Money, Control, and Prestige: A Study of the Determinants Associated with the Adoption Rates of Massive Open Online Courses (MOOCs) in American Postsecondary Education

[Student name removed]

Abstract

Colleges and universities have struggled to provide access to affordable and high quality education amidst decreases in state appropriations, increases in student enrollment, and greater accountability pressures. This has made finding a solution that is politically and economically viable an urgent policy matter. However, higher education is an extremely stable system and transformative change has not been well documented. Massive Open Online Courses (MOOCs) carry the potential to be a significant disruptor of traditional higher education, but the patterns of institutional adoption using theoretical or empirical approaches have not been studied well. This paper assesses when and what factors contributed to the early adoption of MOOCs. Using hazard models, the results suggest that controlling for time, prestigious and wealthy colleges have an estimated risk about 2.3 times higher of adopting MOOCs than poor or low-prestige schools. MOOCs were most likely to be adopted during 2013.

Comment [AJB1]: If possible, in an abstract state the sample size and dataset.

Comment [AJB2]: Out of how many years? This is important context for the abstract.

Introduction

In 2011, the introduction of Massive Open Online Courses (MOOCs) changed the landscape of higher education. Politicians and journalists alike published article after article about the ways this innovation would quickly reconfigure the traditional structure and delivery of higher education such that it would be more affordable, at equal or better quality as face-to-face and, most promising, scalable. The potential of MOOCs captured significant attention due to the financial and structural problems confronting the whole of higher education (i.e. two-year, four-year, public and private alike). Colleges and universities have struggled to provide access to affordable and high quality education amidst decreases in state appropriations, increases in student enrollment and greater accountability pressures, which has made finding a solution that is politically and economically viable an urgent policy matter. However, higher education – like many well-established organizations – has been traditionally reticent to undergo large-scale transformation. When change does occur, valuable opportunities to investigate what promotes or obstructs institutional change and the implications of change emerge.

MOOCs are traditional brick-and-mortar courses converted to an online platform that are free and open to the public. Students can take courses from highly selective colleges and universities such as Harvard or Stanford without having to be Harvard or Stanford students or pay Harvard or Stanford prices. Though initially many universities did not offer credit for MOOCs, such that they offered little in the way of ameliorating the credential crisis; gradually, more and more colleges and universities have begun to offer credits for their courses or at least certificates verifying that the student has in fact completed the course. In some cases, states have even begun to require colleges and universities to accept MOOCs for credit when students apply and enroll.

Comment [AJB3]: Citation needed.

Comment [AJB4]: If you’re going to use “article after article” you need to back that up with a few article citations.

Comment [AJB5]: Citation needed.

Comment [AJB6]: Citation needed

Comment [AJB7]: Citation needed

Comment [AJB8]: Citation needed

Comment [AJB9]: Citation needed

Comment [AJB10]: Citation needed

Few innovations in higher education have garnered such attention or appeared to expand as rapidly and with as much penetration as MOOCs. By winter of 2011, less than one year after its launch, Coursera, a for-profit start-up founded by professors from Stanford University, had enrolled over 1.7 million students in more than 200 courses from 30 plus universities. By fall of 2012, edX the joint start-up from MIT and Harvard registered more than 370,000 students in its first official course (Pappano, 2012; Roth, 2012). Dr. Anant Agarwal, the president of edX, predicted that in just one year, campuses would award students credit for edX certificates and eventually treat MOOC certificates as they currently treat AP coursework (ibid). At the close of 2015, more than 35 million students had signed up for at least one MOOC since 2011 (Shah, 2015) and more than 550 colleges and universities world wide had begun to offer their own MOOCs via one of the emergent platform providers.

However, while advocates laud the creation and growth of MOOCs, the goals of the expansion oftentimes conflict with traditional higher education values, standards, and practices. Although MOOCs portend to decrease costs and improve accessibility, scalability, and quality, they could also destabilize higher education, which could be positively or negatively consequential. As education becomes more widely available through the Internet and other online sources, it becomes increasingly detached from the physical university. Researchers commonly describe this phenomenon as “academic unbundling” or segmentation of higher education (Bowen, 2015; Selingo, 2013; Wellen, 2013). To some critics, the advent of MOOCs represents a cleavage of instruction from the physical campus, undermining the traditional stable and closed nature of higher education, which are characteristics we as a society associate with legitimate learning. Critics are also wary that MOOCs strengthen the relationship between the market and the academy, dissolving the benefits associated with a free and unassociated space

Comment [AJB11]: Citation needed

Comment [AJB12]: Citation needed

Comment [AJB13]: Good! Yes. Do this for all main points throughout.

Comment [AJB14]: Citation needed

Comment [AJB15]: Citation needed

Comment [AJB16]: Citation needed

Comment [AJB17]: Citation needed

Comment [AJB18]: Citation needed

for learning and possible fueling predatory practices that negatively affects students. Such partnerships with the private sector have already led to several unintended consequences. For example, for-profit colleges, which expanded rapidly to fill the demand for college degrees, have recently been under intense federal investigation to look into allegations of deceptive or unfair practices around the market, advertising, sales and services that they provide (Smith, 2015). In the non-profit world, the replacement of public dollars by private dollars in the wake of decreased state appropriations has meant a shrinkage of programs that are not able to be self-sufficient (e.g. the humanities) and/or increased partnerships with laboratories or corporations that oftentimes fund research departments conditional on the corporation's research agendas.

