Supplemental Online Resources Improve Political Methods Education

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Abstract

Introductory research methods courses are increasingly important for undergraduate political science majors, but many students struggle in these courses. Asynchronous Online Supplemental Instruction (OSI) may be a time- and cost-efficient means of supporting these students. However, we know little about the efficacy of these resources in general, or specifically in political methods education. This paper introduces an original OSI resource, "Foundations of Quantitative Research in Political Science," and uses a pre-registered within-subject experimental design to evaluate its impact. We find that access to this resource significantly improves student performance in an introductory political methods course at a large public university. To our knowledge, this study is the first to estimate the causal effects of OSI in political science.

The American Political Science Association (APSA) reports that 82.4% of undergraduate political science and government programs in the United States offer a research methods/statistics course as part of their core curriculum (Davis et al., 2019).[1] Yet, research finds that many political science majors struggle in these courses (Buchler, 2009;

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[1]APSA. 2019. "2017-18 APSA Departmental Survey: Enrollments and Curriculums." This survey was administered online from June 6 to October 15, 2018 to 1,263 departments at four-year colleges and universities offering degrees in Political Science and Government in the U.S., with 383 departments (30.3%) responding.

Adriaensen et al., 2015; Slocum-Schaffer and Bohrer, 2021; Brown et al., 2022; Harden and Esarey, 2022). This, in turn, may negatively impact student retention and time-to-degree in political science programs. Moreover, unless students master the knowledge and skills introduced in these foundational courses, they are disadvantaged in upper-division coursework and in co-curricular and postgraduate opportunities (e.g. research, internships, employment, and postgraduate study) that increasingly require these skills.

To support student learning in challenging courses, some universities have developed optional face-to-face supplemental instruction (SI) or synchronous online supplemental instruction (OSI) that are regularly scheduled to complement course instruction during the semester, and research has found these to be largely successful (Arendale, 2020; Bowman et al., 2021; Dawson et al., 2014; Ogden et al., 2003; Spaniol-Mathews et al., 2016; Moradi et al., 2018). However, providing these resources for students is cost intensive as each semester they require, among other resources, SI leaders, classrooms, and active faculty or staff oversight.

To avoid these costs, asynchronous OSI may present a time- and cost-efficient way to support students in challenging classes given that it does not require instructional support. Yet, the literature has yet to convincingly address whether asynchronous OSI improves student learning in general and has yet to examine their effects in political science specifically. Existing studies to date on OSI remain limited by methodological challenges including small sample sizes (Moradi et al., 2018) and selection bias (Paloyo, 2015; Bowman et al., 2021), with the only experimental study, to our knowledge, having a small sample size (Moradi et al., 2018). Furthermore, this research has focused almost exclusively on STEM courses, with no study to date having studied the impact of OSI in political science or political science methods courses where many students face a greater degree of apprehension towards math.[2]

We believe that it is crucial to understand the impact of asynchronous OSI on political methods education given the increasing role of technology in teaching, the challenging nature of methods courses, the growing importance of methods education for political science, and the time and cost constraints faced by universities, faculty, and student teaching assistants (TAs).

This study contributes to the literature by creating an *asynchronous* OSI resource for an undergraduate political science methods course and to our knowledge is the first to causally analyze the impacts of OSI on student learning in political science. Specifically, building on prior research on high impact pedagogical practices, we develop a series of interactive asynchronous OSI modules to support student learning in the required political methods course for political science majors, Political Inquiry (POLI 30), at the University of California, San Diego (UCSD), which has double the average DFW (D grade, failure, withdrawal) rate of all courses in the Department.[3]

To evaluate the impact of the modules on student learning, we conduct a pre-

[2]To our knowledge, only Warren and Tonsetic (1998) and Ogden et al. (2003) analyze traditional SI in political science courses, but neither analyze OSI, methods courses in political science, or provide causal evidence of their effects on student learning. Other studies, such as Yue et al. (2018) and Skoglund et al. (2018) include political science courses in their sample but do not report results for this subsample of courses.

[3]For the five year period FA 2016-SP 2021 (excluding Summer quarters), the average DFW for all courses in our curriculum was 5%, while the average DFW rate for POLI 30 was 11% (Institutional Research, UCSD.)

registered experiment[4] that randomly assigns each student's access to a subset of the OSI modules and design midterm exam questions to evaluate student knowledge on material covered in lecture and supplemented by the OSI modules.

We find that giving students access to the OSI modules significantly increased student performance and the effect was larger the more students engaged with resources. Our estimates suggest that access to the modules increased student exam question grades by 3.8 percentage points. Using data on treatment compliance, we further find that our OSI resource increased exam question scores by 5.3 percentage points for students who viewed a module and by nearly 11 percentage points for students who took a module quiz.

