Journal of Research on Educational Effectiveness

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uree20

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To cite this article: Elizabeth S. Park & Di Xu (2022): The Effect of Active Learning Professional Development Training on College Students' Academic Outcomes, Journal of Research on Educational Effectiveness, DOI: 10.1080/19345747.2022.2151954

To link to this article: https://doi.org/10.1080/19345747.2022.2151954

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Published online: 20 Dec 2022.

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JOURNAL OF RESEARCH ON EDUCATIONAL EFFECTIVENESS
https://doi.org/10.1080/19345747.2022.2151954

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The Effect of Active Learning Professional Development Training on College Students' Academic Outcomes

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ABSTRACT

Growing literature documents the promise of active learning instruction in engaging students in college classrooms. Accordingly, faculty professional development (PD) programs on active learning have become increasingly popular in postsecondary institutions; yet, quantitative evidence on the effectiveness of these programs is limited. Using administrative data and an instructor fixed effects approach, we estimate the effect of an active learning PD program on student performance and persistence at a large public institution. Findings indicate that the training improved subsequent persistence in the same field. Using a subset of instructors whose instruction was observed by independent observers, we identify a positive association between training and implementation of active learning teaching practices. These findings provide suggestive evidence that active learning PD has the potential to improve student outcomes.

ARTICLE HISTORY
Received 9 August 2021
Revised 10 October 2022
Accepted 11 November 2022

KEYWORDS
Active learning; classroom observation; student outcomes

Between fall 2010 and fall 2018, undergraduate enrollment increased by approximately 3.4 million at four-year institutions, representing a 26% growth (National Center for Education Statistics, 2019). However, during the same period, the national retention rates of all full-time, first-year students attending four-year public institutions—measured by the percentage of students who return to the same institution for their second year—has been stagnant between 76% and 79% (National Student Clearinghouse, 2020). In response to the sizable number of students who withdraw from college within their first year, extensive literature has focused on classroom pedagogy. Specifically, researchers and policymakers raise the concern that the traditional lecture-intensive instruction that dominates college classrooms emphasizes memorization over conceptual learning and is thus "disengaging" for students (e.g., Braxton et al., 2000; Deslauriers et al., 2011; Gasiewski et al., 2012; Pike et al., 2012; President's Council of Advisors on Science & Technology, 2012).

The ongoing conversation about the pitfalls of lecturing in teaching undergraduate-level courses has led to growing enthusiasm surrounding active learning instruction as a way to better engage students in their learning process (Deslauriers et al., 2011;

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Supplemental data for this article is available online at https://doi.org/10.1080/19345747.2022.2151954.
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Gasiewski et al., 2012; Prince, 2004; Wiggins et al., 2017). In contrast to lectures where students passively receive information, active learning emphasizes students' active participation through intentionally designed activities such as discussions, questions asked by the instructor, targeted in-class instructor feedback, in-class clicker questions, and small group active learning tasks or activities (Braxton et al., 2000; Deslauriers et al., 2011).

Indeed, extant studies on active learning identified a positive association between active learning instruction and student engagement. For example, based on student surveys administered across 15 four-year institutions, Gasiewski et al. (2012) found that students reported greater engagement when taught with active learning instruction than lecture-intensive instruction. Perhaps as a result of increased engagement, students taught in active learning classrooms also display better class attendance, retain course materials longer, and perform better on exams compared to students taught in lecture-intensive classrooms across a number of disciplines (Cherney, 2008; Deslauriers et al., 2011; Knight & Wood, 2005).

Given empirical evidence that active learning approaches may improve college student outcomes, faculty professional development (PD) programs on active learning instruction and practices have become increasingly popular at the postsecondary sector (Pfund et al., 2009). At the national level, the National Institute on Scientific Teaching offers multi-day workshops and various professional development opportunities for faculty to incorporate evidence-based teaching practices with support and guidance from expert facilitators. Moreover, institutions across the nation have teaching and learning centers that provide opportunities for faculty to participate in teaching institutes focused on active learning instruction strategies (i.e., University of Southern California's Faculty Teaching Institute, University of Georgia's Active Learning Summer Institute). Despite the rapid increase in training on active learning and the high hopes around it, there is a striking lack of empirical evidence on the effects of these PD programs on classroom instructional practices and on student academic outcomes.

This study addresses this research gap by examining the causal effect of an Active Learning Professional Development (ALPD) implemented during 2018-2020 at a large public institution. Specifically, we link ALPD instructor participation data with detailed student transcript data from all courses offered between fall 2016 and winter 2020 and estimate the effect of ALPD participation on students' current course performance as well as subsequent persistence and performance in the same field of study. To address instructor self-selection into ALPD and possible baseline differences between ALPD participants and nonparticipants, we leverage rich panel data and use an instructor fixed effects approach that compares average student outcomes before and after the participants received the training while using non-participants to control for general contextual changes over time that may affect student outcomes. We further combine this approach with course fixed effects, thus ruling out any between-course variations in course difficulty and student outcomes. In addition, to construct a sample of non-participants who resemble the ALPD participants, we also conduct a robustness check where we first match ALPD participants with observationally similar non-participants and then estimate the instructor fixed effects model with inverse probability weights based on the post-match sample. Moreover, given that students are not randomly assigned, we further conduct a robustness check by estimating a model that includes student and instructor fixed effects. To our knowledge, this is the first study that employs a quasi-experimental design to provide quantitative evidence on the benefits of active learning PD programs on student outcomes in the postsecondary setting.

Our analysis indicates that the ALPD improved the likelihood that a student persists into the next course within the same field by three percentage points, or a 5% increase. We do not observe any difference in student performance in the next course and marginal improvements in students' current course grades. We complement these estimates with in-depth classroom observation data of a subsample of 392 classrooms to shed light into the relationship between ALPD and instructional practices. Our results suggest that the ALPD participation is associated with an increased likelihood of using active learning approaches instead of lecture-intensive instruction. We couch these findings given the current wave of institutions seeking to scale up active learning instruction through institutionalized structures such as professional development.