Comment [AJB19]: Citation needed

Comment [AJB20]: Citation needed

Comment [AJB21]: Citation needed

On the one hand, higher education must innovate to address the fundamental problem of too little access to affordable higher education. On the other hand, higher education is a well-established organization that tends to resist change given that it has survived well in its current state and structure until now. Still, the rapid expansion of MOOCs has signaled an interesting ripple in the well-entrenched and highly resistant institution. However, research on change and diffusion of innovation in higher education is stark, and thus far provides only limited intelligence on the underlying reasons why some colleges and universities undergo non-incremental change, while others do not. The objective of this paper is to assess when and what factors contributed to the early adoption of MOOCs. The findings of this paper will contribute to a larger project on the underlying political and economic reasons underpinning change – either transformative or incremental – in higher education

Comment [AJB22]: Citation needed

Background and Conceptual Framework

The central question asked in this paper is to what extent are postsecondary rates of adoption for MOOCs related to prestige, wealth, and whether the college is publicly or privately

Deleted: a function of

controlled when controlling for the influences of time? The sections below first discuss the theoretical framework that shapes this question and then summarizes the available literature on my primary variables of interest and important characteristics that influence innovation in higher education.

Context and Theoretical Literature

Political scientists have identified two main principles that drive the adoption of a new program or policy: *internal determinants* and *diffusion* (Berry & Berry, 1990, 2014). Internal determinants are political, economic, and social factors that move an organization to innovate. Diffusion of an innovation occurs when it is “communicated through certain channels over time among the members of a social system” (Rogers, 1983, p. 5). Hence, mechanisms of diffusion are interorganizational. Examples of common mechanisms of diffusion are *normative pressures* (i.e., an institution adopts a policy because many organizations are adopting it); *imitation* (i.e., an institution adopts a policy because the perceived leader adopted it); and *competition* (i.e., an institution gains an economic advantage over competitors if it adopts a policy) (Berry & Berry, 2014; DiMaggio & Powell, 1983).

Diffusion scholars employ statistical models that use mechanisms of communication to justify why institutions emulate other institutions when adopting a policy. The leader-laggard model assumes that certain institutions are leaders and that other institutions emulate them. This model incorporates multiple mechanisms; it makes the assumption that leadership is regional or national, if appropriate; and it assumes that the jurisdiction will take cues from one or more pioneers in its region when deciding to embrace a policy (Grupp & Richards, 1975; Rogers, 1983; Walker, 1969). This paper employs the leader-laggard model to frame the discussion and to select the internal determinants and associated mechanisms to estimate the odds that an institution will adopt a MOOC at a given point in time.

Comment [AJB23]: Nice. Well-argued.

Previous Literature on Innovation in Higher Education

Diffusion research was popular in the 1970s and 1980s, but has declined in recent years. Early research focused primarily on using political and economic theories to support the notion that government deregulation would increase institutional innovation (Kerr, 1982; Vught, 1989). Scholars of this era argued that institutions were significantly more motivated to innovate when integrated with the market instead of being politically integrated—or that the more deregulated and autonomous an institution is, the more likely it is to interact with the market for revenue and motivated to innovate. While the market incentivizes private or more autonomous institutions to innovate, politically integrated institutions (e.g., public institutions highly dependent on state funding) face greater bureaucratic barriers, have less efficient operations, and have closed collections of interest groups (Dill, 1997, 2003; Ehrenberg, 2006; Kelly & Hess, 2013). However, some scholars have questioned the benefits of a devolved government. Mettler (Mettler, 2014) recently argued that political gridlock and plutocracy amounted to neglect of the less-selective, non-profit institutions which historically have been the most accessible and affordable of the higher education system. Stricken institutions responded by increasing their prices and restricting admissions to stay afloat. This suggests that reducing government oversight imperils institutions by limiting their ability to effectively act on problems of access, quality, and affordability.

In the late 1980s, declines in state funding coupled with increased demand for higher education prompted many researchers to examine the impacts of decreased funding on access and student outcomes in public higher education. According to the American Council on Education, between 1980 and 2011, all but two states reduced their financial support anywhere from 14.8 percent to 69.4 percent (Mortenson, 2012). Institutions primarily responded to this decrease in state funding by privatizing; they raised tuition levels, partnered more often with the private sector, and restricted programs and courses that were no longer self-sustaining (Slaughter & Leslie, 1997; Slaughter & Rhoades, 2004). However, both public and private institutions have increasingly commercialized their services and products to attract more private-sector revenue (Bok, 2009; Kezar, 2004; Marginson, 2006; Slaughter, 2004). One example of this commercialization is the rise of *learning management systems* (LMS). LMSs are software applications built by the private sector and in their simplest form deploy trainings and track results. Coursera, for example, one of the biggest for-profit providers of MOOCs, is an LMS. These data suggest it is not clear whether public or private colleges and universities would be more likely to innovate compared to the other.