Additionally, following existing research suggesting that OSI may benefit non-traditional and underrepresented students[5] (Peterfreund et al., 2008; Rabitoy et al., 2015; Rath et al., 2007; Buchanan et al., 2019; Yue et al., 2018) and students with lower academic performance (Congos and Schoeps, 1993; Ramirez, 1997; Skoglund et al., 2018), we test for heterogeneous effects across student demographics. Interestingly, we find no evidence that the treatment had statistically significant differential effects on students based on their GPA or underrepresented status.

Finally, we assess students' perceptions of the modules by conducting a voluntary post-experiment survey. Although our sample size was small and self-selection was present, an overwhelming majority reported that the modules helped them learn and achieve higher grades, and that they would recommend the modules to other students.

This study makes four main contributions. First, it introduces a novel asynchronous OSI resource for introductory political methods courses,[6] for which we provide strong causal evidence of positive learning impacts. Second, to our knowledge, our study is the first to utilize a within-subject experimental design to assess the impacts of OSI. The advantages of this design are that it is more fair to students than many alternatives; it allows us to establish causality in student learning; it controls for student-specific characteristics, reducing variance; and it generates a larger number of observations, thus increasing statistical power. Finally, while the positive impacts of traditional SI on student learning have been well established, much less is known about the impacts of OSI, which have become increasingly common, especially since the global pivot to remote learning in the wake of the Covid-19 pandemic. This study thus contributes to the general literature on undergraduate teaching and learning by providing causal evidence that asynchronous OSI can positively, and significantly, impact student learning in challenging courses.

[4]This study was pre-registered prior to collection of outcome data at the EGAP Registry, accessible at https://osf.io/scx6r. This study was conducted with approval of UCSD's Institutional Review Board, protocol #170886.

[5]We find this especially important given the diverse demographics of POLI 30 at UCSD: When we conducted this experiment, Spring quarter of 2021, more than 40 percent of our majors identified as underrepresented minority students.

[6]We intend to make some or all of these resources widely available, contingent on logistical and technical support.

1 Course Background

The Department of Political Science at UCSD requires that all of its undergraduate majors take a 10-week introductory political methods course, POLI 30. This course introduces students to fundamental tools of political inquiry, including quantitative data, statistical software, probability theory, measurement, inference, research design, hypothesis testing, linear regression, and other basic statistical methods. POLI 30 is offered every quarter (Fall, Winter, Spring, Summer) and typically enrolls between 200 and 250 students each quarter during the academic year. The course is taught by multiple instructors, resulting in some variation in course content, but core concepts and learning outcomes remain consistent across instructors. In each offering of the course during the academic year, students meet twice a week for 50-minute lectures led by the course instructor, with an additional weekly meeting (50 minutes) in smaller discussion sections (approximately 30 students per section) led by graduate student TAs.

POLI 30 has double the average DFW rate of all courses in the Political Science curriculum, making it crucial to find ways to improve student learning and performance. The literature has found that students struggle in political methods courses for various reasons. First, students often arrive with varying levels of prior exposure to prerequisite mathematical concepts as well as “fixed mindsets” or preconceptions about their ability to succeed (Buchler, 2009; Adriaensen et al., 2015). Second, the type of learning required in quantitative courses is often significantly different from other courses in the curriculum in that learning tends to be both more linear and cumulative (Buchler, 2009, 527). Third, students often mistakenly assume they can succeed in these classes by memorizing statistical formulae, rather than focusing their efforts on understanding underlying principles and logic (Buchler, 2009). Finally, as has been well established by constructivist theories of learning, mastery requires frequent low-stakes opportunities to practice new knowledge and skills with prompt feedback (Brown et al., 2014). Yet, many of these courses have high student-to-faculty and student-to-TA ratios, which can constrain instructors’ and TAs’ ability to provide the frequent individualized feedback we know students need to succeed.

The authors have also experienced first-hand how many students struggle in the course, and at a large public university like UCSD, these challenges are often exacerbated by the fast-paced nature of the course in a 10-week quarter system, as well by high student-to-faculty (typically between 200 and 250 students) and student-to-TA ratios (about 60 students per TA).

2 Foundations of Quantitative Research in Political Science

To support student learning in POLI 30, we designed and created the ”Foundations of Quantitative Research in Political Science” asynchronous OSI resource.[7] This resource includes ten modules, with the first introducing students to the supplemental materials

[7]Funding for this work was provided by the University of California San Diego’s Course Development and Instructional Improvement Program (CDIIP) grant, AY 2020-21.