Background

Studies conducted in a variety of disciplines document the benefits of active learning instruction on student engagement and performance relative to lecture-intensive instruction. Earlier studies that focus on student perceptions indicate that students in active learning classrooms perceive greater support from peers and faculty (Johnson et al., 1998; Loes et al., 2017; Prince, 2004) and feel empowered to take ownership of their learning relative to those in lecture-intensive instruction (Gasiewski et al. 2012). As students engage with peers and faculty in active learning classrooms, students learn to cooperate with one another and improve communication skills (Johnson & Johnson, 2009). These studies contend that learning to collaborate with others and perceiving greater support are likely to lead to better learning outcomes.

A more recent and growing literature has directly examined the association between active learning and student performance outcomes, and has generally identified positive effects of active learning instruction relative to lecture-intensive instruction (e.g., Deslauriers et al., 2011, 2019; Freeman et al., 2014; Ruiz-Primo et al., 2011; Theobald et al., 2020). For example, in their metaanalysis of 225 studies on the efficacy of active learning in STEM classrooms, Freeman et al. (2014) concluded that active learning increases course exam performance by approximately half of a letter grade (i.e., moving from a B to a B+) compared to lecture-intensive instruction. In addition, active learning has been associated with reduced equity gaps (Park et al., 2021). For example, Theobald et al. (2020) conducted a metaanalysis of 15 studies across 51 STEM classrooms and found a 33% reduction in racial achievement gaps in student exam scores in active learning classrooms compared to lecture-intensive classrooms.

Despite the growing evidence for the promise of active learning instruction in engaging students, its implementation has yet to occur on a large scale in higher education (Stains et al., 2018). One of the reasons for instructors' suboptimal engagement in these practices is a lack of systematic pedagogical training that would enable faculty to apply these practices effectively to their own teaching (Brownell & Tanner, 2012; Mazur, 2009). In response, institutions and teaching institutes have begun to offer various training programs that provide space for cross-disciplinary faculty (and staff) to work together to discuss best practices and create a community of support within structured PD programs (Cox, 2004).

Yet, PD may not necessarily lead to alteration in instructional practices and improved student outcomes if the training is insufficient or if there is inadequate support and incentives for faculty to apply what they have learned to their own teaching. Indeed, the broad literature of teacher PD has increasingly emphasized the complex links between the design and implementation of PD and its effectiveness (Darling-Hammond et al., 2017; Elliott et al., 2016; Pelletreau et al., 2018; Penuel et al., 2007). For instance, the duration of the training, the quality of learning materials and activities, and the presence of collective participation and community support among PD participants can all influence the effect of a PD program (Desimone, 2009; Elliott et al., 2016). Accordingly, researchers have reached consensus that in order to fully understand the value of any particular PD training, it is critical to build an empirical knowledge base that documents how specific programs are designed and implemented, and assess their effectiveness in terms of both teaching practices and concrete student outcomes (Darling-Hammond et al., 2017; Kutaka et al, 2017).

Although PD on active learning pedagogies is increasingly popular in higher education, there is limited documentation of how these programs are designed, and even less is known about their impacts on instructional practices and student achievement. Among the handful of studies that describe such programs, there are substantial variations in the duration and community support across programs (e.g., Ebert-May et al., 2011; Pfund et al., 2009). In this study, we address this research gap about active learning PD training by documenting and rigorously evaluating an active learning PD program at a large, four-year public research university. We describe in detail how the program was designed and implemented, and also empirically assess the impact of the training on students' current course performance and downstream outcomes. Finally, based on detailed class observation data from a subgroup of courses in our sample, we also document the association between the PD training and instructional practices to illuminate possible mechanisms through which the training may influence student outcomes.

Research Design and Data

Program Description: Active Learning Professional Development Training

The active learning professional development (ALPD) under study was implemented at a large public research institution and is open to faculty across all disciplines and ranks. The program introduces faculty to active learning instructional methods and tools in a systematic way by involving participants in hands-on activities to analyze active learning pedagogical strategies and apply evidence-based practices to the participants' own lesson designs. The ALPD was officially launched in fall 2018. At the beginning of each term, several campus-wide emails were sent out to solicit faculty's participation. Because there was limited space available for each session, the program was offered on a first-come, first-serve basis, and the program was typically filled within one day. Since its inception until winter 2020, a total of 105 faculty have gone through the training.[1]

[1]As of Spring 2021, there were 278 instructors listed as either "in progress" or "completed." When we limit the sample to instructors with training dates and certified information the sample dropped to 105.

ALPD includes eight 90 min weekly sessions, through which faculty worked to revamp their own instructional materials to incorporate more active learning under the guidance of an expert facilitator from the Teaching and Learning Center on campus and in a supportive collegial atmosphere. Each session included a short lecture, assignments, and several readings related to topics in that session. Some of the key topics covered include the role of assessment, different forms of feedback, ways to increase inclusivity, linking course goals with assignments and activities, and leveraging technology. For each topic, faculty were first introduced to the general and discipline-specific literature underlying evidence-based practices in active learning, coupled with active learning strategies, instructional tools, and concrete examples that were specific to their discipline. The participants were then guided to apply evidence-based practices and implementation to their own course materials and lesson designs.

Community building and support was an important part of ALPD and several activities have been intentionally designed to facilitate community development. First, to ensure collaborative participation, all applicants to ALPD were required to commit to attending at least six sessions of the eight-session program. In addition, at each session, participants were assigned into small groups of four. The facilitator intentionally assigned participants into different groups for the first few weeks until participants had met everyone and could start selecting their own groups. Each session started with small group discussion, where participants shared their own personal teaching experiences. Finally, some of the assignments were intentionally designed to facilitate collaborative participation. For example, one assignment required participants to redesign a class period and present their work to the group, where all group members would provide feedback to the presenter.

