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Georgetown’s First Six MOOCs: Completion, Intention, and Gender Achievement Gaps

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Abstract

This analysis of Georgetown's first six MOOCs (massive open online courses) comprises three parts, moving from general to specific in scope. I begin with a discussion of demographic factors across all six courses, seeking to answer the following question: "Who takes, and succeeds in these courses?" Next, I discuss the relationship between stated intention and course performance with survey data from a pre-course survey for Georgetown's very first MOOC, an economics course. I end by examining the gender achievement gap in the same economics course.

Keywords

MOOC, gender, online education, STEM

Cover Page Footnote

Thank you, to the GeorgetownX team at CNDLS, especially Yianna Vovides, Rob Pongsajapan, and Anna Kruse. I'm very grateful for the privilege of being the first undergraduate to work with GeorgetownX data. Thank you very much. Thank you, to the INFX523 MOOC team, especially Professor Ted Moran, Rosie O'Neill, and Zhuqing Ding for their helpful feedback and access to data for the on-campus version of the course, INAF-523: Globalization. Thank you, to two friends, Danton Noriega-Goodwin and Aaron Albert, Economics PhD students (and workout partners), for answering my incessant STATA questions. Thank you, to my loving and supportive parents, Paul and Lisa Healy, without whom I simply would not be at Georgetown. Finally, thank you to Professor Cumby, my advisor on this thesis. His keen advice has guided me through every stage of this project, from conception to completion. I could not have written this paper without him.

Chapter 1: Introduction

Introduction

Over the past three years, MOOCs have sparked much debate regarding the future of higher education. These courses promise to democratize higher education, yet much evidence suggests that the courses mainly serve a population of interested learners who already have postsecondary degrees. Regardless of student population, MOOCs also face much criticism for their notoriously low completion rates: ranging from 2-11% on a traditional measure of completion and around 22% for those who intend to earn a certificate (Reich 2014). Many economists acknowledge that low completion rates are actually a good thing, because they reflect more efficient matching, comparable to an amplified version of the shopping period at many universities. However, if we can understand why well-intentioned students drop out of MOOCs, we can design targeted interventions to aid MOOCs in their mission of spreading education, whether to interested learners or those seeking certification.

Meanwhile, in brick-and-mortar classrooms, gender differences in academic persistence and grade sensitivity have emerged as key topics in the conversation around female achievement, especially in STEM fields, which offer lower grades on average. Initial research suggests that MOOCs are not immune to some of the inequalities in achievement that exist in traditional classrooms, yet no research has focused on these gaps. Thus, I will investigate in more detail gender achievement gaps as they occur in MOOCs.

I will aim to combine these two threads of research and focus on achievement gaps, especially gender-based, in MOOC success. No significant research of this kind has been conducted on GeorgetownX's[1] MOOCs. The GeorgetownX team has published three main research reports. "From Planning to Launching MOOCs" focuses on the production of MOOCs and offers advice for other institutions (Demaree et al. 2014). The Dante course (HUMX421-01x) team published an online report, which mainly offered a qualitative analysis of the recently completed MOOC on the *Divine Comedy*[2]. Earlier this year, Vovides et al. published a study in *Learning Analytics Review*, which examines in great depth the language used in the discussion forum of INFX523-01x: Globalization's Winners and Losers. My analysis will add to this body of GeorgetownX research by investigating completion and demographic factors across all six courses

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[1] GeorgetownX refers to Georgetown University's presence on edX, one of the largest online platforms for MOOCs, founded by Harvard and MIT in 2012. GeorgtownX can be located here: https://www.edx.org/school/georgetownx

[2] https://cndls.georgetown.edu/projects/georgetownx/dante/report/

completed thus far and by testing for a form of achievement inequality present in many in-person academic settings.

Chapter 2: Literature Review

I've distilled the relevant literature into three key strands of research, stated in question form for each of the three sections below.

Why should we think about MOOCs differently than we think about traditional educational settings?

MOOCs began capturing headlines in the popular press in 2012, when edX and Coursera, the two largest platforms, were both founded. The courses promised to democratize higher education, evoking romanticized images of impoverished students in India completing MIT engineering courses, for example. Thus far, MOOCs have fallen short of these grand aims: critics point to their low completion rates and users who, on average, already possess fairly high education levels. However, much of this criticism may have been unfairly leveled on MOOCs. We ought to think about MOOCs differently in two key areas: the education market broadly and student performance metrics.

Two prominent economists, Caroline Hoxby of Stanford and Tyler Cowen of George Mason, have looked at MOOCs' implications for the education market. Hoxby importantly distinguishes between nonselective postsecondary education (NSPE) and highly selective postsecondary education (HSPE). For the NSPE segment, characterized by standardized course material and assessments, lack of instructor-student interaction and lack of alumni donation bases, MOOCs seem to make sense. Yet for HSPE (e.g. Georgetown), characterized by massive investments in each student (exceeding full cost of tuition, financed by donations from previous generations of students, i.e. alumni), individualized course material and assessment, and ubiquitous instructor-student interaction, MOOCs seem incompatible with the university's financial model. Hoxby considers the value of an in-person degree versus a series of MOOCs: "If Harvard's *degree* matters in some way that is greater than the sum of Harvard-led courses offered as MOOCs, then Harvard will destabilize the value of its degree by giving credit to its own students for MOOCs led by its own faculty" (Hoxby 2014). Additionally, MOOC students may not feel the same urge to donate to an institution, thus destabilizing the financial model of HSPE.

Cowen emphasizes that MOOCs do carry a few advantages inherent to their format, namely leverage of the best instructors for a wider audience, temporal flexibility of when lectures are consumed, and ease of measurement and experimentation (Cowen 2014). He also predicts that the online education market may bifurcate into an expensive, high-cost tier and a low-cost, near-free one, as the video game industry has done over the past few decades (Cowen 2014).

In response to the criticism of MOOCs' low completion rates, several researchers have argued that we need to re-conceptualize completion and success in MOOCs. Justin Reich, of Harvard, finds completion rates of 2%-11% across Harvard's first nine edX MOOCs. Yet, among those who expressed an intention to complete in a pre-survey, this rate jumped to 22% (Reich 2014). Daphne Koller, one of Coursera's founders, finds nearly identical results in one of Coursera's MOOCs, "Writing for the Sciences" (Koller 2013).

Jennifer DeBoer, noting the drastically different student body composition of MOOCs relative to residential colleges (age, location, intention, etc.) takes an even more extreme view on reconceptualizing educational variables: "If researchers consider MOOCs less as courses than open invitations to engage with particular online resources, then participation patterns are less predictors of achievement than outcome variables in themselves" (DeBoer 2014).

What factors predict student success in MOOCs?

Course Activity Factors

Because MOOCs lend themselves easily to data collection, much research has been done so far on student performance. Broadly speaking, participation activity, intent to complete, and organizational skills seem to predict completion most strongly. Of course, these attributes can change in a given individual over the length of the course. My research will ask if this sort in motivation of change may happen differently for males versus females in response to assessment scores.