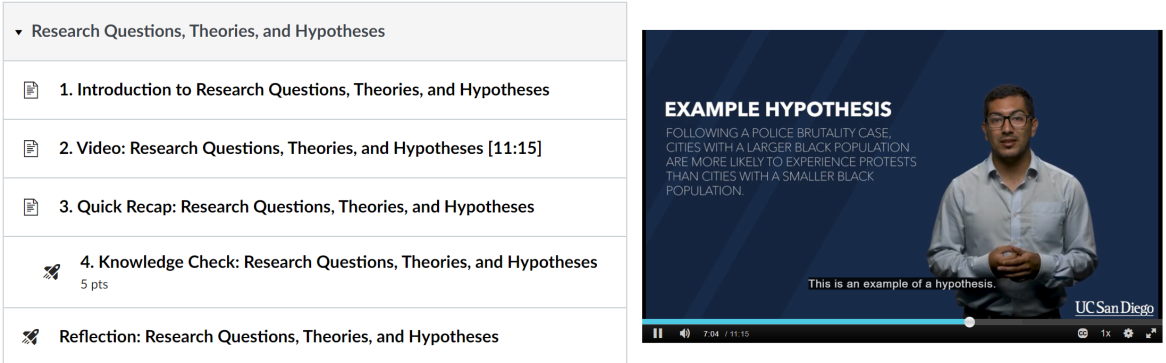

Figure 1: User interface of the OSI modules as seen on Canvas. Left screenshot is from the Canvas menu showing the Research Questions, Theories, and Hypotheses module. Right screenshot is from the Research Questions, Theories, and Hypotheses video.

and the scientific method, and the remaining nine focusing on specific course topics that students have historically struggled with most.

Each module includes: (1) a brief textual overview of the module's content and learning outcomes; (2) one or more short videos (approximately seven to ten minutes) that embed concepts within a motivating political problem, focus on addressing misconceptions, and explain the logic underlying concepts; (3) a brief textual summary or "recap" of the module with links to additional supplementary materials for students to "dig deeper," (4) a "knowledge check"—interactive quiz(zes) with feedback to assess how well students understood the module,[8] and (5) a "reflection" opportunity that invites students to identify what they have learned and provide feedback on the module. Figure 1 displays the user interface of one of the modules and a screenshot from an instructional video.

As noted above, each each module is introduced by a brief textual overview of the module and a clear statement of learning outcomes, which aligns with research on effective pedagogy (Ambrose et al., 2010; Nilson, 2016). Following previous research on teaching political methods (Buchler, 2009; Adriaensen et al., 2015) and insights from constructivist theories of learning (Ambrose et al., 2010; National Research Council, 2000), the modules were designed to introduce fundamental concepts in an intuitive way, rather than a more math-heavy or highly technical approach. The modules introduce real-world political problems to motivate the logic underlying key course concepts, address common misconceptions, and provide examples that highlight the political relevance and potential applications of key course concepts.

Building on research from cognitive and neuroscience (National Research Council, 2000) and multimedia learning (Mayer, 2014), as well as guidance from educational and technology specialists at UCSD,[9] videos were kept relatively short (approximately 7 to 10 minutes) and were filmed in UCSD's professional studio. Each video is accompanied by a "quick recap" that briefly summarizes the main learning objectives of the video as

[8]Some modules include multiple "knowledge checks"/quizzes, and students are encouraged to interact with the modules as often as necessary until mastery is achieved.

[9]April Cha, Instructional Designer, UCSD; Caryn Neiswender, Educational Specialist, UCSD: Galen Davis, Senior Educational Technology Specialist, UCSD; Seth Marshburn, Senior Production Director, UCSD.

recommended by prior research in this area (Ambrose et al., 2010; Brown et al., 2014; Moradi et al., 2018; National Research Council, 2000; Roediger and Karpicke, 2006).

Module summaries are then followed by "knowledge checks" (i.e., quizzes) that provide students with opportunities to check their mastery of the module's concepts. "Knowledge check" questions were carefully designed to probe common misconceptions and question banks were created to enable students to take multiple self-tests with immediate feedback on their level of mastery. The pedagogical value of providing students self-testing opportunities with prompt formative feedback is well established in the literature on human cognition (Ambrose et al., 2010; National Research Council, 2000; Brown et al., 2014; National Research Council, 2000; Roediger and Karpicke, 2006), but as discussed above, is often challenging to implement in large-enrollment courses such as POLI 30.

