Early Exploration of MOOCs in the U.S. Higher Education: An Absorptive Capacity Perspective

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Advanced information technologies have enabled **Massive Open Online Courses (MOOCs)**, which have the potential to transform higher education around the world. Why are some institutions eager to embrace this technology-enabled model of teaching, while others remain reluctant to jump aboard? Applying the theory of absorptive capacity, we study the role of a university's educational IT capabilities in becoming an early MOOC producer. Examining the history of MOOC offerings by U.S. colleges and universities, we find that prior IT capabilities, such as (1) the use of Web 2.0, social media and other interactive tools for teaching and (2) experience with distance education and hybrid teaching, are positively associated with the early exploration of MOOCs. Interestingly, we also find that the effect of educational IT capabilities is moderated by social integration mechanisms and activation triggers. For example, when instructional IT supporting services are highly decentralized, educational IT capabilities have a greater impact on the probability of a university offering a MOOC. In addition, for colleges facing an adverse environment, such as those experience a decline in college applications, the effect of IT capabilities on the exploration of MOOCs is much stronger.

CCS Concepts: • **Applied computing** → **Education**; • **Information systems** → *Collaborative and social computing systems and tools*;

Additional Key Words and Phrases: MOOC, online education, distance learning, absorptive capacity, IT capability

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1 INTRODUCTION

Massive Open Online Courses (MOOCs), with their promise of overturning the century-old model of education, are both disrupting and transforming higher education [Lucas 2014]. Since the introduction of the first MOOC in October 2011, 123 American universities have offered or announced over 1,300 MOOCs as of the time of this writing,[1] the majority of which were delivered on one of the three leading platforms – Coursera, EdX or Udacity. As an IT-enabled innovation, MOOCs

[1]The statistics are based on our analyses of data obtained from https://www.class-central.com/.

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have generated much excitement and debate within the higher education community, and have enthusiastic supporters as well as determined opponents [Vardi 2012]. MOOCs represent a new challenge as well as an opportunity for universities; many consider it a priority to experiment with MOOCs and become an early content producer. However, it is unclear why some universities are swifter to embrace this emerging innovation than others, and to what extent the decision is path dependent, determined by factors such as the accumulation of business-IT knowledge. Because most universities offer MOOCs through partnerships with external technology platforms rather than their in-house infrastructure, some argue that information technology capabilities are less relevant in the decision of exploring MOOCs. The purpose of this article is to take the initial steps in examining *if a university's prior educational IT capabilities remain a factor in shaping the decision to experiment with MOOCs, and to what extent this relationship is influenced by the school's internal coordination structure and external environment.* We apply the theory of absorptive capacity [or ACAP, Cohen and Levinthal 1990; Roberts et al. 2012] to guide our empirical investigation into these questions.

Our study focuses on the early stages of MOOC exploration in which universities make the decision on whether to enter into an agreement with a MOOC platform provider and start developing MOOC(s). Using a longitudinal data set of MOOC offerings by U.S. colleges and universities over a 3-year period, we find that despite often being delivered via external technology platforms, early experimentation with MOOCs is significantly influenced by a schools' prior educational IT capabilities, such as (1) their abilities to use social media, Web 2.0 technologies, or other interactive learning tools, and (2) their experience with e-learning and hybrid learning. Interestingly, we also find that the effect of prior IT capabilities on MOOC exploration is moderated by social integration mechanisms: for example, educational IT capabilities only have a positive effect on MOOC exploration when it is coupled with decentralized provision of educational IT support services. In addition, evidence suggests that universities are more likely to leverage their IT capability to explore MOOCs under an adverse environment, such as when they face a decline in student applications. These findings are consistent with the theory that IT-related absorptive capacity depends not only on the stock of prior related knowledge, but also on contingent factors such as complementary organizational capabilities [Jansen et al. 2005; Van Den Bosch et al. 1999] and activation triggers [Zahra and George 2002].

Our article contributes to prior **information systems (IS)** research in several ways. First, we add to the literature on digital innovations [Fichman et al. 2014] by showing that prior IT capabilities play a key role in the early exploration of technology-enabled innovations in the higher education sector. Interestingly, we find that strong IT capabilities remain critical in the exploration of digital innovations even when the underlying IT infrastructure is not housed internally, but instead provided via a partner's platform. Therefore, our work stresses the continued relevance of business-IT knowledge, particularly in an age when IT infrastructure can be rapidly acquired through outsourcing, cloud computing, and software-as-a-service (SaaS) providers.

Second, we advance the IS research that applies the ACAP theory in the studies of IT-related phenomena. Although the absorptive capacity framework [Cohen and Levinthal 1990] has been widely used to examine firm strategy and behavior [Lane et al. 2001; Van Den Bosch et al. 1999] and IS researchers have leveraged the ACAP concept in the context of IS research questions such as IT assimilation and knowledge transfer [Roberts et al. 2012], most of the earlier work argues that such capability is a function of relevant prior knowledge and have not examined the moderating roles of internal coordination mechanisms and external environment. Our work contributes directly to addressing this gap.

Finally, we contribute to the literature on IT value that so far has placed its emphasis predominantly on the direct return of IT investments, such as their contribution to productivity

[Brynjolfsson and Hitt 2000] or improvement in efficiency [Pang et al. 2014]. We show that IT investments—particularly those in IT human capital—not only improve productivity directly through the use of IT systems, but also enhance IT-related absorptive capacity, which can be particularly beneficial when opportunities enabled by digital innovations arise. Failure to recognize the latter role of IT investments may lead to the underestimation of their true value.

2 LEARNING TECHNOLOGIES IN HIGHER EDUCATION

While universities are conservative institutions that change but slowly over time, the rapid advances in information technology in recent years have precipitated several waves of transformation in the way through which education is delivered, and researchers have studied the adoption of learning technologies by universities. For example, Buchanan et al. [2013] surveyed 114 faculty members in a U.K. university, and a principal components analysis of their instruments revealed two main barriers to the adoption of learning technologies: structural constraints from the university and perceived usefulness of the tools. Research by Shim et al. [2018] looked at open platform adoption from a herding perspective. They found that new platform risk and organizational risk are associated with herding in the early stages of diffusion, while platform benefits and competitive pressure are associated with herding in the later stages of diffusion. Ajjan and Hartshorne [2008] studied faculty adoption of Web 2.0 technologies like text messages, wikis, and social networks. Their result suggested that faculty attitude and perceived behavioral control were significantly associated with the intention to use Web 2.0 technologies. In addition, Echeng and Usoro [2016] showed that perceptions of improved learning experiences from Web 2.0 tools were associated with perceived ease of use, prior knowledge, and performance expectancy.

Several recent studies have also examined the adoption of various forms of e-learning, distance learning and blended learning. For example, Ozdemir and Abrevaya [2007] studied the adoption of technology-mediated distance education. They found that public universities adopted the technology earlier than private schools, presumably because public schools emphasize increased enrollments and affordable education. Interestingly, they also revealed that schools in large cities were less likely to adopt, possibly because students there have lower travel costs to come to campus. Ozdemir et al. [2008] examined the adoption of technology-mediated learning in U.S. universities, and found that it was used more in lower-ranked universities, in states with a high density of population, and at the graduate level. Graham et al. [2013] proposed a framework for the institutional adoption and implementation of blended learning in higher education. Using six case studies, they illustrated that blended learning began at individual faculty level, but institutional policies, structures and lack of support can inhibit the spread of blended learning. Using the unified theory of acceptance and use of technology, Uğur and Turan [2018] found that system interactivity was associated with the intention to use e-learning technologies.

Most relevant to our study is a stream of emerging research that examines the adoption of MOOCs in higher education. In their review of the literature on MOOCs, Liyanagunawardena et al. [2013] categorized articles into ten groups with different themes such as the MOOC concept, case studies, educational theory, technology used in MOOCs, MOOC participants, and MOOC providers. Hollands and Tirthali [2014] identified a set of major objectives of MOOC initiatives, including extending the reach of higher education, maintaining school brand, improving educational outcomes, and fostering teaching innovation. Ospina-Delgado and Zorio-Grima [2016] explored the causal factors associated with the number of MOOCS a university produced using data from Coursera and edX combined with data from the schools' web sites. They applied a fuzzy-set Qualitative Comparative Analysis and found evidence of asymmetric causality: the factors leading to MOOC-intensiveness were different from the factors leading to the lack of MOOC-intensiveness. While our work builds on and expands of this line of inquiry, our empirical investigation is guided

Table 1. A Comparison of MOOCs and E-learning Courses

	MOOC	**E-learning Course**
Structure/Format	A technological design that facilitates the dissemination of the learning activity of participants through one or more platforms.	Use an e-learning platform (such as an LMS†) with a set number of functions and structure designed for interaction with lecturers.
Environment	Open environment	Closed environment
Access	Typically free access	Access on payment of registration fee
Size	Massive participation	Limited group
Course content	Evolves dynamically through learner participation, creation of user-generated content and collaboration	Static content
Support	Support from the community	Support from the teaching staff
Communication	A range of communication tools, including the use of wikis, forums, and social media	Tools provided within the e-learning platform
Purpose	Emphasis on learning process rather than evaluation and accreditation	Evaluation and accreditation oriented

Note: † learning management system.

by the theory of absorptive capacity [Cohen and Levinthal 1990] with an emphasis on IT human capital, the accumulation of business-IT knowledge, and the boundary conditions that shape the path dependency of MOOC adoption.

3 THEORY AND HYPOTHESES

The advent of MOOCs presents a recent example of disruptive innovation in learning technologies. Not only are instructor-student interaction, content delivery, grading and outcome evaluation of MOOCs dramatically changed from a traditional classroom setting, but MOOCs also differ from traditional education in terms of their models of operation. As a way to expand the reach of higher education on a global scale and raise educational levels around the world, MOOCs have great scale economies, offer more flexibility and customization in accessing higher education, and provide an opportunity for start-up universities with entirely different business models [Christensen and Horn 2013]. In addition, there are notable distinctions between MOOCs and various types of online or e-learning courses that many schools are currently offering for degree or non-degree programs. In Table 1, we present a comparison that highlights some of the critical differences between MOOCs and e-learning courses. Given these new features, in this work, we conceptualize MOOCs as a form of digital innovation, consistent with Fichman et al. [2014]'s definition of "a product, process, or business model that is perceived as new, requires some significant changes on the part of adopters, and is embodied in or enabled by IT".