Reich, in the paper cited above, finds that stated intention predicts completion more strongly than any demographic factors. Further, he notes that students who are willing to complete the pre-survey, regardless of their responses, are more likely to complete the MOOC, with an average completion rate of 16.5% versus 5.9% among all students. This self-selection of more active users among survey respondents is crucial to keep in mind when researching MOOCs, since pre-surveys to gauge motivation are usually not compulsory. Reich notes, "27 percent of all registrants, 42 percent of students with at least one action, and 68 percent of students with a non-zero grade completed the survey" (Reich 2014).

Balakrishnan, of UC Berkeley, analyzed student click data from UC Berkeley's Software as a Service MOOC on edX. He finds significance with most of the participation-related variables that we might expect to be significant for predicting whether a student will drop out of the MOOC in the following week (using an in/out state based on last click activity): cumulative percentage of available lecture videos watched, daily unique-thread views in a week, forum posts, and number of times course progress page checked (Balakrishnan 2013).

Banarjee and Duflo, economists at MIT, use a regression discontinuity model to test for the unobserved characteristic of organizational skills. They look at students who registered for MIT's "Challenges of Global Poverty" MOOC 15 days before and 15 days after the registration deadline (edX allows registration after a course has officially started). Referring to the group of late registrants, they write, "students whose behavior shows they are not organized are significantly less likely to succeed in a MOOC...driven by their failure to complete assignments on time rather than their performance conditional on completing them" (Banarjee and Duflo 2014). Even after controlling for stated motivation, the organizational skills revealed by registration time still significantly affected course completion.

Demographic Factors

Older students and students with some postsecondary education seem to fare better in MOOCs than their younger or less educated counterparts, respectively. Reich, in his investigation of nine HarvardX MOOCs finds that older and more educated students had significantly higher odds ratios in a logistic regression on course completion than other groups. In addition, a March 2015 review of the first two years of HarvardX and MITX estimates that the certification rate for students 30 years old and older is 2.5 percentage points higher than those under 30, controlling for other demographic factors. The differential for those with bachelor's degrees is +0.8 percentage points in this same estimation (Ho et al. 2015).

In their 2015 analysis of 20 MOOCs, spanning subjects from engineering to writing, Kizilcec and Halawa identify a significant gender achievement gap. They find that "women were 12 to 20% less likely than men to persist with lectures and assessments. Women, who constituted 34% of learners in the sample, are also 10% (7%) less likely than men to score a grade above the 60th (80th) percentile" (Kizilcec & Halawa 2015). They do not spend much of the paper investigating this gender gap in depth, but offer a brief hypothesis: "The achievement gaps could plausibly result from differences in Internet access, language barriers, or from feelings of psychological threat, such as fears of confirming a negative stereotype or not belonging in the course" (Kizilcec & Halawa 2015).

Two other papers note this gender gap, yet warn that it may not represent a very meaningful difference in learning outcomes. In his 2014 paper mentioned above, Reich writes that "female students and U.S. residents had lower odds ratios of completion than others. Although these estimates are statistically significant, they are substantively modest" (Reich 2014). More recently, in the review of the first two years of HarvardX and MITX courses, cited above, the authors find that the average certification rate for women is 0.2 percentage points lower than for men, controlling for all other demographic factors. However, they caution, "As expected given the large sample sizes, all gaps are statistically significant...however, differences do not necessarily imply meaningful differences. Gender gaps in particular are negligible on average across courses, whereas age and geography gaps are larger in magnitude” (Ho et al. 2015).

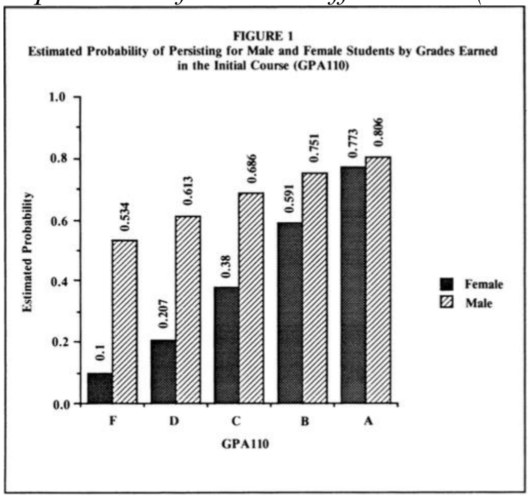
What gender differences exist in educational persistence?

Because I will analyze gender achievement gaps in this paper, I also read the relevant literature on gender differences in academic persistence, which mainly focuses on economics and STEM education, where we see the most variance between outcomes for male and female students. No research on this topic specific to the MOOC setting has been published, so I plan to transition some of the theories described from traditional educational settings into the online space.

Four major papers have shaped the current thinking on gender discrepancies in response to grades. This research deals with in-person, traditional education, rather than with MOOCs. Beyond the brief discussions of gender gaps in MOOCs, cited above, no researchers have spent significant time or effort expanding on this achievement gap. I hope this paper can begin a broader investigation of gender equality in online education.

Horvath uses a logit model, including an interaction term between gender and grade in the class, to investigate persistence in an economics program at a two-year associate’s degree program within a private four-year university in Connecticut. He defines persistence as enrolling in the second economics course after completing the first. Horvath finds that female students are less likely to enroll in the second economics course after receiving grades below the A level: “achievement affected persistence differently for the male students than it did for the female students. Only after earning an A in the first economics course were female students nearly as likely to persist as males earning the same grade. Figure 1 from Horvath’s paper, inserted below, illustrates this phenomenon well. As grades dropped below A, the gap between male and female students' persistence rates increased markedly” (Horvath 1992). He theorizes that females’ lower confidence relative to males may drive this phenomenon: they require more concrete symbols of success (higher grades) than males in order to persist.

Table 1.1: Figure 1 from "Persisting in the Introductory Economics Course: An Exploration of Gender Differences" (Horvath et al.)



More recently, two papers have also investigated gender-based grade sensitivity within the context of major choice. Rask, using data from the Colgate University graduating classes between 1989-2004 models persistence as a series of probits: yes/no for each of the first 4 economics courses in the sequence, and then a multinomial (major/minor/no concentration). Rask's results confirm Horvath's findings, and also specify that female students are especially likely to drop out earlier in the economics sequence. He finds that "women are more sensitive to the relative grade than men and that women are particularly responsive to low grades received in their first two economics courses. Combining this result with the fact that the low grades are more commonly given in the introductory courses, the higher attrition of women documented in the literature seems to be at least partially attributable to their greater sensitivity to grades" (Rask 2008).

Expanding this line of research, Arcidiacono considers STEM/non-STEM enrollment in the context of grade inflation. He introduces a layer of complexity by noting that females have also been observed to have a lower marginal utility cost of studying time. Arcidiacono writes, "this suggests two competing forces which determine gender differences in STEM: female students care more about grades and thus are attracted to nonSTEM courses with higher average grades; female students find studying less costly and are thus drawn to STEM courses which offer higher returns to study effort" (Arcidiacono 2014).