The final section of each module asks students to reflect on their learning and to provide feedback on the module itself—both of which are pedagogical practices that research has demonstrated deepen learning, improve retention, and build metacognitive skills (Ambrose et al., 2010; National Research Council, 2000).[10]

Beyond these common elements of each module, the modules themselves are generally ordered from more foundational to more complex concepts. Depending on their needs, students are free to engage with modules in whichever order they choose.

The ensure that students felt comfortable navigating the resources we chose Canvas[11] to host the modules, as Canvas is the common instructional tool used at UCSD. In typical offerings of POLI 30, students have access to all ten modules on a single Canvas course via a "join" link during the first week of the quarter. Once students join the OSI course, the modules populate their home Canvas page as a separate course.

3 Impact Evaluation

To evaluate the impact of the modules on student learning, we conducted a preregistered experiment using a within-student design. Specifically, we randomly assigned each student's access to a subset of the OSI modules. We then wrote midterm exam questions to evaluate student knowledge, taking care to assess understanding of only course content that was addressed *both* in lectures and in the online supplementary modules, so that no students were unfairly disadvantaged by the design.

Each student taking the exam answered questions for which they received treatment and questions for which they did not receive treatment. For any given student, an untreated question tested their knowledge on a topic that was presented in standard

[10] Questions include: (1) "What are your main takeaways from this module?" (2) "What questions remain for you?" (3) "Do you have any feedback about this module to share? How can this module be improved?" and (4) "Please rate your agreement with the following statements," with statements including (a) "I found this module helpful," (b) "The video(s) in this module improved my understanding of this module's content," and (c) "The knowledge check(s) in this module improved my understanding of this module's content." Questions 3 and 4 were added after we conducted our experiment, but we include them here as a recommendation for obtaining low-effort student feedback, as students may not want to spend the time to answer open-ended questions.

[11] Canvas is an online learning management system (LMS) developed by https://www.instructure.com/ and used by universities, educators, and students to manage and access course content. Canvas is the default LMS at UCSD.

Table 1: Access to modules by treatment group. All groups had access to the Introduction and Research Questions, Theories, and Hypotheses modules. Each group was then randomly given access to two of the four remaining modules.

	Treatment Group					
Module	**1**	**2**	**3**	**4**	**5**	**6**
Introduction	x	x	x	x	x	x
Research Questions, Theories, and Hypotheses	x	x	x	x	x	x
Introduction to Variables	x	x	x			
Confounding and Intervening Variables	x			x	x	
Research Design		x		x		x
Introduction to Inference			x		x	x

course material (textbook, lectures, discussion sections, and office hours), but not also available to them through the relevant OSI module. By contrast, a treated question tested a student's knowledge on a topic presented in both standard course material and OSI module available to them.

For the purposes of the experiment, we created six different Canvas courses, one for each treatment group. Students enrolled in POLI 30 during the Spring quarter of 2021 were randomly assigned to one of these six treatment groups.[12]

Two modules were available for every treatment group: the module that introduced the resources and a module on research questions, theories, and hypotheses (which contained foundational knowledge and was therefore crucial to the comprehension of subsequent modules.) Each treatment group was also provided access to two additional modules randomly selected from a set of four (Introduction to Variables, Confounding and Intervening Variables, Research Design, and Introduction to Inference), with each treatment group having a different set of modules. Table 1 shows a complete description of access to modules by treatment group.

Students were provided with access to their respective Canvas pages during the first week of the course and were notified about materials both via email and in class. Students were also aware that the effectiveness of the resource was being tested, but not aware of design details. Students were sent invitations to their Canvas page multiple times in the weeks leading up to the midterm exam. It is important to note that students were encouraged, but not required, to use the supplementary materials, and no additional incentives (e.g., extra credit points) were awarded for their use.

Five weeks into the 10-week course, students took a midterm exam worth 20% of the course grade. The midterm exam (included in the Appendix) consisted of 18 questions, 13 of which are the focus of our impact evaluation. Four questions (1a-1d) asked about course content that was not covered by the supplemental resources, and one (2a) asked about content taught in the "Research Questions, Theories, and Hypotheses" OSI module, which was available to all six treatment groups. Consequently, these questions were dropped from our study. By limiting ourselves to this subset of 13 questions, we

[12]Students were introduced to the study and the opt-out IRB form during week 1 of the quarter. Our sample consists of undergraduate students at UCSD who were enrolled in the course during Spring term of 2021, excluding those who opted out or did not take the midterm exam. All students who consented to participating in the experiment were assigned to treatment, including students who enrolled late.

Table 2: Mapping between material covered in each module and material covered in each exam question.

