The Potential (and Pitfalls) of Online Instruction for Improving Educational Opportunities and Outcomes in High School

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Abstract

This research focuses on online course-taking in high schools that is increasingly accessed by students falling behind in their progress toward graduation and examines how it is used and whether students gain academically through its use. Utilizing over five million records of online instructional sessions linked to student school records, we find mostly negative associations between online course-taking and math and reading scores, credits earned and grade point averages. Our analysis shows that those with weaker course-taking behaviors gained the least and were possibly set back by online course-taking. Limited resources constrained the implementation of “best practices” and other instructional supports (e.g., live teacher interactions) for online course-taking, including accommodations for students with special needs and assistance with course content.

Key words: online instruction, credit recovery, student engagement, academic achievement

Introduction

K-12 schools are rapidly expanding digital instruction with an aim to transform learning and improve student educational outcomes (Cavanaugh, DiPietro, Valdes, & White, 2007; Henriquez & Riconscente, 1999). Growth in the use of digital and online platforms has been driven by advances in technology that allow it to compete with (or complement) features of face-to-face instruction, as well as by promises to lower educational costs and broaden access. The federal government has contributed to this growth by providing resources for educational technology purchases for public schools and via directives that require states to set aside funds for procuring digital educational resources (Enyedy, 2014). More recently, the locus of growth and implementation activity has shifted from state-level organizations (e.g., virtual schools) to initiatives at district and school levels (Gemin, Pape, Vashaw, & Watson, 2015).

A major area of growth in digital instruction is online course-taking, particularly at the secondary education level, in which instruction occurs "primarily over the Internet, using an online delivery system to provide access to course content" in "multiple settings (in school and/or out of school buildings)" (Gemin et al, 2015, p. 5; Powell, Roberts, & Patrick, 2015). Indeed, one analysis suggested that by 2019, 50 percent of all high school courses will be delivered online, moving beyond credit- and dropout recovery programs to blended learning in core programming for all students (Horn & Staker, 2011). While Gemin et al. (2015) distinguished "supplemental online courses" (students taking one-two courses per school year) from virtual or fully online course-taking, national data on the prevalence of online course-taking in U.S. public schools is not currently available.

A 2009-10 National Center for Educational Statistics survey (Queen & Lewis, 2011) suggested that online courses were primarily made available to expand course offerings, with providing opportunities for recovering course credits for missed or failed classes a secondary aim. Powell et al. (2015) reported that more than 75 percent of school districts used blended and online learning to either increase course offerings or for credit recovery. Gemin et al.'s (2015) recent analysis of a representative sample of 3.8 million online courses showed that nearly three-quarters of online courses taken by public school students were in core subjects (math, science, social studies and language arts). Recognizing online course-taking as a major and growing source of instructional programing for students, more research is needed to identify not only trends in course taking, but also effects of online instruction on student learning and achievement. With many online courses targeting students at-risk of not graduating high school, the potential for differential access to quality learning experiences between online and traditional classroom environments could also have profound implications for equality.

The combination of federal e-Rate program funding and use of Title I funding by low-income school districts to purchase educational technology may have reduced gaps in access to online educational tools for low-income students and students of color in the context of their school day; however, disparities persist in how and for what purposes these tools are used by race and socioeconomic status (Becker, 2000; Hohlfeld, Ritzhaupt, Barron, & Kemker, 2008; Warschauer & Matuchniak, 2010). Research identifies a range of technological, economic, organizational and social factors (in and outside of the instructional environment) that may exacerbate racial and socioeconomic disparities in the use of online technology to support student learning (DiMaggio, Hargittai, Celeste & Shafer, 2004; Zickuhr & Smith, 2012). At the same time, one argument for implementing an online approach to help students stay on track for high school graduation or recover credits from prior course failures is that online courses may offer more opportunities for customizing content and individualizing instruction (Archambault, Diamond, Coffey, Foures-Aalbu, Richardson, Zygouris-Coe, Brown & Cavanaugh, 2010). Students who require additional support or individualized modifications to overcome barriers to learning could also benefit from blended learning models that integrate live, personalized instruction and attention to individual instructional needs (Picciano & Seaman, 2009).

Recognizing that there is enormous variability in how online instructional programs and other digital tools are accessed, used, and supported in schools, and that issues of context and capacity—among schools, teachers and students—also likely play a significant role in determining whether or not students benefit from their use (Burch, Heinrich, & Good, 2016; Means, Toyama, Murphy, Bakia, & Jones, 2010), we explore in a large urban school district: *who* among secondary school students are taking courses online; how intensively and for what purposes, including how they interact with the online tool, and how the integration and use of online instructional programming affects whether or not students make academic gains through its use. For example, does student use of online learning tools increase their opportunities to receive personalized, high quality instruction? What structural factors (e.g., physical environment, technology features and instructional support) in the implementation of online instructional programming impede or support students' access to quality learning opportunities? What policies and strategies at district, school or classroom levels might mediate the effectiveness of online instruction in improving student learning and reducing achievement gaps?

This research focuses on an online instructional tool used primarily (but not exclusively) for credit recovery with high school students who have fallen behind in their progress toward graduation and is used similarly in other school districts across the nation. In the school district we study, the implementation of this online instructional program began in the 2010-11 school year with the objectives of increasing course and credit completion, providing personalized learning opportunities for students who perform less well in the traditional classroom, and improving student achievement. By the 2016-17 school year, 5,678 courses, about 20 percent of all credits accrued in middle and high schools in the district were completed online.

We employ mixed methods in studying the implementation and effects of this online instructional program, drawing on variation in the use of online instruction within and across schools (and over time) that we observe both qualitatively and quantitatively, including in environment and setting, instructional delivery mechanism and style, student and instructor engagement, and policy implementation (Burch et al., 2016). We also specifically focus on factors at the school, classroom, technology provider and student levels that have the potential to influence equity in access to and use of online instructional tools, particularly for students of color, low socioeconomic status, English language learners and students with special needs.

Among our key findings, we see considerable variation in who is assigned to take courses online by school. Schools with the highest rates of online instructional use often serve non-traditional student populations, such as pregnant or parenting students or those formerly incarcerated or expelled. Students with junior or senior class standing and those that meet minimum reading guidelines are more likely to have constructive interactions with the online course platform. Students with weak course-taking behaviors, such as a large proportion of idle time in an instructional session or a low number of sessions or course activities completed, do not appear to gain from participation and may even have experienced setbacks in their academic progress through online course-taking. We observed relatively few opportunities for students to benefit from personalized learning in the classroom. Overall, we find mainly negative associations between online course-taking and intermediate academic outcomes (relative to students taking courses only in traditional classroom settings in the same schools).

Below, we begin with a review of existing research on digital instructional tools, particularly as they are used to enhance K-12 student learning and outcomes at the secondary level, and we also briefly describe the sociotechnical framework that guides our study of digital instructional tools in practice. We then introduce our study samples and data and the focus and methods of our quantitative and qualitative analyses. We follow with the presentation and discussion of our research findings and their implications for policy and practice as online learning continues to expand in K-12 schools.

Background and Framework

The Promise for and Evidence on Digital Educational Tools in K-12 Education

Numerous claims are made regarding the potential for digital instructional tools to transform K-12 education. In terms of curriculum, it is argued that digital education allows for personalized content, facilitates access to more diverse learning resources and wider course offerings, and provides more connected learning opportunities (Burch & Good, 2014). Some digital tools also have the potential to support more effective instructional practices, including promoting critical thinking; expanding the range of opportunities for students to apply their knowledge and skills; tailoring instruction to student experiences and skill levels and making it more relevant to their daily lives; and fostering greater student engagement and motivation for learning (Cavanaugh et al., 2007; Collins & Halverson, 2009; Darling-Hammond & Bransford, 2007). Blended learning—a combination of digital and face-to-face content delivery—is viewed as a fruitful way to marry the flexibility, access, and cost-effectiveness of online learning with the social aspects, individualization, and contextual benefits of face-to-face instruction (Osguthorpe & Graham, 2003). A meta-analysis funded by the U.S. Department of Education (Means et al., 2010) found that blended learning is more effective when the online component utilizes curriculum and instructional methods that differ from those used in face-to-face learning and is collaborative rather than independent. In addition, new strategies and forms of assessment are being built into digital instructional tools, with more rapid feedback loops, structured forms and processes for monitoring student progress, and greater access to assessment information for teachers, parents and students (Burch & Good, 2014).

The potential for personalized instruction facilitated through digital education—allowing for adaptation of the content and logistics of instruction, including the pace, order, location, and lesson material—is attractive for the purpose of better meeting individual student needs, particularly at the secondary level as students' education interests and pathways diverge. At the same time, those advocating for greater use of digital instructional tools for personalized instruction and learning contend that they will be more effective if they are not simply integrated into traditional models of classroom organization and instructional approaches, but rather take full advantage of their capabilities to extend learning opportunities across time (i.e., outside as well as during and the school day), place (i.e., on and off-campus) and networks (Enyedy, 2014). In addition, the research evidence emphasizes the continued importance of live interaction between teachers and students as technology is adopted to improve educational outcomes (Zhao, Lei, Yan, Tan, & Lai, 2005; VanLehn, 2011). Online instructional tools also have the potential to increase student agency and transform the role of the teacher, for example, providing real-time data feedback that teachers can use to support student learning and ensure consistent access to the technology for all students, regardless of need (Brush & Hew, 2006; Halverson et al, 2015).