Yet not all research has confirmed that gender differences do, in fact, exist. Chizmar, using a discrete-time hazard analysis to estimate likelihood of dropping out of the economics major in a given semester, finds no significant differences between male and female students: "after controlling for relative grades in economics and economics credit hours, the hazard profiles of female economics majors are indistinguishable from their male counterparts. This conclusion differs markedly in spirit from those of previous studies that found gender differences in learning and understanding economic knowledge and in participation in economics courses, with men outperforming women"(Chizmar 2000).

Chapter 3: Overview of Demographics & Performance in GeorgetownX's First Six MOOCs

Georgetown joined edX as a charter member in 2012, as the platform's sixth institution, behind founding members MIT and Harvard, along with UC Berkeley, Wellesley, and the University of Texas system. As of April 2015, edX now has 67 members, 38 of which have charter status[3]. Since launching in 2012, GeorgetownX has completed six MOOCs on edX: INFX523-01x/-02x: Globalization's Winners and Losers (offered twice), PHLX101-01x: Introduction to Bioethics, MED202-01x: Genomic Medicine Gets Personal, GUIX-501-01x: Terrorism and Counterterrorism, HUMX421-01x: The Divine Comedy, Dante's Journey to Freedom, Part 1.

Data & Summary Statistics

I obtained data from the GeorgetownX team at CNDLS (Center for New Designs in Learning and Scholarship), an initiative on education research within Georgetown. Specifically, I was given basic demographic information (provided through account registration on edX), date of last login to the courseware for a given course, and grades on the course's assessments, segmented into one-week intervals. The following variables, in Table 3.1 and Table 3.2, were provided in the data sets from CNDLS. One variable warrants an explanation: COMPLETE_P (passive completion). In order to work with a more lenient metric for course completion than the standard for certification[4] (earning a passing grade, ≥75%), I measured the duration from the course start date to date of a student's last login to the courseware. If the last login occurs after the release of the final week's material (*not* the end

[3] https://www.edx.org/schools-partners

[4] Disambiguation on certificate/certification: In many academic settings, the term "certificate" refers to a series of courses on a particular topic, often comparable to an academic minor. In the context of edX (and MOOCs broadly speaking), the terms "certificate" and "certification" refer to the completion of a single MOOC, through the attainment of a passing grade, in most cases 75% (specified when otherwise). Although individual MOOCs may specify additional requirements (e.g. watching every lecture video) for certification, for consistency in my research (and due to dataset limitations), I have simply used the passing-grade standard for all certification rates displayed in this paper.

date of the course), then I consider this student to have "passively" completed the course; in other words, the student clicked through the full span of the course's material. This metric certainly carries some uncertainty; we can envision a situation where a student might enroll in a course, forget about it for 7 weeks, and then suddenly log in during the course's penultimate week, thus counting as a passive completer under my definition. However, given the limitations of my data (I have date of last login, but no other click information throughout the course), it seems reasonable to assume that over many thousands of observations, the duration between course start and last login probably does reflect the period during which a student passively engaged with the course by watching videos, browsing the forum, etc., but not necessarily completing the graded exercises.

Table 3.1: Variables Included in CNDLS Data

Variable	*Description*
STUDENTID	unique id code associated with the student's email address
DATE	date of last login to the courseware
DURATION	duration from start date of the course to DATE (all negative durations have been adjusted to 0)
AGE	age, self-reported date of birth
FEM	self reported, binary =1 if sex="f", =0 if sex= "m"
EDU	self-reported education levels ranging from "none" to "doctorate"
FINAL	final grade in the course, a number between 0-1
CH_X_GRADE	grades for each one-week unit of the course (CH_1_GRADE, CH_2_GRADE, etc.)
MAX_CH_X_GRADE	total points possible in each one-week unit of the course (MAX_CH_1_GRADE, MAX_CH_2_GRADE, etc.)

Then, I created the following variables with simple manipulations of the original data.

Table 3.2: Variables created from original data

Variable	*Description*
COMPLETE_P	"passive" definition of completion, binary =1 if DATE is after the release of the course's last week of material (*not* the end date of the course), =0 if DATE is before the release of the course's last week of material
PASS_GRADE	"active" definition of completion, binary =1 if FINAL>0.75, =0 otherwise (except for MEDX202-01x: Genomics, where passing grade level is 0.80)
AGE_UNDER_18 AGE_19_22 AGE_23_30 AGE_31_40 AGE_41-60 AGE_OVER_60	dummy variables created for age groups; smaller intervals at the younger ages are intended to approximate college aged students and young professionals
BACH_OR_MORE LESS_THAN_BACH EDU_OTHER	I grouped EDU responses into three categories of educational attainment: BACH_OR_MORE (bachelor's, master's, or doctorate), LESS_THAN_BACH (associate's, high school, elementary school) EDU_OTHER (none, other, or left edu blank)
FINAL_PERCENTILE	percentile for final grade, computed only for students with FINAL>0
CUMUL3	cumulative grade, between 0-1, for the first three weeks of assessments in a course
CUMUL3_PERCENTILE	percentile for CUMUL3 grades, computed only for students with CUMUL3>0
NEVER_LOGIN	binary, =1 if final login date is before official start date of the course, =0 if after

Summary Statistics

Table 3.3, below, presents summary statistics for all six MOOCs. At a very broad level, author Jeff Selingo's quip in the *New York Times* aptly sums up the GeorgetownX student population: "the average student in a MOOC is not a Turkish villager with no other access to higher education but a young white American man with a bachelor's degree and a full-time job" (Selingo 2014).

Three points are worth noting here. First, the overwhelming majority of registered students, ranging from 67% to 74%, already have at least a bachelor's degree. Thus, GeorgetownX is no exception to the widely leveled criticism that MOOCs mainly serve students who already have access to education. Next, a significant portion of students sign up for a MOOC but never actually log in during the course (ie, date of last login is before the official start date of the course): the proportion of registered students who actually login during the course ranges from 46% to 65%. However, these login rates, which would seem low in a traditional education setting, may to some extent reflect market efficiency. Because MOOCs do not charge a required enrollment fee, there are virtually no switching costs for a student who signs up for a course and then decides that it doesn't align with her interests. Finally, on a similar note, we observe certification rates ranging from 3% to 11% for students who log in to the course at least once. These rates, which might seem low in a traditional sense, can similarly be explained by the virtually non-existent switching costs in MOOCs: a student may get one or two weeks into the course and realize that they actually aren't interested in the topic. In addition, a student may simply drop out of the course because she has learned all that she was interested in. In their 2015 study of 20 MOOCs, Kizilcec and Halwa found that "17% of respondents in a typical course stopped participating because they had learned all they intended to learn" (Kizilcec & Halawa 2015). In other words, a student might enroll in INFX523: Globalization because she is curious only about the concept of the resource curse in developing countries, which is covered in the first week's lecture videos. Then, after watching the first few videos, she decides to stop logging in to the course, having satisfied her curiosity. Although this hypothetical student did not complete the course in a traditional sense, we ought to consider her learning experience a success to some extent. Thus, we must consider completion in MOOCs as very different from completion in any traditional educational setting.