	Q2			Q3		Q4				Q5			
Module	**b**	**c**	**d**	**a**	**b**	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Introduction													
Research Questions, Theories, and Hypotheses													
Introduction to Variables	x	x	x										
Confounding and Intervening Variables				x	x								
Research Design				x						x	x	x	x
Introduction to Inference						x	x	x	x				

limit our analysis to questions that focused on content covered in the OSI materials that were available to some treatment groups and not others. Table 2 shows a complete description of how modules and questions overlap.[13]

In this study, the unit of observation is student-question. Treated units include those questions answered by students that had access to a relevant OSI module. Untreated units include student answers to questions covered by OSI material but *not* available to them. The main advantage of this research design is that errors associated with differences in skill and effort between students are reduced—each student acts as their own control group.

In total, there were 216 students enrolled in the course during the first week of the quarter. Of those, 189 students took the midterm exam. 46 students were dropped from the study either because they opted out or were minors at time of consent. Thus,, our study includes 143 students and our student-question data set contains 1,859 observations (143 students × 13 questions). Treatment groups ranged in size from 18 to 28. We chose to evaluate the impact of the supplementary material on midterm exam performance so that students could have full access to the content for the remainder of the quarter after they took the exam. The exams were graded by five Political Science PhD students using the Gradescope application.[14]

Several strengths of the research design are worth highlighting. First, the design is straightforward and can be implemented by other scholars. Second, it provides a more ethical way of testing the effects of OSI than other experimental designs since it ensures that all students receive some randomly determined subset of modules—it was not the case that some students were given access while others were not. Third, the design allows us to measure the effects of specific learning outcomes, rather than effects on overall course or exam grades. We provide direct evidence that the modules

[13] Question 3a asks about information covered by two modules, which should bias our estimates towards zero.

[14] Each PhD student graded the same set of questions for all undergraduate students. To ensure consistency, we created a detailed rubric for each question and trained each grader on the grading rubric. Questions 3a and 3b were graded by one of the co-authors of this study, and all remaining questions were graded by PhD students serving as TAs for POLI 30, none of which were directly involved with this study. TAs were not aware of treatment assignments when grading. They also had no access to the online modules, to eliminate the concern that TAs might modify their teaching to fit the material covered by the modules. As a robustness check, we conducted our impact evaluation with a subsample that excludes questions 3a and 3b to account for potential sources of bias. All results are consistent with the main results.

affect the specific outcomes for which they were intended. Fourth, the within-unit design increases the number of observations since each student is observed multiple times, increasing statistical power. In addition, the within-unit design allows for the inclusion of student fixed effects, which absorb student-specific variance. If student performance *across outcomes* looks very different from one student to another, then this fixed effect becomes a good predictor of the outcome and leads to more precisely estimated estimates. Finally, the experimental design allows us to better detect student-level heterogeneity since the within-unit design means that individual treatment effects can be estimated for each student, making it easier to predict and detect heterogeneous effects across subgroups of students.

3.1 OSI Availability

Our experiment was implemented as an encouragement design where the treatment is access to OSI modules. Because non-compliance is present, we first estimate the intent-to-treat effect (ITT); that is, the effect of having access to the instructional materials on question scores. We use OLS linear regression to estimate the ITT.[15]

We estimate the regression using question-student level data. The regression model is:

$$Y_{iq} = \beta Treatment_{iq} + \gamma_i + \lambda_q + \epsilon_{iq} \tag{1}$$

where q denotes each question and i denotes each student. β is the causal coefficient of interest. Y_{iq} denotes student performance in each exam question, which we measure using both percentages (0%-100%) and standardized scores. The treatment is a dummy variable indicating whether student i had access to supplemental modules addressing question q. γ_i are student fixed effects, and λ_q are question fixed effects.[16] The exam question fixed effects should absorb any differences in grading across exam questions as well as factors that affect each question equally across students.

Student fixed effects control for any time-invariant observable or unobservable student-specific characteristic. The within-student design means that each student acts as their own control group, allowing us to estimate within-student variation in outcomes when they received treatment versus when they did not. Finally, because our treatment is assigned at the student level, we cluster the standard errors at the student level for all models.

3.2 OSI Compliance

The experimental design allows us to estimate the effect of the OSI resource on compliers. We can estimate the local average treatment effect (LATE) for compliers, also called the complier average causal effect (CACE), which estimates the average treatment effect (ATE) for compliers—the students that engaged with the treatment (Gerber and Green, 2012, Ch. 5). In this study, the LATE is especially useful because it estimates the effect of the OSI resource on students that engaged with the resource. We

[15] Non-compliance means that we cannot estimate the average treatment effect (ATE) of the modules.

