

# **DISCUSSION PAPER SERIES**

IZA DP No. 15777

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#### **Dora Gicheva**

University of North Carolina at Greensboro

#### **Julie Edmunds**

University of North Carolina at Greensboro

#### Marie Hull

University of North Carolina at Greensboro and IZA

#### **Beth Thrift**

University of North Carolina at Greensboro

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## **ABSTRACT**

# Getting Students to Stick Around: The Effects of Completing an Introductory Course on Persistence for Community College Students\*

This paper studies the impacts of withdrawing from and failing a course, relative to successful completion, on persistence for community college students. We leverage random assignment of students to instructors for identification. Withdrawing from a course reduces the probability of persistence by about 20 percentage points, while the impact of failing is much smaller in magnitude and statistically indistinguishable from zero. Course withdrawals are highly correlated with full institutional withdrawal for the students in our sample, which is in turn linked to lower likelihood of returning the following semester. Our findings reinforce the importance of academic momentum: remaining in a course keeps students attached to college even if they earn a failing grade.

JEL Classification: 121, 123

**Keywords:** community college, persistence, course completion, instructor

effects

#### Corresponding author:

Marie C. Hull
Department of Economics
University of North Carolina at Greensboro
445 Bryan Building
PO Box 26170
Greensboro
NC 27402-6170
USA

E-mail: mchull2@uncg.edu

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#### I. Introduction

Policymakers and practitioners are very interested in understanding how to increase the share of students successfully persisting in college and earning a college degree. This is particularly important for community colleges, where the average graduation rate for first-time, degree-seeking students is less than 30 percent (National Center for Education Statistics, 2021), with higher dropout rates for certain populations such as minority students (Radford, Berkner, Wheeless, & Shepherd, 2010).

Successfully completing courses creates a sense of academic momentum that is necessary for persisting in and graduating from college (Chan & Wang, 2018). Yet, on average, many students struggle to complete courses. For example, in the community college we study, pass rates were 70 percent for face-to-face classes, 62 percent for online courses, and as low as 46 percent for racial minority students in online courses. Lack of successful completion may occur because a student dropped the course or because a student completed the course but failed it. Many interventions focus on increasing the percentage of students who earn a passing grade; in this paper, we examine a different issue. We seek to explore whether withdrawing from versus failing a course makes a difference for subsequent student outcomes, which can help practitioners and policymakers better target interventions aimed to improve persistence.

This issue is especially relevant in community colleges, where persistence and degree completion rates are typically lower than in most four-year institutions. In addition, we have little systematic evidence of the best course of action for students who struggle in a class: should such students be advised to withdraw from the class or be encouraged to remain enrolled until the end of the semester even if this is likely to result in a failing grade? This question is especially

important in light of a recent movement to implement policies that restrict the number of course drops and withdrawals in a student's academic career.<sup>1</sup>

In addition to presenting descriptive analysis of the characteristics of community college students who fail to complete introductory courses and these students' institutional enrollment patterns, our paper examines the causal effects of failing and withdrawing from a class on persistence for marginal students. To our knowledge, this is the first paper to offer causal evidence of the effects of course noncompletion, including withdrawals.

An ideal causal design to answer this question would randomly assign students to either withdraw or fail a course. Given the practical infeasibility of such a design, we utilize analyses that capitalize on a randomized controlled trial conducted at a large community college in the U.S. Southeast, in which students were randomly assigned to sections of the same foundational online courses taught by different instructors. Our identification strategy relies on the fact that there are substantial variations in passing and withdrawal rates for the same course depending on the instructor, so that random instructor assignment affects the outcomes of academically marginal students.

We find that for at-risk community college students, defined as students who are on the margin between completing and not completing a class, withdrawing from a foundational course decreases the probability of being enrolled in or having graduated from any postsecondary institution during the year following the study by about 20 percentage points, while the impact of failing a course is much smaller in magnitude, less precisely estimated, and statistically indistinguishable from zero. As comparison, the average persistence rate of students who pass

<sup>&</sup>lt;sup>1</sup> For example, the University of Texas system, the University of North Carolina system, and the University of Tennessee-Knoxville have imposed policies limiting the number of courses or credit hours that students may drop or withdraw from.

the study courses is 85%. Only 59% of students who fail the class persist into the following semester, but our results suggest that the difference is largely driven by unobserved student characteristics and is not causal. We provide suggestive evidence of a potential mechanism behind the fairly large effect of withdrawing from a course: withdrawing from one class is highly correlated with full institutional withdrawal for community college students, which then makes them much less likely to return the following semester, whereas staying in the class and failing it may not have this effect.

Our interpretation of these findings is that students who finish a course but fail have more academic momentum than students who withdraw. This momentum could come from staying in greater contact with the institution or from keeping up academic behaviors, such as study habits. Additionally, students who fully withdraw from an institution must take additional steps to return, such as applying for readmission or paying fees, which slows down momentum. In sum, this paper highlights the importance of keeping students attached to college, even as they face disruptions to their progress.

#### II. Prior Literature

Understanding the factors that affect persistence in higher education is as critical as ever, with recent research showing increasing gaps in economic outcomes between workers with some college and workers with a degree (Li, Wallace, & Hyde, 2019). While some may be skeptical about the benefits of persisting for marginal students, Ost, Pan and Webber (2018) estimate that students who are marginally induced to complete an additional year of college earn 25% more than students who do not. At community colleges, persistence has historically been a particular concern: persistence rates at public community colleges hover around 60%, while they are above 80% at four-year colleges (National Center for Education Statistics, 2021). Student retention is

also an important issue for the bottom line of institutions, as it affects their financial stability and feeds into publicized rankings used to recruit new students (Freeman, Hall, & Bresciani, 2007).

One key factor affecting persistence is the notion of academic momentum or the behaviors and activities that keep a student moving through college (Chan & Wang, 2018).

Momentum is often defined by the number and type of courses that students take (Adelman, 2006), indicating that if students attain significant credits in key courses, they will be more likely to finish college.

Researchers have shown that the grades students receive significantly affect their persistence rates as do the number of withdrawals that students take (McKinney, Novak, Hagedorn, & Luna-Torres, 2019). Past work has generally shown that the probability of course withdrawal is higher among students who are male, Black, and have weaker academic preparation, as measured by grade point average (GPA) and SAT scores (Bosshardt, 2004; Boldt, Kassis, & and Smith, 2015; McKinney, Novak, Hagedorn, & Luna-Torres, 2019). Online courses have higher withdrawal rates than face-to-face courses, particularly at community colleges (Xu & Jaggars, 2011a; Xu & Jaggars, 2011b; McKinney, Novak, Hagedorn, & Luna-Torres, 2019). However, there is very little research that examines the relative influence of withdrawing or completing the course and failing. One study that examined participation in a single university course found that students who completed the course but failed it were more likely to persist than students who withdrew from the course later in the semester (Bosshardt, 2004). In this study, we explore this question with a much larger sample and a different population.

Our identification strategy relies on the idea that instructors exert influence over students' course outcomes. Hoffman and Oreopoulos (2009) and Carrell and West (2010) established that there exists significant variation among college instructors teaching introductory courses, not just

for course grades but also in the likelihood that a student drops or withdraws from a course. This variation remains even after controlling for the course and term (Hoffman & Oreopoulos, 2009). It still occurs in settings where students are randomly assigned to sections and the curriculum and exams are standardized (Carrell & West, 2010; Braga, Paccagnella, & Pellizzari, 2016). While much of the variation in instructor effectiveness cannot be explained by observable instructor characteristics, a few specific traits have been found to significantly predict student outcomes, such as instructor type (e.g., adjunct) and course-specific teaching experience (Xu & Ran, 2021; De Vlieger, Jacob, & Stange, 2019). The variation in instructor effectiveness is larger for in-person classes but still considerable for online classes (De Vlieger, Jacob, & Stange, 2019).

#### III. Institutional Setting

This study uses data from Project COMPASS, a development project funded under the U.S. Department of Education's First in the World competition. The project was conducted at a large community college in the U.S. Southeast that has over 15,000 full-time-equivalent students enrolled and 7,000 certificates and associate degrees awarded per year. Students at this college are somewhat more diverse than the general population in the region, with a racial/ethnic composition of about 50% White, 22% Black, and 13% Hispanic. One-third of students are enrolled full-time, with the rest part-time, and 38% are Pell grant recipients. The retention rate at the community college is 65% for full-time students and 51% for part-time students, which is higher than the average rate for similar colleges, based on Integrated Postsecondary Education Data System statistics.

The goal of Project COMPASS was to improve course outcomes in introductory asynchronous online courses in three subjects, which we denote as Subject I, Subject II, and

Subject III. The courses are offered by different divisions of the college, including Social Sciences, Business & Public Services Technologies, and Information Technology. To accomplish the project's goal, the three courses were redesigned using a set of "high-tech" tools and "high-touch" strategies. More information about the specific changes and their rationale can be found in Edmunds, Gicheva, Thrift, and Hull (2021). The college assigned some instructors to teach redesigned sections of the study courses, while instruction in the other sections was business as usual. Because the intervention was conducted at the instructor level, we do not need to distinguish between instructor and treatment effects.

Each of the courses in the study is considered a gateway course; they serve as fundamental courses and are required for multiple degree and certificate programs that the community college offers. The courses varied in terms of instructor autonomy in setting the curriculum and identifying materials. In one course, instructors had full autonomy in selecting materials. In the other two courses, instructors used a common course shell that included access to similar materials. One of the main common features of the courses is that they were all offered asynchronously online; the college also offers on-campus versions of these courses, which we do not include in our study. All three courses are designated as transferable to four-year institutions within the state's four-year public university system.