Despite many promising features of digital instructional tools, prior research on their use has found a range of positive, negative or null effects on student achievement (Cole, Kemple, & Segeritz, 2012; Margolin, Kleidon, Williams, & Schmidt, 2011; Chingos et al., 2017; Pane, Steiner, Baird, Hamilton & Pane, 2017). Pane et al. (2017) pointed out that most personalized learning efforts have been implemented in school and classroom settings that continue to employ traditional models of large-group instruction. The modal approach to personalization of learning allows for student self-pacing and additional choices of media for learning, due to the limited capacity of teachers to organize the classroom in ways that support more innovative, independent learning through digital tools (Margolin et al., 2011). Across their predominately charter school sample of schools, Pane et al. (2017) found on average positive, statistically significant effects of learning with technology on mathematics test scores (effect size: 0.09 s.d.) and positive (but not statistically significant) effects on reading (0.07 s.d.). Yet, these average effect sizes masked wide variation in effectiveness—both positive and negative statistically significant effects—across schools and student subgroups.

Research focusing specifically on K-12 online course-taking finds relatively low rates of course completion, generally in the range of 30–55 percent (Carr, 2000; Roblyer, 2006; Simpson, 2004; Stevens, Frazelle, Bisht, & Hamilton, 2016). The few studies that examine online learning at the secondary level emphasize the importance of staff with training to provide instructional support and monitor student progress (Hannum, Irvin, Lei, & Farmer, 2008; Stevens et al., 2016). A study of online course-taking for credit recovery in Montana found that only a handful of schools provided extensive student support, with the role of most teachers limited to addressing classroom management and technology access issues (Stevens et al., 2016). This study also identified student engagement and attendance as critical factors, yet there has been little attention in the literature as to which students enroll in and complete courses online (and how many), or what influences the extent to which they engage and how well they perform. Another concern with rapid growth rates in online instruction (over 100 percent in some states) is the disproportionate share of students with disabilities taking these courses, as well as students of color (Smith & Basham, 2014; Corry, Dardick & Stella, 2016). In Arizona, online school options are seen as one way to increase access and reduce dropout rates for Hispanic or Latino students, despite a lack of conclusive evidence that online schools meet the needs of this particular student population or increase their high school graduation rates (Corry et al., 2016).

Heppen, Sorenson, Allensworth, Walters, Rickles, Stachel Taylor, and Michelman (2017) conducted one of the first K-12 studies using an experimental design to assess the effectiveness of online credit recovery course-taking compared to a face-to-face option. The study followed students in 17 Chicago Public Schools who failed algebra in their first year of high school and were randomly assigned to retake the course in the summer through either an online course provider or a traditional face-to-face course. Of these students, 90 percent were Hispanic or African-American, 86 percent were free- or reduced-price lunch eligible, and 12 percent qualified as students with disabilities. Heppen et al. (2017) described the various ways the courses might have differed when offered online vs. face-to-face—such as content and sequencing, staffing intensity, interactions between instructors and students, and grading and feedback—with more variation expected across these dimensions *within* the face-to-face setting. They reported that the online instruction was delivered mainly in school computer labs, with most communication between students and teachers occurring asynchronously. When comparing student outcomes following the summer courses, they found that students in the online course had significantly lower end-of-course posttest scores and lower credit recovery rates compared to those in the face-to-face course. Contrary to touted advantages of online instructional models for facilitating personalized learning, the authors surmised that the online course may have been less effective in adapting to students' individual needs, in that these courses lacked flexibility for addressing gaps in students' initial skills and understanding of algebra. More rigorous evidence such as this across a wider variety of online course-taking and in more grades and settings is needed to determine if these results generalize beyond this particular online course and context.

Theoretical framing

If online learning and credit recovery at the secondary education level are introduced—not as a cheaper, more flexible way to help students complete (or repeat) courses—but rather to expand learning opportunities and increase student achievement, it is important to understand how these digital instructional tools are implemented and used in practice. We employ sociotechnical theory as a frame for understanding how online instruction is enacted and used, and how human interaction shapes its potential for increasing student learning. Researchers applying a sociotechnical framework in studying technology use have built on structurational models that view technology as embodying structures (developed by technology producers) that are "appropriated" by human action in the use of technology (Orlikowski, 2000). Sociotechnical theory posits that individuals and their social settings shape both understandings and use of adopted technologies in a dynamic process through recurring interactions. In addition, technology users may or may not use technologies as they were designed and can also circumvent prescribed ways of using them. This theoretical perspective also recognizes that structural properties of the digital tools will constrain how they are used, but that their use (in our case, by teachers and students) will also be strongly influenced by users' understandings of those properties and the functionality of the technology, which are in turn affected by intermediaries that provide training, guidance and support for the tools' features and use (Woolgar, 1996).

The Heeks' Design-Reality Gap model addresses the frequent mismatch between intended and actual uses of technology and factors such as financial constraints that can preclude the training and other supports required to implement them in useful ways (Baark & Heeks, 1999). For example, one of the International Society for Technology Education's (ISTE) essential conditions for the effective implementation of educational technology is reliable connectivity and dependable support for equitable access to the technology, which, in turn, can directly affect the amount of instructional time provided to students and the quality of interactions between the student, instructor and technology. In addition, the physical settings in which digital tools are accessed and used, including how classrooms or learning centers are organized and who is present and available to assist students with technological problems and support learning, can also be constraining or enabling in engaging students and guiding their effective use of digital instructional tools. If instructors are to effectively use technology to personalize instruction and student learning, they not only need knowledge of content and the technology itself, but also training on pedagogical methods that facilitate learning and on the various ways in which technology can be used to support student learning (Ertmer & Ottenbreit-Leftwich, 2010). Sociotechnical theory accordingly provides a useful framework for examining how and the extent to which students use digital instructional tools, focusing on their level of engagement, interactions and behaviors, and social aspects of the learning process, rather than generalizing solely on sociodemographic characteristics that may be less useful in discerning how disparities in use emerge (Catterall, 1998; Orlikowski, 2000; Lee & Hannafin, 2016).

Research Methods

Study Samples and Data

This study is set in an urban, Midwestern school district, where approximately one quarter of students in grades 9-12 access course instruction through an online instructional program, both during and outside the school day. Use of this online instructional program began in the 2010-11 school year, when approximately 1,000 students began course-taking in the system. Data from the technology vendor on online course-taking in this district are currently available through the 2015-16 school year, including detailed information on student use for each session initiated by students, course information, and progress toward course completion and performance. We link these data to student record data that include basic demographic information; absences and suspensions; credits earned and GPA; ACT scores, and standardized test scores.

In the analyses of quantitative data we present here, we focus on the 2013-14, 2014-15, and 2015-16 school years. In 2013-14, a total of 78,770 student records, including 6,173 online course-takers, were linked with 1,648,380 vendor records with a match rate of 81.4 percent. In 2014-15, records from 99,530 students, including 7,007 online course-takers, were linked with 2,142,340 vendor records with a match rate of 86.6 percent, and in 2015-16, we linked 101,233 student records (6,017 online course-takers) to 1,599,852 vendor records with a match rate of 83.3 percent. Table 1 presents basic demographic characteristics for this study sample, comparing all high school students in this district to online course-takers that have linked district-online vendor records. As seen in Table 1, a higher proportion of students taking courses online are black and low-income. Online course-takers in the district are also absent more often from school and have lower average fall math and reading test scores than the overall district high school student population.

We also draw on data collected in 158 observations of student online course-taking in 18 high schools across the 2014-15, 2015-16 and 2016-17 school years; these high schools included approximately 90 percent of all students taking courses online in the district in 2015-16. We used a standardized observation instrument developed to evaluate the nature of digital tools and their implementation in digital and blended instructional settings (Burch et al., 2016). The rubric evaluates the extent to which the instructional session facilitates quality learning opportunities for students using a set of indicators or dimensions (described in greater detail in Appendix A) for rating the entire learning experience. The instrument also records narrative comments and vignettes; total instructional time and time on task; the extent to which the format facilitates live interaction between instructors and students, and the functionality/operability of the technology. As we do not identify the students observed, we do not directly link the data collected in the observations to the student-level district-provider data. We analyze these data using rigorous qualitative methods to enrich our understanding of mediating factors—such as the accessibility and reliability of the technology, student/instructor ratios and instructional models, interactions with a live instructor, student engagement, and how course progress is assessed—and the ways in which they constrain or support the role of the online instructional tool in enhancing student learning and outcomes in various school settings.

In addition, we conducted 24 structured interviews with district and school-level administrators and support staff over two years to characterize and understand how malleable factors such as organizational capacity, staffing, training and support decisions, and policy guidance and requirements for implementing the technology influence access to and the effectiveness of the online instructional tool in increasing student learning. The interviews addressed teacher background, training and experience with technology; how the online instructional tool is used in the classroom and integrated with other instructional practices; support received for using the tool; impediments to their access and effective use by students, and needs for additional resources to improve use of the tool and student outcomes.

Study Measures and Methods of Analysis

Treatment measures and student typologies analysis. We conceptualize and investigate "treatment" in online instruction in two primary ways, assessing: (1) who (among the targeted students) accessed courses online when offered the opportunity, and (2) actual use (or enactment) of the instructional tool in the educational setting, including measures of user behavior (i.e., session and course duration, number of courses and number of sessions per course, activities completed per day and idle time per session, and the percentage of sessions taking place outside the regular school day). We draw on the rich data available on student user behaviors and level of engagement with the instructional tool to construct typologies of student use (or "user types"), using k-means cluster analysis. In addition, we integrate information and insights from observations of student use of the tool to flesh out these typologies. By characterizing students based on their user behaviors rather than classifying them based on less predictive sociodemographic attributes (see Figure 1), we shift the focus of the analysis toward factors malleable in the implementation of online course-taking (and informative for policy and practice) and away from those that define group membership by historical group achievement norms or based on a "deficit" mindset (Catterall, 1998; Hu & McCormick, 2012).