Knowledge about the expansion of MOOCs is underdeveloped. The majority of MOOCs research focuses on the impacts on student learning. Generally, they find low-income and low-performing students are less likely to benefit from online courses compared with better prepared students (Glance, Forsey, & Riley, 2013; Jaggars, 2014). Of the work that examines institutional implementation or adoption of MOOCs, none to my knowledge have used empirical or theoretical frameworks to examine why or when colleges and universities decide to adopt MOOCs (Bowen, 2015; Christensen, 2015; Selingo, 2013). Instead, most of these works advocate for innovation as a solution to the higher education crisis. However, the lack of theory or empirical research overlooks the institutional implications of such rapid adoption, including whether adoption results in the intended outcomes such as increased access to higher education or consequences associated with large-scale institutional innovation. Only a few studies have explored why some institutions adopt MOOCs while others do not (Hollands & Tirthali, 2014;

Yuan & Powell, 2013). Hollands and Tirthali (2014) found that institutions adopt MOOCs to maintain brand recognition, improve institutional efficiency, and increase revenue. A national survey by Allen and Seaman (2013) showed that public universities were more likely to offer MOOCs than were private and for-profit schools, which were more likely to be in the planning stages; that large universities (with more than 15,000 students) were more likely to offer MOOCs; and that research/doctoral universities were almost twice as likely as other institutions to adopt MOOCs.

Finally, innovation has also been associated with larger organizations that tend to have acquired more wealth and legitimacy and which are therefore less risk averse than organizations that may not be able to recover well from negative impacts associated with risky and expensive innovations (Rogers, 1983). Four-year institutions have also historically undergone larger transformations earlier than two-year institutions for a variety of reasons including relative differences in funding sources and amount of funding as well as differences in the types of students served and mechanisms of serving them (Altbach, Gumport, & Berdahl, 2011).

The literature loosely connects declining funding, increasing privatization, and disruptive innovation but so far there is no conclusive evidence of a precise link. These limitations make it difficult to pinpoint which factors enable (or limit) innovation, especially in institutions that are widely disparate in terms of funding, government control, and selectivity. What’s more, there may be unintended consequences (positive or negative) which stem from the predictors and mechanisms of diffusion that researchers and policymakers are unaware of and not attending to which affect the effectiveness of any given higher education innovation.

Data and Methods

Data

For this study, I created a new data set that combines data from the Institutional Postsecondary Educational Data System (IPEDS) with data from a website that aggregates the data for MOOCs (Class Central via www.class-central.com). IPEDS, sponsored by the U.S. National Center for Educational Statistics (NCES), is a publicly available longitudinal data set with institutional data for more than 7,000 colleges and universities in the United States. I utilize IPEDS survey data from several files, including the admissions, institutional characteristics, fall enrollment data, and graduation data. Class Central provides an index of most of the MOOCs offered worldwide since their first occurrence in 2011. The data I use from this site include course name, course description, course subject, course dates, course instructor, length of course, university or college that provides the course, and name of the technical platform provider or LMS (such as Coursera, edX, canvas.net, etc.). To collect these data, I used a data crawler called IMPORT.io which is a tool that crawls a website that contains the desired data not readily exportable to a dataset and processes it to be easily read as a data file. The researcher "trains" the crawler to college the desired data and then runs it to collect the data, which results in a data set. To ensure the reliability of the data, I interviewed the founder and CEO of Class Central, Dhawal Shah, and took a random sampling of courses to cross-examine them with the provider and institution websites. I then merged the two data sets using institutional names as the common denominator.

Comment [AJB24]: Need to cite the datasets directly.

Comment [AJB25]: Citation needed

Comment [AJB26]: You mean as the key variable to match. Common denominator infers that you're doing some kind of division.

The analytic sample, or risk set, includes n=3,825 nonprofit, Title IV–eligible two- and four-year institutions in the United States. The academic years examined include 2010–11 through 2014–15. Therefore, the number of periods examined is four and the number of total events included equal 133. I excluded international colleges and universities, which are subject to different political and economic influences as well as university systems that adopted MOOCs because they have different administration concerns that cannot be captured in my data set. I also excluded for-profit colleges because as of March 2014, there was only one for-profit that had adopted a MOOC in the dataset.

The primary independent variables include a log transformed measure of the college or university's yearly cash flow (*lncashflow*), which is calculated from total assets minus total liabilities, prestige a binary variable coded 1 for colleges with high levels of prestige approximated by using the Carnegie rankings (*prestige)*[1] and *public,* a binary variable coded 1 for public institutions. My primary dependent variable is a binary variable for MOOC adoption (1= yes).

Time invariant control measures include whether the institution is a four-year institution (1 = four-year, 0 = 2year) and the institutional size (1 = more than 10,000 students, 0 = less than 10,000 students).

Missing data were accounted for using pairwise deletion in order to preserve data in the regression analyses.

Empirical Strategy

This paper employs a discrete time hazard model to statistically explore the adoption and diffusion of MOOCs. The end result is a "hazard rate," the dependent variable, which comes from administering a logistical regression. EHA is beneficial for several reasons. First, unlike ordinary least squares (OLS), EHA accounts for time invariant and time-varying covariates.

[1] I received access to the Barron's selectivity index, a restricted NCES data set. However, I decided to use only publicly provided IPEDS data. In future iterations of this project, I will incorporate a different variable which combines average test scores on either the SAT or ACT, percent admitted, and Carnegie Rankings to create a ranking system. After an initial attempt, I found that more than 95% of institutions that were in both my data set and the Barron's data set were in the same category. Given this high matching rate and the greater flexibility of not using the restricted data, I opted to use my own selectivity variable, which allows my results to be discussed without first getting approval from NCES.