All students who wished to take one of the study courses were allowed to register for the course but not to choose their section or instructor; this assignment was randomized by the research team. In particular, students were first assigned randomly to a treatment or control condition, after which they were assigned, also at random, to a section within that condition, at which point students could see their assigned instructor. Figure 1 illustrates the assignment process. It is important to note that since the research team worked in partnership with the

Registrar's Office, students had to comply with their assignment and could not changes sections after observing who their instructor is. If an assigned student dropped the class and re-enrolled in the same semester, they were placed in their originally assigned section.<sup>2</sup>

The schedule adjustment period at the college lasts through the first 10% of the semester. During this period, students who no longer want to take a course can drop it; drops do not appear on a student's transcript and the student receives a tuition refund of 75 to 100%, depending on the date when the drop occurred. Withdrawals result in a grade of W on the student's transcript and occur after the schedule adjustment period ends.<sup>3</sup> The college advises students that withdrawals have a negative impact on their eligibility for financial aid and that these decisions should be made in consultation with their instructor and academic advisor. Students do not receive a tuition refund if they withdraw and may need to repay some of their financial aid. Students who complete a course but are dissatisfied with their grade can retake the course in a subsequent semester; only the best grade earned in a course is used for GPA calculations. There is no limit to the number of courses students can withdraw from while enrolled at the college, but satisfactory academic progress, which determines financial aid eligibility, requires a student to complete 67% of the courses she enrolls in and to maintain a cumulative GPA of 2.0. This implies that students who struggle in one or more classes face important tradeoffs if trying to remain eligible for financial aid.

#### IV. Conceptual Framework

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<sup>&</sup>lt;sup>2</sup> More details about the randomization process can be found in Gicheva, Edmunds, Thrift, Hull, & Bray (2020).

<sup>&</sup>lt;sup>3</sup> At the community college we study, the last day to withdraw with a grade of W occurs when the semester is 60% over. After this point, students earn a WP or WF. The two latter grades are relatively uncommon, and we treat all three grades as the same outcome.

Students who are struggling in a course have to make a decision: they can either withdraw from a course or they can remain in the course and face the risk of failure. The decision to withdraw can involve many factors; some are discussed in prior studies such as McKinney et al. (2019) and Bosshardt (2004).<sup>4</sup> At the time of making the withdrawal decision, students have paid full, nonrefundable tuition and invested some effort in the course, though these are sunk costs from an economic perspective. When deciding whether to withdraw from a course, students may weigh the costs of doing so against their individual probability of earning a passing grade in the course given their underlying ability and optimal level of effort in the class.

One of the most significant factors in students' decisions to withdraw from a course is whether they could likely, or even possibly, pass the class (McKinney et al, 2019). If students are likely to fail the class, advisors generally recommend that they should withdraw to avoid a negative impact on their GPA. However, there may be long-term benefits to completing a course, even with an unsatisfactory grade (McKinney, Novak, Hagedorn, & Luna-Torres, 2019). For example, a student may stay more connected to the academic institution and maintain study habits. If a course is required and must be taken again, the student would be exposed to more of the material, which might help the student complete successfully the next time. Thus, the causal effect of withdrawing or failing a course on persistence is ambiguous. Figure 2 demonstrates the potential advantages and disadvantages of either withdrawing from or failing the course.

We can also express some of the relationships shown in Figure 2 mathematically. Suppose that student i's value of remaining enrolled in a course taught by instructor j as opposed to dropping or withdrawing from it depends on the probability of earning a passing grade, which

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<sup>&</sup>lt;sup>4</sup> In this section, the term "withdrawal" is used interchangeably with "drop", but in our institutional context, "drop" officially refers to course changes in the early part of a term that do not appear on a student's transcript. Withdrawals earn a grade of W and occur after the add/drop period ends. We discuss the difference between dropping and withdrawing in more detail later in the paper.

is a function of the student's observed and unobserved characteristics  $a_i$  and an instructor effect  $\eta_j$ , times the value of completing a course successfully. Also relevant is the cost of remaining enrolled, which itself is a function of student and instructor characteristics, as well as the number of courses the student is enrolled in during the current semester,  $h_i$ .<sup>5</sup> The cost includes both monetary and nonmonetary components.

The value of withdrawing is also a function of a random shock  $u_{ij}$  that is specific to the course and another shock  $v_i$  that affects performance in all courses during the current semester. The random terms  $u_{ij}$  and  $v_i$  incorporate the student's connection to the instructor and interest in the course material, the impact on time-to-degree, financial aid implications, or potential academic sanctions. Personal factors, such as work and family commitments and access to resources (e.g., a personal computer), may also play a role. The course-specific random component  $u_{ij}$  can also represent specific practices that nudge students to stay enrolled in a given class. We can write

$$w_{ij} = \begin{cases} 1 \text{ if } W(a_i, \eta_j, h_i, \nu_i, u_{ij}) \ge 0 \\ 0 \text{ if } W(a_i, \eta_j, h_i, \nu_i, u_{ij}) < 0 \end{cases}$$

$$f_{ij} = \begin{cases} 1 \text{ if } W(a_i, \eta_j, h_i, \nu_i, u_{ij}) < 0 \text{ and } F(a_i, \eta_j, h_i, \nu_i, u_{ij}) \ge 0 \\ 0 \text{ if } W(a_i, \eta_j, h_i, \nu_i, u_{ij}) \ge 0 \text{ or } F(a_i, \eta_j, h_i, \nu_i, u_{ij}) < 0 \end{cases}$$

$$(1)$$

where  $w_{ij}=1$  indicates withdrawal and  $f_{ij}=1$  indicates failing the class. It is assumed that  $\frac{\partial W(\cdot)}{\partial a} < 0, \frac{\partial F(\cdot)}{\partial a} < 0, \frac{\partial W(\cdot)}{\partial \eta} < 0, \frac{\partial F(\cdot)}{\partial \eta} < 0.$  It is plausible that for community college students,  $\frac{\partial W(\cdot)}{\partial h} < 0 \text{ and } \frac{\partial F(\cdot)}{\partial h} < 0, \text{ especially when } h \text{ is small: it is less costly to remain enrolled and do}$ 

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<sup>&</sup>lt;sup>5</sup> To simplify the exposition, we do not model the choice of effort that a student can exert. We do not observe any measures of effort in the data.

well in a course if the student is currently enrolled in other courses as well. For example, students who withdraw from all courses in a semester may have to repay a portion of their financial aid. As another example, students enrolled in additional classes other than the course taught by instructor *j* may be more likely to use campus resources such as a library or computer lab. At the same time, higher course loads create time constraints that may increase the cost of completing a course successfully. Thus, the signs of the derivatives with respect to *h* are ambiguous.

Full institutional withdrawal during the current semester, indicated by  $I_i = 1$ , occurs when the student withdraws from all courses:

$$I_i = \prod_{k=1}^h w_{ik} \,. \tag{2}$$

Since we observe students and instructors only in a single course that was part of the experiment, we can write (2) as

$$I_{i} = W(a_{i}, \eta_{j}, h_{i}, \nu_{i}, u_{ij}) \prod_{k=1}^{h-1} W(a_{i}, \eta_{k}, h_{i}, \nu_{i}, u_{ik}).$$
(3)

Thus,  $I_i$  is a function of student and instructor characteristics, course load, and the random shocks. In particular, if a student has a bad draw for  $v_i$ , such as personal circumstances that impact academic performance across the board, she is likely to withdraw from all courses. If a student experiences a bad shock limited to course j, this will impact performance in course j directly and can have effects on institutional withdrawal and also on other courses through h.

The decision to enroll in the following semester is a function of student characteristics summarized by the parameter  $a_i$  and the number of credits remaining until graduation, which in

turn depends on the outcome in course j and other courses  $k \neq j$ . We also assume that there is a cost  $C_R$  of reenrolling if the student withdraws fully from the institution ( $I_i = 1$ ). One reason this assumption is plausible in the community college setting is that students are required to make satisfactory academic progress to maintain future financial aid eligibility. Specifically, they must complete 67% of the courses they enroll in and maintain a 2.0 GPA. In addition, community college students who withdraw from all courses during the current semester may be less likely to be in contact with their academic advisor regarding the registration process for the following semester.

We can write the following equation for the indicator  $e_i$  for enrolling in the following semester:

$$e_{i} = \begin{cases} 1 \text{ if } E(a_{i}, w_{ij}, w_{ik}, f_{ij}, f_{ik}, \varepsilon_{i}) - C_{R} I_{i}(w_{ij}, w_{ik}) \ge 0 \\ 0 \text{ if } E(a_{i}, w_{ij}, w_{ik}, f_{ij}, f_{ik}, \varepsilon_{i}) - C_{R} I_{i}(w_{ij}, w_{ik}) < 0 \end{cases}$$

$$(4)$$

where  $\varepsilon_i$  is a random shock. It is assumed that  $\frac{\partial E(\cdot)}{\partial a} > 0$ . If students are more likely to reenroll if they completed more credits in the previous semester and are thus closer to graduation, we would have that  $E(a_i, 1, w_{ik}, 0, f_{ik}, \varepsilon_i) < E(a_i, 0, w_{ik}, 0, f_{ik}, \varepsilon_i)$  and  $E(a_i, 0, w_{ik}, 1, f_{ik}, \varepsilon_i) < E(a_i, 0, w_{ik}, 0, f_{ik}, \varepsilon_i)$ . An important feature of the model is that withdrawing from a course can have negative effects on persistence beyond the effects of noncompletion through failing. This will be the case when withdrawal from a course is accompanied by  $(I_i = 1)$ , which in turn triggers a cost of reenrolling in the following semester. If the main effect on persistence operates through the cost of reenrolling but not through the number of previously completed credits, this would mean that  $E(a_i, 1, w_{ik}, 0, f_{ik}, \varepsilon_i) = E(a_i, 0, w_{ik}, 0, f_{ik}, \varepsilon_i)$  and  $E(a_i, 0, w_{ik}, 1, f_{ik}, \varepsilon_i) = E(a_i, 0, w_{ik}, 0, f_{ik}, \varepsilon_i)$ .