Table 3.3: Summary Statistics for GeorgetownX's First Six MOOCs

	INFX523-01x *Globalization 1*	*PHLX101-01x* *Bioethics*	*MEDX202-01x* *Genomics*	*GUIX-501-01x* *Terrorism*	*HUMX421-01x* *Dante*	*INFX523-02x* *Globalization 2*
Launch Date	October 1, 2013	April 15, 2014	May 28, 2014	September 24,2014	October 8, 2014	October 24, 2014
Registered Students	28,112	26,839	22,580	17,989	12,241	9,504
Students with login after start date	15,910 (57%)	12,437 (46%)	12,411 (55%)	11,743 (65%)	7,830 (64%)	5,816 (61%)
% Female	40%	51%	49%	33%	51%	42%
% Bachelor's or more	74%	68%	72%	67%	71%	74%
Median Age	28	28	28	29	32	27
Certification Rate	4%	5%	5%	5%	2%	2%
Certification Rate (students with at least one login)	7%	11%	8%	8%	3%	3%
Passive completion rate	29%	27%	28%	26%	33%	26%

In addition, enrollment declined by 66% (from 28,112 registrations down to 9,504) from version 1 to version 2 of INFX523: Globalization's Winners and Losers. Researchers from Harvard and MIT observed that across 11 courses with repeated versions that "participation declined by an average of 43% from the first to the second version" (Ho et al 4).

Are there significant differences in performance between demographic groups?

To investigate course performance across different demographic characteristics, I ran the following three regressions:

I. Logistic regression on NEVER_LOGIN (Who registers but never logs in to the course?)
II. Logistic regression on PASS_GRADE (Who is likely to earn a passing grade?)
III. OLS regression on DURATION (What factors contribute to duration in the course?)

I have included the results of these three regressions on the following pages in Tables 3.4-3.6. Here are the key findings:

I. Logistic regression on NEVER_LOGIN

- In all six MOOCs, students over 60 years old were significantly less likely to never log in (i.e. they actually used the course).
- In five of the six MOOCs (the exception being INFX523-02: Globalization version 2), students with a bachelor's degree or more were significantly less likely to never log in.
- In five of the six MOOCs (the exception being INFX523-01x: Globalization version 1), female students were significantly more likely than males to never log in.

II. Logistic regression on PASS_GRADE

- In three of the six MOOCs (INFX523: Globalization versions 1 & 2 and GUIX-501-01x: Terrorism), female students were significantly less likely to score a passing final grade. Interestingly, the three courses in which females are less likely to score a passing grade are also the three most male-dominated courses, with 77% (Terrorism), 60% (Globalization version 1), and 58% (Globalization version 2) male students. Yet, since the sample size of GeorgetownX courses is so small (n=6), we have no way of empirically testing the relationship between female performance and male/female student makeup. On the other hand, female students were significantly more likely than males to earn a passing grade in Genomics. Without a more detailed analysis of the Genomics course, I would point to females' overrepresentation and performance in biology and biology-related fields as an attempt to explain this statistic. Among Georgetown undergraduates, the biochemistry (59%), biology of global health (78%), and biology (65%) majors are predominantly female[5]. Yet, with a 49% female share in the Genomics MOOC, more research is probably needed for a satisfactory explanation. None of the researchers cited in the literature review discuss MOOC performance gaps by discipline; every paper reviewed here simply aggregates MOOCs on various topics. This idea of differences in gender discrepancies depending on academic discipline or gender makeup in online courses certainly warrants further research.

III. OLS regression on DURATION

- In all six MOOCs, female students, on average, persisted for fewer days between course start and last login date.
- In five of the six MOOCs (the exception being Globalization version 1), students over 60 years old were significantly more likely to have more days between course start date and last login date.

I was surprised to see that education level was not a significant predictor of course outcome in regressions II and III. Even joint tests of significance for all education level variables did not yield sufficiently low p-values. Although other researchers have found that more educated students have higher certification rates (see literature review), the GeorgetownX data do not seem to support this idea.

Unfortunately, I have not been able to investigate geographic differences across all six MOOCs. Other researchers have typically found that students based in the US have lower certification rates than those outside the US. The 2015 HarvardX/MITX report calculated that the certification rate for US students was 1 percentage point lower than that of non-US students, controlling for all other demographic factors (Ho et al. 2015). I was able to work with self-reported country of origin on the pre-course survey for INFX523-01x: Globalization version 1. As Tables 4.1 and 4.6 show, 19% of the survey respondents reported US as country of origin, and they did have lower completion outcomes: 15% for certification (overall for survey respondents: 18%) and 35% for passive completion (overall for survey respondents: 45%). However, because my regressions in Chapters 4 and 5 draw from the overall student population, I cannot include country of origin as a variable. Furthermore, country of origin is not nearly as useful as country of residence (which was not provided in my dataset), since we can easily imagine many students immigrating to the US from foreign countries early on in their lives. For instance,

[5] Information provided by the Georgetown University College Deans Office

the 19% figure from the survey respondents is much lower than the 29% USA-based figure in the 2015 MIT/Harvard report, probably a reflection of such immigration patterns (Ho et al. 2015).

Logistic regression on NEVER_LOGIN:

$$NEVER\_LOGIN = \beta_0+\beta_2 FEM+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$$

Table 3.4: Logistic regression[6] on NEVER_LOGIN

	INFX523-01x Globalization 1	*PHLX101-01x Bioethics*	*MEDX202-01x Genomics*	*GUIX-501-01x Terrorism*	*HUMX421-01x Dante*	*INFX523-02x Globalization 2*
n	25,888	24,531	20,184	16,180	10,777	8,455
Intercept	0.773	1.179	0.824	0.620	0.580	0.503
FEM	0.969 (0.224)	1.093*** (0.001)	1.194*** (0.000)	1.307*** (0.000)	1.419*** (0.000)	1.293*** (0.000)
BACH_OR_MORE	0.939* (0.076)	0.773*** (0.000)	0.827*** (0.000)	0.824*** (0.000)	0.783*** (0.000)	0.924 (0.212)
EDU_OTHER	1.109 (0.199)	0.958 (0.562)	1.023 (0.793)	0.991 (0.930)	0.882 (0.261)	1.126 (0.474)
AGE_19_22	1.124 (0.137)	1.189*** (0.007)	1.068 (0.377)	1.108 (0.225)	1.279** (0.029)	1.425*** (0.003)
AGE_23_30	1.191** (0.024)	1.423*** (0.000)	1.337*** (0.000)	1.091 (0.297)	1.313*** (0.013)	1.394*** (0.006)
AGE_31_40	1.047 (0.569)	1.174** (0.017)	1.130 (0.126)	0.902 (0.232)	1.111 (0.359)	1.256* (0.072)
AGE_41_60	0.891 (0.164)	0.856** (0.023)	0.790 (0.004)	0.665*** (0.000)	0.747** (0.011)	0.942 (0.654)
AGE_OVER_60	0.585*** (0.000)	0.484*** (0.000)	0.388*** (0.000)	0.270*** (0.000)	0.410*** (0.000)	0.507*** (0.001)

** p<0.1, ** p<0.05, *** p<0.01*

[6] For this regression and all following logit regressions, coefficients are displayed as odds ratios and values in parentheses are p-values for each coefficient. The baseline group is: male (FEM=0), less than bachelor's degree (LESS_THAN_BACH left out), 18 years old or younger (AGE_18_UNDER left out).