The theory of absorptive capacity [Cohen and Levinthal 1990] offers a useful framework in analyzing the early exploration of digital innovations in the higher education sector such as MOOCs. Under the context of organizational learning, absorptive capacity is defined as an organization's ability to "recognize the value of new, external knowledge, assimilate it, and apply it to commercial ends" [Cohen and Levinthal 1990]. Prior research has emphasized that the development of absorptive capacity over time requires the accumulation of relevant knowledge [Lane and Lubatkin 1998], and is usually path-dependent [Roberts et al. 2012]. In addition, it has been argued that the relationship between absorptive capacity and competitive advantage is contingent on a variety of boundary conditions, which include activation triggers, social integration mechanisms, appropriability regimes, and power relationships [Todorova and Durisin 2007; Zahra and George 2002].

As we noted earlier, most MOOCs offered by universities were delivered in partnership with external platforms such as EdX or Coursera, who provided both the IT infrastructure and in some cases a variety of IT services such as multimedia production. Therefore, it is not immediately apparent that certain elements of the ACAP theory, such as its path dependency, remain relevant under this context. For example, can third-party IT support services substitute the need for internal accumulation of business-IT knowledge when schools explore MOOCs? In the rest of this section, we present a formal discussion of the roles of some critical elements in the model, including the antecedents such as prior knowledge and capabilities, and two contingent factors—social integration mechanisms and activation triggers—in the development of absorptive capacity, and how they influence the early exploration of IT-enabled innovations such as MOOCs.

3.1 Educational IT Capabilities and Early Exploration of MOOCs

We maintain that there exists a positive relationship between a university's prior educational IT capabilities and the likelihood of exploring MOOCs. We follow prior literature and define IT capability as "the ability to mobilize and deploy IT-based resources in combination or co-present with other resources and capabilities" [Bharadwaj 2000]. Under this definition, the key IT-based resources include both physical IT infrastructure and human IT resources such as technical and managerial IT skills, as well as IT-enabled intangibles such as knowledge assets and other related organizational capabilities. A strong IT capability contributes to the exploration of IT-enabled innovations through two interrelated processes: (1) it helps accumulate business-IT knowledge, thereby enhancing an organization's IT-related absorptive capacity [Roberts et al. 2012]; and (2) an expansive business-IT knowledge base is conducive to the identification, assimilation, and the exploitation of external knowledge related to new IT-enabled innovations. We elaborate on these two processes in some detail.

First, business-IT knowledge is referred to as "the combination of IT-related and business-related knowledge possessed by and exchanged among IT managers and business unit managers", and it is an integral component of an organization's overall absorptive capacity [Boynton et al. 1994; Nelson and Cooprider 1996]. In the context of universities where educational professionals enjoy high degrees of autonomy, such business-IT knowledge is likely to be possessed by two types of individuals: faculty members and supporting IT professionals. IT competence of faculty members includes IT-related explicit and implicit knowledge the faculty members possess which enables them to pursue excellence in education. For example, frequent and repeated use of learning management systems, online assessment tools, or the use of social media and Web 2.0 tools for educational purposes by faculty members strengthen their understating of the use of IT to achieve effective content delivery and student performance evaluation.

Similarly, business competence of IT professionals (e.g., university IT staff members) refers to "the set of business and personal knowledge and skills possessed by IT professionals that enable them to understand the business domain, speak the language of business, and interact with their business partners" [Bassellier and Benbasat 2004]. For example, a critical component of such competence is the knowledge of IT-business integration, or the ability to visualize the ways that IT contribute to organizational performance and seek synergies between IT and business activities [Brown and Sambamurthy 1999]. Stronger educational IT capabilities at a university enhance an IT professional's understanding of the role IT plays in promoting effective learning and in achieving other strategic objectives of the university.

Second, schools that have accumulated greater business-IT knowledge are more likely to recognize the opportunities presented by emerging digital innovations in teaching such as MOOCs, and are better positioned to assimilate and exploit these innovations. For example, schools that have already experimented with various types of e-learning and hybrid learning may have acquired important insights about the cost structure, the scalability, the format of interactions, as well as limitations related to technology-enabled distance learning. When presented with new IT-enabled innovations such as MOOCs, they are better able to assess the potential benefits, and take actions to exploit these opportunities.

In addition, it is well known that related knowledge and knowledge diversity lowers the knowledge barriers present in the exploration of complex technology innovations. In the case of MOOCs, such barriers may appear a daunting obstacle for some universities. For example, unlike a traditional classroom setting, MOOCs typically attract a much larger audience and offer limited interaction between the instructors and students, and MOOC instructors must find creative ways to engage students and prevent student attrition. Teaching a MOOC is mostly conducted in an asynchronous fashion, instead of face-to-face with synchronous communications. MOOCs are enabled by advanced information and communication technologies such as wikis, discussion boards, video tutorials and other Web 2.0 technologies, many of which are unfamiliar to college faculty. Therefore, even experienced instructors and highly skilled supporting IT professionals may encounter difficulties adapting to this new form of teaching and must experiment with various approaches to achieve desirable outcomes. On the other hands, schools with greater accumulation of business-IT knowledge may be able to overcome these obstacles by relating the new innovation to their prior knowledge, and recombine their existing knowledge to acquire new competence through the processes of learning by using [Attewell 1992].

It should be noted that while universities often partner with a third-party platform provider such as Coursera that helps with providing the IT infrastructure, the use of these IT platforms to deliver MOOCs requires capabilities beyond having the infrastructure ready. The accumulation of business-IT knowledge—often embedded in IT human capital and other organizational intangible assets—is key to the effective use of the external platforms. In the case of MOOC adoption, business-IT knowledge involves achieving effectiveness of teaching through the use of a variety of interactive technologies, and it resides in the course instructors and their IT supporting staff. Such knowledge cannot be sourced from the MOOC platform providers, whose primary responsibility is building the IT infrastructure and the delivery platform required by MOOCs. In summary, we propose:

Hypothesis 1. Universities with a higher level of prior educational IT capabilities are more likely to become early MOOC explorers.

3.2 Social Integration Mechanisms

One of the important contingent factors in the ACAP model is the social integration mechanisms, which "can facilitate the sharing and eventual exploitation of knowledge" [Zahra and George 2002]. It has been shown that certain organizational structures are conducive to building connectedness among knowledge workers by increasing their interactions, and therefore promote problem solving and the generation of creative ideas [Sheremata 2000]. As a result, the effective use of social integration mechanisms may lower the barriers between knowledge assimilation and knowledge transformation, leading to higher absorptive capacity [Todorova and Durisin 2007].

In the context of using IT platforms in the educational sector, a critical determinant of knowledge sharing and dissemination is the interaction between the faculty and the IT professionals that support various IT functions and services. Therefore, the organizational structure under which IT professionals provide educational IT support services to the faculty represents an important social integration mechanism that bonds knowledge holders. We argue that there is a complementarity between high educational IT capabilities and decentralized provision of educational IT support services in driving IT-related absorptive capacity in a university. Prior studies on IT governance [Sambamurthy and Zmud 1999] point out whether an organization pursues a decentralized way of IT decision making is predicated on the extent to which line managers in the operating units possess the requisite business-IT knowledge. For example, in firms where line managers are not equipped with sufficient business-IT knowledge and lack the understanding of IT management practices, imposing decentralized IT decision rights may result in a poor fit and inferior performance [Boynton et al. 1994; Brown and Magill 1998].

As we argued in the previous subsection, a higher educational IT capability results in the accumulation of business-IT knowledge. In the context of a university, this business-IT knowledge most likely resides in the academic units instead of the central university IT operation, embedded in the faculty members and their departmental supporting IT professionals. Academic units are highly autonomous entities and have idiosyncratic needs that are best addressed locally. IT staff deployed at academic unit level have a deeper understanding of these idiosyncratic needs, and have built social bonds with faculty members in their respective departments or schools through repeated interactions. In addition, the exchange and sharing of business-IT knowledge between faculty members and IT professionals are more effective if the IT supporting staff and instructors are collocated, especially for sharing tacit knowledge. Collocated faculty and staff often find it easier to develop coordination and social capabilities. Therefore, the decentralized distribution of business-IT knowledge requires a compatible social integration mechanism—decentralized provision of educational IT support—to facilitate the absorption of new knowledge and the exploration of new opportunities.

Hypothesis 2. Decentralized provision of educational IT support services positively moderates the relationship between educational IT capabilities and early MOOC exploration.

3.3 Activation Triggers

Prior research has conceptualized ACAP as a dynamic capability [Zahra and George 2002], which enables a firm to reconfigure its combination of resources and adapt to the changing market conditions. Relatedly, activation triggers, or 'events that encourage or compel a firm to respond to specific internal or external stimuli,' have been highlighted as an important contingent factor in the model of ACAP [Zahra and George 2002]. These events include internal triggers such as organizational crises, or external triggers such as disruptive innovations that may impact the industry as a whole. Firms that experience internal or external triggers are more likely to expand their effort to seek external knowledge [Huber 1991], because the triggering events may break existing frames and render the internal knowledge base obsolete [Fosfuri and Tribó 2008]. As the intensity of a trigger increases, firms are more inclined to invest in resources to develop capabilities that helps acquire and assimilate externally generated knowledge. For example, Hyundai Motor Company, in its effort to acquire external knowledge and expand its knowledge base, proactively created a sense of crisis as a strategic way of stepping up its learning intensity [Kim 1998].