At the end of the 8-week training, faculty received a certificate of completion if they were observed by independent classroom observers using the Classroom Observation Protocol of Undergraduate STEM (COPUS) (Smith et al., 2013).[2] Using the COPUS protocol, observers recorded both the instructor's and students' behaviors in each two-minute period of a class session. Specifically, trained observers identified what the instructor did using 12 instructor behavioral codes (i.e., lecturing, answering student questions) and what the students did using 13 student behavioral codes (i.e., listening, asking questions) in each two-minute interval.[3] ALPD trained instructors were awarded a certificate of completion if the observer confirmed that the instructor lectured less than 50% of the class period and incorporated instructor-student interactions as well as student-student interactions. Some of the incentives for receiving the certificate include priority scheduling at the technology-enabled active learning classrooms, using the certificate as a second piece of evidence of instruction quality for tenure/promotion review, and the opportunity to help facilitate future ALPD. 42% of the 105 trained faculty in our data were certified whereas the remaining faculty completed just the training.

[2]Although the COPUS protocol was initially developed to observe STEM classroom instructions, it has also been used in observing non-STEM classrooms (Denaro et al., 2021).

[3]For example if the observer tallies 13 times that the instructor lectured during a 50-minute course, we would say that the instructor lectured 52% of class time (13/25).

Data

We leverage three data sources to examine the effect of active learning professional development training on current and subsequent student outcomes. The first source of information comes from detailed administrative data. We first identified all courses offered between fall 2016 through winter 2020 and then pulled information on all students who took any of these courses taught by either ALPD participants or non-participants ($N = 1{,}022$ courses). Among these observations, 36% of the student enrollments ($n = 54{,}130$ unique students) were in courses that have within-course variations in instructors by ALPD participation (i.e. courses with some sections taught by ALPD participants and some sections by non-participants).[4] We exclude summer terms partly because fewer courses are offered during the summer and partly because summer courses follow different lengths and possibly different structure than courses offered in the fall, winter, and spring terms. In addition, given the goal of this study, we exclude courses that are not instruction focused, such as independent study, undergraduate research courses, and lab sessions. The data include the name of the course, term-year in which it was offered, class size, the class location, and the primary instructor of record, as well as student demographic characteristics and prior academic achievement profiles. We next merge the administrative data with ALPD participation data which include a list of instructors who participated in the training and the term when each participant completed the training as well as their certification date if the instructor pursued a certification.

The third data source is classroom observation data. Starting in the 2018-2019 academic year, all undergraduate courses (i.e., excluding discussions, seminars, or labs) that enrolled at least 60 students at this institution were solicited to be observed using the COPUS protocol. A total of 392 classes across 289 unique instructors were observed by winter 2020. Among these instructors, 71 went through the ALPD training by the time of the observation while 218 instructors did not.[5]

Student Outcomes

In assessing the effectiveness of ALPD, we consider both current and subsequent student academic outcomes in the same field of study. Specifically, we begin our inquiry with student contemporaneous course performance, as measured by course grade on a 1–4 grading scale. Yet, current course grades alone may not be sufficient in fully capturing the impact of ALPD for two reasons. First, current grades may not be a reliable measure of actual learning due to instructor grading leniency. Indeed, existing studies on teacher effectiveness indicate that students tend to receive lower grades in introductory coursework from instructors who are most effective in preparing students for subsequent

[4]Because of the way the data were obtained, we have a relatively large proportion of courses for which ALPD instructors did not teach the course. We have conducted analyses by limiting the sample to courses that were taught by both ALPD participants and non-participants and found that our results were similar regardless of this restriction.

[5]A total of 250 classes between fall 2018 and winter 2020 were observed twice within the same term by independent observers affiliated with the Teaching and Learning Center and an additional 142 classes were observed once during this timeframe for a total of 392 classes. For classes that were observed twice, we averaged the classroom observation records.

advanced courses (Carrell & West, 2010). In the context of the current study, if ALPD also influences instructors' grading practices, a change in average student grades may not necessarily reflect actual improvement (or deterioration) of teaching quality.

In addition, the effects of ALPD may unfold in different ways and some of them may not show in immediate course performance. In particular, existing studies have advocated for the promise of active learning in promoting student interest in a subject area (e.g., Gasiewski et al., 2012), which arguably can be better captured through subsequent individual choices such as enrolling in another course in the same field of study than immediate performance outcomes.

Therefore, we build on the existing literature on teaching effectiveness (e.g., Carrell & West, 2010; Figlio et al., 2015; Xu, 2019; Xu & Solanki, 2020), and further include downstream outcomes to provide a more comprehensive understanding of the impact of ALPD. Specifically, we use subsequent field persistence—whether a student took another course in the same field of study in the immediate next term—to measure student interests in a subject. In addition, we also examine students' performance in the next course to capture possible lasting impacts of ALPD on learning and engagement in the same field of study.[6]

Sample Description

Table 1 shows the summary statistics of the average outcome measures (panel A), characteristics of students (panel B), and characteristics of course-sections (panel C) taught by three groups of instructors: (1) instructors who never participated in the ALPD ("ALPD Non-participants" in column 1–3); (2) ALPD participants during the terms prior to the training ("ALPD Participants: Pre-Training" in column 4–6); and (3) ALPD participants during the terms after the training ("ALPD Participants: Post-Training" in column 7–9). Results presented in panel A reveal several baseline differences between ALPD participants and non-participants prior to the training, where the ALPD participants seem to be associated with consistently better student outcomes. This highlights the importance of accounting for the baseline differences between the ALPD participants and nonparticipants in estimating the impact of ALPD on student outcomes. Raw comparisons between the pre- and post-training periods among ALPD participants suggest that students' average grades in subsequent courses are higher in courses taught by ALPD participants during the post-training terms. Yet, these differences may be partly due to different courses taught by each group and the characteristics of students enrolled in those courses.

Indeed, results presented in panels B and C revealed a number of differences in the type of courses taught and the characteristics of students between the ALPD participants and nonparticipants prior to the training, as well as between the pre-training and post-training terms among the ALPD participants. Specifically, compared with the nonparticipants, ALPD participants during the pre-training terms taught courses with a larger proportion of transfer students and students with lower high school GPA and SAT

[6]To construct subsequent course achievement measures, we first looked at the entire course-taking records of each student and identified the next course within the same field for every course taken between fall 2016 to spring 2020 excluding summer terms. Repeat courses were excluded from next course persistence and performance.