K-means cluster analysis is an iterative process that divides the available cases into k number of groups and then assigns each case to the cluster with the closest centroid (minimizing the Euclidian distance between each case and it's assigned cluster) (Steinley, 2006; Saenz, Hatch, Bukoski, Kim, Lee, & Valdez, 2011). After each assignment, the procedure updates the cluster centroids, reassigning cases as needed as it proceeds through the data, with the resulting clusters selected to minimize the error sum of squares (Steinley, 2006). Since many of the variables were on different scales, we standardized the variables on a common range, a procedure established by Milligan and Cooper (1988) as an alternative to z-score standardization, which can distort underlying group structures (Dillon, Mulani, & Frederick, 1989). We determined the number of clusters, three each in the 2015-16 and 2014-15 school years and four in 2013-14, using Ward's (1963) hierarchical method (Knight, 2014; Steinley & Brusco, 2007). We then used discriminant function analysis to establish the stability of cluster membership (Knight, 2014) and found that the analysis correctly classified 94 percent or more students in each cluster in each school year. Additional details on this methodological approach are provided in Appendix B.

Control variables. In assessing the effectiveness of online course-taking in improving student outcomes, it is critical to identify and control for the selective differences between students who use the tool and those who do not, and in models examining actual use, the factors associated with stronger levels of engagement and intensity of use. For high school students in this district, course failure (in traditional day-school course settings) is a primary criterion that determines who takes courses in the online instructional program, although student use of the tool varies both within and across schools and classrooms in the district. Table 1 shows the demographic characteristics of students before they began online course-taking in a given school year, which we control for when predicting student outcomes. Key demographic controls include identification as an English language learner, special education status, and economic disadvantage (free or reduced-price lunch eligibility).

Outcome measures and quantitative analysis of student outcomes. Online course performance —including course pass rates, on-time completion, course grades and the percentage of courses disabled—was estimated only for students taking courses online. The information on student course-taking behaviors, and the student typologies constructed based on those data, were used to assess their relationship to course performance, controlling for student and school characteristics.

We then extended the analysis of the effects of online course-taking to examine student intermediate outcomes, including the relationship between any use and types of use to their standardized test scores, credits earned and grade point average. In all of these analyses, we adjusted for student "baseline" characteristics (i.e., before they begin online course-taking in a given school year) to account for substantial differences between users and non-users (and among different types of users). We also restricted our comparison of online course-takers and non-users to high schools where the online instructional tool is made available. The primary methods of estimation we employed include: 1) fixed-effect models, which examine student changes in outcomes over time while adjusting for school and grade factors that remain fixed, or stable, across the course of the school year, along with student characteristics and the percentage of online course-takers in each school, and 2) inverse propensity score weighting with regression adjustment (IPWRA) that aims to align the observed characteristics of online course-takers and non-users at baseline in assessing the relationship of online course-taking to student outcomes. For brevity, we present estimates from the fixed effects regressions, given that they were very comparable to the IPWRA estimates (see additional discussion in Appendix C), although we do not claim to have overcome all limitations to the validity of causal inference due to the selective differences between online course-takers and non-users. We performed each of these sets of analyses—exploring predictors and typologies of use and estimating short-term and intermediate educational outcomes—for each school year (2013-14, 2014-15, and 2015-16) to assess the consistency and dynamics of these relationships over time.

Qualitative and mixed methods analysis. In qualitative analyses, we employed a constant comparative method to explore and explain malleable factors in the implementation of online instruction. We developed analytic codes to apply to interview and observation data to establish initial findings, and coding trees and data were then input into NVivo, a qualitative coding software. Three qualitative team members manually coded all narrative vignettes, comments, and notes from observations in NVivo, and then we cross-coded excerpts to establish reliability and examine any discrepancies. Manual coding was layered over auto-coding, where sections of the observation data were placed into codes via the auto-code function based on relevant constructs, and the team reviewed the auto-coding process for accuracy and alignment to the code tree. Following manual coding of these data, analytic memos were developed using an iterative, deductive process to identify and analyze emergent themes within key analytic codes.

We employed a tightly integrated, mixed methods approach (Burch & Heinrich, 2015), in which emerging findings from the qualitative and quantitative analyses were regularly shared both within the research team and with our district partner and combined throughout the research process. This has aided in optimizing sampling strategies for observations, improving the sensitivity and validity of our measures, refining our conceptual and empirical models, and deepening our understanding of the relationships of online course-taking to student learning and outcomes. Accordingly, we integrate the discussion of qualitative and quantitative results below, reflecting how these analyses have proceeded jointly and enriched our interpretation of the data.

Results

Who Takes Online Courses, and What are "Typical" Student User Behaviors?

Table 2 shows that the proportion of high school students in the district taking online courses in any given high school ranged considerably by high school, from a low of less than one percent to a high of over 93 percent, as well as within high schools over time. These differences reflect numerous factors, including the types of school programs offered, the student bodies served, policy changes in the district over these years that influenced who was directed to take courses online, and administrative decisions at the school level about staffing and management of online instruction. For example, several of the high schools with the highest rates of online course-taking serve particular student populations, such as pregnant and parenting students and those returning to the classroom from incarceration or expulsion. In addition, logistic regressions estimated to predict any online course-taking by high school students (available on request from the authors) showed that the rate of student absences from school was one of the strongest, statistically significant and consistent predictors of online course-taking and that the likelihood of online course-taking (presumably to recover credits) increased significantly by grade level. Across the three school years studied, African-American students were significantly more likely to take courses online, but the likelihood of use varied from year to year by other student characteristics such as gender, economic disadvantage (operationalized as free lunch eligibility), English language learners and students with special needs or disabilities.

As noted earlier, we focus our analysis of online course-taking primarily on student user behaviors, with the aim to understand relationships in the implementation of online course-taking and inform policies and strategies at district, school or classroom levels for improving student use and educational outcomes. This approach also recognizes that estimating average effects across diverse types of student users could mask important variation in the association between online course-taking and student outcomes. The student typologies analysis (using k-means cluster and discriminant function analysis) identified four student user groups across the three school years, which we have labeled: *Engaged Users, Moonlighters, Nominal Exerters* and *Incompatible Strugglers*. Below, we describe these four groups of student users in terms of their course-taking behaviors, and Tables 3-5 present descriptive statistics on student-level user behaviors (at the session level) and demographic characteristics by user types and school year.

Beginning with school year 2013-14, in which all four types of users were identified (see Table 3), it is apparent that the *Incompatible Strugglers* and *Nominal Exerters* accomplished less in their online courses than the other two student user groups. Students in these two user groups completed fewer activities per day, had more idle time in the system, and took fewer courses, while at the same time logging more sessions per course. The following excerpt from a classroom observation describes a typical online course-taking session with a student showing little engagement and making minimal progress:

> *The student entered a direct instruction lesson on scenes in Romeo and Juliet, but his cell phone was also in his hand, and he was texting. Some announcements were coming in loudly over the PA system and students were walking around. The student toggled between his phone and the lesson on the screen, texting while the lecture played and talking to a student nearby. He was playing a game on his phone and attending less and less to the lecture. The instructor came by and told him to take notes, but he did not follow through.*

The student in the observation had full access to instructional environment. There were no technical difficulties, and there was an instructor encouraging the student to work effectively. However, the content of the video lecture did not engage the student, who demonstrated a preference for peer socialization and the content available through his cell phone. Instructors frequently cited difficulty in minimizing student distractions, particularly cell phone related ones. District policy did not allow teachers to take away phones, but in the 2014-15 school year, some schools started using cell phone pouches that allowed teachers to lock phones inside, so students could hold onto but not access their phones. Teachers reported initial increases in course progress that filtered off as students learned how to open the pouches on their own.

The *Incompatible Strugglers* appear distinct from the *Nominal Exerters* in that they were more likely to be in an earlier high school grade (9th or 10th grade) in 2013-14, and they were also slightly more likely to be English language learners and to qualify as economically disadvantaged. Additional analysis also showed that they were more likely to be taking a math course. In interviews, instructors in classrooms where students accessed their courses online described why this group of users was less compatible with the online course-taking system:

> *Some of the underclassmen are in here all day and it is not working very well; underclassmen do not appreciate the opportunity of making up classes, they do not work... They are not at the reading level of the program. I would love to screen the kids to make sure they are at the 7th grade reading level, but I don't have that ability.*
>
> *Many 9th graders had IEPs; but if there is no one there to help them, they shouldn't be in the [online] classroom.*
>
> *The [online instructional] program… started with 9th grade repeaters, but juniors and seniors progress better because they are more motivated to get out.*

Recognizing that the underclassmen were often unprepared academically and likely less motivated to make progress in their online courses, the school district began discouraging its use by 9th and 10th graders. By the 2015-16 school year (see Table 5), *Incompatible Strugglers* were no longer identified in the analysis as a distinct user group.

Engaged Users, alternatively, were idle in the online course-taking system least often, completed more activities per day with less session time, and accordingly, completed their courses in fewer sessions. Even so, they do not appear to be a more advantaged group in terms of student characteristics; they were most frequently absent among the four groups, more likely to be African-American, and in 2014-15 and 2015-16, they were more likely to be economically disadvantaged as well. The *Moonlighters*, who were also relatively more productive users of the online course-taking system, are distinguished primarily by their high rate of online instruction taking place outside of the regular school day (more than 80 percent of online sessions). In contrast to the *Engaged Users*, the *Moonlighters* were less likely to be students with special needs or to be economically disadvantaged, and they were more likely to be in 12th grade. Their prior year academic performance (as measured by standardized test scores) was also stronger than students in the other user groups.