Comment [AJB27]: You haven't defined what an event is yet. So your reader doesn't know what this 133 is. Please provide a section on your dependent variable, which is the event in question.

Comment [AJB28]: Please provide a citation for each of these variables that justifies its inclusion here. What research did you use to guide your selection of variables?

Comment [AJB29]: Please refrain from using footnotes and endnotes. They always confuse a reviewer. Sure, in policy this happens some, but it's good practice to try to put your point right in the text.

Comment [AJB30]: Give a little more. This is the most important part of your study. Tell your reader more about this variable.

Comment [AJB31]: Citations needed to the methods read to do these models. S&W 2003 for sure.

Comment [AJB32]: Start here with why DTHM is an attractive analytic strategy to study the event under question with the type of data you have and cite the methods literature.

Comment [AJB33]: What is EHA?

Comment [AJB34]: Please talk about the central issues of DTHM in that it controls for the conditional dependence of an event occurring over time and cite S&W 2003.

However, unlike OLS, if observations go unobserved such that the dataset does not include whether the individual or in my case the college or university experienced the event – the adoption of MOOCs – censoring occurs.

Two types of censoring exist: *left censoring* and *right censoring*. Left censoring occurs when an event time is unknown because the beginning of time is not observed (i.e. the individual experienced the event before the study began). Right censoring takes place when an event time is unknown (i.e. when an event is not observed during the study time). For example, a subject might leave the study or may experience the event after the conclusion of the research project. Because I have data from the “start of time” for institutional adoption of MOOCs, my study is not affected by left censoring. However, I cannot account for the right censoring as colleges and universities are continually adopting MOOCs, but right censoring is not as critical an issue as left censoring, which tends to happen either because of poor study design or because of some issue that is endogenous to the study and that would bias the results. Additionally, unlike the hazard function, which can increase, decrease or remain the same, the survivor function will never increase. Because researchers commonly assume independent censoring, I could use the risk set to estimate what would have happened to the entire remaining population if there were no censoring by extrapolating my finding to future groups over a four-year period of time.

The basic equation presented below is estimated with a cross-sectional time series logit model, and the results are presented as maximum likelihood estimates.

$$ADOPT_{i,t} = a_t + B_1(FOURYEAR)_{i,t} + B_2(INSTSIZE2)_{i,t} + B_3(PUBLIC)_{i,t} + B_4(PRESTIGE)_{i,t} + B_5(LNCASHFLOW)_{i,t}$$

In this equation, $ADOPT_{i,t}$ is the conceptual dependent variable (hazard rate), which are the odds that an institution *i* will adopt a MOOC in year *t*, given that the state has not adopted a MOOC the

Comment [AJB35]: Please make sure to cite the literature from the course and your additional readings that you used to learn how to run this model.

Comment [AJB36]: Citation needed

Comment [AJB37]: Citation needed

Comment [AJB38]: State how the data is formatted and why and cite the methods.

Deleted: will be

year prior. A constant a_t denotes each of the four time periods (AY 2011-12, 2012-13, 2013-14, 2014-15). $FOURYEAR$ is a binary variable that indicates whether a the college or university is a four-year institution. *INSTSIZE2* is a binary indicator for whether a school has a total student enrollment that exceeds 10,000 students. *PUBLIC* is a binary variable that denotes whether an institution is public. *Prestige* is a binary measure based on Carnegie rankings for doctoral/research institution, where the top-ranked universities are research universities (Research I and Research II). *LNCASHFLOW* is a continuous measure of the fiscal health of an institution calculated by taking subtracting the total liabilities from total assets.[2]

Results

Descriptive Results

Table 1 presents the descriptive statistics for variables used in this study. On average, more colleges and universities have less than 10,000 students; there are more four-year than two year colleges; roughly half of the schools are public; fewer than 10 percent of the schools are highly prestigious, and there is very little variation about the mean in terms of available cash flow.[3]

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
event	14841	0	1	.01	.097
instsize2	14483	0	1	.29	.454
fouryear	14841	0	1	.65	.477
public	14841	0	1	.49	.500
prestige	14841	0	1	.07	.255

[2] SOMETHING I NEED HELP WITH: To estimate only the impact of resources on adoption and not the impact adoption might have on resources, should CASHFLOW be a lagged variable?
[3] Should the Ns be the same for this table? Some of these colleges do not report their financial data and so it is hard to get this total number. I'd have to go entirely with listwise deletion which would limit my sample. Please advise.

Comment [AJB39]: You should give four of these in the equation above.

Comment [AJB40]: Note very early here in this section that there's only what, 133 events? That's a big deal to say early. To what extent is DTHM robust to extremely small event occurance? Do S&W 2003 address this? Does anyone else?

Comment [AJB41]: Yeah, cashflow as lag is an interesting idea. On first blush, I'd say yes. Use last year's cash flow as this year's cash flow won't have an effect on MOOC uptake until next year.

Comment [AJB42]: N's should be the same for each variable as it's listwise deletion.