Table 1. Summary statistics.

	(1) ALPD non-participants	(2)	(3)	(4) ALPD participants: pre-training	(5)	(6)	(7) ALPD participants: post-training	(8)	(9)	(10)	(11)
	M or %	*SD*	Count	*M* or %	*SD*	Count	*M* or %	*SD*	Count	Pre vs. Post	Pre-ALPD vs. Non-ALPD
Panel A. Student outcomes											
Current course grade	2.95	1.02	589,603	3.08	0.97	80,195	3.13	0.96	27,917	0.05	−0.13
Next course (%)	0.68	0.47	589,603	0.75	0.43	80,195	0.73	0.44	27,917	−0.04	−0.15
Next course grade	3.03	0.99	398,679	3.06	0.99	59,628	3.20	0.98	20,221	0.15	−0.03
Panel B. Student-level characteristics											
Women (%)	0.52	0.50	589,603	0.51	0.50	80,195	0.49	0.50	27,917	−0.03	0.02
Black (%)	0.03	0.17	589,603	0.03	0.18	80,195	0.04	0.19	27,917	0.03	−0.01
Latinx (%)	0.25	0.43	589,603	0.26	0.44	80,195	0.26	0.44	27,917	0.00	−0.02
AAPI (%)	0.56	0.50	589,603	0.54	0.50	80,195	0.54	0.50	27,917	−0.01	0.02
White (%)	0.13	0.34	589,603	0.14	0.34	80,195	0.13	0.34	27,917	−0.01	−0.01
Other (%)	0.03	0.18	589,603	0.03	0.17	80,195	0.04	0.18	27,917	0.03	0.01
URM (%)	0.48	0.50	589,603	0.49	0.50	80,195	0.50	0.50	27,917	0.01	−0.03
Transfer student (%)	0.17	0.37	589,603	0.20	0.40	80,195	0.22	0.41	27,917	0.04	−0.1
First-generation (%)	0.49	0.50	572,541	0.51	0.50	77,914	0.49	0.50	27,191	−0.04	−0.04
Low-income (%)	0.32	0.47	589,603	0.34	0.47	80,195	0.32	0.47	27,917	−0.05	−0.05
Weighted HS GPA	3.89	0.35	589,603	3.86	0.34	80,195	3.89	0.38	27,917	0.08	0.08
SAT Math	633.77	95.85	513,460	624.65	95.81	67,308	631.53	100.68	23,148	0.07	0.1
SAT Verbal	572.39	93.15	513,411	568.69	93.46	67,307	581.54	95.10	23,144	0.14	0.04
Panel C. Course-section level characteristics											
STEM (%)	0.52	0.50	589,603	0.43	0.50	80,195	0.49	0.50	27,917	0.11	0.18
Offered in an active learning classroom (%)	0.08	0.27	589,603	0.04	0.21	80,195	0.24	0.42	27,917	0.68	0.12
Small class (fewer than 61 seats) (%)	0.22	0.42	589,603	0.15	0.36	80,195	0.17	0.38	27,917	0.06	0.18
Instructors	1,359			75			30				
Course-by-term	7,568			878			289				
Observations	589,603			80,195			27,917	697,715			

Note. Columns 10 and 11 shows the extent to which the two groups are different from one another, calculated using Hedge's g. AAPI: Asian American and Pacific Islanders; URM: Underrepresented Racial Minorities defined as Black, Latinx, Southeast Asians/Pacific Islanders, and Native Americans. The sample was limited to courses that were offered during fall 2016 to winter 2020, excluding summer terms. Courses that have fewer than 20 students and directed research/independent study courses were excluded in all analyses. Only those who took another course in the same field are observable for next course grade. Courses that were taken as a repeat course were not considered in determining next course persistence or grades.

scores. The participants were also more likely to teach large classes (enrollment size> =60) than nonparticipants. Looking at ALPD participants' pre-training and post-training terms, ALPD participants during the post-training terms taught students with, on average, higher high school GPA and SAT scores than ALPD participants during the pre-training terms. The differences in student composition and class size may be partly driven by different fields of study between the participants and nonparticipants, where the participants seem to be more heavily concentrated in non-STEM disciplines.

In a similar vein, there are also noticeable differences in student characteristics between pre-training and post-training periods among the ALPD participants, where courses taught in the post-training terms had students with better pre-college academic performance. In addition, courses taught in the post-training periods were more heavily concentrated in STEM fields than in the pre-training periods. These differences may be partly driven by general changes in student composition as well as course offering over time at this institution, which highlight the importance of accounting for between-course and over-time variations in student outcomes in estimating the impact of the training on student outcomes.

To obtain an understanding of how our sample instructors compare to the university as a whole, Supplemental Appendix Table 1 shows the comparison between ALPD participants and the population of instructors who taught during the study timeframe. Among the participants, there are fewer engineering instructors than the population as a whole. In terms of the teaching load and characteristics of courses taught, ALPD participants assumed a heavier teaching load and were more likely to teach undergraduate courses than graduate courses.[7] Finally, there are more assistant or associate professors and teaching-focused professors among the participant group relative to all instructors at this university.