Associations Between Student Online Course-taking Behaviors and Course Performance

The descriptive analyses of student course-taking behaviors suggest that, in general, they were using the online system more efficiently over time, with the ratio of idle to active minutes per session steadily declining among all user types (and reduced by about 40 percent for the *Engaged Users*). Table 6 summarizes the results of OLS regressions showing how the course-taking behaviors relate to students' online course performance—course pass rates, on-time completion of courses, course grades and the rate at which courses were disabled by instructors—controlling for student demographic characteristics, their prior test score performance, course subjects, grade level and school attended. The results show that a higher proportion of idle time per session is a strong, statistically significant predictor of lower course passing rates, on-time completion rates and course grades. For example, *for each additional percentage point of time idle*, on average, course pass rates and on-time rates fell by about one half to two-thirds of a percent; this is relative to average course passing rates of about 36 percent in 2013-14, 43 percent in 2014-15 and 45 percent in 2015-16. Course grades (on a scale of 0 to 100) were about .13 to .30 points lower. Alternatively, students who were spending more time in a given online session and completing more activities per day performed better on all four measures of online course performance. Although we don't report the relationship between student characteristics and course performance in Table 6, we found consistent (negative) associations between student absences and all measures of course performance, and positive associations between use by students in 11th or 12th grade and course performance.

Online Credit-Recovery Policies Enacted by the School District

Through classroom observations, interviews and research briefings with district staff, we identified specific strategies that the district has developed and implemented to address some of the challenges and concerns highlighted above and to improve online course-taking and student outcomes. These include specific guidance and directives for implementing "best practices" on the part of both students and instructors, beginning in the 2015-16 school year:

- Student note-taking during online instructional videos and note-checking by instructors before allowing a student to start a course quiz or test;
- Expectations for instructors to do weekly check-ins of student progress and complete progress report forms;
- Regular monitoring of student online course-taking during class periods, such as through a local area network (LAN) system;
- Disabling of courses when students consistently fail to meet progress goals, and requiring them to engage with an instructor to get restarted in the system, and
- Limiting students to taking only two online courses simultaneously.

The following excerpts from observations of online course-taking in classrooms illustrate some of these practices:

> *The teacher was emphasizing to the students that they needed to strive for the goal of completing three percent of their coursework per week. He told them to focus more and to take advantage of the resources they have both during and after the school day to work in [the online instructional system]. He asked to see their notes when they requested access to an assessment (quiz).*

By setting weekly progress goals in conjunction with weekly one-on-one student-teacher check-ins, teachers provided students regular feedback and directed them toward more manageable goals. The process of taking notes can help students in learning content and provide focus for future studying, as well as support their successful completion of online course assessments. The practice of asking students to show notes before allowing access to an online assessment also increases the likelihood that students view and interact with the instructional content and resources available online and may also discourage behaviors such as guessing answers or otherwise attempting to complete the quiz without learning the content.

Students who did not meet goals established by teachers and the district to incentivize adequate course progress often had their online courses disabled, and some were reassigned to an alternative class setting where they could receive more in-person and one-on-one assistance from an instructor. The policy intent was to prevent students from spending extensive time in online courses without making progress toward course completion.

> *During the session, the instructor told students that if they save a quiz, the answers are locked in and cannot be changed later. He offered to check their answers before they save. He stated: "Everyone is behind, and no one seems to have a sense of urgency." Another teacher entered the room to make an announcement. He said that students who don't get to 12 percent by next Thursday will have their accounts suspended. He tells the students that he is available every day from 4-6 pm (Mon.-Thurs.) and that [the online instructional system] is available 24/7.*

Above, the instructor also offered to check student answers before they submitted an assessment. This practice, encouraged by the district, made instructors aware of the questions students did not answer correctly. On occasion, this led to re-teaching and targeted, blended instruction, where the instructor helped students to better understand the content underlying the questions they had answered incorrectly. More often, however, instructors told students which questions they had answered incorrectly, in which case some students went back to review their notes, but more commonly, students used a process of elimination to determine the answers (for the questions then known to be wrong).

Limited resources sometimes constrained the implementation of these “best practices” and other instructional supports (e.g., live teacher interactions) for online course-taking. One teacher explained that she was supposed to have 20 students in the classroom, but that on any given day, she might have as many as 45 students; she reported having 65 students in her classroom the previous year. Another teacher explained how a high student-teacher ratio limited his interactions with students:

> *We need smaller class sizes than we have; I think I could do it well with 35. One class we saw was 74 students; ideally, we would have 25-30 students. We need more time for one-on-one interactions with the students.*

Our descriptive (ANOVA) analysis of classroom observation data aligned with the above teacher's observation, revealing a negative association between observed student-teacher ratios student digital citizenship (i.e., appropriate use of technology), p=0.047. And in cases where substitute teachers were present but lacking experience with or ability to log into the online course-taking system, instructional supports might be completely absent, as seen in the following classroom observation:

> *The first thing the sub said as students were coming in was, "I can't check your work today. I can't help you." The sub had no way to interact with the resources, and therefore, had no real interaction with the students.*

In addition, a few instructors described problems with using the LAN, explaining that it has not consistently worked with some of the operating systems in use (e.g., Chrome).

At the same time, we saw many examples of creative and concerted efforts by teachers to follow the district's guidance and improve online course-taking supports, including teachers who tracked and encouraged student progress toward goals using charts and incentives (e.g., certificates, rewards) and those who developed their own instructional materials to aid student interactions with the system. For example, in the effort to provide students with more structure for note-taking, one teacher watched the online courses himself and created "guided notes" in order to help students identify the material in the online instructional videos that would be important to know for the end-of-course assessments.

Associations Between Online Course-taking and Intermediate Academic Outcomes

As discussed above, in accord with how we measured treatment (online course-taking) in this study, we estimated fixed effects (and IPWRA) models to examine associations between any online course-taking and types of use with intermediate academic outcomes, limiting the analysis to students enrolled in high schools where online courses were made available and adjusting for stable school and grade-level factors, student characteristics, pre-treatment measures of the outcomes, and the percentage of online course-takers in each school (see again Appendix C for further details). Table 7 presents fixed effects estimates of the average effects (associations) of any online course-taking to standardized test scores, GPA and credits earned at the end of the school year, along with standard errors (statistically significant coefficients in bold). As seen in Table 7 (and Appendix C), all of the average associations between online course-taking and intermediate outcomes are negative, although most are statistically insignificant. In 2013-14 and 2014-15, online course-takers performed (statistically) significantly worse on standardized tests in math and reading, and in 2015-16, GPAs were significantly lower among online course-takers. Examining associations by type of student user (see Table 8 and Appendix C) reveals similar (mostly negative) associations, although it is clear that the *Incompatible Strugglers* gained the least and were possibly set back by online course-taking. The IPWRA estimates in Appendix C likewise show no positive, statistically significant associations between intermediate outcomes and online course-taking and some negative, statistically significant associations across the four student user groups. In separate (session-level) analyses comparing online course-taking only among the different student user types (available upon request from the authors), the *Engaged Users* and *Moonlighters* earned significantly more credits and had higher end-of-year GPAs than the other two user groups (who exhibited poorer course-taking behaviors). Overall, however, in comparison to students taking all courses in traditional classroom settings in a given school year, we find no statistically significant, positive associations between online course-taking and intermediate educational outcomes.

Insights from Qualitative Analysis on Lack of Student Academic Gains

The classroom observations and interviews with teachers, as well as discussions of the findings with district staff, suggested possible reasons for the lack of positive associations between online course-taking and student achievement. One consistent concern reported in teacher interviews was the low reading levels among students directed into online course-taking. One teacher indicated that many students enrolled in the course were at 3rd-5th grade reading levels and that the mismatch between their reading levels and the level of reading required in the online courses was a "big de-motivator." In addition, for students for whom English is a second language, teachers found that the language accommodations in the online course-taking system were not adequate. A teacher pointed out that the translation function in the system occurs in text (not voice) format, so students have to be able to read the text while the online instructor is talking in English. However, it is more often the case that students understand the spoken language but do not know or learn the written (native) language.

Another recurrent challenge was the apparent lack of accommodations in the online course-taking system for students with special educational needs. Teachers indicated that they typically did not have access to information about student IEPs or extra resources to support their needs; as one teacher explained:

> *I have someone with an IEP in my second hour... nothing in [the online course-taking system] really accommodates them. They expect the teachers to accommodate them.*

Some instructors made efforts to meet these students' needs, particularly if they had experience or training in special education. For example, one teacher printed the transcripts of online videos and had the student highlight them, while another found practice tests and worked with students outside the online system on content support. Several teachers also mentioned a resource room where special education students could work on online courses with their IEP teacher, although this depended on whether the IEP teacher possessed technical knowledge required to support use of the online course-taking system:

> *I think that many of the special ed kids are frustrated. I have a very good relationship with my special ed teacher, so a lot of the kids that have me for class go to the resource room to work on this. She is also trained [in the system] and has her own account, which makes a difference.*

We also saw many student behaviors that suggested a lack of engagement in the learning process, such as the following examples from classroom observations:

> *The student did not interact much at all with the software (i.e., didn't progress through the screen). The aide checked in with her at the beginning of class and told her to get going, that "she is smart and can do it." There was no direct interaction with a teacher after that point. The student just talked to another student next to her. The student would click on a screen when the teacher walked by, otherwise she would just stare at the screen and talk with her friend.*

> *The student spent some of the class period with videos running and answering problems, but she was easily distracted. She talked with classmates, used her phone, and did not have headphones in to hear the audio. She made minimal progress in the videos. After filling in answers to the assessment (mostly incorrect), she went up to the teacher's desk multiple times for a list of questions that were wrong before changing them (randomly?) and going back to check again.*

The frequent observation of disengaged students was consistent with the substantial proportion of students identified each year in our analysis as Incompatible Strugglers or Nominal Exerters.