Based on the discussion above, we can make a distinction between correlational and causal relationships between course outcomes and persistence:

- A correlational relationship between the outcome in a given course j and persistence  $e_i$  is driven by factors common to all courses, namely  $a_i$  and  $v_i$ .
- A causal effect of the outcome in a given course j on persistence  $e_i$  is driven by factors specific to course j such as instructor characteristics  $\eta_j$  and the random error  $u_{ij}$ .

Our framework assumes that instructor j can impact course outcomes  $w_{ij}$  and  $f_{ij}$  but does not enter the function for  $e_i$  directly, and that instructor assignment is uncorrelated with student characteristics  $a_i$ . In many postsecondary settings, we would expect student and instructor characteristics to be correlated, for example if students of lower ability tend to choose "easy" instructors. The key feature of the setting we study is that students are randomly assigned to instructors. This allows us to identify causal impacts of course outcomes on institutional withdrawals during the current semester and on future persistence.

#### V. Data and Methodology

#### a. Data

Our sample includes students who participated in Project COMPASS between the Fall 2016 and Fall 2018 semesters. We exclude students who registered for the course and were randomized by the research team but were dropped administratively for nonpayment, dropped the class before they were assigned by the Registrar's Office to their allocated section, or dropped the class before the start of the semester with a grade of "NA," which indicates that a student never attended the class and had no interaction with the instructor or exposure to any course content. We define these cases as "no shows" whose decision to drop the class is

independent of their instructor assignment; we exclude them in order to increase the precision of the estimates. For students who participated in the study in a given semester and then reenrolled in the same study course in a subsequent semester, we drop observations after the first term. A small number of students enroll in two or three study courses during the same semester or in different semesters; we treat their data as separate observations but include an indicator for multiple course enrollment in the regression models.

Table 1 shows the number of observations in the data by subject and semester, while Appendix Table A.1 shows the number of students that each instructor taught in different semesters during the study period. Most instructors taught multiple sections of the same course; the number of students assigned to each instructor in a given semester varies between 18 and 128, with section sizes determined by each department based on various capacity constraints.

We infer persistence based on data from the National Student Clearinghouse (NSC). We define students to be persisting if they present in the NSC data as having enrolled in or obtained a degree from any postsecondary institution during the six months following the semester when they participated in the study.

The main explanatory variables of interest are the outcomes in the study courses, for which we use administrative data provided by the college. Students are recorded as having dropped the class if they were not enrolled past the schedule adjustment period. We define passing the class as completing with any grade higher than F. Other administrative data that we use as covariates in the analyses include student demographic information (gender, race, ethnicity, and age), disability status, and whether the student received a Pell grant during the study semester. Some of the analyses use information on the number of credit hours attempted by

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<sup>&</sup>lt;sup>6</sup> Results including no-shows are available in Appendix Table A.5.

a student at the start of the semester during which they were included in the study. In most cases, the number of attempted credits does not include the study course if the student dropped it before the start of the semester.

We construct a standardized measure of baseline student ability by combining available information on placement test scores, including the SAT, ACT, and Accuplacer tests. Because not all community college students have placement test scores, we supplement this information with high school GPA; when this is not available either, we use cumulative GPA at the start of the study semester. Baseline achievement scores are unavailable for 18 percent of students, in which case we use other covariates to impute them. The empirical models include an indicator for whether achievement is imputed for a given student.

#### b. Empirical Model: Persistence

It is difficult to isolate a causal relationship between failing or withdrawing from a class and subsequent persistence in postsecondary education because unobserved student characteristics that determine course outcomes are likely also correlated with persistence. We are interested in estimating the following equation for student *i* taking a course with instructor *j*:

$$Persist_{i} = f(\alpha_{0} + \alpha_{1}Withdraw_{ij} + \alpha_{2}Fail_{ij} + X_{i}\alpha_{3} + Z_{j}\alpha_{4} + \varepsilon_{ij}), \tag{5}$$

where  $X_i$  are student characteristics;  $Z_j$  includes controls for subject and semester; and  $\varepsilon_i$  is a random error. Here the outcome  $Persist_i$  refers to institutional persistence, while the explanatory variables  $Withdraw_{ij}$  and  $Fail_{ij}$  are specific to the single course j. The coefficients  $\alpha_1$  and  $\alpha_2$  can tell us how changing the outcome for a student to a passing grade instead of withdrawing, or passing instead of failing, affects the student's persistence.

The model in equation (5) cannot on its own give us unbiased causal estimates of the effects of noncompletion because unobserved student characteristics that determine course outcomes are likely also correlated with persistence:  $Cov(Withdraw, \varepsilon) \neq 0$  and  $Cov(Fail, \varepsilon) \neq 0$ .

The full underlying model can be written as a system of simultaneous equations:

$$Withdraw_{ij} = f(\beta_0^W + \beta_1^W W_{-i,j} + X_i \beta_2^W + Z_j \beta_3^W + u_{ij}^W)$$

$$Fail_{ij} = f(\beta_0^F + \beta_1^F W_{-i,j} + X_i \beta_2^F + Z_j \beta_3^F + u_{ij}^F)$$

$$Persist_i = f(\alpha_0 + \alpha_1 Withdraw_{ij} + \alpha_2 Fail_{ij} + X_i \alpha_3 + Z_j \alpha_4 + \varepsilon_i)$$

$$(6)$$

The estimates for  $\alpha_1$  and  $\alpha_2$  will be biased if we ignore the correlations in the error terms  $u_{ij}^k$  and  $\varepsilon_i$  that are due to unobservable student characteristics.

The variables in  $W_{-i,j}$  that determine course outcomes but do not enter the persistence equation directly play a crucial role for the identification of the system of equations in (6). We use instructor j's average withdrawal and fail rates for the study course, excluding the outcome of student i. As long as the variables in  $W_{-i,j}$  are truly excludable from the persistence equation, the system in (6) is identified, and we can obtain unbiased estimates for  $\alpha_1$  and  $\alpha_2$ . Excludability in this setting comes from random assignment of students to instructors.

Identification relies on the assumption that instructors affect persistence only through students' outcomes in the course they teach. Because students are assigned to instructors at random, observed and unobserved student characteristics should not differ systematically by instructor. In Appendix Table A.2 we show descriptive statistics separately for students assigned to instructors whose withdrawal or fail rate is above versus below the median relative to other

instructors in the sample teaching the same subject. The results suggest that students assigned to instructors with different withdrawal or fail rates have similar characteristics but differ in their outcomes. It should be noted that instructors with higher withdrawal and fail rates tend to teach larger sections, so there are more students assigned to them. This could be part of the mechanism that generates a relationship between instructor assignment and course outcomes.

The exclusion restriction may be violated if instructors affect student outcomes in subsequent classes. For example, an effective instructor can help students establish good study habits that may help them succeed in subsequent classes. This, however, is unlikely to be the case in the setting that we conduct our study in since we use asynchronous online courses with limited instructor-student interaction. It is also possible that instructors with high withdrawal or fail rates are less effective across the distribution of student ability, and that students who learn more of the material are more likely to persist. The theory in Section IV assumes that persistence is a function of credits earned but not the "quality" of these credits. This assumption is plausible because we look at short-term persistence – from one semester to the next – while having a better grasp on the foundational material taught in the study courses can be expected to have effects in the longer term, when students are taking higher-level courses in their chosen field of study. In other words, we expect getting an F versus a D in a class to matter much more for persistence into the following semester than getting a B versus an A. To explore this idea further, we estimate a version of the system of equations in (6) in which we focus on students who passed the course and find no effect of earning a better grade on persistence.

We define the instructor effects in the vector  $W_{-i,j}$  as instructor j's average withdrawal and fail rates in the study course for all students across all semesters in the sample excluding student i. We construct these measures as the number of students in instructor j's classes,

excluding student i, who withdrew or who failed divided by the total number of students in instructor j's classes excluding those who dropped before the end of the schedule adjustment period. The set of instrument variables we use in the analyses also includes indicators for two particularly influential instructors. One of the instructors was a co-PI for Project COMPASS, took a lead in the course redesign, and implemented additional course features aimed at increasing student engagement; this instructor's sections had lower withdrawal rates than the sections of most other instructors in the study. The other instructor's sections had a considerably higher fail rate (22%) than the rest of the sample (mean of 6.5% and range 0% - 15%) and a low withdrawal rate (3.8% compared to a sample average of 21% and range of 7% - 35%). Controlling for these two instructors increases the predictive power of the instruments.