Comment [AJB43]: It looks like you're reporting the n's from the full long-form dataset with multiple rows per college. Instead, report the n for the total number of colleges, not college multiplied by year.

lncashflow	11997	0	24.36	17.62	1.83
Valid N (listwise)	11993				

A preliminary multiple regression was conducted to calculate the Mahalnobis distance to identify outliers and examine multiple collinearity among the model predictors (*instsize2, fouryear, public, prestige,* and *lncashflow*). Data screening led to the elimination of 4 cases, which exceeded the critical chi-square value (df = 9, critical chi-square criterion = 27.877, p < .001). Although not required in logistic regression, evaluation of linearity justified a natural log transformation of the only continuous variable in this study (*cashflow*) into *lncashflow*. According to the results in the coefficients table, all tolerance statistics exceed .1, indicating there are no issues of multicollinearity (see Table 2).

Comment [AJB44]: Good.

Table 2: Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-.096	.011		-9.063	.000		
	d2	.008	.003	.034	3.156	.002	.671	1.491
	d3	.018	.003	.074	6.781	.000	.671	1.489
	d4	.013	.003	.055	5.095	.000	.673	1.485
	instsize2	.003	.003	.014	1.236	.217	.586	1.707
	fouryear	-.003	.003	-.015	-1.255	.209	.561	1.783
	public	-.008	.003	-.038	-2.976	.003	.493	2.030
	lncashflow	.005	.001	.095	8.747	.000	.673	1.486
	prestige	.063	.004	.164	15.925	.000	.741	1.349

a. Dependent Variable: event

The Lifetable (Table 3) summarizes the sample distribution of event occurrence. The data represent study findings, which tracked the adoption of Massive Open Online Courses of 3,825 colleges and universities over four years (2011-12 to 2014-15). No colleges or universities left

Comment [AJB45]: Left isn't really the right word here. It's more that you have everyone, and no colleges closed. Right? It's a full population study, which is a strength of the study.

prematurely during the study; however, 3,685 institutions were right censored at the end of the study. At the start of the study 100 percent of the colleges and universities had not adopted MOOCs; by the end of the study, 96 percent of colleges and universities still had not adopted any MOOC. The hazard rate, which is the conditional probability that a college or university will experience the event in a given time period, given that it did not experience it in any earlier time period, was the highest during year three (1.6 percent). In comparison, the survival rate, the cumulative risk associated with event occurrence at each period, was the lowest point in year three (97.4 percent). The median survival time is 4.0 years. Figure 1 in Appendix A includes a graph of the hazard and survival curves for the sample.

Comment [AJB46]: Awesome. Well-stated!

Comment [AJB47]: Well, because you don't have much of the event happening in the sample, it's tough to make this point. I'd say you can't calculated it, which is fine for this question and data.

Comment [AJB48]: These should be here in the main report. They're cool. Hazard dropped in year 4? That's a big deal. Have we started down from the top of the hype curve? I recommend the Gartner report (you can get to it through CU libraries) titled "Hype Cycle for Education, 2015"

Table 3: Life Table[a]

		Number of colleges and universities			Proportion of colleges and universities	
Year	Time Interval	That did not adopt MOOCs	That adopted MOOCs	Censored at the end of the year	That adopted MOOCs during the year	That did not adopt MOOCs during the year
0	[0,1)	3825	0	0	-	1.0000
1	[1,2)	3825	7	0	0.0018	0.9982
2	[2,3)	3818	32	0	0.0084	0.9898
3	[3,4)	3786	59	0	0.0156	0.9744
4	[4,5)	3727	42	3,685	0.0113	0.9634

a. Median survival time is 4.0

Comment [AJB49]: You can use the actual year here, as time and year are the same in this study. It makes it easier for the reader to follow.

Comment [AJB50]: Yeah, not sure about this one.

Analytic Results

Table 4 reports findings for seven discrete-time hazard models for the year the institution first adopted a MOOC, where D1-D4 are a set of time indicators representing each year of the

Deleted: my

model.[4] Model A includes only the main effect of time; Model B includes the main effects of time plus *instsize2*; Model C includes the main effects of time plus *fouryear*; Model D includes the main effects of time *public*; Model E includes the main effects of time plus *lncashflow*, a measure of the total assets minus total liabilities; Model F includes the main effects of time plus *prestige*; and, Model G includes the main effects of time plus all the substantive predictors: *instsize2*, *fouryear*, *public*, *lncashflow*, and *prestige*.

Not accounting for any differences caused by the substantive predictors, Model A reports that the likelihood that an institution will adopt a MOOC increases from year one to year three, but then begins to taper in year four. The baseline for Model A is the entire sample since it does not include any substantive predictors.

Comment [AJB51]: Also state with Model A how the logits convert to odds. These should match the life table. It's a good check of the unconditional model.

Model B reports on the risk of MOOC adoption after introducing the first exogenous predictor, institutional size (instsize2) and the main effect of time. Similar to Model A, the results suggest an increase in the risk of MOOC adoption until after year three when the risk begins to decline slightly. In this group, the baseline for the α's in this group is *Instsize2* = 0. Colleges and universities that are larger, therefore, have an increased risk of adopting MOOCs compared to smaller colleges and universities. The estimated odds large colleges and universities (enrollment >= 10,000 students) will adopt MOOCs is almost eight times greater than small colleges and universities (e^2.046 = 7.73).