Other students appeared to be somewhat engaged in getting through their online courses, but not necessarily in learning. We observed distinct differences between active and passive engagement among students, where in the latter case, they moved through the program, sometimes taking notes, but not necessarily engaging with the content, as shown below:

> *The student was working on a lesson on the Mongol Empire when the observation began, reading a source document and taking notes. He entered an assessment mode (about halfway through the observation) and went to Google to search for answers to the questions. In some cases, the student copied and pasted the exact assessment question into Google to find the answers.*

> *The student works quietly in the corner of the room away from other students. She progresses through the assessment, using the Internet to find answers. She copies and pastes some content from Wikipedia. At about the 20-minute mark, the student asks the teacher to check her work, which she does. The teacher tells her to change the answers to two questions. The student goes back to the internet to find the answers.*

Observations such as these raise the question of whether the goal of online credit-recovery is to simply provide students an opportunity to earn credits needed to graduate, or whether an important aim is to provide an alternative instructional environment and flexibility for students who may not have been successful in a traditional classroom setting to master content needed for life after graduation. These findings also raise concerns about whether students taking courses online are learning at the same level as those in traditional classrooms as they earn course credit.

One of the barriers to students mastering content in the online setting may relate to the fact that some classroom instructors struggled to provide assistance to students when they were challenged in their online courses, particularly in subjects outside their content expertise. In an interview, one teacher explained her difficulty with providing math support:

> *As a non-math person, I find it difficult. I can do it if I watch the whole video, but I don't have the time to watch the entire video to answer the questions with a student.*

We observed a lack of math content expertise limiting the efficacy of instructor assistance more often than in other subjects. This lack of content knowledge may contribute to why students enrolled in math courses were more likely to be identified as *Incompatible Strugglers* than students enrolled in other courses. In response to this concern, some schools have placed content teachers in lab settings where online courses are accessed, and one school grouped course subjects by period so all students were working on math modules that session, allowing content teachers to come in and provide extra instructional help to more students. To date, the efficacy of this strategy has been mixed. For example, in one observation the content teacher was reported to be effectual and engaged, while another sat in a corner working on his/her own stuff, and a third just gave the students the answers.

Finally, for some of the students, academic progression may be a secondary aim to the implicit goal of the online instructional program in providing a "safe space" for students who might otherwise not be in school. This theme came out in observations and interviews, particularly in contexts where lab instructors were managing the intersection of the classroom with students' complicated lives. For example, one teacher was describing how "these kids have so much baggage and drama in their lives" when a pregnant and parenting youth coordinator came into the room to speak with two of the students. One of the students had only one class to finish but was not progressing well. The teacher pointed to another student who she said had emotional problems and had made very little progress. The student came into the classroom, put her head down and just slept throughout the period without logging onto a computer. The instructor indicated that she was 19 already but at the 11th grade level in terms of her credits, and that she would probably "just sit here until she is 21 and will call it a day." Another teacher explained during an observation that if a student is making progress, she does not harass them. "This lab becomes a place for EBD (emotionally, behaviorally, disabled) students to decompress for a period so they are better able to deal with their other classes." In fact, some teachers went out of their way to extend support to students outside the regular school day:

> *The teacher will take emails from kids until 9:00pm at night (and often much later) to unlock or help them progress through a course. He showed me an email from 12:30 am the previous night and said, "If kids are motivated enough to work at home, the least I can do is respond."*

In interviews and research briefings, teachers and other staff suggested that if it were not for the online course-taking option, some of these students would not be in school at all or would be disruptive in the regular classroom. Analyses in progress of students' longer-term outcomes, including high school completion and post-high school plans and activities, may shed further light on whether these students ultimately benefit from online course-taking and efforts the district is making to improve its implementation.

Discussion and Conclusions

As online credit recovery programs continue to expand, concerns are growing that a corresponding rise in high school graduation rates may not reflect student learning. For example, a Fordham Institute report pointed out that in the same year that national high school graduation rates reached new heights in 2015, data from the National Assessment of Educational Progress showed that the percent of 12th graders ready for college-level reading and math declined by two percentage points in math and one percentage point in reading (Noonan, 2016). Some school districts, such as Los Angeles Unified School District, have explicitly linked their highest graduation rate success to the use of online course-taking. In the large, urban school district where we studied online instruction, the proportion of high school students taking online courses ranged widely across schools, from a low of less than one percent to a high of over 93 percent. In addition, our analysis of *who* is taking courses online identified distinct user groups with very different course-taking behaviors and online course performance. Some of the students facing the most severe barriers to completing high school—i.e., pregnant and parenting students, those returning to the classroom from incarceration or expulsion and those with high absence rates and low reading levels—were among those most likely to be taking their courses online.

Our analysis of high school student course-taking behaviors and performance suggested that some high school students may be less likely to gain (or may even be set back) when assigned to take courses online. In particular, students in their first years of high school, not meeting minimum reading-level guidelines, and who were more likely to be repeating a math course—an economically disadvantaged group that we labeled the *Incompatible Strugglers*—performed most poorly in online instruction, with the highest rates of idle time and lowest session durations and number of activities completed per day. These findings are consistent with the experimental results of Heppen et al.'s (2017) study of online credit recovery in Chicago Public Schools, which found that students who failed algebra in their first year of high school and were assigned to retake the course online attained significantly lower end-of-course post-test scores and lower credit recovery rates compared to those in face-to-face courses. In fact, the district we studied came to recognize that these underclassmen tended to be less motivated and unprepared academically for online course-taking and subsequently discouraged use of the online instructional system among this group.

Alternatively, our analysis also identified two groups of more engaged online course-takers, distinguished by their completion of more activities per day with less session time and more courses in fewer instructional sessions. Among these two groups, we found differential access to evening course-taking by family socioeconomic status, with greater evening use by the *Moonlighters* who were less likely to be economically and academically disadvantaged. One of the potential strengths of online learning is the opportunity for students to access and learn content outside the traditional school day (Enyedy, 2014), thus, these findings raise concerns about disparate access to devices, Internet, and instructional assistance in out-of-school settings that could support students in progressing toward high school graduation outside of school hours. This flexibility could be particularly important for the many online course-takers in our sample who had substantial family and work obligations and often split the traditional school hours (e.g., morning and afternoon) between education and work.

Over the three years that we observed the implementation of online instruction, we saw few instances where the use of online instructional programming appeared to support student access to personalized, high-quality instruction. There were minimal opportunities to adjust to or supplement core curriculum and instructional delivery in the online course-taking system, with a lack of accommodations for all students and particularly those with special educational needs. Many instructors also struggled to respond to student requests for content assistance in their online courses, a finding that is consistent with that of Stevens et al. (2016) but also refutes a core argument in support of the use of online technology, i.e., that it affords opportunities for increased customization of content and individualization of instruction (i.e., Archambault et al., 2010). Not surprisingly, given these findings, we saw many student behaviors that suggested a lack of engagement in the learning process, such as texting on cell phones, searching other websites, and distracting fellow students. We also observed passive engagement, where students continued to progress through the online program but without engaging with the content, e.g., disconnecting from the instructional video audio and then guessing at quiz or test answers. In general, we found little in the way of tailored instruction, curricular relevance or other types of individualization that prior research suggests may enhance student engagement (Cavanaugh et al., 2007; Darling-Hammond & Bransford, 2007).

Our analysis of average associations between online course-taking and student intermediate outcomes—comparing online course-takers with students taking all courses in traditional classroom settings and adjusting for selection into online instruction using fixed effects and IPWRA methods—found no positive relationships and some statistically significant, negative associations between online course-taking and math and reading scores, credits earned and grade point averages. Examining these associations by the student user types we identified, we found a larger number (and magnitude) of negative associations for the student user group with the most ineffectual course-taking behaviors (*Incompatible Strugglers*). However, in the absence of random assignment to use of this online instructional tool, and in light of our analysis showing selection into use based on distinct characteristics—including school absences, special educational needs, limited English proficiency and poorer academic progress (in terms of test scores and credit accumulation)—we do not interpret these associations as effects of online course-taking and acknowledge limitations to validity of inferences in this analysis.

In the effort to address the challenges to equipping instructors and students with the capabilities and supports necessary to use online instructional tools effectively, the district we studied has been working to identify best practices and implement policy changes with the goal of improving student course-taking behaviors and outcomes. Examples of these policies include (1) requiring students to take notes during online instruction and show their notes to instructors before being allowed to re-take a course assessment; (2) providing instructor access to LAN systems to better monitor student progress in the classroom; (3) asking instructors to meet weekly with students to discuss their progress in the program; (4) disabling use of the online instructional system for students not making progress and redirecting them to instructors for additional assistance, and (5) limiting students to taking only two online courses simultaneously to support progression and completion. Our longitudinal analysis that is in progress and our ongoing observations and analysis of data from the online instructional program should allow us to examine associations between these policies and student outcomes over a longer time period.