Logistic regression on PASS_GRADE, for students with DURATION>0:
$PASS\_GRADE = \beta_0+\beta_2 FEM+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\imath$

Table 3.5: Logistic regression on PASS_GRADE for students who logged in at least once

	INFX523-01x Globalization 1	*PHLX101-01x Bioethics*	*MEDX202-01x Genomics*	*GUIX-501-01x Terrorism*	*HUMX421-01x Dante*	*INFX523-02x Globalization 2*
n	14,460	11,174	10,900	10,432	6,796	5,076
Intercept	0.097	0.135	0.044	0.055	0.027	0.050
FEM	0.843** (0.011)	1.063 (0.318)	1.271*** (0.001)	0.587*** (0.000)	0.818 (0.140)	0.581*** (0.000)
BACH_OR_MORE	0.999 (0.992)	0.957 (0.627)	1.018 (0.877)	1.138 (0.174)	0.851 (0.404)	1.510* (0.064)
EDU_OTHER	1.137 (0.534)	0.882 (0.508)	0.987 (0.955)	0.665 (0.133)	0.713 (0.453)	2.073 (0.116)
AGE_19_22	0.733 (0.108)	0.654*** (0.006)	1.030 (0.903)	0.978 (0.933)	0.175** (0.014)	0.652 (0.268)
AGE_23_30	0.672** (0.036)	0.720** (0.027)	1.372 (0.179)	1.464 (0.115)	0.716 (0.480)	0.566 (0.142)
AGE_31_40	1.017 (0.930)	1.008 (0.960)	1.694** (0.029)	1.753 (0.022)	1.435 (0.440)	0.724 (0.418)
AGE_41_60	1.290 (0.195)	1.275 (0.116)	3.310*** (0.000)	2.378*** (0.000)	2.643 (0.032)	1.306 (0.498)
AGE_OVER_60	1.268 (0.340)	1.384* (0.070)	4.649*** (0.000)	3.086*** (0.000)	3.840*** (0.004)	2.741 (0.020)

** p<0.1, ** p<0.05, *** p<0.01*

OLS regression on DURATION, for students with DURATON>0:

$DURATION = \beta_0+\beta_2 FEM+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$

Table 3.6: OLS regression on DURATION for students who logged in at least once

	INFX523-01x *Globalization 1*	*PHLX101-01x* *Bioethics*	*MEDX202-01x* *Genomics*	*GUIX-501-01x* *Terrorism*	*HUMX421-01x* *Dante*	*INFX523-02x* *Globalization 2*
n	14,460	11,174	10,900	10,432	6,796	5,076
Intercept	39.383	36.996	44.65881	46.871	38.611	39.96416
FEM	-3.449*** (0.000)	-2.095*** (0.000)	-4.501*** (0.000)	-3.245*** (0.000)	-4.752*** (0.000)	-4.577154*** (0.000)
BACH_OR_MORE	-0.083 (0.889)	-.451 (0.397)	-0.926 (0.218)	1.485** (0.047)	0.924 (0.192)	-0.568 (0.512)
EDU_OTHER	1.908 (0.166)	-.068 (0.951)	1.147 (0.466)	-1.886 (0.299)	0.414 (0.778)	1.816 (0.436)
AGE_19_22	0.538 (0.675)	0.716 (0.437)	3.680*** (0.005)	1.027 (0.517)	0.781 (0.609)	-1.840 (0.238)
AGE_23_30	-0.191 (0.880)	-0.752 (0.412)	4.207*** (0.002)	-1.715 (0.265)	-0.408 (0.783)	-0.524 (0.742)
AGE_31_40	1.554 (0.236)	0.665 (0.493)	6.654*** (0.000)	0.3117 (0.844)	0.873 (0.567)	0.685 (0.680)
AGE_41_60	2.736** (0.042)	0.506 (0.605)	8.697*** (0.000)	1.223 (0.442)	3.787** (0.012)	3.471** (0.043)
AGE_OVER_60	2.454 (0.167)	3.567*** (0.002)	11.864*** (0.000)	7.455*** (0.00)	4.639*** (0.004)	5.985*** (0.009)

** p<0.1, ** p<0.05, *** p<0.01*

Chapter 4: Intention & Completion in INFX532-01x: Globalization's Winners and Losers

In 2013, Georgetown ran its first MOOC on the edX platform, titled "INFX523-01x: Globalization's Winners and Losers: Challenges for Developed and Developing Countries."[7] The course description is as follows: "This course will examine how the spread of trade, investment, and technology across borders affects firms, workers, and communities in developed and developing countries. It investigates who gains from globalization and who is hurt or disadvantaged by globalization."[8]

The course began on October 1, 2013 and lasted 7 weeks. The students had two weeks to complete the final week's material; thus, final grades were computed and certificates awarded on December 2, 2013. In addition, students were given the opportunity to complete a pre-course survey, administered by Georgetown via third-party survey software, which captured more detailed personal information than edX and asked about students' motivations and expectations for the course. Of the 28,906 registered students 3,979 (13.8%[9]) opted to take the survey.

I. Pre-Course Survey

I used the pre-course survey responses in conjunction with course data to investigate gender and stated intention level in the context of MOOC performance. I claim that completing the pre-course survey signals at least one of two qualities that influence course performance: engagement and a propensity to evaluate one's experience. I will first discuss how the population of survey respondents differs from the overall student population. As Table 4.1 below, shows, survey respondents tend to be older, more educated, and are more likely to be female than the overall population of students (note than n-sizes differ for each characteristic because not all users complete every field). For context's sake, the overall course's split of 60% male/40% female almost exactly mirrors the split of undergraduate economics majors in Georgetown University's College of Arts and Sciences, which is 61% male/39% female[10].

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[7] The course ran again in 2014; in this chapter I will discuss only the 2013 iteration

[8] Description from the edX website: https://www.edx.org/course/globalizationswinners-loserschallengesgeorgetownx-infx523-02x - .VRwUxJPF8qY

[9] Survey data were matched with course data on email address, and 794 users provided a different email address on the survey than they did on edX registration, so for my analysis, n=3,185 for analyses of survey respondents.

[10] Information provided by the Georgetown University Economics Department: of the 342 Economics majors, 208 are male and 134 are female (as of February 2015).

Table 4.1: Summary Statistics for INFX523-01x: Globalization's Winners and Losers

	All registered students	*Survey Respondents*
n	28,112	3,185 (13.8%)
% Female	40%	48%
Median Age (years)	28	30
% Bachelor's degree or more	68%	74%
Country of origin: US	n/a	19%
Certification rate	4%	18%
Certification rate, excluding students who never log in	7%	20%

Who is likely to complete the survey?