[16] We do not include question fixed effects in models that measure the dependent variable as standardized scores.

estimate the LATE using an instrumental variables (IV) approach (Gerber and Green, 2012, 157-160).

We measure compliance in two ways. First, we measure compliance by whether students viewed at least one page at least once. This is a conservative measure that simply identifies whether a student was exposed to the treatment by looking at the modules available to them. Of the 182 students in the dataset, 122 students viewed at least one page. Second, we measure compliance by whether a student completed at least one quiz. This measure of compliance captures actual engagement with the treatment.

To estimate the LATE we use an IV approach, where we regress the outcome on the treatment, using treatment assignment as an instrument. We use the two-stage least squares (2SLS) to estimate the LATE. The first stage is:

$$Treated_{iq} = \beta_1 Treatment_{iq} + \gamma_i + \lambda_q + \epsilon_{iq} \tag{2}$$

where $Treatment_{iq}$ denotes whether student *i* had access to online supplemental modules addressing question q. $Treated_{iq}$ denotes whether student i used online supplemental modules addressing question q. Results for the first stage show that the treatment assignment is a valid and strong instrument for whether students used the modules.[17]

In the second stage, we regress the outcome on the fitted values from the first stage:

$$Y_{iq} = \beta_2 \hat{T}reated_{iq} + \gamma_i + \lambda_q + e_{iq} \tag{3}$$

The coefficient of interest is Y_{iq}, which estimates the LATE. The reduced form for this instrumental variable is the ITT analysis from the previous section.

3.3 Heterogeneous Effects

To explore heterogeneous effects, also known as treatment-by-covariate effects (Gerber and Green, 2012, Ch. 9) or conditional average treatment effects (CATE), we obtained de-identified student information on cumulative GPA prior to taking POLI 30 and minority student status.[18] We estimate heterogeneous effects using linear regression:

$$Y_{iq} = \delta Treatment_{iq} \times StudentChar_i + \gamma_i + \lambda_q + \epsilon_{iq} \tag{4}$$

where $StudentChar_i$ denotes the student-specific characteristic for which we have data (underrepresented or GPA.) The interaction between this variable and the treatment assignment will allow us to estimate the heterogeneous effects of interest, making δ the main coefficient of interest.

[17] We report the results of the first stage in the Appendix.

[18] While we pre-registered the model specification presented here, we did not pre-register the particular student-specific covariates to be analyzed as there was uncertainty about which student-specific information would be made available to us by UCSD. The results should therefore be considered exploratory.

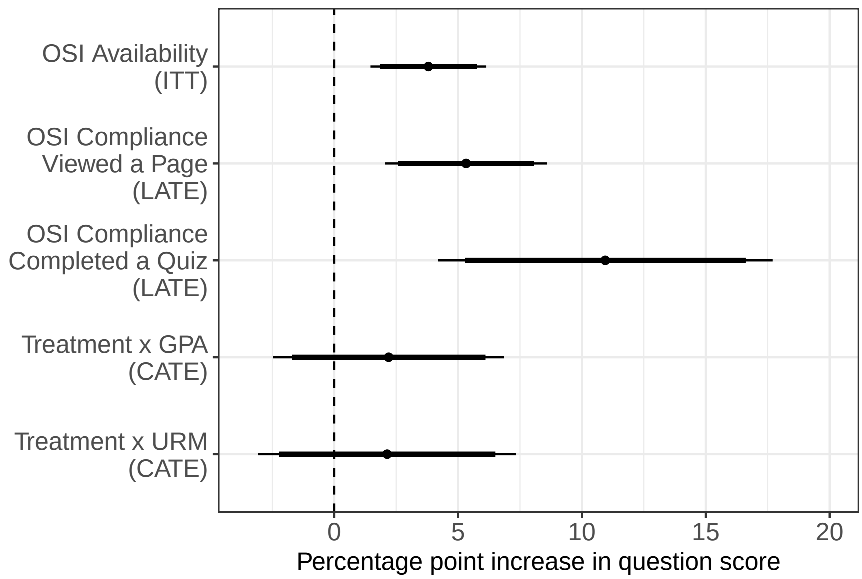

Figure 2: Plot shows point estimates from the main results using exam question scores in percent as the outcome measure with 90% and 95% confidence intervals represented with thick and thin lines, respectively. From top to bottom, plot shows effect of OSI availability (ITT), effects of OSI use (LATE) measured as viewing a page and completing a quiz, respectively, and effects of OSI conditional on student GPA and underrepresented status on exam question scores. Analysis includes student and question fixed effects. Robust standard errors are clustered at the student level.