In reality, our data contain a fourth possible course outcome, in addition to withdrawing, failing, and passing, not captured in the system of equations in (6): registering for the course but dropping it before the start of the semester or during the first-week schedule adjustment period. We find that instructor assignment has almost no predictive power over the latter outcome, which prevents us from estimating a separate equation for drops as part of the system in (6). To address the problem of not having a strong predictor for dropping the class that is excludable from the persistence equation, we conduct two versions of the analysis. First, we combine dropping and withdrawing from the class into a single outcome. Second, we treat dropping and withdrawing as separate outcomes but assume that the error term in the equation for drops is uncorrelated with  $\varepsilon_i$  and that instructors do not impact drops, which means that this outcome is

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<sup>&</sup>lt;sup>7</sup> We verified the robustness of the results to alternative instructor effect measures calculated by excluding the outcomes of all students in student *i*'s section of the course. This method requires us to exclude from the analysis instructors who taught a single section during the project period and produces noisier estimates, but the results remain qualitatively similar.

exogenous and can be included in the persistence equation without biasing any of the coefficient estimates.

If dropping the class is a randomly occurring event unrelated to the likelihood of withdrawing from or failing the class as well as to the instructor effectiveness measures, combining drops with withdrawals introduces measurement error in the withdrawal indicator leading to attenuation bias in the estimated effect of withdrawals. In this case, including withdrawals as a separate outcome is preferable, as it gives an unbiased and more precise estimate of the effects we are interested in. If drops are not random but determined by unobserved student characteristics similar to the unobservables driving other outcomes or are driven in some part by instructor effects, the estimates for the effects of withdrawing and failing would be biased if we include an indicator for dropping the class without modeling the correlation in the error terms. Then, combining drops and withdrawals and using instructor assignment as identifying variation is the preferred strategy. Comparing the results from the two approaches allows us to draw inferences under both scenarios.

We estimate all equations as linear probability models. This approach generally produces unbiased and consistent estimates under the least restrictive set of distributional assumptions and has the additional advantage of producing coefficient estimates that are easily interpretable. Since in these online courses, students assigned to the same section did not have much opportunity to interact with each other, we allow for clustering of the errors at the instructor rather than the section level, even though most instructors taught multiple sections over the study period.

We do not include the number of attempted credits as a control in the system of equations in (6) due to endogeneity concerns: it may be correlated with instructor assignment depending on

when it is measured because some drops occur very early in the semester, before the number of attempted credits is recorded for administrative purposes. We conduct robustness checks in which we control for the number of attempted credits; the results, which are not shown in the paper but are available on request, do not change much. Including attempted credits also does not change the interpretation of the results much if the excluded variables tend to impact course outcomes for students within a narrow range of attempted credit hours.

#### VI. Results

#### a. Descriptive Statistics

We begin by exploring the relationship between student characteristics and academic outcomes descriptively in Table 2. Students who withdrew from and those who failed the study course tend to be similar in that they had lower academic achievement, as measured by cumulative GPA from prior semesters or the standardized baseline ability measure that we construct. Students who dropped early and those who withdrew later in the semester are similar in that they attempted fewer credits during the semester when they were included in the study. Over 40 percent of students in the sample attempted between 6 and 11 credits, regardless of their course outcome: part-time enrollment is common for community college students. The students who failed and those who passed were equally likely to attempt a full-time course load, 12 or more credits, while students who dropped and those who withdrew were disproportionately more likely to attempt fewer than 6 credits.<sup>8</sup>

Table 2 also shows that course completion is highly correlated with subsequent persistence for the students in the sample. Students who withdrew are least likely to re-enroll at

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<sup>&</sup>lt;sup>8</sup> Attempted credits are lower for students who dropped partly because attempted credits were measured shortly after the start of the semester, after some of the drops occurred.

the community college or another institution of higher education in the subsequent semester; only 48% of them do, while 85% of students who completed the class with a grade of D or better persisted in college. Overall, the descriptive statistics in Table 2 suggest that students who withdraw and students who fail a class are similar in that they have lower baseline academic achievement.

#### b. Instructor Effects

The bottom two rows of Table 2 show the average instructor withdrawal and fail rates by course outcome excluding the student's own outcome. Students who dropped or withdrew took the class with instructors with higher average withdrawal rates, and students who failed took the class with instructors with higher fail rates. This observation is suggestive of instructor effects, which are important for our identification strategy because the empirical model in (6) is contingent on the assumption that instructors play a role for students' course outcomes. We provide further evidence on instructor effects in this section.

Table 3 shows the coefficients of correlation between the average instructor withdrawal, fail, and drop rates. For instructors who taught online sections of the study courses in the two semesters before the sample period, we also use data on their baseline average withdrawal and fail rates for the same courses, and we include the baseline rates as separate variables in the correlation matrix in Table 3.9 The correlations suggest that there is consistency in instructor withdrawal and fail rates across semesters: current and past withdrawal rates are highly positively correlated, and so are current and past fail rates. The share of an instructor's students who fail a class is negatively correlated with the proportion of students who withdraw, both in the current and in past semesters. These trends are consistent with the idea that instructors differ in systematic ways in whether they

<sup>&</sup>lt;sup>9</sup> Baseline course outcome data are available for 22 of the 37 instructors in the sample.

encourage students to withdraw from a class versus completing the class but with a failing grade. The negative correlation between withdrawal and fail rates suggests that many of the marginal students who are induced to stay in a class instead of withdrawing may be earning a failing grade. Then it is important to know which outcome is less detrimental in the longer term.

To obtain empirical estimates of the share of variance in student outcomes accounted for by instructors, we estimate random effect models for student *i* and instructor *j*:

$$y_{ij} = \mu + u_j + e_{ij}.$$

We estimate the random effects model separately for each of the four course outcomes. Table 5 shows the estimates for the variances of the terms  $u_j$  and  $e_{ij}$ , and the share of the total variance explained by the instructor effects:

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}.$$

The results suggest that instructors have moderate influence on whether a student withdraws, fails, or passes; the estimate of  $\rho$  is between 0.028 and 0.042 for these outcomes, meaning that instructor assignment accounts for 3 to 4 percent of the variance. The magnitude of these numbers reflects the multitude of factors that play a role for course outcomes. Instructor effects have smaller explanatory power for whether a student drops the class before the end of the first week ( $\hat{\rho} = 0.018$ ).

To understand instructor effects fully, it is important to think about the counterfactual outcome for a student who is assigned to an instructor with high withdrawal rate and is nudged to withdraw from the class. Were this student induced to stay in the class by a different instructor or a targeted policy, she may have failed it or earned a passing grade. While we cannot state with

certainty what students' counterfactual outcomes would have been, we can examine more closely the margins at which instructor effects operate.

To examine more formally the impact of instructor assignment on course outcomes, we estimate a multinomial logit model with four possible outcomes: dropping (D), withdrawing from (W), failing (F), and completing (C) the class. The probability of outcome k for student i taking a course with instructor j is expressed as:

$$\Pr(y_{ij} = k) = \frac{e^{\{X_{ij}\beta^k\}}}{e^{\{X_{ij}\beta^D\}} + e^{\{X_{ij}\beta^W\}} + e^{\{X_{ij}\beta^F\}} + e^{\{X_{ij}\beta^C\}}}.$$

We normalize the coefficients to make withdrawing the base outcome and report the coefficient estimates for  $\beta^k$ , which measure how a one-unit increase in X changes the relative probability that a student will have a different outcome k rather than withdrawing from the class. The instructor effectiveness measures  $W_{-i,j}$  used as covariates in this analysis also include the share of students dropping the class. Other covariates in these models control for student characteristics, subject, and semester. These coefficients estimates are shown in Table 5.

The results suggest that a 10 percentage point increase in instructor j's withdrawal rate (slightly more than a standard deviation) corresponds to a relative risk ratio of failing versus withdrawing from the class of  $e^{-0.2933} = 0.745$  and relative risk ratio of completing versus withdrawing from the class of  $e^{-0.3842} = 0.674$ . An increase in the instructor's fail rate increases the probability of failing versus withdrawing substantially (relative risk ratio of 9.9), and the average share of students who drop the class is positively related to the probability of dropping relative to withdrawing, although the result is only significant at the 10 percent level. These results imply that instructor assignment matters for students' academic outcomes in the courses we study, especially when it comes to completing a course versus withdrawing from it

versus failing. Because assignment of students to instructors is random, the observed relationships cannot be due to self-selection of students to teachers based on unobserved characteristics.

While it is beyond the scope of this paper to examine what drives differences in outcomes across instructors teaching the same course, we have data on some instructor characteristics – education, tenure at the college, and an indicator for participating in the course redesign intervention – that we can use as covariates in place of the average withdrawal, fail, and drop rates in a similar multinomial logit model of students' course outcomes. We find that instructors who participated in the intervention have fewer students drop and more students fail the class. Fewer students fail when the class is taught by a more experienced instructor, while instructor educational background does not seem to play a role. For some instructors, the research team conducted observation analysis as part of the study and assigned scores for several instructional practices. We use these scores as covariates in another multinomial logit analysis of course outcomes. These results imply that instructor practices such as posting personalized videos and announcements and integrating activities meant to reduce barriers for minority students are correlated with lower withdrawal rates. The results from these two sets of analyses are available in Appendix Tables A.3 and A.4.