Activation triggers, or "shocks" [Pfeffer 1981], are often associated with turbulent environments. Prior research on organizational learning has suggested that under the context of a stable knowledge environment, the focus of knowledge absorption is on exploitation. In contrast, under the context of a turbulent knowledge environment, the focus of knowledge absorption is on exploration [Van Den Bosch et al. 1999]. As a result, in a turbulent environment, organizations are more likely to develop organization forms and combinative capabilities that facilitate high scope and flexibility of knowledge absorption, which lead to higher level of outward-looking absorptive capacities.

Following the literature on the role of activation triggers [Todorova and Durisin 2007; Zahra and George 2002], we argue that universities may also experience triggering events that at times induce them to increase their learning intensity, leading to higher likelihood of leveraging their IT capability to acquire external knowledge and explore new innovations. For universities, a plunge in the number of student applications is a troubling signal, which may indicate that the school is suffering from a declining reputation. Therefore, universities that experience declining application numbers will try to seek alternative ways of boosting their reputation and attracting students; they are more likely to leverage IT-related absorptive capacity to explore IT-enabled teaching innovations.

Hypothesis 3. A decline in the number of college applications at a university positively moderates the relationship between educational IT capabilities and early MOOC exploration.

4 DATA

We assembled a unique longitudinal data set of MOOC offerings by higher education institutions in the United States, their institutional characteristics, and their use of educational IT during academic years 2011-2012, 2012-2013, and 2013-2014. The dataset consists of three major components, collected from three separate sources.

MOOC Offerings. We developed a web scripting tool and obtained the complete list of MOOCs that were ever offered on any MOOC platform by the end of academic year 2014 from a MOOC aggregation service provider, Class Central. Class Central continually scans for MOOCs from all MOOC platform providers and places them in a central repository, starting from the introduction of the very first MOOC, *Introduction to Artificial Intelligence*, offered by Sebastian Thrun and Peter Norvig from Stanford University in October 2011. In addition to the title and instructors of each MOOC, Class Central provides information such as a link to the actual course URL, a short description of the course, the subject of the course, the higher education institution by which the MOOC is created, the provider (platform) on which the MOOC is offered, the start date and the duration of the course, and so on.

We present a summary of MOOC offerings during our sample period by the sponsoring universities and by subjects in Figure 1 and Figure 2, respectively. We observe that while the subjects of the courses vary widely, the most popular subject is computer science (235 out of 1,122 MOOCs), followed by Statistics & Data Analysis. In total, 123 universities offered MOOCs during the 3-year period after the introduction of the first MOOC, and the heavy adopters tend to be nationally renowned private schools and flagship state universities, consistent with prior surveys suggesting that a major incentive of exploring MOOC is to maintain a school's reputation and prestige [Hollands and Tirthali 2014].

Institutional Characteristics. We obtain various institutional characteristics, including student enrollment, completion, and graduation profiles, as well as other student/faculty information from the **Integrated Postsecondary Education Data System (IPEDS)** data center. IPEDS is the core postsecondary education data collection program by the National Center for Education Statistics, which conducts a system of surveys designed to collect data from all primary providers of postsecondary education. The data is widely used by many educational study organizations, such as *College Board, Peterson's*, and *U.S. News & World Report* to compile their publications.

Educational IT. Our third source of data is the **Educause Core Data Service** (or **CDS**) survey, from which we derive our measures of educational IT capabilities and IT support services of U.S. higher education institutions. Educause is a nonprofit association which focuses on "analysis, advocacy, community building, professional development, and knowledge creation to support the

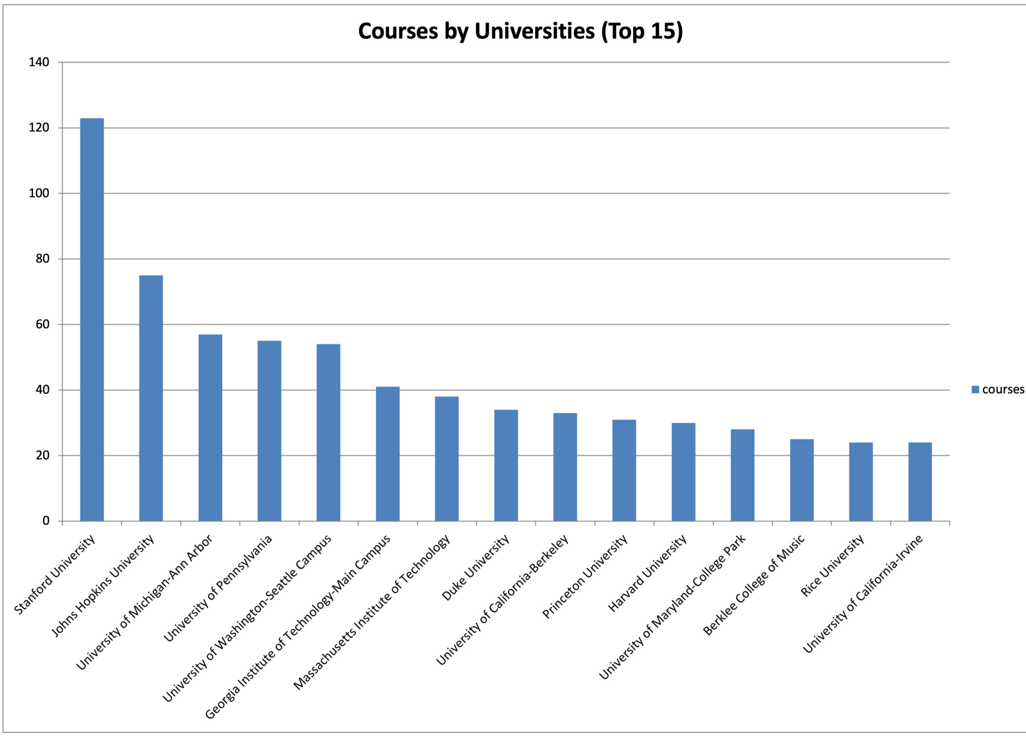

Fig. 1. MOOC Offerings by Universities, Top 15.

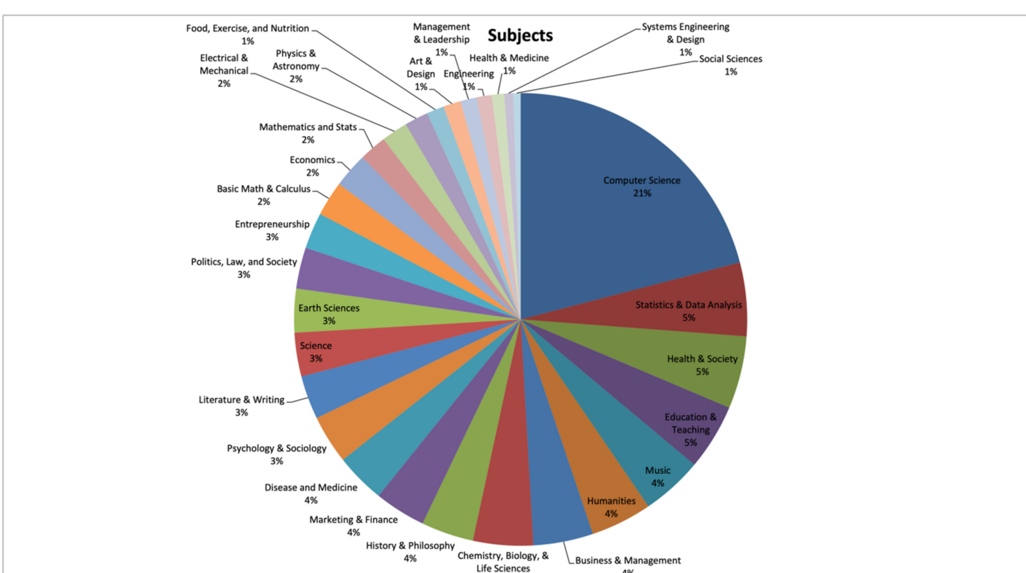

Fig. 2. MOOC Offerings by Subjects.

transformative role that IT can play in higher education."[2] The organization has drawn over 1,800 colleges and universities and over 300 corporations serving higher education IT as its members. The annual CDS survey is organized into a set of *required modules* that collect basic, core IT information and *optional modules* that collect more details on specific IT domains.[3] Participating institutions often use CDS data for communicating the value of IT, benchmarking IT budgets and staffing, and comparing IT department structure and service delivery with peer schools.

4.1 Sample

The unit of our analyses is the university level since major MOOC platforms sign contracts with universities and not individual faculty members. Schools that offer MOOCs do so by contracting with one of the major delivery platform providers, with the two parties working out an agreement specifying the number of MOOCs to be delivered in the next few years. To assemble our data set, we started with the set of schools surveyed by IPEDS. Among the 123 universities that eventually have ever offered one or more MOOCs in any academic year by the end of our sample period, the vast majority of them (108 universities, or 88%) belong to the "degree-granting, primarily baccalaureate or above" category, while MOOC offerings by other categories are extremely rare. To focus on a more homogeneous population of universities, and to help rule out alternative explanations due to structural differences between various types of universities, we remove the schools in all other categories from our sample of analyses and use the schools within the category of "degree-granting, primarily baccalaureate or above". Next, we examine the *control of the institution* of the MOOC adopters, which can be either *public, private not-for-profit*, or *private for-profit*. Because none of the *private for-profit* schools offered any MOOCs during our sample period, and because the for-profit schools use a very different accounting system than the not-for-profit organizations, we further remove *private for-profit* schools from our sample. The set of schools remaining in IPEDS was then matched with the Educause CDS survey database, and we retrieved the universities that fall into the intersection of the two data sources.

Our data is organized in a panel format with a duration of 3 years. To maintain the compatibility with IPEDS and Educause CDS surveys, the time series of the sample are coded as academic years (which we define as September 1st to August 31 of the next year) instead of calendar years. Because the very first MOOC offering started during academic year 2011-2012 (in October 2011), our sample period consists of three academic years: 2011-2012, 2012-2013, and 2013-2014. To allow for a causal interpretation, all the independent variables are lagged for one year, meaning that we use institutional characteristics and IT capabilities in academic year *(t-1)* to predict MOOC offering in year *t*. In total, our final sample consists of 1,405 observations with 589 universities over a 3-year period, representing an unbalanced panel.