Identification Strategy

To account for instructor self-selection into the PD training, we compare average student outcomes of ALPD participants after they completed the training to average outcomes of the same instructor before the training. This approach has been used widely in the education literature to address any time-invariant factors at the individual level such as ability in estimating the causal impact of educational investment (e.g., Cellini & Chaudhary, 2014; Jacobson et al., 2005; Jepsen et al., 2014; Xu & Trimble, 2016). In addition to instructor fixed effects, we also include course fixed effects to compare average academic performance of students in different sections of the same course, as well as term fixed effects to account for general changes in student composition and outcomes over time. We estimate the following equation:

$$Y_{ijsct} = \alpha_j + \beta_1(ALPD_{jt}) + X_{ijsct}\beta + \theta_{sct}\pi + \gamma_c + \phi_t + \varepsilon_{ijsct}$$

where Y_{ijsct} is the outcome for student i taught by instructor j in section s of course c offered during term-year t. α_j refers to instructor fixed effects that control for all observed and unobserved instructor-level characteristics that are constant over time. $ALPD_{jt}$ captures whether an instructor has already received the ALPD training in a given term, which

[7]On average, the ALPD participants taught four credits per term whereas all instructors at this institution taught about two credits on average per term. In addition, ALPD participants taught fewer graduate courses and were more likely to teach undergraduate courses compared to the population of instructors.

is identified as "0" during the terms leading up to when the instructor received the training and switches to "1" during the term after the instructor received the training and each term thereafter. X_{ijsct} includes student-level covariates such as students' race/ethnicity and high school GPA and θ_{sct} refers to section-level attributes such as enrollment size of a section. The equation also includes course fixed effects γ_c that control for any between-course variations in student composition and performance, and quarter-year fixed effects φ_t that help address overall fluctuations in student composition and outcomes over time due to other contextual factors. Accordingly, β_1 can be interpreted as additional changes in student performance as a result of ALPD training aside from other changes that would have occurred in the absence of the ALPD training.

When estimating students' subsequent course grade in the same field of study, we draw on prior literature and further include next class fixed effects (e.g., Figlio et al., 2015; Ran & Xu, 2019). By doing so, we are able to compare grades of students in the same next class with variations in taking a prior course with an instructor who had received ALPD versus an instructor who had not. This is to address the concern that learning experiences in a course may influence a student's subsequent course choice. For example, if a student had particularly inspiring experiences with an ALPD instructor, the student may intentionally opt into another course taught by the same instructor. In a similar vein, prior experiences may also influence the difficulty of the next class a student selects. By including next section fixed effects, we are able to account for selection biases that arise from students shopping across different next classes within a field by comparing student performance in exactly the same section. All of our estimates are clustered at the instructor level to account for correlation in student outcomes within an instructor (e.g., Figlio et al., 2015).

As a robustness check, we first re-estimated all of the main results after matching ALPD participants with observationally similar non-participants through propensity score matching method. We first obtained data that include instructor-level pretreatment characteristics and estimated the propensity score using a probit function. Then, we conducted nearest-neighbor matching with replacement to match control instructors with treated instructors based on observable characteristics (Stuart, 2010). With this matched data, we estimated the treatment effect using the instructor fixed effects model and inverse probability weights. Next, we re-estimate the main results by including student and instructor fixed effects. For this estimation, only 33% of students took multiple courses from ALPD instructors across terms indicating limited variation in our variables of interest.

Results

Impact of ALPD Training on Student Outcomes

Table 2 presents the estimated effect of participating in ALPD on three student outcome measures: current course grade (column 1), whether or not a student took another class in the same field in the immediate next term (column 2), and the grade received in that next class (column 3). The results indicate that students who took a course with an instructor who had received ALPD on average had higher course grades by 0.006 grade points on a 0–4 grading scale, although this effect is marginally significant at the 0.1 level.

Table 2. Effect of the ALPD on student outcomes.

	(1) Course grade	(2) Next course persistence	(3) Next course grade
ALPD trained	0.006+	0.032**	−0.016
	(0.003)	(0.012)	(0.012)
Instructor FE	Yes	Yes	Yes
Next section FE	No	No	Yes
R^2	0.150	0.160	0.060
Instructors	1,464	1,464	1,451
Student-by-section-term observations	697,715	697,715	478,505
Average student outcomes taught by instructors without training	2.968	0.689	3.033

Note. ALPD: Active Learning Professional Development. The sample was limited to courses that were offered during fall 2016 to winter 2020, excluding summer terms. Courses that have fewer than 20 students and directed research/independent study courses were excluded in all analyses. All models include course fixed effects, entry term fixed effects, and term-year fixed effects. Next course grade analysis further includes next section fixed effects. Student-level covariates include students' race, gender, transfer status, low-income status, first-generation status, SAT math, SAT verbal, and weighted HS GPA. We also include the number of students in the course to account for class size, the proportion of transfer students, first-generation college students, low-income students, and women in the course, and the average high school GPA and course grades of students in the course. Only those who took another course in the field has next course grade. Courses that are taken as a repeat course are not considered in the calculation. Standard errors are clustered at the instructor level.
$+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The effect of the ALPD becomes more pronounced when we examine students' subsequent persistence in the same field. Specifically, students who took a course with an ALPD instructor in post-training terms were three percentage points more likely to persist within the field compared to students who took the same course with the same instructor in pre-training terms. Considering that the average next course persistence rate in our sample is 68%, a three percentage point increase would represent a 5% improvement. Finally, column 3 presents results on subsequent course performance conditional on enrolling in another course in the same field of study. The estimated impact of ALPD is small and not significantly different from zero. Taken together, our results suggest that ALPD is associated with marginal improvements in current course performance and modest boost in field persistence.[8,9]

[8]We also conducted heterogeneity analyses to see whether the effect of the training differs depending on the infrastructure (i.e., whether the course is offered in an active learning classroom), the size of the class, whether the course is an upper or lower division course and whether the course is a STEM/non-STEM course. Classroom layouts, for example, can allow for easier adoption of active learning techniques such as in-class group activities (Beichner & Saul, 2003; Dori & Belcher, 2005). As such, if the class is offered in a classroom designed to facilitate active learning, instructors may be more effective in raising student performance. Similarly, class size is an important consideration that determines whether active learning is adopted, with smaller class sizes being more conducive to active learning implementation (Carbone & Greenberg, 1998; Freeman et al., 2014; Heim & Holt, 2018). We further explore whether the impact is concentrated among lower division courses given that a majority of studies examining teaching effectiveness in higher education have focused on introductory/lower division courses (Figlio et al., 2015; Xu & Solanki, 2020). In all instances, we did not find that the impact of ALPD training is moderated by the classroom infrastructure, class size, whether the course is an upper division course or lower division course, and whether the course is a STEM course. In particular, the standard errors of the tests for interaction are large given our sample size such that we cannot reject the null hypothesis of no interaction effect.