In the below logistic regression with ANSWER_SURVEY as the dependent variable (a binary variable that equal 1 if a student completed the survey and 0 if not), the coefficients on FEM, BACH_OR_MORE, AGE_41_60, and AGE_OVER_60 are significant at the 5% level. So, controlling for other demographic factors, female students, more educated students, and older students are more likely to take the survey.

$$ANSWER\_SURVEY= \beta_0+\beta_2 FEM+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$$

Table 4.2: Logistic regression on ANSWER_SURVEY

n	25,888
Intercept	0.095
FEM	1.532*** (0.000)
BACH_OR_MORE	1.152** (0.015)
EDU_OTHER	0.978 (0.868)
AGE_19_22	0.809* (0.099)
AGE_23_30	0.830 (0.138)
AGE_31_40	1.088 (0.513)
AGE_41_60	1.689*** (0.000)
AGE_OVER_60	3.074*** (0.000)

** p<0.1, ** p<0.05, *** p<0.01*

Survey Self-Selection Effect 1: Student Engagement

One of the most obvious ways in which people who take the time to answer a survey differ from those who don't lies in their proactivity and engagement. As Reich states quite simply, "Presumably, a student who is willing to complete a survey is more willing to do everything else to complete a course" (Reich 2014). There are certainly other differences, discussed below, but this first effect suggests that survey respondents might engage more with the MOOC and show higher levels of course activity. Indeed, survey respondents are more likely to begin the course and more likely to earn a passing grade than non-respondents.

As I discussed in relation to Table 3.3, many students enroll in MOOCs and then never log in once the course has started. To investigate which students are likely to begin the course at all, I ran a logistic regression on the dummy variable NEVER_LOGIN (equals 1 if last login date precedes official start date of the course, 0 if otherwise).

$$NEVER\_LOGIN = \beta_0+\beta_2 FEM+ \beta_2 ANSWER\_SURVEY+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$$

Table 4.3: Logistic regression on NEVER_LOGIN, including ANSWER_SURVEY

n	25,888
Intercept	0.891
FEM	1.051* (0.065)
ANSWER_SURVEY	0.065*** (0.000)
BACH_OR_MORE	0.958 (0.242)
EDU_OTHER	1.113 (0.204)
AGE_19_22	1.096 (0.261)
AGE_23_30	1.169* (0.052)
AGE_31_40	1.069 (0.423)
AGE_41_60	0.993 (0.937)
AGE_OVER_60	0.747** (0.022)

* *p<0.1, ** p<0.05, *** p<0.01*

The coefficient on ANSWER_SURVEY was significant, with a very low odds ratio: survey respondents were .06 times as likely not to log in as non-respondents, or 15.4[11] times as likely to begin the course as non-respondents.

From this point on, I will restrict the sample to students with duration in the course greater than 0 days. While understanding which groups of students sign up and never use a MOOC is of some value, a thorough analysis restricted to students who actually do start the course can bring more value to educators. In addition, dropping all the students that skew the data toward the 0 day duration will give

[11] The odds ratio coefficient on ANSWER_SURVEY, .065, implies that survey respondents are .065 as likely to *not* begin the course, thus they are 1/.065= 15.4 times as likely to begin the course.

more clarity to analyses that ask questions about events happening during the course.

When we restrict the sample to students who have a duration greater than 0, survey respondents have a much higher certification rate than non-respondents (i.e., they are more likely complete the course in an active sense) but respondents are no more likely to have a last login date on or after the release of the last week's material (i.e., complete the course in a passive sense). Thus, survey respondents are not necessarily more likely to stay in the course, but the ones who do stay participate and achieve more.

Survey Self-Selection Effect 2: Evaluation of expectations and experience

I found that survey respondents are no more likely than non-respondents to stay in the course in a passive sense (as judged by last login date). In fact, survey respondents actually have a lower mean duration of days in the course, controlling for all demographic characteristics. I ran the following OLS regression on duration in the course for users who logged in at least once during the course:

$$DURATION = \beta_0 + \beta_2 FEM + \beta_2 ANSWER\_SURVEY + \beta_2 BACH\_OR\_MORE + \beta_2 EDU\_OTHER + \beta_2 AGE\_19\_22 + \beta_2 AGE\_23\_30 + \beta_2 AGE\_31\_40 + \beta_2 AGE\_41\_60 + \beta_2 AGE\_OVER\_60 + \varepsilon_\iota$$

Table 4.4: OLS regression on DURATON, including ANSWER_SURVEY (for students with DURATION>0)

n	14,460
Intercept	39.714
FEM	-3.287*** (0.000)
ANSWER_SURVEY	-2.350*** (0.000)
BACH_OR_MORE	-0.046 (0.938)
EDU_OTHER	1.908 (0.165)
AGE_19_22	0.489 (0.702)
AGE_23_30	-0.222 (0.861)
AGE_31_40	1.608 (0.219)
AGE_41_60	2.959** (0.028)
AGE_OVER_60	2.887 (0.104)

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

As indicated by the significant negative coefficients on FEM and ANSWER_SURVEY, female students and survey respondents have lower durations in the course than males and non-respondents, respectively. As we saw above, survey respondents are more likely to begin the course. However, they are also much more likely than non-respondents to drop out of the course within the first week, sufficiently so to pull their mean duration below that of non-respondents. To further investigate early dropouts, I ran the following logistic regression with FIRST_WK_DROP as the dependent variable (binary, equal 1 if 0<DURATION<8 and 0 otherwise, i.e. last login was during the first week of the course):

$$FIRST\_WK\_DROP = \beta_0+\beta_2 FEM+ \beta_2 ANSWER\_SURVEY+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$$

Table 4.5: Logistic regression on FIRST_WK_DROP, for students with DURATON>0

n	14,460
Intercept	0.220
FEM	1.215*** (0.000)
ANSWER_SURVEY	1.477*** (0.000)
BACH_OR_MORE	0.997 (0.968)
EDU_OTHER	0.940 (0.677)
AGE_19_22	0.757** (0.033)
AGE_23_30	0.905 (0.436)
AGE_31_40	0.846 (0.208)
AGE_41_60	0.731** (0.023)
AGE_OVER_60	0.807 (0.245)

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Controlling for gender, education, and age, survey respondents are 47.7% more likely than non-respondents to drop out of the course within the first week. Interestingly, female students are also 21.5% more likely than males to drop out during the first week. Why might survey respondents be more likely to drop during the first week? Perhaps they are more conscientious or evaluative of their experience. In other words, the kinds of people who take a pre-course survey are very conscious of their own preferences and are therefore willing to stop logging in to a MOOC if their expectations are not met for any reason. Conversely, it may be the case that taking the survey actually *causes* students to become aware of their own expectations (because they need to articulate them in writing), and then drop the course when those expectations are not met. In addition, intention to complete does not seem to shed any light on this phenomenon: students who state a high intention level (on Q54 of the survey, mentioned below in the section on intention) are not significantly more or less likely to drop out during the first week than those who mark a low intention level. The mean value for FIRST_WK_DROP is identical for students who intend to complete and students who intend just to browse, at 0.21 for both groups.

The two histograms below display the distribution of students by duration in the course (all students on the left, survey respondents on the right, restricted to students with DURATION>0 for both groups). As indicated by the regression on FIRST_WK_DROP above, the main difference between these two groups lies in the first column: 18.47% of the survey respondents dropped out of the course within the first week, while only 13.44% of overall users did so.