4.2 Variables

4.2.1 Dependent Variable. The primary dependent variable we are interested in is the MOOC exploration decision by a university in an academic year. It is worth noting that decision typically happens first at the university level when it signs an agreement to create MOOCs in partnership with a delivery platform. Once an overall agreement is in place, the university has to interest and incentivize individual faculty members to develop a MOOC; the university may provide support

[2] https://www.nccpsafety.org/resources/affiliates-alpha/e.

[3] The modules include IT Organization, Staffing, and Financing; IT Support Services; Educational Technology Services; Research Computing Services; Data Centers; Communications Infrastructure Services; Information Security; and Information Systems and Applications.

Table 2. Number of MOOC Adopters by Academic Year

Academic year	Non-adopters	Adopters	Total
2011-2012	455	6	461
	(98.70%)	(1.30%)	(100%)
2012-2013	446	35	481
	(92.71%)	(7.28%)	(100%)
2013-2014	406	57	463
	(87.69%)	(12.31%)	(100%)
Total	1307	98	1,405
	(93.02%)	(6.98%)	(100%)

ranging from little or none to extensive assistance through an instructional design staff and video recording services.

We match the data of MOOC offering history collected from Class Central with the universities in our sample, and create a binary indicator variable $MOOC\_offering_{i,t}$, which is set to 1 if university i offered at least one MOOC during academic year t, and 0 otherwise. In some of the robustness tests, we also use an alternative definition of the dependent variable, which is the *number* of MOOC offerings by university i in academic year t.

In Table 2, we present a summary of the number of universities that have offered MOOCs by academic year. We observe a strong trend of growing popularity of MOOCs in higher education, but the overall level of adoption remains low in the early stages. While there are only six universities that explored MOOCs (or a 1.30% adoption rate) in academic year 2011-2012, the number grows to 35 (a 7.28% adoption rate) in year 2012-2013 and 57 (a 12.31% adoption rate) in year 2013-2014.

4.2.2 Independent Variable and Moderating Variables. Our independent variable of interest captures the use of educational IT—a proxy for IT capabilities in education, and the moderator variables measure the degree of decentralization of educational IT support services, and the drop in the number of applications as an activation trigger. We derive these measures from Educause CDS survey data and the IPEDS database.

Educational IT Capabilities. One of the modules in the Educause CDS survey is designed to collect data on the use of educational technology by universities. Specifically, the survey respondents were asked to rate the use of a series of learning technologies or practices in their schools during the prior fiscal year. These technologies consist of 21 items that range from the use of Web 2.0 tools (such as wikis and blogs), the use of social media (such as Facebook and Twitter), the practice of e-learning and hybrid learning, technology enabled teaching (such as simulation, clickers, collaboration tools and lecture capture), to the adoption of e-books and e-textbooks. The survey respondents indicate the status of the use of each technology as one of the following: (1) no discussion to date, (2) considered but not pursued, (3) experimenting/considering, (4) in planning, (5) deployed sparsely, or 6) deployed broadly. We create a Likert scale for each technology use, with the value 1 assigned to "no discussion to date" and value 6 assigned to "deployed broadly".

To generate meaningful categories of the educational IT capabilities and reduce the dimensionality of the data, we used *exploratory factor analyses* (EFA) to identify the underlying factors associated with these measurement items. We perform an EFA using iterated principal factors method, and the result is presented in Table 3. The scree plot of eigenvalues after the factor analysis is presented in Figure 3. Both Kaiser's stopping rule (i.e., retaining factors with Eigenvalues greater than (1) and the scree test suggest that there are three major underlying factors [Rencher 2003]. The factor loadings, using orthogonal varimax rotation, are presented in Table 4, where we only

Table 3. Major Factors of Educational IT

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	5.02491	3.04882	0.4218	0.4218
Factor2	1.97609	0.8842	0.1659	0.5877
Factor3	1.09189	0.27443	0.0917	0.6793

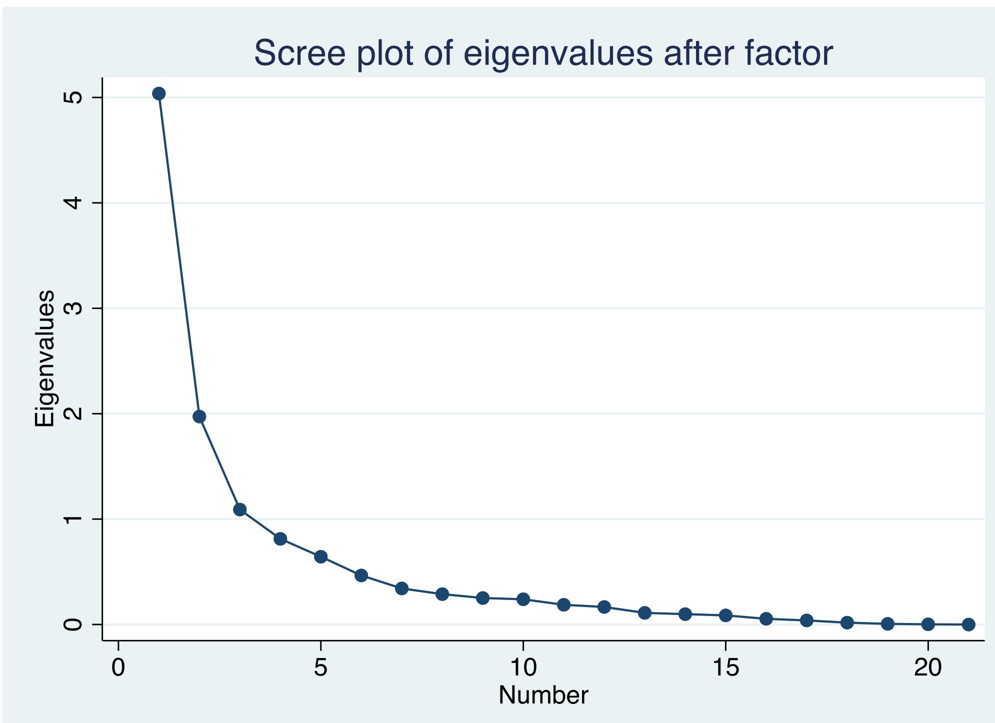

Fig. 3. Scree Plot after Factor Analysis.

retain the factor loadings greater than 0.4 (i.e., blanks represent abs(loading) < .4). By examining the measurement items associated with each factor, we find the first factor (IT1) is mainly associated with the use of Web 2.0, social media, and other interactive tools for educational purposes. The second factor (IT2), in contrast, is primarily associated with a university's prior experience with distance education and hybrid teaching. The third factor (IT3) captures the adoption of digital content in teaching. Therefore, we use these three principal factors as the dimensions of educational IT capabilities. Particularly, for each factor (IT1, IT2, or IT3), we take the average score of the measurement items that load heavily on the factor (i.e., items with loading > 0.4) as the value of that variable. Our method follows closely that used in Hitt and Bryjolfsson (1997, p.95), who use principal component analyses to identify factors related to work systems from survey data.

Decentralized Educational IT Support Services. The Educause CDS survey also includes a question with regard to the organizational unit that is primarily responsible for 14 types of educational technology support services. These support services include designated instructional technology center, instructional technologist's assistance, faculty group training in the use of educational

Table 4. Factor Loadings of Educational IT Capabilities

Variable	**Factor1 (Interactive Tools)**	**Factor2 (Online Education Exp.)**	**Factor3 (Digital Content)**	**Uniqueness**
Blog	0.4742			0.715
Collaboration tools				0.8243
Distance learning – local instructor and remote students		0.8776		0.2593
Distance learning – remote instructor and local students		0.6331		0.5782
Document management				0.8228
E-learning		0.8349		0.3159
E-portfolios				0.8559
E-books			0.8567	0.1995
E-textbooks			0.7544	0.2947
Facebook	0.4778			0.7723
Gaming	0.5195			0.7097
Hybrid courses		0.6482		0.554
Information literacy				0.8564
Interactive learning	0.4277			0.6665
Learning objects	0.4429			0.6475
Lecture capture				0.7739
Mobile apps	0.4721			0.7349
Open content	0.498			0.7282
Simulation	0.4883			0.7369
Twitter	0.6073			0.619
Wiki	0.6109			0.5685

technology, support for learning management system, and special support services for distance education, to name a few. For each support service, the respondent indicates if it is: (1) primarily provided by central IT; (2) shared between central IT and other admin or academic units; (3) primarily provided by other admin office; (4) primarily provided by academic department, school or college; (5) primarily provided by multi-campus system; or (6) not provided. We count the number of measurement items for which the associated service is *provided primarily by academic department, school or college*. The count number (with a range of 0-14) is used to measure the degree of decentralization of educational IT support services.[4]

Decrease in Applications. We operationalize the activation trigger as the decline in the number of applications a university receives. IPEDS reports detailed application numbers for all U.S. colleges and universities every year. The decline in the number of applications for school i in year t is calculated as $application_{i,t-1} - application_{i,t}$. Intuitively, if a school experiences a decline in applications, this variable takes on a positive value. We also tried an alternative operationalization

[4]As an alternative measure of decentralization, we also calculate a ratio of (# of services provided by academic department, school or college)/(# of total services offered), in which we exclude the services that are not offered. All the findings are robust to the use of this alternative measure.

of the activation trigger as the *percentage* decrease in application numbers, and all our findings are robust to this alternative variable definition.

4.2.3 Control Variables.

Institutional Characteristics. We control for financial information related to a university such as average *in-state tuition* and *out-of-state tuition* for full-time undergraduate students. We include as controls the total number of *undergraduate students* and *graduate students* (both full-time and part-time) who are enrolled in the school, and *control of institution* (public or private) in our model. To control the degree of strategic importance of IT to the universities, we also include a binary indictor of whether the institution's *strategic plan* includes strategies and directions of IT, which is derived from the Educause CDS survey.