4 Results

We find that access to the OSI modules significantly increased student performance. Figure 2 visualizes the main results using exam question scores in percent as the outcome variable. On average, having access to the modules increased question scores by 3.8 percentage points, which translates to an increase of 0.14 standard deviations. While these estimates may appear small, they translate to about one third of a letter grade increase in the overall exam grade. That is, the average effects suggest that if students had access to the treatment for all four modules, their exam grades would have increased by 3 points out of 100. Further, point estimates from the LATE analysis of compliers suggest that questions scores were 5.3 points higher when students viewed at least one page related to that question, and nearly 11 percentage points higher when students completed at least one quiz. Finally, we do not find evidence that treatment effects varied across students depending on their GPA or underrepresented status.

Table 4 in the Appendix shows the full regression output of the main results for both ITT and LATE estimations using both measures of the outcome variable. Models 1 and 4 show the results for OSI availability (ITT) while Models 2, 3, 5, and 6 show the second stage results for OSI compliance (LATE) using both measures of compliance (viewing a page and completing a quiz). For the IV-2SLS models, we estimate the first-stage cluster-robust F statistics and find that they are above conventional levels for a strong instrument, meaning that the treatment assignment is a valid instrument for both measurements of compliance (F = 425.8 for page views and F = 116.3 for quiz completion). The instrument being randomly assigned as part of an experimental design further validates its use.[19]

As expected, the LATE estimates are larger than the ITT estimates,[20] and LATE estimates for compliance measured as quiz taking are larger than those of compliance measured as exposure to the treatment. Figure 2 and Table 4 show that giving students access to OSI resources improved question scores (Models 1 and 4), and the effect was larger for students who viewed the resource (Models 2 and 5), and even larger for students who engaged with it (Models 3 and 6). This suggests that the OSI modules help students more the more they engage with them.

Regarding heterogenous effects, we find that the direction of both interaction estimates are positive, perhaps suggesting that students with higher GPAs and underrepresented students benefited more from the modules, however, the estimates are not statistically significant at any conventional level (Table 5 in the Appendix shows full regression output). We therefore find no evidence that our modules had differential impacts on students depending on their GPAs or underrepresented status.

5 Survey Results

In addition to encouraging empirical results, we received positive feedback from students. We conducted a survey at the end of the POLI 30 course to elicit student views on the course and the supplemental modules. While the sample is relatively small, it suggests that the modules were well-received.

Of those who answered the survey, 17 out of 19 respondents reported using the resources. All 17 of these students reported that the resources were helpful (Yes/No question, "Did you find these resources helpful?") Further, on a scale of 0-5, where 0 indicates "strongly disagree" and 5 indicates "strongly agree," students generally agreed that the resources helped them get a better grade (mean = 4, range = 3-5); that they would recommend these resources to future POLI 30 students (mean = 4.53; range = 3-5), and that they would like to continue having access to the materials (mean = 4.63; range = 3-5).

6 Moving Forward

Research shows that many political science undergraduate students find it difficult to learn political methods and statistics. This paper presents a successful effort to improve student learning in political methods with OSI modules. Through an experiment, we find that the modules significantly and substantially improved student learning, as measured by student performance on midterm exam questions. We also find that all students benefited equally from access to the modules regardless of their prior academic performance (as measured by incoming cumulative GPA) or minority student status. This study suggests that asynchronous OSI may be a relatively time- and cost-efficient way to improve education in political science methods courses. While substantial work is required upfront to design and create such resources, their maintenance requires

[19]We report results for the first stage in the Appendix.

[20]The ITT estimates are the reduced form of the 2SLS-IV model.

Table 3: Student-level summary statistics: modules use, GPA, and question scores.

Variable	N	Mean	Median	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Page views	143	29.25	24.00	27.93	0.00	4.00	42.50	141.00
Quiz completions	143	2.64	3.00	2.90	0.00	0.00	4.00	8.00
Incoming GPA	141	3.48	3.61	0.50	1.10	3.29	3.84	4.00
Mean Question Score	143	78.10	80.77	13.26	29.21	71.36	87.44	98.97