Figure 4.1: Duration in INFX523-01x: all students with at least one login

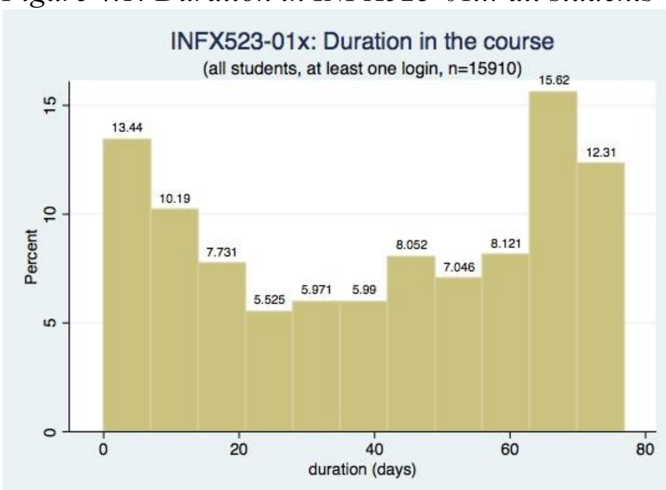
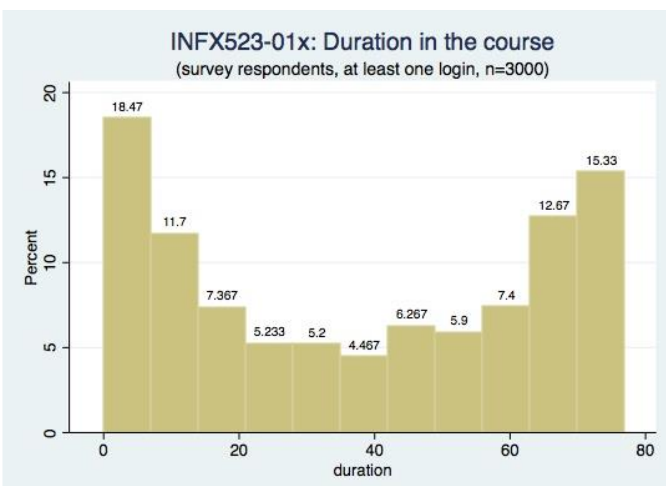


Figure 4.2: Duration in INFX523-01x: survey respondents with at least one login



Thus far, I've discussed the self-selection effects of simply taking the survey. I found two somewhat opposing effects: survey respondents are more likely both to actively complete the course for a certificate and to drop out in the first week. Now, I'll discuss how differences in intention and motivation levels among survey respondents affect course performance.

II. Intention and Completion

Two of the most important questions on the survey gauge students' intentions for taking the course. Question 14 asks, "How important is it to you to receive a certificate for this course?"[12], and Question 54 asks, "What are your expectations for your achievement in this course?"[13] I have used Q54, the more general gauge of intention, in the summary statistics on completion rate and intention below, but I include responses to both questions as variables in all relevant regressions. 73% of survey respondents selected the choice "To complete all course activities and earn a certificate" for Q54, a conspicuously high figure that probably reflects the self-selection for engagement mentioned above. Researchers from MIT and Harvard found that 57% of students intended to earn a certificate (Ho et al. 14). Yet this lower figure may point to a less amplified self-selection effect, because about one third of students responded to the Harvard/MIT pre-course surveys, versus the GeorgetownX figure of 13.8%. In other words, a survey with a lower response rate might select for students with higher levels of proactivity and engagement, because the survey is somehow more difficult to access or respond to.

Among survey respondents, differences in intention level do seem to matter. 23% of those who intend to earn a certificate go on to do so, a very similar rate to the 22% figure that Reich found (Reich 2014). Then, at lower intention levels, we see certification rates barely above the 4% overall rate: 5% for students who only intend to participate in topics of interest, and 6% for students who intend to browse. Finally, I've also included the certification rate for students who participated in the first graded exercise, 27%, to demonstrate that actual course activity predicts success even more strongly than survey responses.

[12] Q14 presented a scale from 1 to 5, with 1 being "not at all important" and 5 being "very important"

[13] Responses for Q54 included: (1) "To complete all course activities and earn a certificate", (2) "To complete most course activities, but not earn a certificate", (3) "To complete only the activities for topics I am interested in", (4) "To browse the course activities and readings"

Table 4.6 Certification Rate and Passive Completion in INFX523-01x

		Certification Rate	*Passive Completion Rate (Last login on or after final content)*
All students n=28,112	Overall	4%	29%
	Logged in at least once	7%	51%
	Attempted first exercise	27%	64%
Survey Respondents n=3185	Overall	18%	45%
	Country of origin: US	15%	35%
	Logged in at least once	20%	48%
	Intention: certificate	23%	47%
	Intention: most activities	10%	40%
	Intention: only activities of interest	5%	40%
	Intention: browse	6%	40%

Chapter 5: The Gender Achievement Gap in INFX523-01x/02x: Globalization's Winners and Losers

As mentioned above in the literature review, Kizilcecc and Halawa find a significant gender gap in their 2015 analysis of 20 MOOCs. Female students were both less likely than male students to score above both the 60th and 80th percentiles. They offer potential hypotheses for females' lower performance: "the [gender-based] achievement gaps could plausibly result from differences in Internet access, language barriers, or from feelings of psychological threat, such as fears of confirming a negative stereotype or not belonging in the course" (Kizilcecc & Halawa 2015). As discussed in relation to Table 3.3, the GeorgeotwnX MOOCs I am investigating seem to support Kizilcec's hypothesis of females "not belonging in the course" : I found that females are less likely to earn a passing grade in courses where they are underrepresented.

In order to test the grade sensitivity hypothesis (discussed in the literature review) regarding gender discrepancies in persistence in STEM/Economics courses, I will investigate versions 1 and 2 of INFX523: Globalization, essentially a course in international economics. I computed percentiles for the final grades in the courses, and then dummy variables of the form "BELOW_Xth" or "ABOVE_Xth", which denote whether a particular observation was below or above the Xth percentile for final grade. I created these dummy variables for above/below the 60^{th}, 75^{th}, and 80^{th} percentiles. To begin, here are a few key gender differences in this course:

- As shown in Table 3.5, females were 16% (42%) less likely to earn a passing grade in Globalization version 1 (2).
- As shown in Table 3.6, the duration from course start date to last login was 3.5 (4.6) days shorter for females in Globalization version 1 (2).
- Finally, to compare gender differences in these two versions of the Globalization MOOC to Kizilcecc and Halawa's results, I have run logistic regressions on scoring below the 60^{th} and below the 80^{th} percentiles for final grades. I found that, as the two tables below display, females are 18% (29%) more likely to score below the 60^{th}(80^{th}) percentile, respectively, in version 1; and females are 35%/46% more likely to score below the 60^{th}(80^{th}) percentile, respectively, in version 2.