[9]Supplemental Appendix Table 2 shows a breakdown of the next course that students in our sample took. About half of the courses are lower division courses and the other half are upper division courses. In addition, 56% of the courses students took in the next term are non-STEM while 44% of the courses are STEM courses. 84% of the courses that students took as their next course are taught in small class settings (under 100 student seats per class), indicating that persistence effects are concentrated in small classes.

Relationship between Training and Instructional Practices

In view of the positive effects of the ALPD training on student persistence, we then explore whether such benefit is partly driven by altering instructors' teaching practices. We look at a subset of instructors whose classroom was observed using the COPUS protocol. When using the observation data to code instructional approaches, we follow the criteria used for ALPD certification in defining active learning classes—lecturing less than 50% of the class period. Out of the 392 classes observed, 34% are classified as active learning.

We see that the instructors in courses that are categorized as active learning were more likely to display varied activities during class (i.e., pose questions, move through class). Figure 1 shows the distribution of instructor activities performed during class time. The figures provide a visual contrast in instructor behaviors in lecture-intensive classes (figure on the left) versus active learning classes (figure on the right). Most notably, instructors in lecture-intensive classes spent 80% of two-minute intervals of observed class time lecturing whereas the corresponding percent is 25% of observed class time. In addition, instructors in active learning classes, on average, spent more than a quarter of the class time posing questions and moving through class compared to only 5% in lecture-intensive classes. This behavioral breakdown aligns with the prior literature on the characteristics of lecture-intensive versus active learning instruction (Braxton et al., 2000; Deslauriers et al., 2011; Stains et al., 2018).

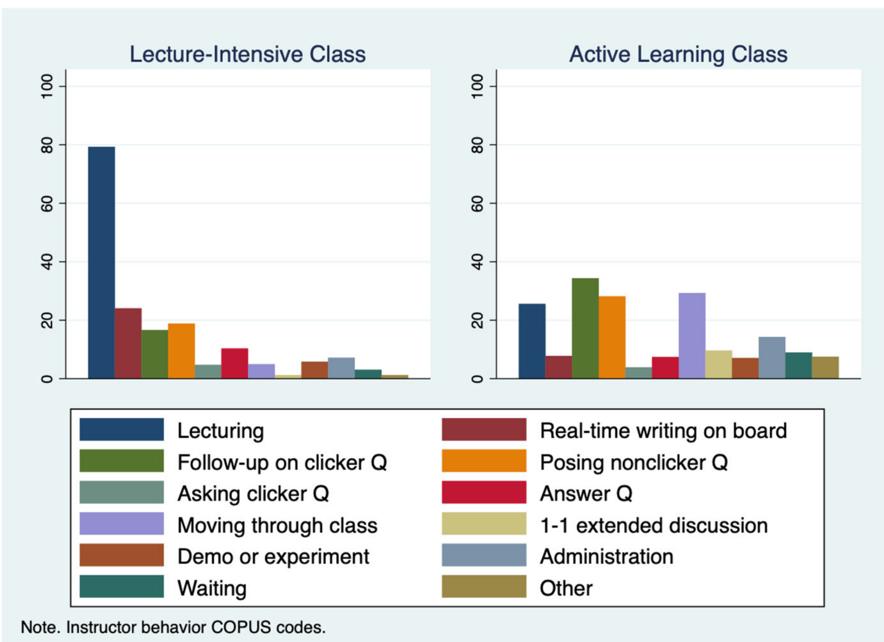

Figure 1. Distribution of instructor behavior in active learning and lecture-intensive class. *Note*. Active learning classes are defined as classes where the instructor was categorized as lecturing less than 50% of class time according to the COPUS codes. The graph depicts instructor behaviors only. $n = 289$ instructors across 392 course-sections.

Appendix Figure A.1 provides a snapshot of student behaviors in active learning instruction versus lecture-intensive instruction classrooms by showing the distribution of students' activities performed within each two-minutes interval of the observed class time.

Table 3 presents the estimated correlation between ALPD training and the likelihood of using active learning instruction. Due to the small sample size of instructors with class observation data, we conduct a cross-section comparison between instructors who had received ALPD by the time of the classroom observation and instructors who had not on their likelihood to implement active learning. Column 1 presents the raw comparison between the two groups while column 2 further includes available class-level covariations, such as student composition, enrollment size, field of study, and term-year fixed effects.

Our results indicate that ALPD trained instructors were 17 percentage points more likely to implement active learning instruction than non-ALPD trained instructors ($p < 0.001$) (column 1). This relationship remains significant at the 0.1 level after we

Table 3. Likelihood to implement active learning approaches.

	(1) No covariates	(2) With term FE
ALPD instructor	0.171**	0.105+
	(0.054)	(0.054)
Average course grade		0.170**
		(0.049)
Average % of low-income students		0.384
		(0.371)
Average % of first-gen students		0.265
		(0.301)
Average % of women		0.191
		(0.145)
Average % of RM students		−0.467+
		(0.243)
Average % of transfer students		−0.249
		(0.205)
Average HS unweighted GPA		−0.029
		(0.033)
Indicator of STEM course		0.014
		(0.055)
Class size		−0.001**
		(0.000)
Term fixed effects		X
Constant	0.300**	0.017
	(0.028)	(0.249)
R^2	0.025	0.195
Instructors	289	289
Section-by-term	392	392

Note. ALPD: Active Learning Professional Development. Some instructors were observed twice. Courses were selected based on the following criteria: large classrooms (84+ seats) and lecture halls. Graduate courses and undergraduate discussions sections were excluded. Instructors were given the option to opt-out. There are 71 instructors who completed the training in this data and 218 instructors who did not complete the training.
$+p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

further control for all available covariates ($p = 0.053$) (column 2).[10] The positive estimates across models provide suggestive evidence that the ALPD training increases the likelihood of implementing active learning instruction.