At the same time, our findings showing that limited resources have sometimes constrained the implementation of best practices and other instructional supports, such as live teacher interactions, for online course-taking suggests that more fundamental changes may be needed to see positive effects on student learning and educational outcomes. Some research indicates these students may be better served by a blended learning model that incorporates more access to live, personalized instruction to supplement online content (Picciano & Seaman, 2009; Osguthorpe & Graham, 2003). In addition, the integration of complementary (rather than duplicated) live and digital instruction could enhance students' educational experiences in this and comparable school settings (Means et al., 2010). However, the concerns raised in our research about who is targeted for use of online course instruction at the secondary level—i.e., many students who face substantial barriers to learning, such as lower reading levels, special educational needs, and personal/family challenges—suggests that a mismatch between student capabilities for engaging with and progressing in these systems may not be readily overcome without more substantial investments in instructional supports. These could minimally include greater involvement of special education teachers, considerably lower student-teacher ratios, and ready access to course content assistance outside of the instructional system to support learning that the typical lab-style environments for online course-taking do not easily facilitate with students working on a wide range of course subjects/topics. Ultimately, in the absence of substantial investments in blending learning and other instructional and environmental supports, districts may have to re-evaluate strategies that target academically disadvantaged students and instead prioritize students with a stronger track record of prior academic success for credit recovery to avoid exacerbating educational inequalities and negatively affecting student educational outcomes through the use of online instruction.

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Figure 1: Theory of Action for How Online Course-taking Behaviors Mediate Student Outcomes

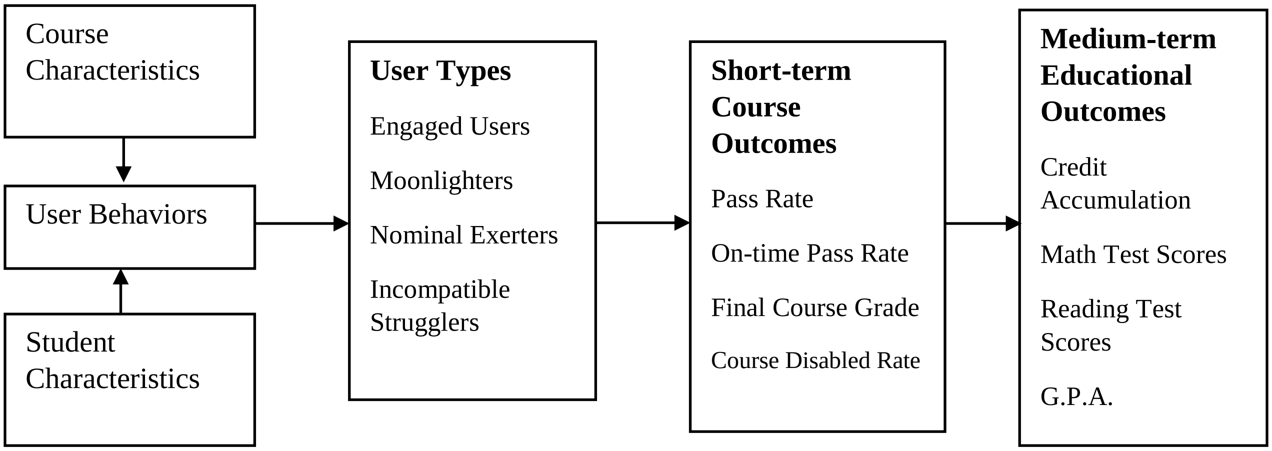

Table 1: Student Characteristics	**2013-14** All High School Students	District-Online User Records	**2014-15** All High School Students	District-Online User Records	**2015-16** All High School Students	District-Online User Records
Total number of students	20,984	4,676	20,581	5,175	21,922	4,976
Asian	0.06	0.02	0.06	0.02	0.06	0.02
Black	0.62	0.68	0.62	0.66	0.60	0.68
Hispanic	0.20	0.20	0.20	0.22	0.22	0.20
White	0.10	0.10	0.12	0.08	0.10	0.08
Female	0.48	0.46	0.48	0.46	0.48	0.46
English language learner	0.08	0.06	0.08	0.06	0.08	0.04
Free lunch-eligible	0.78	0.82	0.82	0.86	0.73	0.75
Student with special needs	0.22	0.22	0.22	0.22	0.22	0.24
Percent of days absent	0.18	0.22	0.17	0.20	0.20	0.26
Average Test Score-Fall Math	222.13	218.95	216.72	216.30	727.58	714.81
Average Test Score-Fall Reading	214.99	213.04	209.90	209.49	677.78	656.32

Table notes: Our analysis comparing behaviors of online course-takers with linked district records to those for whom we could not link their district records showed a consistent difference over time: those without linked records had shorter course durations. However, they also had lower on-time course passing rates, suggesting that the shorter course durations might not have implied successful completions (in a shorter time period). In the absence of links to district records for the latter group, we are not able to compare their demographic characteristics. A table with the details of this comparison is available from the authors upon request.

Table 2: Percentage of Students Taking Courses Online by High School and School Year

	2013-14		2014-15		2015-16	
High Schools Offering Online Courses All School Years, 2013-14 to 2015-16	Total # of students	% Taking courses online	Total # of students	% Taking courses online	Total # of students	% Taking courses online
H.S. A	242	42.56	245	68.16	257	36.19
H.S. B	1227	30.40	1267	32.28	1329	31.30
H.S. C	727	26.27	822	19.95	962	14.97
H.S. D	1041	27.47	889	39.37	918	25.82
H.S. E	1690	26.75	1688	28.73	1822	22.89
H.S. F	248	52.42	245	64.90	247	62.75
H.S. G	1482	0.34	1477	7.58	1467	16.84
H.S. H	507	29.78	518	14.48	562	13.35
H.S. I	1345	37.62	1147	31.91	1094	29.98
H.S. J	167	67.66	159	69.18	194	38.66
H.S. K	1593	17.70	1592	34.74	1562	34.06
H.S. L	1191	12.51	1323	26.46	1524	20.21
H.S. M	1314	16.13	1393	18.09	1350	30.96
H.S. N	947	4.86	934	5.03	940	0.64
H.S. O	797	45.42	711	39.52	696	19.83
H.S. P	159	86.16	177	41.81	199	4.02
H.S. Q	786	10.81	810	35.06	864	30.09
H.S. R	998	12.83	870	10.00	860	23.14
H.S. S	561	0.18	569	0.18	592	0.51
H.S. T	122	93.44	161	87.58	209	86.60
H.S. U	337	38.58	353	51.56	368	49.46
H.S. V	163	1.84	160	0.63	199	13.07
H.S. W	246	53.66	253	46.64	230	19.13
H.S. X	56	1.79	22	4.55	47	6.38
H.S. Y	31	22.58	41	58.54	68	8.82
H.S. Z	128	11.72	119	1.68	138	5.80
H.S. AA	29	3.45	62	4.84	79	6.33
H.S. BB	271	35.42	200	64.00	238	51.26

Table 3: Course-Taking Behaviors and Student Demographics by User Type (2013-14)*

	Incompatible Strugglers (N=512)		Nominal Exerters (N=1,653)		Moonlighters (N=701)		Engaged Learners (N=2,523)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Course Duration (Minutes)	4,182.47	3,148.07	7,813.18	5,710.25	8,306.99	5,919.75	8,312.36	7,258.04
Completed Activities (Per Day)	2.63	4.43	4.28	6.74	6.52	10.86	6.55	11.62
Session Time (Minutes)	89.29	56.98	107.64	59.85	144.27	75.08	138.78	74.96
Idle/Session Time Ratio	0.26	0.25	0.22	0.21	0.24	0.23	0.25	0.23
Number of Sessions (Per Course)	76.18	60.16	76.34	51.87	63.31	52.33	37.66	29.36
Number of Courses	1.70	1.09	2.81	2.14	3.60	2.75	4.93	4.40
Percentage Night School	11.37	31.75	3.46	18.27	84.83	35.88	2.74	16.32
Percentage Absent	15.26	15.68	19.99	17.51	18.48	17.93	25.22	21.85
Percentage Special Education	23.64	42.53	22.14	41.53	15.94	36.65	22.22	41.58
Percentage English Language Learner	6.36	24.44	4.97	21.74	6.10	23.96	4.94	21.67
Percentage Free/reduced lunch	83.64	37.04	81.55	38.80	75.79	42.88	82.83	37.73
Percentage Female	45.68	49.87	47.36	49.95	49.41	50.05	45.27	49.79
Percentage Black	64.09	48.03	64.98	47.72	65.35	47.63	72.06	44.88
Percentage Hispanic	23.86	42.67	21.91	41.38	20.87	40.68	17.75	38.22
Percentage White	8.86	28.45	9.26	29.00	10.04	30.08	8.14	27.35
Percentage 9th Grade	42.27	49.46	20.63	40.48	16.34	37.01	24.42	42.97
Percentage 10th Grade	30.00	45.88	23.34	42.32	20.28	40.24	22.74	41.93
Percentage 11th Grade	25.23	43.48	35.92	47.99	38.39	48.68	33.77	47.31
Percentage 12th Grade	2.50	15.63	20.11	40.09	25.00	43.34	19.07	39.29
Standardized Fall MAP Reading SS	0.02	0.83	-0.16	0.87	-0.02	0.89	-0.26	0.94
Standardized Fall MAP Math SS	-0.03	0.85	-0.22	0.81	-0.11	0.89	-0.32	0.86

* Course-taking behaviors were calculated at the session versus student level.