#### c. Effects of Noncompletion on Persistence

Having established the importance of instructors for students' outcomes in a course, we turn to the model in (6), which addresses the question of the effects of withdrawing from or failing a class on persistence. Table 6 presents the estimated coefficients from an ordinary least squares (OLS) specification for equation (5) (columns 1 and 2), as well as from the instrumental variable specifications based on the system of equations in (6) (columns 3 and 4). The estimated

coefficients from the OLS estimation mirror the descriptive statistics in Table 2, with a 32 percentage point reduction in persistence associated with drops or withdrawals; the magnitude of the correlation increases to 37 percentage points when withdrawals are considered on their own. Failing a course is correlated with a 26 percentage point lower rate of persistence as compared to students who successfully complete the course.

The IV results suggest that withdrawing from one of the study courses causes a 19-21percentage point reduction in subsequent persistence, which supports the idea that part of the difference in persistence between completers and students who drop or withdraw from a class is driven by unobserved student characteristics. The estimated effect of a withdrawal is only slightly smaller in magnitude when drops and withdrawal are combined compared to when they are considered as separate outcomes. The estimated causal effect of failing has a point estimate of 4 to 5 percentage point reduction in persistence but is statistically indistinguishable from zero once the correlation in the error terms in the failing and persistence equations is accounted for in the IV models. The standard errors for IV estimates are around 0.05 for withdrawals and 0.1 for fails, so it is possible that failing still has a small negative impact on persistence, but it is statistically indistinguishable from zero due to noise. It should also be noted that although the magnitudes of the IV coefficient estimates for withdrawing and failing are quite different, they are not statistically different from each other (p-values of 0.13 and 0.15, depending on the specification). We also see from Table 7 that dropping a class has a large negative relationship with persistence, possibly more so than failing; as we discuss in Section VII, we believe this is driven by full institutional withdrawals and student disengagement from higher education.

Table 6 also shows the estimated first-stage coefficients on the instruments and F-statistics, which confirm that instructor assignment predicts course outcomes. The F-statistics for

the withdrawal and fail equations are 140.9 and 350.8, respectively, in the model with withdrawals as a separate outcome and 84.3 and 282 when withdrawals are combined with drops. We also report Anderson-Rubin (AR) test statistics (Anderson & Rubin, 1949), based on which we fail to reject the null hypothesis that the coefficients on the endogenous variables are jointly equal to zero.

Appendix Table A.5 shows results including the students we label as "no-shows" (students who were dropped administratively for nonpayment, who dropped the class before the Registrar's Office placed them in their assigned section, or who dropped the class with a recorded grade of "Never Attended"). Combining drops and withdrawals results in noisier estimates when "no-shows" are included because many of them are arguably randomly occurring events independent of instructor assignment. The point estimates for the effect of failing a class are more than twice as large in magnitude in these specifications, but still not statistically different from zero. We also examine whether there are any other particularly influential instructors by estimating the specification in column 3 of Table 6 sequentially excluding each instructor with the exception of the lead instructor and the instructor with high fail rate. The results, shown in Appendix Figure A.1., suggest that other individual instructors do not play a large role on their own.

#### d. Grade Effects on Persistence

To examine the extent to which instructor quality may impact persistence beyond the hypothesized channel of course noncompletion, we estimate the relationship between final grades in the study courses and persistence into the semester following the study. We restrict the sample for these analyses to students who completed the class with a grade of D or better. This sample restriction is nonrandom, so our results should be interpreted as suggestive evidence. At

the same time, sample selection is relatively unlikely to be an issue in this setting because students who are on the margin between completing and not completing a course are unlikely to be on the margin between earning an A or a B, so we do not expect the errors in the selection and grade equations to be strongly correlated.

Table 7 shows estimation results from three sets of models, where we vary the definition of the explanatory variable of interest from earning an A, to earning an A or B, to earning an A, B, or C. The odd-numbered columns show results from OLS specifications, while the results in the even-numbered columns show IV results where the student's grade is instrumented with the instructor's average withdrawal and fail rates and the two specific instructor indicators.

The bottom panel of the table shows the first-stage results, which suggest that instructors with higher withdrawal and fail rates assign more D's relative to B's and C's compared to instructors with low withdrawal and fail rates. It is possible that instructors with lower completion rates are less effective across the distribution of student ability, with the exception of the top of the distribution. However, the IV results show no relationship between course grades and semester-to-semester persistence for students who pass. This is consistent with the theoretical framework in Section IV, which assumes an impact of the number of completed credits on persistence but no immediate impact of student learning on persistence. The estimated relationship in the OLS specifications is positive and significant, which is also consistent with our model because the positive coefficients are likely driven by the underlying ability parameter  $a_i$ .

#### VII. Potential Mechanisms

The results in the previous section are indicative of a large negative effect of withdrawals on subsequent persistence and much smaller or null effects of failing. These findings are

somewhat surprising given that failing and withdrawing are often discussed as equivalent outcomes in terms of non-completion. We propose in the conceptual framework in Section IV that withdrawing from a course differs from failing it in that the effect of withdrawals on persistence can operate through an additional channel, namely institutional withdrawal.

Withdrawing fully from the institution means that a student drops all courses prior to the end of the term. Students who fail one or more of their classes, including those who fail all classes they are registered for, remain enrolled in the institution for the duration of the whole semester. We argue that reenrolling after a full institutional withdrawal is associated with an additional cost to the students and makes persistence less likely. For example, students who withdraw fully from the institution may not receive advising emails or registration reminders for the following semester or may take on full-time employment thus shifting their focus from school to work. Overall, we expect students who remain enrolled for the whole semester to be more engaged with the institution and more likely to continue in the following semester. It should be noted that this mechanism is much more likely to be applicable to community college students than for students are four-year institutions, where persistence rates are typically higher and where complete withdrawal from an institution can be considered a more substantial step.

We can use NSC data to look more closely at the relationship between course withdrawals, institutional withdrawals during the semester when students participated in the study, and persistence the following semester. We use the student's status in the NSC data for the study semester: students with a status of "W" ("Withdrawn") or "A" ("Leave of absence") are considered withdrawn from the institution.<sup>10</sup> Table 8 explores the frequency of full institutional

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<sup>&</sup>lt;sup>10</sup> The NSC indicates that the "W" status may not reflect institutional withdrawals accurately: "A 'W' status in the single student search does not necessarily mean that the student has withdrawn from the institution. It can mean the student was enrolled, but did not return for an additional term. Whenever you see a 'W' status, you should compare the status first started and term end dates. If the dates are the same, it means the student completed the term but did

withdrawals by showing the share of students withdrawing from the institution during the current semester broken down by the student's attempted course load. Students with 3 or fewer attempted credits were enrolled in the study course and possibly one more, if they dropped the intervention course before credits were recorded. For these students, 70% of course withdrawals overlap with full withdrawal from postsecondary education during the given semester. The share goes down as the number of attempted credits increases. Yet, even among students attempting 10 or more credits, 33% of students withdrawing from the study course also withdrew from the institution; the corresponding share is 6% for students who dropped. This suggests that students' withdrawal from one course is highly correlated with whether the student remains enrolled in the institution through the end of the semester. It is likely that full institutional withdrawal is driven by factors outside of the college's control; however, it is also possible that factors specific to a single course, such as the assigned instructor, could trigger a withdrawal from that course may in turn lead a student to withdraw fully from the institution. We expect that this scenario may be more likely for students taking fewer credits.

We also observe that institutional withdrawals in the current semester are highly negatively correlated with subsequent persistence. Table 9 shows that among students who withdrew fully, only 31% came back in the following semester and 41% returned at any point during the following year. The persistence rates for students who dropped or withdrew from the study course but remained enrolled at the community college or another postsecondary institution during the current semester are considerably higher: 65% for semester persistence and 74% for annual persistence. Persistence rates are higher for students who remained enrolled but failed the study course (59% and 67%, respectively) than for students who withdrew fully from

not re-enroll in (or was not retained by) that institution." We verify that there are no students in our sample with the same enrollment start and end dates.

the institution. The corresponding shares are even higher, 85% and 90% respectively, for students who remained enrolled in the institution and completed the study course with a passing grade. The statistics in Tables 8 and 9 suggest that course withdrawals may affect persistence through full institutional withdrawal.

In the context of this study, we cannot definitively show that the lower persistence rates among students who withdraw from a study course are due to an increased likelihood of full institutional withdrawal. We take these statistics as suggestive evidence only. Still, they are consistent with the idea that students who complete their courses have more academic momentum and a greater attachment to higher education.

#### VIII. Conclusion

It is difficult to isolate a causal relationship between failing or withdrawing from a class and subsequent persistence in postsecondary education because unobserved student characteristics that determine course outcomes are likely also correlated with persistence. Using a setting in which students are randomly assigned to instructors of different sections of the same class, we find that withdrawing from a class decreases the probability that a community college student remains enrolled or completes a degree over the next six months by around 20 percentage points. We find that completing a class with a failing grade does not impact persistence negatively or has only a small impact. Withdrawing from a single course may lead to full withdrawal from the institution, which we posit to be an additional hurdle for students without strong attachment to postsecondary education. Our study is the first to present causal estimates of the effects of noncompletion on persistence in postsecondary education.

The magnitude of the estimated withdrawal effects is fairly large. It should be noted that our identification strategy estimates treatment effects for students who are on the margin

between completing and not completing a class. These students are likely very different from individuals who are certain to pass the class or those who would have withdrawn or failed regardless of which instructor they were assigned to. In addition, course withdrawal may have particularly large effects on persistence for community college students, who generally have high drop-out rates and may have less academic momentum. It may be difficult for these students to return to school following a semester when they withdraw from most or all of their courses. We do not necessarily expect our results to hold in a four-year institution setting.