Is There Additional Value of Receiving a Certificate of Completion?

Our results thus far suggest that receiving the ALPD training is associated with small improvement in course performance and modest boost in subsequent field persistence. As mentioned in the background section, at the end of the training, all ALPD participants were offered the opportunity to receive a certification of completion upon successful classroom observation. The classroom observation and feedback associated with the certification process may create additional space for instructors to reflect on their practices and apply what they have learned to their own teaching. In addition, the certificate of active learning may also serve as a label which, in turn, may influence instructors' self-identity and behavior (Hayes et al., 2021).

To estimate the effect of receiving the certificate in addition to the ALPD training, we use the same empirical strategy but restrict our sample to the ALPD participants. Specifically, we flag a "0" for courses offered during the terms before an instructor receives the certificate and a "1" after receiving the certificate. Instructors who went through ALPD but never received the certificate would not contribute to the estimator directly, but could help take into account possible evolution of the training effects on student outcomes over time. The estimates presented in Table 4 are consistently small and nonsignificant, suggesting that there is no additional boost induced by receiving the certification on students' outcomes. In other words, the positive impact of ALPD on

Table 4. The effect of certification on student outcomes.

	(1) Course grade	(2) Next course persistence	(3) Next course grade
ALPD certified	0.006	0.000	0.027
	(0.009)	(0.034)	(0.045)
Instructor FE	Yes	Yes	Yes
Next Section FE	No	No	Yes
R^2	0.307	0.340	0.319
Instructor	89	89	89
Student-by-course-term observations	41,925	41,925	29,897
Average student outcomes taught by instructors without training	3.120	0.731	3.154

Note. ALPD: Active Learning Professional Development. The sample was restricted to 89 instructors who received ALPD training. The instructors who are not observable in the data for the post-trained period (i.e., did not teach after getting trained) or did not receive certification were removed from the sample. 45 of the 89 trained instructors who were deemed to have lectured less than 50% were certified. Therefore, for the 45 certified instructors, we changed their post-period to the term when they were certified. For the remaining instructors who were trained but not certified, their pre-trained periods were removed.
$+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

[10]We may be concerned that ALPD participants and non-participants differ in their instructional approaches even in the absence of the training. Accordingly, we further conduct a pre- versus post-training comparison among ALPD participants only and control for all available covariates. The estimated coefficient shown in Supplemental Appendix Table 3 is positive (coefficient = 0.13, $p = 0.187$) and fairly comparable to the estimate shown in Table 3 column 2 that is based on the cross-sectional comparison. However, since only 71 ALPD participants have pre and post classroom observation data, the sample size is too small to yield a precise estimate.

current and downstream outcomes presented in Table 2 is primarily driven by participating in the training rather than going through any additional certification process.

Robustness Check

We obtained additional instructor-level data and conducted a robustness check to explore the extent to which our results are influenced by the large number of courses for which there is no treatment instructor as well as the likelihood that participants and non-participants are observationally different from one another. Specifically, we used propensity score matching techniques to match non-participants with participants based on instructor-level pretreatment characteristics. In estimating the propensity score, we included instructor department affiliation, instructor title and rank, and a number of pretreatment teaching characteristics (i.e., prior to fall 2018) such as the number of upper division courses taught, the number of pre-requisite courses taught, the number of large versus small courses taught, the number of independent studies offered, and the number of graduate courses taught. We conducted k-nearest neighbor matching where k refers to the number of similar neighbors to which treated units will be matched, and in our case, we run the algorithm multiple times with $\{k = 1,2,3,4,5\}$. During the matching process, ALPD participants who had no near matches from the group of non-participants (using a caliper of width equal to 0.1 standard deviation of the propensity score) were dropped from the analysis. Through each iteration of the matching process, we checked whether we had succeeded in balancing the covariates and concluded that $k = 5$ resulted in the smallest standardized difference in means across the covariates. Thus, the final matched sample includes 100 ALPD participants and 358 non-participants who are matched to the participants.

In Supplemental Appendix Table 4–6, we show the pre-match and post-match standardized differences in means. Prior to matching instructors, we note several differences across teaching characteristics and instructor rank. For instance, ALPD instructors are more likely to be assistant or associate professors than the non-participant group. The matching algorithm achieved satisfactory overlap between the ALPD participants and non-participants, and improved the balance between the two groups along observable characteristics

Supplemental Appendix Tables 7 and 8 show the estimated results using the instructor fixed effects and inverse probability weights based on the post-matched sample. The estimated effects are similar in magnitude and direction as those from our main analyses. We see improvements in next course persistence among students who took a course with an ALPD participant than observationally similar non-participant. Moreover, these results also indicate no additional boost to receiving the certificate above and beyond receiving the training.

Finally, students are not randomly assigned to different courses and thus systematic differences of students across courses and terms may bias our results. To address this concern, we conduct a student and instructor fixed effects approach, capitalizing on the fact that over half of the students in our study sample have taken more than one course across terms. Supplemental Appendix Table 9 shows these results and further supports our main findings that students who took a course with an ALPD instructor in post-training terms were more likely to persist within the field compared to students who took the same course with the same instructor in pre-training terms.

Limitation and Future Research

While our study provides a first step in rigorously documenting the effect of an active learning PD on college student outcomes, our small sample size limits the conclusion we can draw on the positive effect of the PD on student outcomes. A follow-up study with a larger sample size will bolster the finding that the PD resulted in improved student outcomes. In addition, as shown in Supplemental Appendix Table 1, our study population primarily consists of assistant/associate professors or teaching-focused professors who take on heavier teaching loads at a large, public university. Thus, future research is needed to shed light on whether the impacts of ALPD may be larger or smaller on faculty who were not represented in our sample (Simons et al., 2017). Some methodological caveats are also worth noting. Our main empirical strategy compares the average student outcomes of the same instructor before and after the PD, while netting out time trends using a fixed effects model. One potential threat to this model is possible presence of time-varying factors that are not captured in our data, such as individual proclivity to adopt active-learning approaches overtime even in the absence of the ALPD training. If there are overtime changes that are different between the participants and non-participants, our results may be biased. Future studies that collect instructor characteristics longitudinally may wish to explore these possibilities.