Comment [AJB52]: Nice. Well interpreted.

Model C reports that the risk of adopting MOOCs after introducing the substantive predictor *fouryear* (baseline *fouryear* = 0) to the main effect of time illustrates again a constant increase in the risk of adopting MOOCs until the end of year three but a decrease in year four.

Comment [AJB53]: So, adding variables one at a time is a strategy. But, can they be lumped together in blocks using theory and previous research? Can you load a few together to build towards testing your central question? One at a time and then taking out the one you just ran makes each forward model difficult to compare and interpret.

This is pretty much up to you as the researcher, as there is no correct answer, but it would help with the flow maybe.

[4] These data are parameter estimates or logits and not presented as odds or probabilities. The α's predict the baseline logit hazard function and are reported as MLEs; the β's assess the effects of substantive predictors. Each α requires identification of the baseline group, and the baseline group varies for each model.

Controlling for the effects of time, the odds four year institutions adopt MOOCs is almost six times higher than two-year institutions to adopt MOOCs (e^1.787 = 5.97).

Comment [AJB54]: This is a cool study. A very interesting idea to test it this way. And it works! ☺

Model D shows the risk of adopting MOOCs after introducing the variable *public*, an indicator for whether the school is public versus private (baseline = 0), to the main effect of time. This variable is not statistically significant, suggesting there is no difference in the risk of adopting MOOCs between public and private colleges and universities.

Model E introduces the measure *prestige* to the main effect of time and reports that very prestigious universities (Research I and Research II colleges according to the Carnegie ratings) have a risk 20 times higher than non-prestigious colleges and universities (e^3.003 = 20.15) of adopt MOOCs, controlling for time. Again the risk for adoption increases with time until year four, at which point it stars to decrease.

Comment [AJB55]: Neat!

Model F introduces the last substantive predictor, the logged cashflow variable (*lncashflow*) to the main effect of time. This model illustrates the same pattern of changes over time, but also shows that the estimated odds of first adopting a MOOC are approximately 6 times higher for colleges and universities with more positive cash flow than colleges and universities with presumably less disposable income (e^1.086*2 = 5.92, note adjustment to odds ratio calculation made for continuous variable).

Comment [AJB56]: So, for your future work in this area, these effects all say to me, first, yeah, Model G is important to run them all together, but what about interaction effects? Money and prestige? Don't go nuts on interactions, as they need to be theory based, but a couple would be cool for a future study (maybe the final if you go with a DTHM?)

Model G indicates that when all predictors are included that in addition to time being significant, the risk of adopting MOOCs is significantly higher for prestigious and financially well off colleges and universities compared to those that are not. Specifically, after controlling for time, prestigious colleges and universities that benefit from a higher, positive cash flow have an estimated risk of about 2.3 times higher of adopting MOOCs than less prestigious and poorer colleges and universities.

In addition to the coefficients presented in Table 4, there are a number of other values that can be used to analyze and understand how well the model fits the data. The log-likelihood is not really useful on its own but is useful for computing the deviance statistic, which is commonly used to assess model fit (Singer & Willett, 2003, p. 398). However, better modeling does result in increasing LL values for each added parameter, which is the case in my table. Deviance measures how much worse the model is in comparison to the best possible model that could be fit. That is, the better the fit of the model the smaller the deviance will be. In this case, Model G has the most parameters (6) and the smallest deviance (1016.63), while Model A has the fewest parameters (4) and the greatest deviance. However, Model D, which focuses on whether a university is public is only marginally smaller (1405.41). When the difference in deviance is small compared to the critical chi-square value, researchers fail to reject the null hypothesis, which indicates the reduced model is not substantively worse than the less parsimonious model (i.e., the model with more parameters). Both the deviance-based hypothesis tests and the Wald-Chi Square statistics ($df = 1$, critical chi-square at $p < .001 = 10.83$) demonstrate the null model should be rejected in favor of the more parameterized models (see p. 398-399).

Because the LL statistic inevitably increases with each addition new parameter, we use the AIC and BIC to correct for this effect. The AIC and BIC essentially penalize the LL statistic for the number of parameters present in the model. When we cannot calculate the deviance for non-nested parameters we also use the AIC and BIC to assess the benefit of a fully saturated model. Model G has the smallest AIC and BIC values, suggesting that again Model G has the best fit of any of the other models even though it has the greater number of parameters (AIC = 1028.63; BIC = 1045.97).

Table 4: Results of fitting seven discrete-time hazard models to the year of first adoption of Massive Open Online Courses (*n* =3,825, *n events* = 140)