While our results may not necessarily be generalizable to students at four-year institutions or students who are not close to the margin of completing a class, the findings emphasize the importance of course completion for at-risk students and the potential of high returns to resources spent toward this end. They suggest that a key problem for at-risk students may be the loss of academic momentum. If this is the case, continual efforts to reach out to students who withdrew from a course and to ease the return of students who withdraw from all courses may be especially helpful to improve student retention.

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Figure 1. Project COMPASS Randomization Process

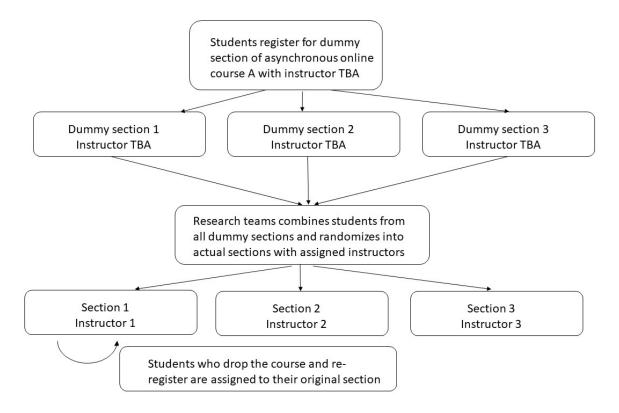


Figure 2. Conceptual Framework

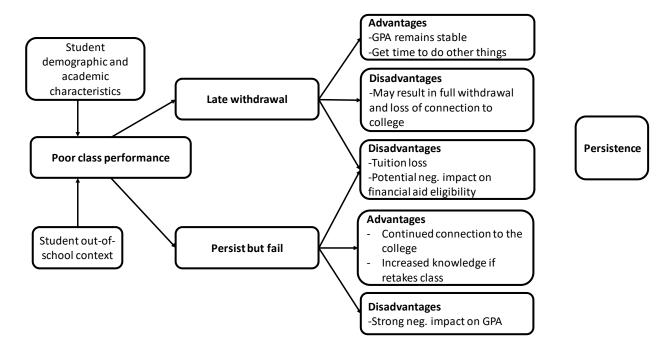


Table 1. Sample Sizes

Subject	<b>Fall 2016</b>	Spring 2017	<b>Fall 2017</b>	Spring 2018	<b>Fall 2018</b>
I	653	404	493	458	0
II	0	396	474	350	0
III	0	0	208	180	175

Table 2. Descriptive Statistics by Course Outcome

	Dropped	Withdrew	Failed	Passed
Female	0.628	0.601	0.648	0.627
Hispanic	0.091	0.073	0.115	0.097
Black	0.399	0.432	0.475	0.249
White or Asian	0.474	0.416	0.352	0.591
Age	27.4	25.6	25.2	25.8
	(9.5)	(8.7)	(8.7)	(9.1)
Disability	0.022	0.021	0.008	0.015
Pell eligible	0.526	0.56	0.625	0.445
WTCC GPA	2.58	2.17	1.92	2.74
	(0.87)	(0.93)	(0.88)	(0.85)
Has WTCC GPA	0.68	0.548	0.59	0.684
Achievement measure	-0.044	-0.205	-0.342	0.195
	(1.06)	(0.96)	(0.98)	(0.97)
Has achievement measure	0.835	0.785	0.785	0.825
Number of attempted credits	7.08	8.53	9.93	10.00
	(4.80)	(4.62)	(3.64)	(4.00)
Attempted $0-5$ credits	0.339	0.209	0.092	0.108
Attempted 6 – 11 credits	0.408	0.428	0.456	0.431
Attempted 12 or more credits	0.253	0.362	0.452	0.461
Persistence	0.639	0.484	0.59	0.849
Instructor average withdrawal rate	0.262	0.268	0.226	0.233
	(0.093)	(0.077)	(0.098)	(0.092)
Instructor average fail rate	0.076	0.071	0.102	0.074
	(0.049)	(0.045)	(0.056)	(0.051)
N	363	803	261	2364

N = 3,791. Standard deviations of the continuous variables are show in parentheses. See Section V for definition of the achievement measure.

Table 3. Correlations between Instructor Average Fail, Withdrawal, and Drop Rates in the Current and Prior Semesters

	Avg withdrawal rate: current semester	Avg fail rate: current semester	Avg drop rate: current semester	Avg withdrawal rate: baseline	Avg fail rate: baseline
Avg withdrawal rate: current					
semester	1				
Avg fail rate: current semester	-0.25	1			
Avg drop rate: current semester	0.41	-0.05	1		
Avg withdrawal rate: baseline	0.56	-0.35	-0.08	1	
Avg fail rate: baseline	-0.19	0.60	0.03	-0.34	1

N = 37 for current semester. N = 22 for baseline. The baseline sample is restricted to instructors who taught the study course in the year prior to the study.

Table 4. Variance Decomposition Results for Instructor Effects

Outcome	Between variance $(\hat{\sigma}_u^2)$	Within Variance $(\hat{\sigma}_e^2)$	Fraction of variance due to instructors (ρ̂)
Dropped	0.0015	0.085	0.018
Withdrew	0.0052	0.162	0.031
Failed	0.0018	0.063	0.028
Completed with D or better	0.0089	0.205	0.042

N = 3,791. Results from a random effects model with no covariates.

Table 5. Correlates of Course Outcomes

	Outcome			
	Drop	Fail	Pass	
Instructor average withdrawal rate	-1.958	-2.946***	-3.943***	
Č	(1.391)	(1.003)	(1.068)	
Instructor average fail rate	1.351	9.850***	-0.435	
	(1.743)	(0.960)	(0.979)	
Instructor average drop rate	3.679*	-0.305	-0.295	
	(1.971)	(1.328)	(0.717)	
Age	0.086***	-0.051	-0.008	
	(0.032)	(0.051)	(0.019)	
Age squared	-0.001**	0.001	0.000	
	(0.000)	(0.001)	(0.000)	
Female	0.149	0.187	0.345***	
	(0.157)	(0.142)	(0.087)	
Hispanic	0.500**	0.662***	0.368**	
	(0.241)	(0.241)	(0.149)	
Black	-0.166	0.155	-0.708***	
	(0.120)	(0.143)	(0.083)	
Other race, non-white and non-Hispanic	-0.695***	0.072	-0.522***	
	(0.257)	(0.364)	(0.161)	
Disability	-0.005	-1.158*	-0.374	
	(0.385)	(0.684)	(0.346)	
Pell eligible	-0.136	0.207	-0.153	
	(0.152)	(0.213)	(0.104)	
Achievement measure	0.160*	-0.052	0.408***	
	(0.085)	(0.078)	(0.066)	
Imputed achievement measure	-0.416**	-0.073	-0.421***	
	(0.181)	(0.188)	(0.118)	
Included in study in prior semester	0.304	-0.326	-0.200	
	(0.232)	(0.300)	(0.177)	
Enrolled in multiple study courses	0.246	0.095	-0.004	
in current semester	(0.316)	(0.398)	(0.236)	
Subject I	0.045	-0.100	0.083	
	(0.202)	(0.200)	(0.129)	
Subject II	0.001	0.005	0.368*	
	(0.308)	(0.244)	(0.206)	

<sup>\*</sup> p<0.1, \*\* p<0.05, \*\*\* p<0.01. Coefficient estimates from multinomial logit model relative to withdrawals. The errors are clustered at the instructor level. N=3,791.