Moreover, future research is needed to provide insights on the conditions for effective implementation of PD programs on active learning instruction at scale. For instance, an effective training program that is tailored to the specific needs of the program participants while also cognizant of the unique context of the institution may lose its effectiveness when taken at scale. Indeed, a number of studies conducted in K-12 settings have documented the challenges associated with scaling up effective small teacher PD programs (e.g. Cabell et al., 2011; Kraft et al., 2018). In addition, studies should examine different structures of active learning training (i.e., summer workshops offered by a national institute versus campus-level training) and whether certain training formats are more effective at improving student outcomes. Future studies that are able to document and relate elements of the large-scale training with changes to instructor practice and student outcomes will further complement the findings of the study.

Relatedly, designing and implementing a resource-intensive program such as the ALPD may be associated with high personnel costs of staffing experienced program facilitators. Accordingly, the effects of such programs need to be considered relative to program costs. The field would benefit from additional analyses benchmarking the program cost and the efficacy of the training. If intensive face-to-face guidance and interactions over a sustained amount of time—which is a key feature of the ALPD program examined in the current study—is found to be at the core of effective models for active learning PD programs, then this approach in improving college classroom instruction is likely to require substantial financial investment. Although such costs should not be prohibitively expensive, it will be helpful to conduct cost-effectiveness analysis for systematic comparisons and evidence-based choice between different approaches to reforming college instruction. This would also imply that the benefits identified in our study may not hold for programs with limited support and resources.

Finally, it is important to note that our study only focuses on short-term academic outcomes while theories of active learning have underscored several nonacademic and long-term benefits that are not fully captured in the current study, such as students' stress-level, test anxiety, development of social skills, long-term college and field persistence, and graduation rates (Ballen et al., 2017; Loes et al., 2017). These possible benefits are important considerations and warrant attention in future studies to fully understand the effects of active learning training on student outcomes.

Discussion and Conclusion

The growing evidence on the promise of active learning instruction in engaging students has spurred increasing interests in promoting active learning approaches in the college classroom (Freeman et al., 2014; McKeachie, 1990; Pfund et al., 2009; Prince, 2004; Ruiz-Primo et al., 2011; Theobald et al., 2020). Despite the expansion of professional development efforts on active learning and the high hopes surrounding them, there is limited knowledge about the impacts of these programs on teaching practices and student achievement outcomes (Ebert-May et al., 2011). To address this gap, we leverage detailed college administrative data and program participation data and use a quasi-experimental design to estimate the impact of participating in an Active Learning Professional Development (ALPD) on students' contemporaneous and downstream outcomes.

Consistent with the existing literature on active learning, we find that ALPD is associated with an increase in marginal improvement in concurrent course grade; the estimated effect is small in magnitude and is only marginally significant at the 0.1 level. Yet, we also find that ALPD is associated with a more pronounced increase in subsequent persistence into another course in the same field–a 5% improvement from the baseline persistence rate of 68%. Our subsequent exploratory analyses using classroom observation data reveal a positive association between ALPD and active learning teaching practices, providing suggestive evidence that the impact on students' outcomes may be driven by instructors' implementation of active learning approaches. Indeed, the magnitude of the effect on field persistence estimated in the present study corresponds to other studies that examined the relationship between active learning opportunities and downstream persistence outcomes. For example, Loes et al. (2017) found a five percentage point increase in second year college persistence when students are provided with more collaborative learning opportunities in the classroom. In a similar vein, Braxton et al. (2000) also identified a five percentage points increase in students' intent to reenrolll in the following term when comparing classrooms with high in-class discussions with low in-class discussions. Our results extend previous findings that professional development on active learning, by promoting the use of active learning approaches in the classroom, may increase students' persistence in the field. Accordingly, our results also highlight the importance of taking student subsequent outcomes into account when evaluating the effectiveness of any active learning PD training programs.

Our study is related to the broad literature on teacher professional development that underscores the complex relationship between specific program design features and the effectiveness of a program. These discussions have led to growing efforts in documenting implementation details of a PD program and assessing its impacts on student achievement outcomes across K-12 settings. Our study contributes to this literature by providing detailed description on how a successful active learning PD program was administered and implemented at the college setting, as well as assessing its effectiveness on student outcomes. From a theoretical perspective, there has been a growing consensus on several conditions under which PD programs might produce more favorable outcomes, including sustained duration, coherence, collective participation, active learning, and local support (Darling-Hammond et al., 2017). The ALPD program in the current study combines several of these key features. For instance, the program involved highly committed and experienced program facilitators with a coherent training agenda, and a requirement of continuous and active participation from all participants during an 8-week time span. In addition, a number of activities were also intentionally designed to facilitate building a supportive and collaborative professional development community, aligning with existing literature on features of effective PD (Cox, 2004; Elliott et al., 2016). Therefore, our study complements the current literature that is primarily conducted at K-12 settings by lending support for incorporating these features in designing effective teacher PD programs on college instruction.

The findings from our study indicate that the professional development on active learning instruction may lead to increased persistence in the field through instructional improvement in the college classrooms. We encourage researchers to conduct similar research to bolster these results and to illuminate specific conditions under which such PD programs may produce favorable outcomes. Taken as a whole, our study lends suggestive support to PD programs on active learning as a promising way to innovate college instruction and improve student outcomes. As such, professional development may be a way to institutionalize the use of active learning in higher education.

Open Research Statements

This manuscript was not required to disclose open research practices, as it was initially submitted prior to JREE mandating open research statements in April 2022.

Acknowledgements

We thank Brian Sato, Andrea Aebersold and Mayank Verma for helpful conversations and feedback. Ashley Harlow, and Sabrina Solanki have also provided helpful suggestions on the manuscript. All mistakes are our own.

Funding

This work was supported by the National Science Foundation under grant number 1612258 and 1565073.

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