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
Parameter Estimates and Asymptotic Standard Errors							
D_1	-6.410***	-7.566***	-7.903***	-6.506***	-7.401***	-27.464***	-23.405***
	(0.448)	(0.476)	(0.552)	(0.457)	(0.465)	(1.427)	(1.715)
D_2	-4.604***	-5.735***	-6.102***	-4.700***	-5.553***	-25.413***	-21.387***
	(0.183)	(0.244)	(0.371)	(0.205)	(0.220)	(1.318)	(1.631)
D_3	-3.943***	-5.045***	-5.440***	-4.039***	-4.804***	-24.556***	-20.502***
	(0.134)	(0.207)	(0.349)	(0.161)	(0.174)	(1.284)	(1.61)
D_4	-4.254***	-5.328***	-5.752***	-4.349***	-5.053***	-24.835***	-20.743***
	(0.157)	(0.222)	(0.359)	(0.181)	(0.191)	(1.285)	(1.609)
instsize2		2.046***					0.406
		(0.206)					(0.298)
fouryear			1.787***				0.220
			(0.346)				(0.406)
public				(0.193)			-0.122
				(0.175)			(0.216)
prestige					3.003***		0.851***
					(0.183)		(0.286)
lncashflow						1.086***	0.843***
						(0.064)	(0.085)
Goodness-of-fit							
LL	-703.32	-642.21	-681.08	-702.71	-579.39	-519.04	-508.32
Deviance	1406.63	1284.41	1362.15	1405.41	1158.77	1038.07	1016.63
n parameters	4	5	5	5	5	5	9
AIC	1414.63	1294.41	1372.15	1415.41	1168.77	1048.07	1028.63
BIC	1426.19	1308.86	1386.60	1429.86	1183.22	1062.52	1045.97
Deviance-based Hypothesis Tests							
H_0: $\beta_{instsz.} = 0$		122.22***					-
H_0: $\beta_{\mathrm{foury.}} = 0$			44.48***				-
H_0: $\beta_{\mathrm{public}} = 0$				1.22			-
H_0: $\beta_{\mathrm{prest.}} = 0$					247.86***		-

Comment [AJB57]: Odd formatting here as some of the cells are wrapping. Sometimes for a table like this you just need to decrease the font a little and see if it flies.

Also, for at least your final model, please report effect sizes. For logit models that's an Odds Ratio. S&W 2003 give the conversion equation, as logits are difficult to interpret.

Comment [AJB58]: As demonstrated in the example papers, also needed is the pseudo-R-squared. R-squared for logits is an estimate, and SPSS gives two. Good practice is to report both.

H_0: $\beta_{\mathrm{lncas.}} = 0$					368.56^{***}	-
Wald Hypothesis Tests						
H_0: $\beta_{instsz.} = 0$	98.23^{***}					1.855
H_0: $\beta_{\mathrm{foury.}} = 0$		26.69^{***}				0.29
H_0: $\beta_{\mathrm{public}} = 0$			1.221			0.32
H_0: $\beta_{\mathrm{prest.}} = 0$				270.05^{***}		8.88
H_0: $\beta_{\mathrm{lncas.}} = 0$					290.38^{***}	97.96^{***}

~p <.10, *p <.05; **p <.01; *** p <.001

Discussion and Concluding Remarks

The results from Table 4 illustrates that the most prestigious and wealthiest of universities are the most likely to adopt MOOCs. Specifically, universities with the highest distinction of research according to Carnegie rankings and those with positive cash flow are both associated with higher risks of adopting MOOCs compared to colleges and universities that are not Research I or Research II institutions or which are more financially constrained. There is no evidence supporting the claim that public institutions may be more likely to innovate than private colleges and universities, calling into question whether financial motivation plays a significant role in innovation to increase revenue. I also find that once cash flow and prestige are introduced into the model, the size of an institution and whether or not it is a four-year institution become non-significant. Finally, I also find that universities had the highest risk of adopting MOOCs in year three, after which the risk of adoption began to decline.

Deleted: statistically

There are several implications for these findings. For one, that wealthier institutions have higher hazard rates than poorer institutions is not surprising; as the literature points out, it is these institutions that are the least risk averse because of their greater financial cushion. Additionally, because MOOCs are quite expensive to produce, it may be that these wealthier institutions are the only organizations capable of producing them – even if poorer institutions were inclined to adopt MOOCs and market themselves to a global audience. Regarding the null finding for public universities, it is surprising indeed that there is no statistically significant result, either positive or negative. The privatization literature suggests that more market-oriented education organizations will be more innovative than those more heavily oriented to the public service mission. Extrapolating out from this theory, we would expect to find either lesser resourced public institutions have a higher rate of adoption compared to their private counterparts; or the opposite, private colleges and universities that have less regulatory oversight and more autonomy to innovate.

These findings help to clarify what really happened in the initial frenzy of MOOCs. While the hype of MOOCs has receded somewhat in the media and critics and advocates have become more tempered in their reviews over the last year or so, the findings of this study suggest the early attention paid to their rapid rise and disruptive force in higher education may have been accelerated or exaggerated. The scale at which the innovation expanded is in fact quite small as is illustrated by the hazard rate of 1.6 percent during year three, the year with the highest risk associated with adoption. It is important to keep in mind that the majority of colleges and universities in the United States have not adopted MOOCs and the risk for adoption remains very small.

However, that there was indeed a noticeable and statistically significant trend associated with the diffusion of MOOCs at such an early point in their history is noteworthy and indicative of the occurrence of incremental change that could have substantive impacts on the structure and delivery of higher education in the future. In particular, the fact that 140 organizations implemented MOOCs in the first four years is fairly impressive. Even more interesting is that no institution acted because of an explicit policy mechanism, but instead on its own accord. Most times, to get widespread change – legislation must be enacted and then agents must be held accountable. In this case, higher education institutions acted without direct state or federal oversight. One wonders then, is it the case here, as bottom up theorists would argue, that innovation is more successful if it emerges organically from within the institution instead of from the top-down?