Student Profile. We use a series of student characteristics as control variables. *Admission rate* is closely related to selectivity of students, and it is defined as the number of admissions made divided by number of applications received from first-time, degree-seeking undergraduates for the academic year. Full-time *student retention rate*, as well as *6-year completion rate* of Bachelor's degree (defined as number of completers within 150% of normal time / adjusted cohort for 4-year institutions), is also included. In addition, we control for the percentage of full-time, first-time undergraduate students that receive any form of *financial aid*.

Faculty Profile. We include two characteristics of the faculty that are likely to be associated with a university's exploration of MOOCs. The first is the percentage of faculty members that are either tenured or on the tenure track. From IPEDS, we retrieve the number of faculty that are either tenured or on track, and divide this number by the total number of instructional faculty to get the *percentage of faculty that are tenured or on the tenure track*. The second control is related to faculty compensation. It is likely that highly compensated professors are more capable at their jobs and are more willing to experiment with new technology and incorporate new pedagogical methods. Because faculty members are hired under different contracts, we operate this variable as *average salary of faculty* on an equated 9-month contract.

School Resources. Because MOOCs require considerable investments of financial and human resources, we also control for resource endowment of the sample universities. First, we measure *financial resource* of a university by the value of endowment assets per full-time equivalent student. Income generated from endowment assets is instrumental in maintaining academic excellence of many universities. Second, instructional faculty is the most valuable asset of any higher education institution and is particularly relevant in MOOC exploration decisions as faculty members are ultimately responsible for the planning, design, and teaching of MOOCs. We use the average number of full-time instructional faculty per full-time equivalent student to measure the *human capital resource*.

We present in Table 5(a) the summary statistics of our major dependent variable, independent variables and control variables. The correlations among the variables are provided in Table 5(b).

5 RESULTS

5.1 Baseline Results

We use binary logistic models as a starting point to analyze how MOOC exploration decisions are shaped by educational IT capabilities, decentralization of IT support services, and activation triggers. Compared to linear probability models (LPMs), logistic regressions relax the assumption on the distribution of the error terms, and address shortcomings such as heteroscedastic errors and the out-of-the-range probability predictions produced by LPMs [Greene 2003]. The results of the logistic models are presented in Table 6. In all the columns the dependent variable is the binary indicator variable of whether a university i offered any MOOCs in academic year t, while all the

Table 5a. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
MOOC exploration	0.070	0.255	0.000	1.000
# of MOOCs offered	0.462	2.754	0.000	54.000
Interactive Tools (IT1, on scale 1-6)	4.113	0.934	1.000	5.700
Online Education Exp. (IT2, on scale 1-6)	4.462	1.344	1.000	6.000
Digital Content (IT3, on scale 1-6)	4.158	1.241	1.000	6.000
Decentralization (on scale 0-14)	0.639	1.771	0.000	14.000
Decrease in applications (Thousands)	− 0.416	1.360	− 8.894	8.286
IT strategic plan	0.675	0.469	0.000	1.000
Faculty per FTE student	0.063	0.036	0.012	0.494
Endowment asset per FTE student (Hundreds of Thousands)	0.798	2.023	0.000	23.987
Percentage of faculty on Tenure/Tenure Track	0.737	0.197	0.000	1.000
Equated 9-month salary, FT faculty (Thousands)	76.279	17.298	40.509	148.403
Admission rate	0.604	0.197	0.064	0.998
Full-time student retention rate	81.320	10.357	45.000	100.000
6-year graduation rate	0.630	0.183	0.118	0.964
Percentage receiving financial aid, FE undergraduate	85.825	13.589	38.000	100.000
In-state tuition (Thousands)	20.648	14.456	0.000	45.580
Out-of-state tuition (Thousands)	25.457	10.470	0.070	45.580
All students, Undergraduate (Thousands)	8.606	8.880	0.234	59.382
All students, Graduate (Thousands)	2.667	3.484	0.000	22.018
Private school	0.554	0.497	0.000	1.000

Notes: Number of observations: 1405. Number of schools: 589.

explanatory variables are lagged for one year. We also include a set of time period (academic year) fixed effects in all models. We use heteroscedasticity robust standard errors clustered by universities in all the models. For brevity, the coefficients of the various school level control variables are suppressed. In column 1 of Table 6, we present the results from a baseline model of pooled logistic regression. To examine the potential moderating effects of decentralization of IT support services and activation triggers, in column 2 we include interaction terms between these two measures and the university's IT capabilities.

Table 5b. Correlations Table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	MOOC exploration	1.00																				
2	# of MOOCs offered	0.61	1.00																			
3	Interactive Tools (IT1)	0.18	0.12	1.00																		
4	Online Edu. Exp. (IT2)	0.09	0.05	0.33	1.00																	
5	Digital Content (IT3)	0.05	0.03	0.45	0.22	1.00																
6	Decentralization	0.11	0.17	0.06	0.12	0.06	1.00															
7	Decrease in App.	−0.13	−0.12	−0.08	−0.07	−0.02	−0.05	1.00														
8	IT strategic plan	−0.09	−0.08	0.09	0.16	0.10	0.02	0.02	1.00													
9	Faculty per student	0.28	0.27	0.09	−0.31	0.01	0.05	−0.13	−0.20	1.00												
10	Endowment per student	0.17	0.18	0.01	−0.40	0.00	−0.03	−0.06	−0.14	0.58	1.00											
11	Tenure/Tenure Track	−0.05	−0.04	0.02	−0.14	0.04	−0.02	0.03	0.05	−0.05	0.02	1.00										
12	9-month salary	0.38	0.31	0.24	−0.11	0.08	0.10	−0.23	−0.12	0.53	0.46	0.10	1.00									
13	Admission rate	−0.24	−0.23	−0.09	0.29	0.00	−0.06	0.21	0.16	−0.48	−0.50	0.00	−0.57	1.00								
14	Student retention rate	0.27	0.22	0.17	−0.33	0.04	0.03	−0.13	−0.15	0.51	0.42	0.11	0.68	−0.54	1.00							
15	6-year graduation rate	0.24	0.21	0.10	−0.43	0.00	−0.05	−0.11	−0.18	0.56	0.47	0.13	0.62	−0.52	0.88	1.00						
16	Pct. financial aid	−0.19	−0.19	−0.19	0.12	−0.06	−0.06	0.10	0.13	−0.29	−0.26	−0.06	−0.55	0.47	−0.44	−0.38	1.00					
17	In-state tuition	0.04	0.06	−0.10	−0.54	−0.11	−0.08	−0.02	−0.16	0.47	0.41	0.00	0.33	−0.41	0.50	0.66	−0.06	1.00				
18	Out-of-state tuition	0.15	0.14	−0.03	−0.52	−0.08	−0.05	−0.09	−0.19	0.53	0.42	0.01	0.49	−0.47	0.63	0.75	−0.21	0.93	1.00			
19	Students, Undergrad.	0.26	0.14	0.30	0.41	0.17	0.17	−0.18	0.04	−0.14	−0.19	−0.05	0.26	0.08	0.10	−0.09	−0.24	−0.55	−0.33	1.00		
20	Students, Grad.	0.42	0.35	0.29	0.35	0.13	0.22	−0.27	−0.03	0.17	−0.06	−0.18	0.51	−0.14	0.26	0.14	−0.27	−0.21	−0.02	0.76	1.00	
21	Private school	−0.05	−0.01	−0.19	−0.46	−0.13	−0.10	0.04	−0.10	0.31	0.30	−0.07	0.08	−0.25	0.28	0.46	0.18	0.91	0.74	−0.65	−0.33	1.00

While the pooled logistic models do not take advantage of the panel data structure of our setting, we explicitly control for time-invariant, unobserved university characteristics by using random effect panel data logistic models, which further decompose the error term into a school-specific component and a population component. We present the results in column 3 (for the main effects) and column 4 (for the interaction effects). For comparison, we also include the results from conditional logit (also known as the fixed-effects logit) models in column 5 (for the main effects) and column 6 (for the interaction effects), which further relax the assumption that the unobserved school effects are orthogonal to the regressors. Because the conditional logit model only uses observations of schools that switched status (schools that offered MOOCs in some years but not others) in the estimation [Baltagi 2008, p.211), the use of such models would result in dropping large number the observations from our sample. This is because, for a large number of schools, the dependent variable does not vary over the years (they either never offered any MOOCs or offered MOOCs consistently in all three years). A Hausman test comparing the conditional logit model (column 5) and random effects logit model (column 3) suggests that differences in coefficients are not systematic ($p = 0.982$). This test provides some evidence that support the orthogonality assumption and justify the use of the random effects logistic model.

Finally, an increasingly popular approach for estimating longitudinal binary response data that accounts for unobserved heterogeneity is the **generalized estimating equations (GEE)** method [Wooldridge 2002]. The coefficients of the GEE estimate describe how the population-averaged response rather than one individual's response is conditioned on the covariates. Instead of attempting to model the within-subject covariance structure, the GEE method treats it as a nuisance and simply models the mean response. In the GEE framework, the covariance structure does not