Table 4: Course-Taking Behaviors and Student Demographics by User Type (2014-15)*

	Incompatible Strugglers (N=1,146)		Moonlighters (N=896)		Engaged Learners (N=3,572)	
	Mean	SD	Mean	SD	Mean	SD
Course Duration (Minutes)	5,897.95	4,094.71	7,703.49	5,251.31	7,019.93	5,682.68
Completed Activities (Per Day)	3.25	4.89	5.42	9.02	5.13	8.56
Session Time (Minutes)	108.94	112.57	174.17	157.46	145.41	124.59
Idle/Session Time Ratio	0.19	0.20	0.20	0.21	0.18	0.19
Number of Sessions (Per Course)	105.22	66.14	71.33	63.33	45.11	30.89
Number of Courses	1.83	1.22	3.24	2.38	3.96	3.38
Percentage Night School	4.05	19.71	81.28	39.01	2.96	16.95
Percentage Absent	18.37	17.03	16.31	16.74	22.00	20.02
Percentage Special Education	24.14	42.82	15.87	36.56	20.76	40.57
Percentage English Language Learner	6.97	25.48	5.61	23.02	6.37	24.43
Percentage Free/reduced lunch	85.96	34.76	83.45	37.19	87.37	33.23
Percentage Female	47.11	49.94	50.27	50.03	45.30	49.79
Percentage Black	60.76	48.85	61.16	48.77	70.42	45.65
Percentage Hispanic	26.69	44.26	23.66	42.53	19.03	39.26
Percentage White	8.57	28.00	11.02	31.34	7.41	26.20
Percentage 9th Grade	28.48	45.16	18.60	38.94	22.30	41.63
Percentage 10th Grade	29.90	45.80	22.98	42.10	23.62	42.48
Percentage 11th Grade	30.20	45.94	31.33	46.41	32.00	46.65
Percentage 12th Grade	11.41	31.81	27.09	44.47	22.08	41.49
Standardized Fall MAP Reading SS	-0.06	0.93	0.00	0.95	-0.10	0.96
Standardized Fall MAP Math SS	-0.13	0.88	-0.04	0.95	-0.10	0.90

* Course-taking behaviors were calculated at the session versus student level.

Table 5: Course-Taking Behaviors and Student Demographics by User Type (2015-16)*

	Nominal Exerters (N=1,631)		Moonlighters (N=617)		Engaged Learners (N=2,293)	
	Mean	SD	Mean	Mean	SD	Mean
Course Duration (Minutes)	5,778.86	3,514.69	7,378.86	4,679.10	7,957.66	5,724.93
Completed Activities (Per Day)	3.85	4.73	5.84	7.89	6.66	8.92
Session Time (Minutes)	70.37	63.47	102.76	92.6	114.68	84.96
Idle/Session Time Ratio	0.16	0.21	0.17	0.22	0.15	0.19
Number of Sessions (Per Course)	74.25	43.85	58.18	43.18	36.70	22.28
Number of Courses	2.09	1.18	3.37	2.35	4.65	3.62
Percentage Night School	3.85	19.24	82.53	37.97	2.92	16.85
Percentage Absent	22.57	19.76	26.73	22.44	31.27	23.50
Percentage Special Education	24.86	43.24	17.19	37.76	26.69	44.25
Percentage English Language Learner	4.85	21.49	3.43	18.21	4.42	20.57
Percentage Free/reduced lunch	77.16	41.99	70.36	45.71	78.00	41.44
Percentage Female	43.78	49.63	52.15	50.00	43.21	49.55
Percentage Black	66.92	47.07	64.26	47.97	71.36	45.22
Percentage Hispanic	19.89	39.93	24.02	42.76	19.22	39.41
Percentage White	8.63	28.09	9.18	28.90	6.71	25.03
Percentage 9th Grade	21.27	40.94	17.19	37.76	25.45	43.57
Percentage 10th Grade	25.28	43.47	21.88	41.38	21.39	41.01
Percentage 11th Grade	31.01	46.27	34.18	47.48	33.35	47.16
Percentage 12th Grade	22.44	41.74	26.76	44.31	19.82	39.87
Standardized Fall MAP Reading SS	-0.13	0.94	0.01	0.91	-0.15	0.90
Standardized Fall MAP Math SS	-0.22	0.97	0.00	0.83	-0.23	1.00

* Course-taking behaviors were calculated at the session versus student level.

Table 6: Relationship of Student Online Course-Taking Behaviors to Course Performance

Outcome:	*2013-14*		*2014-15*		*2015-16*	
Course disabled rate	(n=133,340)		(n=83,753)		(n=61,107)	
Predictors:	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Class duration	-0.002	0.005	0.015	0.010	**0.041**	0.016
Completed activities/day	**-0.218**	0.026	**-0.265**	0.040	**-0.785**	0.085
Mean % idle time	**0.233**	0.064	0.166	0.100	**0.671**	0.090
Mean session duration	**-0.201**	0.029	**-0.138**	0.049	**-0.225**	0.059
Number sessions/course	**-0.147**	0.018	**-0.106**	0.028	**-0.433**	0.040
Night school use	-1.514	1.263	-1.888	1.902	-1.066	2.693
Day & night use	-0.656	1.654	-3.231	2.363	0.692	2.980
Course pass rate						
Predictors:	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Class duration	0.001	0.006	**-0.051**	0.011	**-0.077**	0.015
Completed activities/day	**0.585**	0.039	**0.519**	0.069	**0.796**	0.085
Mean % idle time	**-0.527**	0.136	**-0.679**	0.137	**-0.710**	0.087
Mean session duration	**0.365**	0.043	**0.423**	0.059	**0.238**	0.060
Number sessions/course	**0.241**	0.022	**0.220**	0.033	**0.505**	0.041
Night school use	0.894	1.677	**4.535**	2.176	0.571	2.694
Day & night use	1.819	2.097	**7.600**	2.961	-1.900	2.946
On-time completion rate						
Predictors:	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Class duration	**-0.013**	0.005	**-0.059**	0.011	**-0.134**	0.015
Completed activities/day	**0.270**	0.031	**0.385**	0.059	**0.580**	0.083
Mean % idle time	**-0.217**	0.079	**-0.561**	0.120	**-0.637**	0.081
Mean session duration	**0.194**	0.036	0.114	0.061	-0.024	0.050
Number sessions/course	**0.122**	0.020	**0.100**	0.033	**0.266**	0.043
Night school use	1.525	1.621	0.750	2.253	-0.261	2.532
Day & night use	-3.053	1.915	4.859	3.182	-0.689	3.002
Course grade						
Predictors:	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Class duration	**0.008**	0.001	**0.006**	0.003	**0.016**	0.004
Completed activities/day	**0.135**	0.013	**0.101**	0.016	**0.173**	0.024
Mean % idle time	**-0.129**	0.036	**-0.212**	0.051	**-0.303**	0.035
Mean session duration	**0.067**	0.011	**0.087**	0.014	**0.055**	0.015
Number sessions/course	**0.014**	0.004	-0.003	0.006	**0.048**	0.009
Night school use	0.035	0.352	0.890	0.458	-0.257	0.579
Day & night use	0.354	0.495	-0.685	0.563	-0.092	0.720

Note: Estimation method is OLS regression. Coefficients in bold are statistically significant at α=0.05.

Table 7: Estimated Average Associations between Online Course-Taking (Compared to No Use) and Student Intermediate Academic Outcomes by School Year

	2015-16			2014-15			2013-14		
Outcomes	N	Coef.	S.E.	N	Coef.	S.E.	N	Coef.	S.E.
Math test score	7,250	-0.062	0.035	4,802	**-0.091**	0.041	11,003	**-0.036**	0.018
Reading test score	7,162	-0.047	0.027	4,759	**-0.081**	0.027	10,905	**-0.064**	0.015
GPA	13,476	**-0.075**	0.037	10,582	-0.037	0.043	11,997	-0.003	0.037
Credits earned	12,537	-0.067	0.084	10,072	-0.105	0.103	8,530	-0.135	0.083

Note: estimation method: fixed effects regression; coefficient estimates in bold are statistically significant at α=0.05.

Table 8: Comparison of Intermediate Academic Outcomes of Online Course-Takers vs. Non-Users by Student User Type and Year

		Engaged Users		**Moonlighters**		**Nominal Exerters**		**Incompatible Strugglers**	
Outcomes		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
	N				**2015-16**				
Math test score	6,977	-0.058	0.050	-0.081	0.050	-0.041	0.074	n.a.	
Reading test score	6,898	-0.034	0.042	-0.054	0.036	-0.054	0.068	n.a.	
GPA	13,557	-0.008	0.038	**-0.109**	0.043	0.026	0.064	n.a.	
Credits earned	12,606	0.104	0.073	-0.206	0.125	0.217	0.139	n.a.	
	N				**2014-15**				
Math test score	4,802	-0.076	0.043	-0.001	0.069	n.a.		**-0.129**	0.048
Reading test score	4,987	-0.063	0.029	0.035	0.081	n.a.		-0.094	0.052
GPA	10,582	-0.019	0.041	-0.007	0.058	n.a.		-0.089	0.059
Credits earned	10,072	-0.036	0.080	0.103	0.144	n.a.		**-0.320**	0.148
	N				**2013-14**				
Math test score	11,003	-0.030	0.022	0.011	0.036	**-0.085**	0.024	**-0.047**	0.023
Reading test score	10,905	**-0.050**	0.014	**-0.060**	0.037	**-0.071**	0.029	**-0.052**	0.021
GPA	11,997	0.016	0.034	0.094	0.061	0.012	0.036	**-0.139**	0.048
Credits earned	8,530	-0.068	0.116	0.018	0.145	-0.122	0.101	-0.185	0.103

Estimation method: school and grade-level fixed effects regressions (N=number of students in schools taking courses online)
Note: Coefficients (estimates) in bold are statistically significant at α=0.05.

