPA. Other included regressors include: (i) prior cumulative grade point average, (ii) an indicator for student gender, (iii) student age, (iv) course fixed effects, (v) session (time) fixed effects, and (vi) home campus fixed effects. The estimation sample is limited to those students who have address information. Standard errors are clustered at the section level. *p<.05, **p<.01, ***p<.001