Table 6. Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	Binary Logistic		Random Effects Logistic		Fixed Effects Logistic		Population-averaged Logistic	
Interactive Tools (IT1)	0.601**	0.409	0.728**	0.463	3.150*	0.000	0.619**	0.366
	(0.297)	(0.314)	(0.291)	(0.384)	(1.731)	(0.682)	(0.272)	(0.275)
Online Edu. Exp. (IT2)	0.343*	0.350	0.570***	0.453	2.191**	0.569	0.473**	0.319
	(0.205)	(0.222)	(0.214)	(0.281)	(0.900)	(0.861)	(0.206)	(0.221)
Digital Content (IT3)	−0.265	−0.249	−0.243	−0.363	−1.776	−0.340	−0.153	−0.260
	(0.173)	(0.195)	(0.161)	(0.224)	(1.173)	(0.479)	(0.116)	(0.168)
Decentralization	0.064	−3.997***	0.089	−4.785***	–	–	0.081	−3.553***
	(0.074)	(1.350)	(0.078)	(1.516)			(0.066)	(1.133)
Decrease in app.	0.021	−0.632	0.085	−0.623	0.158	3.669*	0.092	−0.208
	(0.093)	(0.780)	(0.085)	(1.010)	(0.295)	(2.182)	(0.079)	(0.725)
IT1*decentralization		0.430**		0.479*		0.233		0.332**
		(0.218)		(0.247)		(0.544)		(0.147)
IT2*decentralization		0.421***		0.515**		1.852**		0.400***
		(0.159)		(0.200)		(0.759)		(0.143)
IT3*decentralization		−0.050		−0.031		1.453**		−0.015
		(0.112)		(0.137)		(0.653)		(0.098)
IT1*decrease app.		−0.067		−0.095		−0.772		−0.113
		(0.228)		(0.216)		(0.553)		(0.212)
IT2*decrease app.		0.200*		0.248**		0.317*		0.209**
		(0.110)		(0.117)		(0.181)		(0.104)
IT3* decrease app.		−0.007		−0.035		−0.319		−0.062
		(0.091)		(0.128)		(0.221)		(0.084)
School level controls	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Model fit	Pseudo R2 = 0.4914	Pseudo R2 = 0.5212	Wald chi2(22) = 136.56 Prob > chi2 = 0.0000	Wald chi2(28) = 136.70 Prob > chi2 = 0.0000	Pseudo R2 = 0.814	Pseudo R2 = 0.875	Wald chi2(22) = 166.92 Prob > chi2 = 0.0000	Wald chi2(28) = 183.23 Prob > chi2 = 0.0000
Observations	1,405	1,405	1,405	1,405	158	158	1,405	1,405
Number of schools	589	589	589	589	56	56	589	589

Notes: Robust standard errors in parentheses in all models. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. School level controls include: IT strategic plan, faculty/student ratio, endowment per student, faculty salary, tenured/tenure track faculty ratio, admission rate, student retention rate, graduation rate, pct. of student receiving financial aid, in-state tuition, out-of-state tuition, undergraduate enrollment, graduate enrollment, and private school.

need to be specified correctly to get robust estimates of regression coefficients and standard errors [Gardiner et al. 2009]. We present the regression results of population-averaged panel GEE models with binomial distribution and a logistic link function in column 7 (for the main effects) and column 8 (for the interaction effects) of Table 6.

We find partial support for Hypothesis 1 that educational IT capabilities are associated with MOOC exploration in all the models across different model specifications. Particularly, the results from column 1, 3, 5, and 7 (for the main effects) suggest that two of the three measures of educational IT capabilities are significantly associated with the likelihood that the university will explore MOOCs: the use of Web 2.0, social media, and other interactive tools for educational purposes (IT1), and the school's prior experience with distance education and hybrid teaching (IT2).

The results also suggest that the adoption of e-books and e-textbooks (IT3) is not associated with the probability of MOOC offering. The marginal effects of the estimated coefficients are quite substantial: for example, calculation based on the results from column 7 (the population-averaged panel logistic model) suggest that a unit increase in IT1 (which has a mean of 4.11 and range of 1-5.7) leads to an increase of 85.7% (=exp(0.619)-1) in the probability of offering MOOCs ($p < 0.05$). Similarly, a unit increase in IT2 (which has a mean of 4.46 and range of 1-6) leads to an increase of 60.5% (=exp(0.473)-1) increase in the probability of offering a MOOC ($p < 0.05$). Interestingly, the analyses show that schools with a highly compensated faculty are more likely to offer MOOCs, suggesting a positive relationship between quality of school instructors and early exploration of disruptive technologies.

We also find partial support of Hypothesis 2 under the different model specifications, as the interaction terms of *IT1 * IT decentralization*, and *IT2 * IT decentralization* are both positive and significant in columns 2, 4, and 8. The lack of significance of *IT1 * IT decentralization* in column 6 is likely due to the combination of reduced sample size (the sample is limited to schools that switched status) and limited within-school variations as a result of the use of fixed effect logit model. The results suggest that the contribution of educational IT capabilities on MOOC exploration is significantly moderated by IT support services decentralization. For example, the marginal effect calculations based on column 8 (the population-averaged panel logistic model) show that when IT decentralization is at a low level (10% quantile of the sample, or at IT decentralization = 0), one unit increase in IT1 is associated with 44.2% (=exp(0.366 + 0*0.332)−1) increase in the probability of MOOC exploration (and not significant). However, when IT decentralization is at a high level (90% quantile of the sample, or IT decentralization = 2), a unit increase in IT1 is associated with a 180.1% (=exp(0.366 + 2*0.332)−1) increase in the probability of MOOC exploration ($p < 0.01$). The marginal effect of IT2 is similarly moderated by IT decentralization: when IT decentralization is at a low level (at IT decentralization = 0), one unit increase in IT2 is associated with 37.6% (=exp(0.319)−1) increase in the probability of MOOC exploration (and not significant). However, when IT decentralization is at a high level (at IT decentralization = 2), a unit increase in IT2 is associated with a 206.2% (=exp(0.319 + 2*0.400)−1) increase in the probability of MOOC exploration ($p < 0.01$). Clearly, our regression results are consistent with the theory that stronger educational IT capabilities need to be coupled with flexible social integration mechanism in driving the exploration of IT-enabled innovations.

We find partial support for Hypothesis 3 as well, as indicated by the positive and significant coefficient estimates of *IT2 * Decrease in applications* in column 2, 4, 6, and 8. The results indicate that the contribution of prior experience in e-learning and hybrid learning on MOOC exploration is greater when the school faces a turbulent environment. For example, based on the results from column 8, when a school operates in a stable environment where there is no change in application numbers, a unit increase in IT2 leads to a 37.6% (=exp(0.319)−1) increase in the probability of MOOC exploration (and not significant). However, if the school experiences a drop of 1,000 applications, the same increase in IT2 is associated with 69.6% (=exp(0.319 + 0.209*1)−1) increase in the likelihood of MOOC exploration ($p < 0.01$). However, we do not find that our activation trigger moderates the relationship between the use of social media or Web 2.0 technologies and the exploration of a MOOC. Prior literature has emphasized the differences between **potential ACAP (PACAP)**—the ability to acquire and assimilate knowledge—and **realized ACAP (RACAP)** – the ability to transform and exploit knowledge [Zahra and George 2002]. We conjecture that although activation triggers may induce schools to explore the use of social media and Web 2.0 technologies and enhance its potential ACAP, the conversion of potential ACAP into realized ACAP may depend on other contingent factors. These factors include social integration mechanisms or power

Table 7. Alternative Models and Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Random effects Probit		Survival model		Count model with the number of MOOCs as dependent	
Interactive Tools (IT1)	0.459***	0.287	0.483**	0.375	0.382**	0.190
	(0.175)	(0.235)	(0.224)	(0.265)	(0.159)	(0.331)
Online Edu. Exp. (IT2)	0.334***	0.287*	0.302*	0.327*	0.415***	0.205
	(0.129)	(0.173)	(0.166)	(0.189)	(0.113)	(0.163)
Digital Content (IT3)	−0.154	−0.238*	−0.188	−0.180	0.003	0.115
	(0.096)	(0.137)	(0.126)	(0.150)	(0.087)	(0.088)
Decentralization	0.059	−2.933***	0.056	−2.871***	0.103**	−1.940**
	(0.049)	(0.951)	(0.057)	(0.920)	(0.045)	(0.866)
Decrease in app.	0.043	−0.366	0.043	−0.850	0.092**	−6.956**
	(0.051)	(0.623)	(0.064)	(0.704)	(0.047)	(3.323)
IT1*decentralization		0.287*		0.327*		0.379*
		(0.148)		(0.190)		(0.195)
IT2*decentralization		0.319**		0.270**		0.137*
		(0.127)		(0.112)		(0.077)
IT3*decentralization		−0.015		−0.016		−0.122*
		(0.085)		(0.083)		(0.062)
IT1*decrease app.		−0.059		0.029		0.205
		(0.130)		(0.151)		(0.163)
IT2*decrease app.		0.152**		0.142**		1.604***
		(0.072)		(0.072)		(0.575)
IT3* decrease app.		−0.238		0.015		−0.007
		(0.137)		(0.078)		(0.263)
School level controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	N/A	N/A	yes	yes
Model fit	Wald chi2(22) = 119.11 Prob > chi2 = 0.0000	Wald chi2(28) = 112.48 Prob > chi2 = 0.0000	LR chi2(20) = 291.69 Prob > chi2 = 0.0000	LR chi2(26) = 311.08 Prob > chi2 = 0.0000	Wald chi2(22) = 484.93 Prob > chi2 = 0.0000	Wald chi2(28) = 724.64 Prob > chi2 = 0.0000
Observations	1,405	1,405	1,405	1,405	1,405	1,405
Number of schools	589	589	589	589	589	589

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. School level controls include: IT strategic plan, faculty/student ratio, endowment per student, faculty salary, tenured/tenure track faculty ratio, admission rate, student retention rate, graduation rate, pct. of student receiving financial aid, in-state tuition, out-of-state tuition, undergraduate enrollment, graduate enrollment, and private school.

relationships – possibly through some complex three-way complementarities – leading to the lack of significance of *IT1 * Decrease in applications*.

5.2 Alternative Models and Measurements

We further probe the robustness of our findings by relaxing the assumptions of our empirical models and exploring alternative model specifications or different measures of the key variables. We present the results of these robustness tests in Table 7. First, we test the validity of our findings by examining alterative assumptions about the distribution of the error term: instead of assuming a binomial distribution of the errors, we use a normal distribution of the errors and run the panel data random effects Probit models. The results are presented in column 1 (for the main effects) and column 2 (for the interaction effects) of Table 7. We find the estimates are similar to those resulted from the panel data logistic models.