Table 6. Effects of Noncompletion on Persistence

(1) (2) (3) (4)		OLS		]	IV
Withdrew from course  -0.369*** -0.207*** (0.018)  Failed course -0.255*** -0.257*** -0.207*** -0.040 -0.046 (0.039) -0.220*** -0.220*** -0.161*** (0.029) -0.161**  -0.299**  First stage: withdrawals Instructor avg withdrawal rate -0.194 -0.232* (0.167) -0.194 -0.232* (0.167) -0.112*** (0.029) -0.112*** (0.167) -0.109  Lead instructor with high fail rate -0.006 -0.025 (0.040) -0.030  Instructor avg withdrawal rate -0.006 -0.025 (0.040) -0.034)  First stage: fails Instructor avg withdrawal rate -0.006 -0.025 (0.040) -0.033 (0.059) -0.033 (0.059) -0.058  Instructor avg fail rate -0.017 -0.015 -0.012 -0.017 -0.015 -0.012 -0.017 -0.015 -0.012 -0.017 -0.015 -0.015 -0.012 -0.017 -0.015 -0.016 -0.056*** 0.058*** -0.056*** 0.058*** -0.017 -0.016 -0.016 -0.012 -0.012 -0.016 -0.012 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.016 -0.012 -0.012 -0.016 -0.012 -0.		(1)	(2)	(3)	(4)
Withdrew from course  -0.369*** -0.207*** (0.018)  Failed course -0.255*** -0.257*** -0.040 -0.046 (0.039) -0.220*** -0.220*** -0.220*** -0.161*** (0.029) -0.161***  -0.299**  (0.165) -0.147  Instructor avg withdrawal rate -0.194 -0.232* (0.167) -0.194 -0.232* (0.167) -0.112*** (0.029) -0.006 -0.025  Instructor with high fail rate -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.006 -0.025 -0.011 -0.017 -0.015 -0.017 -0.017 -0.015 -0.017 -0.016  F-statistic (withdrawals) F-statistic (withdrawals) F-statistic (fails) AR test statistic	Dropped or withdrew	-0.322***		-0.194***	
Control   Cont	••	(0.015)		(0.051)	
Failed course	Withdrew from course	,	-0.369***		-0.207***
Dropped course			(0.018)		(0.049)
Dropped course	Failed course	-0.255***	-0.257***	-0.040	-0.046
Tirst stage: withdrawals		(0.039)	(0.038)	(0.100)	(0.096)
	Dropped course		-0.220***		-0.161***
Instructor avg withdrawal rate $0.404**$ $0.299**$ (0.165)       (0.147)         Instructor avg fail rate $-0.194$ $-0.232*$ (0.167)       (0.129)         Lead instructor $-0.099***$ $-0.112***$ (0.029)       (0.030)         Instructor with high fail rate $-0.006$ $-0.025$ (0.040)       (0.034)         First stage: fails $0.045$ $-0.033$ Instructor avg withdrawal rate $-0.045$ $-0.033$ (0.059)       (0.058)         Instructor avg fail rate $0.585****$ $0.589****$ (0.111)       (0.107)         Lead instructor $-0.017$ $-0.015$ (0.012)       (0.012)         Instructor with high fail rate $0.056***$ $0.058***$ (0.017)       (0.016)         F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79			(0.029)		(0.025)
(0.165) (0.147)	First stage: withdrawals				
Instructor avg fail rate $-0.194$ $-0.232*$ (0.167)       (0.129)         Lead instructor $-0.099***$ $-0.112***$ (0.029)       (0.030)         Instructor with high fail rate $-0.006$ $-0.025$ (0.040)       (0.034)         First stage: fails $-0.045$ $-0.033$ Instructor avg withdrawal rate $-0.045$ $-0.033$ (0.059)       (0.058)         Instructor avg fail rate $0.585***$ $0.589***$ (0.111)       (0.107)         Lead instructor $-0.017$ $-0.015$ (0.012)       (0.012)         Instructor with high fail rate $0.056***$ $0.058***$ (0.017)       (0.016)         F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79	Instructor avg withdrawal rate			0.404**	0.299**
Lead instructor $(0.167)$ $-0.099***$ $-0.112***$ $(0.029)$ $(0.030)$ Instructor with high fail rate $-0.006$ $(0.040)$ $(0.034)$ First stage: failsInstructor avg withdrawal rate $-0.045$ $(0.059)$ $(0.058)$ $-0.033$ $(0.059)$ $(0.0111)$ $(0.111)$ $(0.107)$ Lead instructor $-0.017$ $(0.012)$ $-0.015$ $(0.012)$ Instructor with high fail rate $0.056***$ $(0.017)$ $(0.016)$ $0.058***$ $(0.017)$ $(0.016)$ F-statistic (withdrawals) $84.3$ $84.3$ $140.9$ F-statistic (fails) $AR$ test statistic $282.0$ $350.8$ $2.91$ $350.8$ $2.79$				(0.165)	(0.147)
Lead instructor $-0.099^{***}$ $-0.112^{***}$ $(0.029)$ $(0.030)$ Instructor with high fail rate $-0.006$ $-0.025$ $(0.040)$ $(0.034)$ First stage: fails       Instructor avg withdrawal rate $-0.045$ $-0.033$ $(0.059)$ $(0.058)$ Instructor avg fail rate $0.585^{***}$ $0.589^{***}$ $(0.111)$ $(0.107)$ Lead instructor $-0.017$ $-0.015$ $(0.012)$ $(0.012)$ $(0.012)$ Instructor with high fail rate $0.056^{***}$ $0.058^{***}$ $(0.017)$ $(0.016)$ F-statistic (withdrawals) $84.3$ $140.9$ F-statistic (fails) $282.0$ $350.8$ AR test statistic $2.91$ $2.79$	Instructor avg fail rate			-0.194	-0.232*
				(0.167)	(0.129)
Instructor with high fail rate $-0.006$ $(0.040)$ $-0.025$ $(0.040)$ First stage: fails $-0.045$ $(0.059)$ $-0.033$ $(0.059)$ Instructor avg fail rate $0.585***$ $0.589***$ $(0.111)$ $(0.107)$ Lead instructor $-0.017$ $(0.012)$ $(0.012)$ Instructor with high fail rate $0.056***$ $0.058***$ $(0.017)$ $(0.016)$ F-statistic (withdrawals)       84.3 $140.9$ F-statistic (fails)       282.0 $350.8$ AR test statistic       2.91 $2.79$	Lead instructor			-0.099***	-0.112***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(0.029)	(0.030)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Instructor with high fail rate			-0.006	-0.025
Instructor avg withdrawal rate $-0.045$ $(0.059)$ $(0.058)$ Instructor avg fail rate $0.585***$ $0.589***$ $(0.111)$ $(0.107)$ Lead instructor $-0.017$ $-0.015$ $(0.012)$ $(0.012)$ Instructor with high fail rate $0.056***$ $0.058***$ $(0.017)$ $(0.016)$ F-statistic (withdrawals)       84.3 $140.9$ F-statistic (fails)       282.0 $350.8$ AR test statistic       2.91 $2.79$				(0.040)	(0.034)
Instructor avg fail rate $(0.059)$ $(0.058)$ Instructor avg fail rate $0.585***$ $0.589***$ $(0.111)$ $(0.107)$ Lead instructor $-0.017$ $-0.015$ $(0.012)$ $(0.012)$ Instructor with high fail rate $0.056***$ $0.058***$ $(0.017)$ $(0.016)$ F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79	First stage: fails				
Instructor avg fail rate $0.585***$ $0.589***$ (0.111) $(0.107)$ Lead instructor $-0.017$ $-0.015$ (0.012) $(0.012)$ $(0.012)$ Instructor with high fail rate $0.056***$ $0.058***$ (0.017) $(0.016)$ F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79	Instructor avg withdrawal rate			-0.045	-0.033
(0.111) (0.107) Lead instructor -0.017 -0.015 (0.012) (0.012) Instructor with high fail rate 0.056*** (0.017) (0.016)  F-statistic (withdrawals) 84.3 140.9 F-statistic (fails) 282.0 350.8 AR test statistic 2.91 2.79				(0.059)	(0.058)
Lead instructor       -0.017 (0.012) (0.012)         Instructor with high fail rate       0.056*** (0.017) (0.016)         F-statistic (withdrawals)       84.3 140.9         F-statistic (fails)       282.0 350.8         AR test statistic       2.91 2.79	Instructor avg fail rate			0.585***	0.589***
Instructor with high fail rate $(0.012)$ $(0.012)$ 0.056***       0.058***         (0.017)       (0.016)         F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79				(0.111)	(0.107)
Instructor with high fail rate       0.056***       0.058***         (0.017)       (0.016)         F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79	Lead instructor			-0.017	-0.015
(0.017)     (0.016)       F-statistic (withdrawals)     84.3     140.9       F-statistic (fails)     282.0     350.8       AR test statistic     2.91     2.79				, ,	(0.012)
F-statistic (withdrawals)       84.3       140.9         F-statistic (fails)       282.0       350.8         AR test statistic       2.91       2.79	Instructor with high fail rate			0.056***	0.058***
F-statistic (fails) 282.0 350.8 AR test statistic 2.91 2.79				(0.017)	(0.016)
AR test statistic 2.91 2.79	F-statistic (withdrawals)			84.3	140.9
_,, _	` ,			282.0	350.8
	AR test statistic			2.91	2.79
P-value of AR statistic 0.57 0.59	P-value of AR statistic			0.57	0.59
Adjusted R-squared 0.128 0.136 104 107 $k = 0.1 \cdot k \cdot n < 0.05 \cdot k \cdot k \cdot n < 0.01 \cdot N = 3.791$ The dependent variable is an indicator for per-					

<sup>\*</sup> p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01. N = 3,791. The dependent variable is an indicator for persistence into the semester following the study. The reported errors are clustered by instructor. The models include controls for student characteristics, subject, and semester. The AR test statistic is based on Anderson & Rubin (1949).

Table 7. Grade Effects on Persistence

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Final grade is A	0.045*	-0.021				
	(0.023)	(0.084)				
Final grade is A or B			0.081***	-0.0036		
			(0.021)	(0.11)		
Final grade is A, B, or C					0.15***	-0.051
					(0.039)	(0.15)
First-stage results						
Instructor average withdrawal rate		-0.42		-0.84***		-0.49***
		(0.29)		(0.22)		(0.15)
Instructor average fail rate		-0.45		-0.77**		-0.64***
		(0.38)		(0.36)		(0.21)
Lead instructor		0.085		-0.050		-0.035
		(0.059)		(0.041)		(0.027)
Instructor with high fail rate		0.047		0.027		0.082*
-		(0.070)		(0.071)		(0.042)
F statistic		44.9		14.0		13.1

<sup>\*</sup> p < 0.1; \*\*\* p < 0.05; \*\*\*\* p < 0.01. N = 2,364. The sample is restricted to students who completed the course with a grade of D or higher. Each coefficient in the top panel is from a separate model. The dependent variable is an indicator for persistence into the semester following the study. The reported errors are clustered by instructor. The models include controls for student characteristics, subject, and semester.