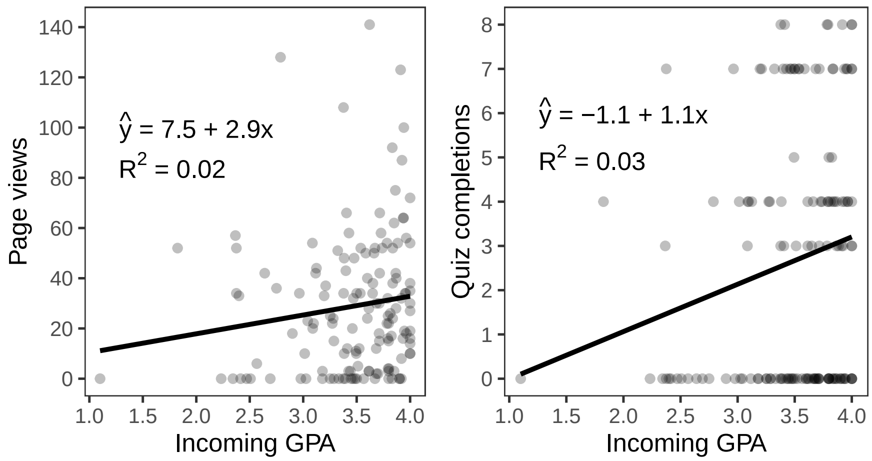

Figure 3: Correlation between incoming GPA and module use measured as viewing the modules and completing a module quiz.

minimal work and does not place additional burdens on faculty or TAs beyond guiding students to them.

With regard to the generalizability of our results, an important consideration is the fact that the experiment was conducted during spring quarter 2021 during the COVID-19 pandemic, which may have influenced students' use of our resources. On the one hand, students had become unusually adept at learning online after almost three quarters of online courses. This may have meant that students were more open to engaging with our OSI resource. On the other hand, it is also possible that many students were experiencing online learning fatigue, making them less likely to utilize the OSI resource. How students engage with OSI resources in a post-pandemic context where classes are in-person will matter for how effective they are.

We also found that encouraging students to engage with the OSI modules is a challenge, particularly those who would potentially benefit most from them. For example, whereas more than 80% of students viewed at least one page, only 51% completed at least one quiz (Table 3).[21] Yet, we find a positive correlation between incoming GPA and use of supplemental modules (p-values of 0.11 and 0.025 for page views and quiz completions, respectively. See Figure 3). In other words, students who struggle academically were less likely to engage with the supplemental modules.

Given that political methods and statistics courses remain a core element of undergraduate political science curricula nationally, and given evidence of the ways in which students struggle in these courses, we present evidence that OSI resources such

[21] We report additional descriptive statistics in the Appendix.

as ours can play an important role in supporting student learning and closing achievement gaps in these courses. They may also be of benefit to faculty and TAs who teach these courses, especially those who teach in resource constrained environments that are often characterized by high student-to-TA and faculty rations. Our hope is that these materials can be widely shared, replicated, or used in ways to inspire new projects to support student learning in this critical area of our undergraduate curriculum.

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A Main Results: Regression Output

Table 4: Main results: Effects of OSI on student grades in exam questions. Models 1-3 use question grades in percent as outcome measure. Models 4-6 use standardized question grade as outcome measure. Models 1 and 4 estimate the ITT, models 2 and 4 estimate the LATE using module view as compliance, models 3 and 6 estimate the LATE using quiz taking as compliance.

	Question Score					
	Percent			Standardized		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (OSI available)	3.801***			0.143***		
	(1.371)			(0.050)		
Compliance (viewed a page)		5.325***			0.198***	
		(1.870)			(0.069)	
Compliance (completed a quiz)			10.943***			0.418***
			(3.886)			(0.146)
Model	OLS	IV-2SLS	IV-2SLS	OLS	IV-2SLS	IV-2SLS
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Question FE	Yes	Yes	Yes	No	No	No
Observations	1,859	1,859	1,859	1,859	1,859	1,859
R^2	0.466	0.465	0.461	0.257	0.255	0.250

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by student in all columns.

Table 5: Heterogeneous treatment effects: treatment-by-covariate effects of OSI access on exam question grades given students' incoming cumulative GPA and underrepresented minority status. Models 1 and 2 use question grade in percent as outcome. Models 3 and 4 use standardized question grade as outcome.

	Question Score			
	Percent		Standardized	
	(1)	(2)	(3)	(4)
Treatment	-3.861	3.343^{**}	-0.177	0.134^{**}
	(9.543)	(1.570)	(0.353)	(0.059)
Treatment × GPA	2.197		0.092	
	(2.620)		(0.097)	
Treatment × URM		2.136		0.059
		(3.464)		(0.130)
Student FE	Yes	Yes	Yes	Yes
Question FE	Yes	Yes	No	No
Observations	1,833	1,703	1,833	1,703
R^2	0.469	0.465	0.258	0.255

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered by student in all columns.