ONLINE ONLY APPENDICES

Appendix A: Dimensions of Digital and Blended Instruction Rated in Observations

The following dimensions of digital and blended instruction and the settings in which they are used are rated by the observation instrument we employ in this study.

- ***Physical environment***: How and where students access the instructional setting, including the technological setting and any associated limitations, and who else in the same physical environment as the student could assist with technological problems and support learning;
- ***Technology and digital tools:*** How students access instruction, including internet connectivity, hardware and software in use, and the safety, operability and accessibility of the technology;
- ***Curricular content and structure***: Content and skill focus, who developed it and where it is located (e.g., software loaded onto a tablet, paper workbook), stated learning objectives, sequence and structure, level of rigor or intellectual challenge, and ability to meet and adapt curricular content to student needs;
- ***Instructional model and tasks***: Role of instructor and software in instruction (what drives instruction); purpose or target of instruction; student/instructor ratio and grouping patterns, multimodal instruction; order of thinking required and application of technology in instructional tasks, and ability to meet/adapt instructional model and tasks to student needs;
- ***Interaction:*** How much interaction with a live person, and does the technology affect the ability of the instructor or student to positively interact with one another and the instructional resources?
- ***Digital citizenship:*** Are students using the technology as intended by the instructor and/or instructional program?
- ***Student engagement:*** Overall student engagement levels, level of student self-regulation and persistence, and level of community within the instructional setting;
- ***Instructor engagement:*** Overall instructor engagement levels (passive or active) and instructor efforts to encourage engagement;
- ***Assessment/feedback***: Who develops and manages the assessment (instructor, provider via software), structure, and whether it is individualized to student learning and relevant to stated learning goals.

Appendix B: K-Means Cluster Analysis

We expand here on the methodological notes in the main body of the text to decribe the k-means cluster analysis (used to identify student user groups) and highlight key decision points and decisions made in the course of the analysis.

Variable Selection

For inclusion in the k-means cluster analysis, variables had to meet the following conditions: (1) measured student interactions with the online course platform, (2) were not highly correlated with another included measure, and (3) were controlled directly by the student. For instance, we did not include information on the type of courses enrolled in or whether a student's course was disabled, as these were influenced by school-level policy. We also excluded characteristics, such as race, gender, or poverty status, over which students had no control. The following variables met all criteria for inclusion in the k-means cluster analysis: course duration, the number of activities completed per day, average session time, idle to session time ratio, number of sessions per course, number of courses, and percentage of coursework completed at night.

Number of Cluster Identification

To identify the number of clusters in the k-means cluster analysis, we used Ward's (1963) hierarchical method (Knight, 2014; Steinley, 2007). Based on the resulting dendrograms (see the example below from Ward's hierarchical method for the 2013-14 school year), we selected the largest number of distinct groups identified for each school year, prioritizing groups with a large enough number of students to have practical significance, around 500 or more students or 10-15 percent of each sample. Using this process, individuals are assigned to a group in a manner than minimizes the within-cluster variance of each group. When interpreting the dendrogram, the larger the distance on the y-axis before lines merge, the more distinct the groups. In 2014-15 and 2015-16, we identified three distinct groups, with the cut-off point at approximately 100 on the dissimilarity measure. In 2013-14, we identified four distinct groups, with a cut-off point closer to 200 on the dissimilarity measure. The dissimilarity measure we report is calculated based on the Euclidean distance between group means.

Appendix C: Additional Information on Methods for Estimating Associations between Student Use of Online Instruction and Intermediate Educational Outcomes

In modeling associations between student use of online instruction and educational outcomes, we began with a basic fixed effects model for estimating average effects of online course-taking on student-level outcomes in a given school year:

$$A_{jst} = \alpha O_{jt} + \beta_1 X_{1jt} + \beta_2 A_{jst-1} + \beta_3 P_{st} + \pi_s + \mu_{gt} + \varepsilon_{jst} \qquad (1)$$

where A_{jst} is the achievement/intermediate outcome of student j attending school s in year t; O_{jt} is an indicator if the student accessed instruction online in year t; X_{1jt} are student characteristics at the start of the school year in which instruction is accessed online (including student demographics, percent absent in prior year, special educational needs, etc.); A_{jst-1} is the prior year assessment/outcome measure; P is the percent of students in a given school that access online instruction; π_s is a school fixed effect; μ_{gt} are grade by year fixed effects, and ε_{jst} is the random error term. In addition, we limited the analysis sample to schools where the online instructional program was made available for use, to ensure greater comparability of the educational environments of program users and non-users.

In the above model, the coefficient on the online instruction variable indicates, on average, if there was an association (positive or negative) between online course-taking and student intermediate outcomes in these settings, controlling for student characteristics and time-invariant school and/or classroom and grade year effects, as well as time-varying rates of online instruction use in schools. This model would only identify *effects* of online course-taking if it was reasonable to assume that no other unobserved, time-varying factors influenced online course-taking and student educational outcomes (the conditional independence assumption). As this is a relatively strong assumption, we also estimated inverse propensity score weighting models with regression adjustment (IPWRA, a double-robust estimator). This doubly robust estimation method uses probability weights from a model that predicts treatment status (i.e., online course-taking) to obtain outcome-regression parameters that account for the fact that each student is observed in only one of the potential outcomes. The estimated inverse-probability weights are used to fit weighted regression models of the outcome for each treatment level and to obtain predicted outcomes for each student, and average treatment effects (i.e., the contrasts of the averages) are then computed from these estimates of treatment effects. Estimating the IPWRA models provides a robustness check on the fixed effects model results but is not expected to resolve any difficult selection issues that may be present.

In both the fixed effects and IPWRA analyses, treatment was measured in two distinct ways: (1) any online instructional use (among those in online-using schools), and (2) typologies of online instructional use (based on measures of user behaviors that were used to identify the typologies via k-means cluster analysis). The fixed effects model shown above represents the first specification with any online instructional use as the treatment measure. To modify the fixed effects model to depict the typologies analysis, the O_{jt} indicator would be replaced by multiple indicator variables for the student typologies (where the reference category is no online course-taking). The IPWRA model uses a probit model to predict treatment status in the estimation of any online instructional use, and it also accommodates a multi-value treatment framework, where a multinomial logit or probit model is used to predict the typologies of use in the first stage of estimation (for this alternative treatment specification).

The IPWRA model results that correspond to the fixed effects model results reported in Tables 7 and 8 are presented below (in Tables C.1 and C.2, respectively). The results are highly comparable to the fixed effects model results, with a few negative, statistically significant estimates of associations between any online course-taking and average intermediate outcomes (Table C.1). Likewise, the IPWRA findings in Table C.2 suggest that the *Incompatible Strugglers* were possibly set back in their academic progress through online instruction, with poorer intermediate outcomes than comparable students not taking courses online. As noted above, this student user group was no longer identified in our analysis after the 2014-15 school year, ostensibly because the school district recognized that these younger students were struggling and began to discourage their use of the online instructional program.

Table C.1: Estimated associations between online instruction (compared to no use) and intermediate academic outcomes by school year

Estimation method: inverse probability weighting with regression adjustment									
	2015-16			**2014-15**			**2013-14**		
Outcomes	N	Coef.	S.E.	N	Coef.	S.E.	N	Coef.	S.E.
Math test score	7,250	-0.052	0.028	4,802	**-0.073**	0.024	11,003	-0.031	0.017
Reading test score	7,162	-0.050	0.026	4,759	-0.059	0.030	10,905	**-0.053**	0.023
GPA	13,476	**-0.080**	0.017	10,072	-0.020	0.020	11,997	-0.032	0.020
Credits earned	12,537	-0.086	0.053	10,582	-0.042	0.056	8,530	-0.087	0.062

Table C.2: Comparison of Intermediate Outcomes for Typologies of Online Course-Takers with Non-using Students by School Year

Estimation method: Inverse propensity score weighting with regression adjustment

					2015-16				
Outcomes	N	Engaged Learners		Moonlighters		Nominal Exerters		Dedicated Strugglers	
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Math test score	5,172	-0.076	0.044	-0.052	0.050	-0.025	0.077	n.a.	
Reading test score	5,070	-0.079	0.045	-0.042	0.043	-0.026	0.078	n.a.	
GPA	13,557	-0.031	0.028	**-0.112**	0.026	0.013	0.038	n.a.	
Credits earned	12,606	0.087	0.087	-0.129	0.080	0.203	0.127	n.a.	
	N				**2014-15**				
Math test score	5,063	**-0.083**	0.034	0.084	0.067	n.a.		**-0.116**	0.039
Reading test score	4,987	-0.033	0.037	0.119	0.083	n.a.		-0.077	0.050
GPA	11,833	-0.038	0.022	0.022	0.034	n.a.		**-0.073**	0.026
Credits earned	11,317	-0.059	0.065	0.158	0.105	n.a.		**-0.248**	0.078
	N				**2013-14**				
Math test score	11,003	-0.039	0.020	0.031	0.032	**-0.076**	0.023	-0.057	0.031
Reading test score	10,905	-0.057	0.026	-0.102	0.058	**-0.082**	0.032	**-0.033**	0.030
GPA	11,201	-0.014	0.030	0.044	0.051	**-0.019**	0.030	**-0.162**	0.040
Credits earned	*(The IPWRA models did not converge to provide effect estimates for credits earned in 2013-14.)*								