Table 8. Share of Students Withdrawing Fully During the Current Semester, by Number of Attempted Credits

_	Number of attempted credits			
	0-3	4-6	7-9	10+
Share of full institutional withdrawals among students who dropped the class	0.20	0.22	0.09	0.06
Number of observations	110	60	68	125
Share of full institutional withdrawals among students who withdrew from the class	0.70	0.46	0.41	0.33
Number of observations	154	145	149	355

Table 9. Institutional Withdrawals and Persistence

Institutional withdrawal status	Share of students persisting semester-to- semester	Share of students persisting year-to- year
Did not withdraw from institution;		
completed course with a passing grade	0.85	0.90
Did not withdraw from institution;		_
completed course with a failing grade	0.59	0.67
Did not withdraw from institution;		
dropped or withdrew from course	0.65	0.74
Withdrew from institution	0.31	0.41

## Appendix

Table A.1. Number of Students in the Study by Instructor and Semester

Subject	Instructor	Fall 2016	Spring 2017	Fall 2017	Spring 2018	Fall <b>2018</b>
	1	56	42	0	44	0
	2	58	43	53	48	0
	3	65	48	62	58	0
	4	59	40	64	74	0
	5	60	40	56	46	0
	6	28	24	0	0	0
	7	0	0	31	23	0
I	8	0	0	27	41	0
	9	28	19	30	18	0
	10	54	0	0	0	0
	11	128	43	54	64	0
	12	56	39	0	0	0
	13	0	23	0	0	0
	14	61	43	62	42	0
	15	0	0	54	0	0
	1	0	49	57	0	0
	2	0	27	0	0	0
	3	0	0	60	0	0
	4	0	52	60	60	0
	5	0	48	61	0	0
II	6	0	52	59	0	0
11	7	0	46	60	103	0
	8	0	0	0	50	0
	9	0	48	60	90	0
	10	0	0	57	0	0
	11	0	24	0	47	0
	12	0	50	0	0	0
	1	0	0	27	25	42
	2	0	0	25	0	22
	3	0	0	27	21	0
	4	0	0	0	0	24
III	5	0	0	27	25	22
111	6	0	0	24	20	20
	7	0	0	24	24	0
	8	0	0	28	21	24
	9	0	0	0	22	0
	10	0	0	26	22	21

Table A.2. Student Characteristics by Instructor Withdrawal and Fail Rate

	High instructor withdrawal rate	Low instructor withdrawal rate	t- statistic	High instructor fail rate	Low instructor fail rate	t- statistic
Female	0.62	0.62	0.14	0.63	0.62	0.61
Hispanic	0.092	0.093	-0.08	0.093	0.092	0.08
Black	0.32	0.32	-0.01	0.31	0.33	-0.74
White or Asian (non-Hispanic)	0.53	0.52	1.09	0.53	0.51	1.21
Age	26.0	25.7	0.75	25.7	26.1	-1.07
-	(9.09)	(9.05)		(8.97)	(9.26)	
Disability	0.017	0.016	0.29	0.018	0.013	1.33
Pell eligible	0.49	0.49	0.06	0.50	0.48	1.08
WTCC GPA	2.58	2.56	0.67	2.56	2.60	-1.09
	(0.90)	(0.93)		(0.92)	(0.90)	
Has WTCC GPA	0.65	0.64	0.72	0.66	0.64	1.15
Achievement measure	0.077	0.029	1.34	0.048	0.066	-0.49
	(0.99)	(1.00)		(0.99)	(1.00)	
Has achievement measure	0.81	0.82	-0.22	0.82	0.81	1.08
Number of attempted credits	9.43	9.38	0.38	9.47	9.29	1.25
	(4.33)	(4.28)		(4.32)	(4.27)	
Dropped course	0.097	0.094	0.27	0.098	0.092	0.53
Withdrew from course	0.26	0.16	7.95***	0.20	0.24	-2.96**
Failed course	0.060	0.079	-2.24*	0.092	0.027	7.63***
Completed the course	0.64	0.75	-7.20***	0.71	0.67	2.28*
Persistence	0.72	0.74	-1.38	0.73	0.73	0.04
N	2448	1343		2011	1780	

<sup>\*</sup> p<0.1, \*\* p<0.05, \*\*\* p<0.01. The high and low withdrawal and fail rates are subject-specific and are generated based on the median in the sample of instructors in the data.

*Table A.3. Instructor Characteristics and Course Outcomes* 

	Droj	pped	Withdrew		F	Failed	
		Marginal effect		Marginal effect		Marginal effect	Marginal effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Has PhD	-0.063	-0.002	-0.280	-0.051	0.037	0.037	0.016
	(0.256)	(0.019)	(0.312)	(0.052)	(0.042)	(0.042)	(0.046)
Tenure	0.006	0.001	-0.004	0.001	-0.006**	-0.007**	0.004
	(0.024)	(0.002)	(0.022)	(0.004)	(0.003)	(0.003)	(0.003)
Intervention	-0.345***	-0.030***	-0.106	-0.018	0.036***	0.037***	0.012
instructor	(0.126)	(0.011)	(0.172)	(0.026)	(0.013)	(0.013)	(0.026)

<sup>\*</sup> p<0.1, \*\* p<0.05, \*\*\* p<0.01. Coefficients and marginal effects from multinomial logit model that includes indicators for subject and semester and student characteristics: quadratic in age; indicators for gender, race, ethnicity, missing race and ethnicity, disability, Pell eligibility, enrollment in multiple study courses, and having taken a study course in the past; baseline test score measure and indicator for imputed test score. The standard errors are clustered at the instructor level. N=3,791.

*Table A.4. Relationship between Observation Scores and Course Outcomes* 

		Dropped		Withdrew		Failed		Passed
	Mean		Marginal		Marginal		Marginal	Marginal
	(SD)		effect		effect		effect	effect
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Synchronous events	0.78	0.052	0.004	-0.018	-0.006	0.182	0.012	-0.009
	(1.11)	(0.071)	(0.006)	(0.062)	(0.009)	(0.120)	(0.007)	(0.010)
Announcements	1.65	-0.269**	-0.022**	0.076	0.022	-0.405**	-0.025*	0.025
	(0.76)	(0.127)	(0.011)	(0.093)	(0.014)	(0.197)	(0.013)	(0.016)
Instructor	1.15	-0.250***	-0.020***	-0.200***	-0.026***	0.224	0.019	0.027***
personalized videos	(1.14)	(0.082)	(0.008)	(0.057)	(0.009)	(0.196)	(0.014)	(0.010)
Reducing barriers	0.31	0.347**	0.042***	-0.399**	-0.058**	-0.406	-0.023	0.039*
for minorities	(0.43)	(0.170)	(0.016)	(0.175)	(0.027)	(0.360)	(0.023)	(0.021)
Threaded	2.18	0.125*	0.013**	-0.204***	-0.037***	0.356*	0.025*	-0.001
discussions	(0.82)	(0.069)	(0.006)	(0.066)	(0.009)	(0.183)	(0.013)	(0.011)

<sup>\*</sup> p<0.1, \*\* p<0.05, \*\*\* p<0.01. Results from multinomial logit model that includes indicators for subject and semester and student characteristics. Synchronous events include seminars, lectures, and webinars. Examples of announcement include reminders, affirmations, and texting app sign-up. Activities related to reducing barriers for minorities include minority images and announcements of campus events related to cultural diversity/inclusiveness. The reported standard errors are clustered at the instructor level. N=1,625.

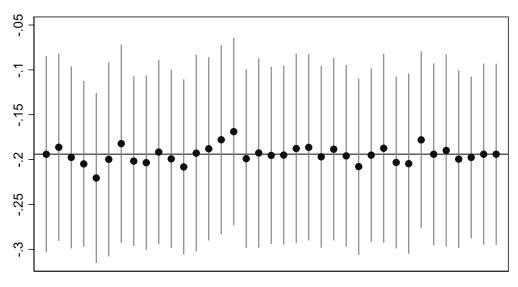
Table A.5. Effects of Noncompletion on Persistence – Including No-Shows

	0	LS	IV		
	(1)	(2)	(3)	(4)	
Dropped or withdrew	-0.324***		-0.162***		
	(0.015)		(0.059)		
Withdrew from course		-0.364***		-0.160***	
		(0.018)		(0.057)	
Failed course	-0.250***	-0.251***	-0.125	-0.122	
	(0.039)	(0.039)	(0.098)	(0.102)	
Dropped course		-0.282***		-0.218***	
		(0.022)		(0.025)	
F-statistic (withdrawals)			88.1	131.3	
F-statistic (fails)			326.9	333.8	
AR test statistic			2.44	2.47	
P-value of AR statistic			0.65	0.65	
Adjusted R-squared	0.133	0.135	0.106	0.107	

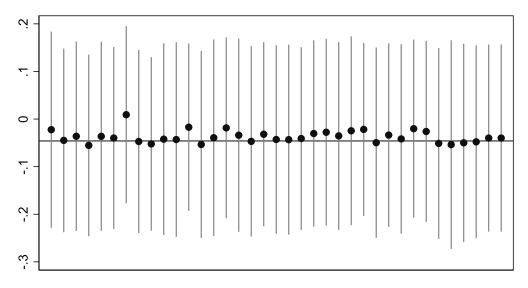
<sup>\*</sup> p < 0.1; \*\*\* p < 0.05; \*\*\* p < 0.01. N = 4,183. The dependent variable is an indicator for persistence into the semester following the study. The reported errors are clustered by instructor. The models include controls for student characteristics, subject, and semester. The AR test statistic is based on Anderson & Rubin (1949).

Figure A.1. Instrumental Variable Results for the Effect of Noncompletion on Persistence Excluding Individual Instructors

### A. Dropped or Withdrew



#### B. Failed Course



Note: Results for the IV specification in column 3 of Table 7 sequentially excluding each instructor with the exception of the lead instructor and the instructor with high fail rate. The lines show 95% confidence intervals.