Second, we use hazard models as an alternative to analyze the role of educational IT capabilities, the decentralization of IT support services, and activation triggers in determining the time to event—in this case, the offering of MOOCs. *Hazard models* (also referred to as *survival, duration, or event history model*) are useful in our setting because they directly model time to event, allow for the occurrence of multiple hazard events (e.g., under our context, a university may offer MOOCs multiple times during the sample period), and provide an approach to address the incomplete observation of survival times when censoring occurs [Hosmer et al. 2008]. Specifically, we chose the Cox proportional hazard model as our model specification. This model is a semi-parametric specification that makes no assumption of the functional form of the baseline hazard and assumes that covariates multiplicatively shift the baseline hazard function. We present the results from the Cox proportional hazard models in column 3 (for the main effects) and column 4 (for the interaction effects) of Table 7. Again, we find our results are robust to this alternative specification.

Finally, we try a different measure of the dependent variable: instead of using a binary indicator of MOOC exploration, we use the number of MOOC offerings by university i in academic year t. Since this measure represents count data, we employ panel count data models and specify a negative binomial distribution with log link function, again estimating the model using population-averaged GEE techniques. We present the results in column 5 (for the main effects) and column 6 (for the interaction effects) of Table 7. We note that the results are consistent with what we find when using binary exploration indicators as the dependent variable. In general, we find robust evidence that supporting the hypothesis that stronger educational IT capabilities (e.g., the use of Web 2.0 and social media, or prior experience in distance learning) lead to a higher probability of exploring MOOCs, and the positive relationships are significantly stronger when they are coupled with a higher level of decentralization of IT support services. In addition, the relationship between prior experience in distance learning and MOOC exploration is positively moderated by the drop in application numbers. However, our results consistently reveal that the adoption of digital content shows no effect in determining MOOC exploration.

5.3 Endogeneity of Educational IT Capabilities

While we have demonstrated the robustness of our findings across various model specifications, another concern over the validity of our results is the degree to which our measures of educational IT capabilities are endogenous, possibly due to unobserved school heterogeneities. Although we have controlled for the effects of many confounding factors such as the quality of instructors (through faculty salary), the cost of attending the school (through tuition) or its selectivity of students (through admission rate), there may still be unobserved school-level characteristics that are correlated with educational IT capabilities. We have taken several measures to address these endogeneity concerns.

First, we try to control for unobserved school reputation explicitly, by using an alternative data source other than IPEDS: the best colleges ranking data compiled by the *US News and World Report*. The *US News and World Report* ranking data is widely used by potential applicants when they apply for college, and by university administrators for benchmarking and peer comparisons. We expect this variable to pick up any reputation effects that are not completely captured by the set of institutional characteristics that are already included in our model. The *US News and World Report* published this ranking data for national universities, national liberal arts colleges, and regional universities separately. To allow for a parsimonious model, we create a series of categorical variables that incorporate reputation effects, with the following categories: 1) national universities, ranked 1-50; 2) national universities, ranked 51-100; 3) national universities, ranked 101-150; 4) national universities, ranked after 150; 5) national liberal arts colleges, ranked 1-50; 6) national liberal arts colleges, ranked 51-100; 7) national liberal arts colleges, ranked 101-150; 8) national liberal arts colleges, ranked after 150; and 9) regional universities and colleges. We add the set of categorical variables into our model using a panel data random effects logistic regression, and present the results in column 1 (the main effects) and column 2 (the moderation effects) of Table 8. We note that all the major findings are robust to unobserved university reputation effects.

Second, we aim to further control for unobserved school heterogeneities by incorporating the role of different types of schools. For example, research schools may have a greater incentive to explore MOOCs because their faculty members may want to infuse their latest research findings into teaching and use MOOCs as a channel to add to the impact of their research. The Carnegie Classification of Institutions of Higher Education is a framework for classifying colleges and universities in the United States, and is often used to identify groups of roughly comparable institutions. We add the set of categories from Carnegie classifications into the panel data random effects logistic regression, and present the results in column 3 (the main effects) and column 4 (the moderation effects) of Table 8. Again, all the findings are not significantly changed.

Third, the incentive for MOOC exploration may also depends on the degree of competition that a school is experiencing. Although the universities and colleges in our sample are not-for-profit organizations, they compete with each other on many dimensions. For example, a school in an urban setting with many peer schools competes for students, especially for those who want to study in the geographical area. They also compete in terms of recruiting the best talent to fill faculty positions and to perform instructional and research duties. In addition, schools compete with one another for potential employers of their graduating students and external research funding opportunities. Some of these factors may also influence MOOC exploration decisions: for example, a university that has a monopoly in its local market may have little incentive to offer MOOCs. To control for its potential effect, we create a variable that represents the number of peers a university competes with in its local market. Particularly, for each university in our sample, we find the metropolitan area—defined as **CBSA**, or **core based statistical area**—in which the university is located. The variable is defined as the number of universities (other than the focal institution) that are in the same Carnegie classification and operate in the same CBSA as the focal school. The results of the random effect logit models that incorporate the competition effect are presented in column 5 and 6 of Table 8, which are consistent with earlier findings.

Lastly, while it is impossible to control for all the unobserved heterogeneities that could be correlated with our measure of educational IT capabilities, we use **instrumental variable (IV)** methods to address the remaining endogeneity concerns. The ideal set of IVs should satisfy: 1) correlated with educational IT capabilities, and 2) uncorrelated with the error term such as school reputation. We find two such instruments for a school's educational IT capabilities – these variables reflect the characteristics of IT workers in the labor market where the school is located. We define the labor market at the CBSA level, consistent with the unit of survey conducted by the **Bureau of Labor Statistics (BLS)**. The first instrument is the number of jobs (employment) in computer-related occupations[5] per 1,000 jobs in the metropolitan area where the school is

[5]According to BLS's classification of occupations, computer-related occupations include computer systems analysts (15-1121), computer programmers (15-1131), application software developers (15-1132), system software developers (15-1133), database administrators (15-1141), network and computer systems administrators (15-1142), computer support specialists (15-1150), information security analysts, web developers, and computer network architects (15-1179), and all other computer occupations (15-1799).

Table 8. Endogeneity of Educational IT Capabilities – School Heterogeneities

	(1)	(2)	(3)	(4)	(5)	(6)
	Controlling for US News Ranking		Controlling for Carnegie Classifications		Controlling for Local Competition	
Model	Random Effects Logistic Model					
Interactive Tools (IT1)	0.705**	0.474	0.727**	0.467	0.696**	0.455
	(0.294)	(0.391)	(0.287)	(0.404)	(0.279)	(0.384)
Online Edu. Exp. (IT2)	0.513**	0.419	0.437*	0.318	0.537***	0.449
	(0.240)	(0.328)	(0.231)	(0.332)	(0.205)	(0.281)
Digital Content (IT3)	−0.237	−0.364	−0.221	−0.376	−0.227	−0.352
	(0.164)	(0.231)	(0.157)	(0.243)	(0.155)	(0.226)
Decentralization	0.082	−4.641***	0.075	−5.149***	0.079	−4.743***
	(0.080)	(1.544)	(0.074)	(1.582)	(0.075)	(1.518)
Decrease in app.	0.083	−0.659	0.096	−0.317	0.083	−0.637
	(0.087)	(1.050)	(0.083)	(1.060)	(0.082)	(1.013)
IT1*decentralization		0.452*		0.486*		0.474*
		(0.251)		(0.248)		(0.247)
IT2*decentralization		0.509**		0.577***		0.514**
		(0.203)		(0.211)		(0.200)
IT3*decentralization		−0.028		−0.028		−0.034
		(0.138)		(0.145)		(0.137)
IT1*decrease app.		−0.089		−0.134		−0.094
		(0.219)		(0.222)		(0.217)
IT2*decrease app.		0.249**		0.220*		0.246**
		(0.123)		(0.126)		(0.117)
IT3* decrease app.		−0.035		−0.027		−0.031
		(0.130)		(0.135)		(0.128)
US News Ranking	yes	yes	–	–	–	–
Carnegie Classifications	–	–	yes	yes	–	–
Local Competition	–	–	–	–	−0.026	−0.021
					(0.052)	(0.060)
School level controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Model fit	Wald chi2(30) = 129.23 Prob > chi2 = 0.0000	Wald chi2(36) = 129.91 Prob > chi2 = 0.0000	Wald chi2(35) = 132.45 Prob > chi2 = 0.0000	Wald chi2(41) = 133.23 Prob > chi2 = 0.0000	Wald chi2(23) = 136.87 Prob > chi2 = 0.0000	Wald chi2(29) = 136.91 Prob > chi2 = 0.0000
Observations	1,405	1,405	1,405	1,405	1,405	1,405
Number of schools	589	589	589	589	589	589

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. School level controls include: IT strategic plan, faculty/student ratio, endowment per student, faculty salary, tenured/tenure track faculty ratio, admission rate, student retention rate, graduation rate, pct. of student receiving financial aid, in-state tuition, out-of-state tuition, undergraduate enrollment, graduate enrollment, and private school.

Table 9. Endogeneity of Educational IT Capabilities - Instrumental Variables Tests

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Linear Probability Models			Probit Models		
	Un-instrumented	IV tests		Un-instrumented	IV tests	
		First stage	Second stage		First stage	Second stage
IT labor supply		0.018***			0.018***	
		(0.003)			(0.004)	
IT labor wage (Thousands)		−0.019***			−0.015***	
		(0.004)			(0.005)	
IT capabilities	0.015**		0.130*	0.384***		1.197***
	(0.007)		(0.067)	(0.128)		(0.181)
Decentralization	0.003	0.043***	0.009	0.033	0.042***	0.013
	(0.004)	(0.013)	(0.006)	(0.037)	(0.013)	(0.032)
Decrease in app.	0.002	−0.055***	−0.010	0.006	−0.055***	−0.021
	(0.006)	(0.017)	(0.007)	(0.043)	(0.017)	(0.044)
School level controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Model fit	R-squared = 0.2837	R-squared = 0.2861	Pseudo R2 = 0.4893	Wald chi2(20) = 154.00 Prob > chi2 = 0.0000		
Observations	1,405	1240	1240	1,405	1240	1240
Number of schools	589	521	521	589	521	521

Notes: In the IV regressions, 165 observations are dropped due to the availability of labor supply and labor wage. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. School level controls include: IT strategic plan, faculty/student ratio, endowment per student, faculty salary, tenured/tenure track faculty ratio, admission rate, student retention rate, graduation rate, pct. of student receiving financial aid, in-state tuition, out-of-state tuition, undergraduate enrollment, graduate enrollment, and private school.

located. This variable reflects the ease with which a school is able to find qualified IT professionals in the local labor market to fill its IT staff. The second instrument is the median annual wage of computer-related occupations in the local market. The increase in IT labor price is associated with a school's higher costs of delivering IT service, and therefore inhibits the development of IT capabilities. We obtain these two variables from the BLS Occupational Employment Statistics database. We expect that the first instrument, the amount of local IT labor supply, to be positively correlated with educational IT capabilities while the second instrument, the wage of IT labor, to be negatively correlated with educational IT capabilities. Because these two instruments are measures of local labor markets, there is no reason to believe that they should be directly correlated with unobserved school characteristics such as a school's reputation, and therefore serve our purpose as valid IVs.