Because of the nature of MOOCs and their novelty in higher education as well as our limited general understanding about transformative versus incremental change in higher education, there are many questions still unanswered by this study. What factors distinguish early adopters from late adopters? To what extent do these actions reflect institutional response to political and economic pressures environmental pressures to change? Or alternatively, were there inter-institutional politics that catalyzed or suppressed institutional adoption? What about the impacts of the external but rapidly developing higher education market on the decisions to adopt MOOCs or not? For example, as the market for STEM degrees continues to flourish, are colleges and universities more likely to offer STEM courses over humanities? With regards to looking toward the market for revenue replacement, what relationships do we see between for-profit providers and different types of colleges and universities?

Establishing the initial rates of adoption as well as the influence of some substantive political and economic predictors of institutional change are first steps to understanding higher education response to the emergence of a technological innovation. This innovation acts as both a threat to the stability of the institution and a solution to the challenges the collection of colleges and universities will continue to face in the future. This tension between preservation of the institution and the exigency to make education more affordable provides a ripe area for future research.

Comment [AJB59]: Overall, this is an excellent start on the Midterm. The model appears to be correctly run. However there are a few comments throughout on reporting additional information, such as the R-squared. Issues for this report are mainly about citations and framing. Please see the comments throughout.

Currently this paper is a B+ (88%). However, through a revision I believe that it could become a very strong A if not 100%.

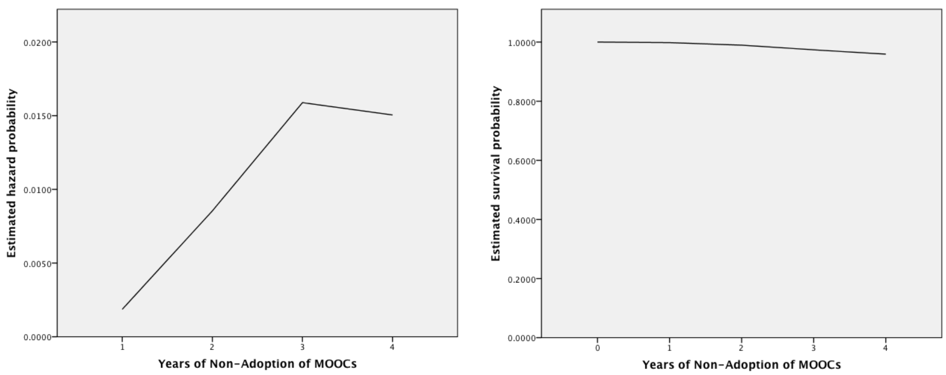

Figure 1. Estimated hazard function (left) and estimated survival function (right) from study on the timing of adoption of post-secondary adoption of Massive Open Online Courses (MOOCs).

APPENDIX A: TABLES AND FIGURES

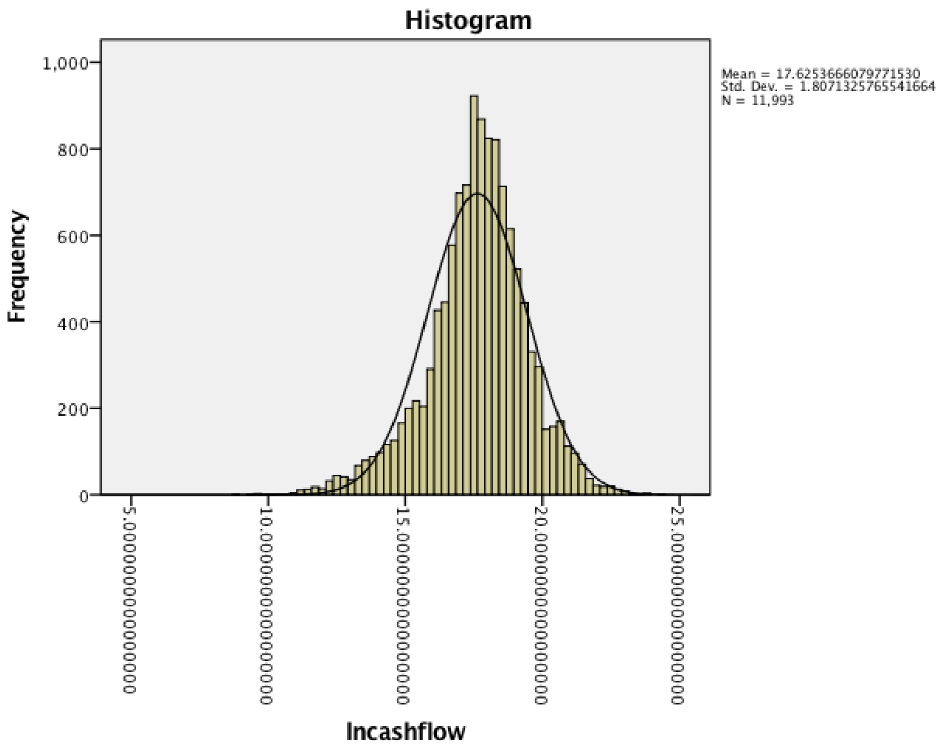

Figure 2 . Histogram demonstrating normality of logged cash flow (lncashflow) variable.

APPENDIX B: Syntax & Output

[Syntax and output removed]