Because there are no well-developed IV methods for binary logistic regression, we employ two alternative methods: the IV methods for **linear probability models (LPM)**, and the IV method for binary Probit models [Newey 1987]. In addition, to avoid the difficulty of instrumenting for all three dimensions of educational IT capabilities (IT1, IT2, and IT3) separately, we create a single index of educational IT capabilities by combining IT1 and IT2,[6] the two dimensions that have been shown to be significantly associated with MOOC exploration. In column 2 and 3 of Table 9 we present the result from the IV regression for the linear probability model, using a two-stage

[6]The results are also consistent when we combine IT1, IT2 and IT3 into a single index of educational IT.

least square (2SLS) estimation. For comparison purposes, we also present the un-instrumented LPM results in column 1.

The first stage results (in column 2) show that both IT labor supply and IT labor wage are significantly associated with educational IT capabilities. As we expected, local IT labor supply is positively correlated with a school's educational IT capability ($p < 0.01$), and IT labor wage is negatively associated with educational IT capability ($p < 0.01$), suggesting that our IVs are not weak. This is confirmed by the weak identification test: the Kleibergen-Paap rk Wald F statistic has a value of 15.68, which is greater than the rule of thumb value of 10, and also greater than the Stock-Yogo critical value at 15% maximal IV size (11.59). The Hansen J statistic has a value of 2.38, which cannot reject the null that the overidentification constraints are valid ($p > 0.1$). In the second stage (column 3), the coefficient estimate of IT capability is positive and significant, and the marginal effect after the correction for endogeneity appears to be larger, suggesting that presence of endogeneity issues is likely to cause a downward bias. In column 5 and 6 of Table 9, we present the results from an IV Probit model. For comparison, the un-instrumented Probit model result is presented in column 4. Similar to the results from the LPM, we find that in the first stage, both IT labor supply ($p < 0.01$) and IT labor wage ($p < 0.01$) are significantly associated with educational IT capability, and in the second stage, IT capability has a positive and significant impact on MOOC exploration. Overall, the results from the IV regressions show that our findings are robust to the endogeneity issues, and the presence of endogeneity likely leads to more conservative estimates of the effect of educational IT capabilities on MOOC exploration in the baseline models.

6 CONCLUSIONS AND DISCUSSION

6.1 Summary of Findings and Theoretical Contributions

We have constructed a novel dataset from several sources to examine how prior educational IT capabilities, social integration mechanisms, and activation triggers jointly influence universities' decisions to explore the IT-enabled innovation of Massive Open Online Courses. Consistent with the theory of absorptive capacity [Cohen and Levinthal 1990], we show that such decisions are path-dependent: schools that have developed stronger prior educational IT capabilities are more likely to become a MOOC creator. In addition, we find that social integration mechanism plays an important moderating role, and educational IT capabilities only have a positive effect when they are coupled with decentralized provision of IT supporting services. This result highlights the role of complementary organizational capabilities in shaping IT-related absorptive capacity [Jansen et al. 2005]. Finally, schools facing an adverse environment, such as those experiencing a decline in student applications, are more likely to leverage their IT capabilities to explore innovations such as MOOCs. Our research therefore deepens the understanding of how IT-related factors—including investments made by universities in creating both IT knowledge and organizational structure—determine their reaction to emerging digital innovations that may potentially disrupt and transform higher education, and how such relationships are conditional on the environment in which they operate.

Theoretically, our work makes several important contributions. First, with the proliferation of cloud computing and the Software-as-a-Service model, many schools nowadays outsource a large part of their IT operation and are increasingly relying on external vendors in managing their IT infrastructure. While it helps improve efficiency and reduce initial deployment costs, such service-centric application may constrain the in-house accumulation of business-IT knowledge and lead to a potential danger of hollowing out of IT human capital [Levy and Murnane 2005]. Our empirical analyses suggest that even when the infrastructure of digital innovations can be acquired with relative ease, the adoption and effective use of them still require IT-related absorptive capacity [Roberts et al. 2012], which is dependent on historical IT investments. Therefore, path dependency is likely to continue to play a role in future waves of digital innovation.

Second, we extend prior IS research on absorptive capacity that almost exclusively model ACAP as a function of prior related knowledge but has so far overlooked the role of a variety of boundary conditions. Our results suggest that in a university with faculty who have highly specialized knowledge, co-locating IT support staff with the faculty enhances the creation of IT-related absorptive capacity, highlighting the role of social integration mechanisms. This finding also echoes earlier studies that stress the role of complementary organizational capabilities in developing absorptive capacity [Jansen et al. 2005; Van Den Bosch et al. 1999]. Our interpretation is that in a highly decentralized, autonomous organization with less hierarchical control, decentralized social integration mechanisms form the basis of *coordination capabilities* [Malone and Crowston 1994] that enhance the management of the dependence among faculty and IT professionals, bringing together different sources of expertise. These mechanisms also help develop *socialization capabilities* [Van Den Bosch et al. 1999] that offer organizational members a consistent set of beliefs and produce shared ideology. In this way, decentralized IT support service enhances knowledge exchanges within academic units and amplifies the effect of prior knowledge. We also show that in a university context, the activation triggers that often lead to heightened organizational learning intensity may differ from those associated with for-profit organizations. For example, instead of declining profitability or sales revenue, the triggering events are more likely to be associated with non-pecuniary environmental changes, such as the loss of reputation or attractiveness perceived by the community that the university serves.

Finally, our work adds evidence to recent IT value research that focuses primarily on the direct return of IT investments [Brynjolfsson and Hitt 2000; Brynjolfsson and Milgrom 2012; Melville et al. 2004]. Our finding suggests that, similar to R&D investments [Cohen and Levinthal 1990], IT investments—particularly those in IT human capital—serve two purposes: they not only create value for the investing organization directly through the use of the systems, but also indirectly contribute to the development of IT-related absorptive capacity that helps an organization to identify, assimilate, and exploit knowledge from its external environment. While most of the studies in this research stream have focused on firm productivity or efficiency gains, we present evidence from an alternative perspective—IT investments have important implications for organizational learning capabilities and the ability to explore emerging technological innovations, therefore linking the role of IT capabilities with intangible benefits [Kleis et al. 2012; Saunders and Brynjolfsson 2016].

6.2 Practical Implications

Our work also provides practical guidance for education professionals. MOOCs are a potentially transformational and disruptive technology for universities. They are a part of a broader set of technologies that universities can use to create blended and flipped classes as well as online classes that feature synchronous interactive sessions. However, there are some fundamental differences between MOOCs and other IT-enabled distance learning: for example, the network effects and scale economies associated with MOOCs are greatly amplified, which imply that early entries may establish some degree of first-mover advantage. Our results suggest that not all schools are on an equal footing – despite the fact that most MOOCs are delivered through external IT platforms, the exploration of MOOCs remains path-dependent, and strong educational IT capabilities, particularly those embedded in human IT capital and intangible assets, cannot be acquired overnight. First-mover advantages are most likely to be harvested by schools that already possess such IT capabilities. These institutions are most likely to become disruptors that threaten the survival of schools that remain solely as content consumers of MOOCs.

For schools that want to embrace the emerging MOOC innovation, our research points to the need for prioritizing their IT capability building. Among a broad set of educational technologies, the use of social media, Web 2.0 tools, and other interactive learning tools should receive greater attention. They also need to experiment with various types of e-learning and hybrid learning to acquire insights and gain experiences. Furthermore, they should acquire organizational capabilities that are compatible with advanced IT capabilities and build structures and social mechanisms that facilitate knowledge exchange and integration in a decentralized fashion. Although these observations are obtained from the specific case of MOOCs, they are likely to be applicable to the exploration of future technology-enabled innovations in higher education as well.

In addition, due to organizational inertia [Kelly and Amburgey 1991], many schools may suffer from resistance to change and therefore will be slow in exploring innovative ways of teaching that harness the power of the latest technological progresses. Our findings regarding activation triggers suggest that these schools may consider intentionally creating a sense of crisis as a strategic way of motivating more intensive organizational learning from the external environment. Combined with IT human capital investments, this strategy may help schools overcome their inertia and compete in the future in an increasingly interconnected environment.

It is clear from our observation and personal experience that MOOCs require extensive resources to develop. Flagship public universities and elite private schools have more resources to invest in innovations like MOOCs, and they have existing IT capabilities to support the faculty. MOOCs may also have strong network effects [Parker and Van Alstyne 2005]: for example, as the number of registrants for a course increases dramatically, it is easier for the learners to find classmates and join virtual discussion forums and local study groups, to access learning materials and study guides accumulated by past students on wikis and blogs, and to seek peer assessments, and so on. As a result, first mover advantages associated with MOOCs and other innovations may create a "winner take all" setting that further places non-elite schools at a disadvantage. As various programs featuring MOOCs become more popular, smaller schools with limited resources are at risk of missing out on a major innovation in higher education, especially if they are tuition-dependent and lose students who find MOOC-based programs more attractive. Under such situations, our study highlights the need for MOOC platforms to offer customized supporting services beyond IT infrastructure to better help those institutions catch up with the accumulation of business-IT knowledge and the acquisition of relevant IT capabilities.

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