BELOW_60th = β_0+β_2*FEM*+ β_2*BACH_OR_MORE*+ β_2*EDU_OTHER*+ β_2*AGE_19_22*+ β_2*AGE_23_30*+ β_2*AGE_31_40*+ β_2*AGE_41_60*+ β_2*AGE_OVER_60*+ε_ι

Table 5.1: Logistic regression on BELOW_60th

	INFX523-01x Globalization 1	*INFX523-02x Globalization 2*
n	3,329	807
Intercept	1.212	1.193
FEM	1.178** (0.028)	1.351* (0.055)
BACH_OR_MORE	1.190 (0.106)	0.930 (0.752)
EDU_OTHER	0.716 (0.164)	0.405 (0.144)
AGE_19_22	1.148 (0.535)	1.631 (0.198)
AGE_23_30	1.131 (0.570)	1.362 (0.420)
AGE_31_40	0.904 (0.651)	1.292 (0.518)
AGE_41_60	0.816 (0.365)	0.944 (0.884)
AGE_OVER_60	0.931 (0.795)	0.576 (0.227)

$BELOW\_80th = \beta_0 + \beta_2 FEM + \beta_2 BACH\_OR\_MORE + \beta_2 EDU\_OTHER + \beta_2 AGE\_19\_22 + \beta_2 AGE\_23\_30 + \beta_2 AGE\_31\_40 + \beta_2 AGE\_41\_60 + \beta_2 AGE\_OVER\_60 + \varepsilon_\iota$

Table 5.2: Logistic regression on BELOW_80th

	INFX523-01x Globalization 1	*INFX523-02x Globalization 2*
n	3,229	807
Intercept	4.572	3.235
FEM	1.289*** (0.006)	1.463* (0.051)
BACH_OR_MORE	1.027 (0.838)	0.708 (0.230)
EDU_OTHER	0.704 (0.204)	0.985 (0.985)
AGE_19_22	0.839 (0.542)	1.431 (0.438)
AGE_23_30	0.861 (0.596)	1.607 (0.310)
AGE_31_40	0.649 (0.133)	1.432 (0.455)
AGE_41_60	0.669 (0.166)	1.321 (0.557)
AGE_OVER_60	1.066 (0.861)	0.932 (0.895)

To test the theory of grade sensitivity, I created a proxy for the decision-making models used in the literature I've discussed above (i.e. the decision to continue with an economics major after taking a semester of introductory economics). Thus, I computed percentiles for the cumulative grades after the first three graded assessments. I then looked at how the likelihood to keep clicking through the course and log in at least once on or after the release of the last week's material (the passive, lower-threshold definition of completion) for groups of students above and below the 75th percentile. As a brief aside, the variable EDU_OTHER was dropped from this regression of the high-achieving group coincidentally; all 24 observations in that group with EDU_OTHER=1 also all had COMPLETE_P=1. I doubt there is any significant systematic reason as to why these 24 students passively completed the course beyond coincidence. As the tables below display, female students above the 75th percentile were not significantly more or less likely to passively complete the course than their male counterparts. Yet, below the 75th percentile, female students were significantly less likely than males to passively complete the course (0.73 times as likely in Globalization version 1, 0.71 times as likely in Globalization version 2). Thus, the lower-achieving group of female students differs significantly from their male counterparts in their decision to continue with the course, but the high-achieving group does not. This difference may be due to sensitivity to receiving lower grades, or some other unobservable characteristic. For instance, lower grades might actually reflect declining interest in the course, which then prompts students to drop out. Thus, female students might be more likely to drop out as their interest declines, rather than as sensitivity to receiving poor feedback. However, without more research on unobservable characteristics, like interest, the regressions below do seem to support the theory of grade sensitivity in the literature discussed above.

$COMPLETE\_P = \beta_0+\beta_2 FEM+ \beta_2 BACH\_OR\_MORE+ \beta_2 EDU\_OTHER+ \beta_2 AGE\_19\_22+ \beta_2 AGE\_23\_30+ \beta_2 AGE\_31\_40+ \beta_2 AGE\_41\_60+ \beta_2 AGE\_OVER\_60+\varepsilon_\iota$

Table 5.3: Logistic regression on passive completion for students above the 75th percentile after the first 3 graded assessments

	INFX523-01x Globalization 1	*INFX523-02x Globalization 2*
n	791	214
Intercept	28.081	11.338
FEM	0.931 (0.856)	0.770 (0.544)
BACH_OR_MORE	1.146 (0.805)	1.181 (0.799)
EDU_OTHER	(omitted)	(omitted)
AGE_19_22	1.085 (0.945)	0.272 (0.273)
AGE_23_30	0.533 (0.572)	0.409 (0.479)
AGE_31_40	2.182 (0.530)	0.309 (0.359)
AGE_41_60	1.009 (0.994)	1.410 (0.799)
AGE_OVER_60	0.737 (0.838)	1.586 (0.771)

Table 5.4: Logistic regression on passive completion for students at or below the 75th percentile after the first 3 graded assessments

	INFX523-01x Globalization 1	*INFX523-02x Globalization 2*
n	2,548	652
Intercept	2.045	1.276
FEM	0.734*** (0.000)	0.709** (0.041)
BACH_OR_MORE	0.864 (0.232)	0.468*** (0.002)
EDU_OTHER	1.189 (0.545)	1.932 (0.356)
AGE_19_22	0.762 (0.301)	0.914 (0.829)
AGE_23_30	0.741 (0.242)	1.282 (0.552)
AGE_31_40	1.067 (0.805)	1.897 (0.142)
AGE_41_60	1.059 (0.830)	2.356** (0.049)
AGE_OVER_60	1.716 (0.108)	3.227** (0.029)

In order to ensure that running two separate regressions (one for the below 75th percentile group and one for the above 75th percentile group) was the appropriate approach. I conducted a log likelihood ratio test. The constrained model was a logistic regression on COMPLETE_P on the entire population of students who had a positive cumulative grade for the first three assessments (i.e., anyone with a percentile, either above or below the 75th). The unconstrained model consisted of the two specifications, the logistic regressions on COMPLETE_P for the populations of students above and below the 75th percentile. I calculated the following test statistics: 245.25 (Globalization version 1) and 49.96 (Globalization version 2), both greater than the critical value at the 95% confidence level, 15.51 (χ^2 , 8df). Thus, for both versions of the Globalization MOOC, the covariates differ significantly enough between the constrained and unconstrained regressions to warrant running two separate regressions for gender differences, as I have done above.

Online versus On-campus: comparison between INFX523 and INAF523: Globalization

The INFX523: Globalization MOOC was created from a course offered on campus at Georgetown, INAF-523: Globalization: Challenges for Developed Countries, also taught by Professor Theodore Moran. The course has been offered for about twenty years. I obtained enrollment and grade data from 2001-2013[14] for this course in order to investigate gender and performance. The course enrollment (41% female), mirrored the gender breakdown in versions 1 and 2 of the Globalization MOOC (40% and 42% respectively). However, final grade earned in the course did not differ significantly by gender. A 95% confidence interval for the difference between mean male final grade and mean female grade included -.1736887 to .0497462. In addition, grading policies seem to have remained consistent since 2001: final grades did not differ significantly by year.

The lack of a gender gap in the on-campus version of the course is not inconsistent with the literature on grade sensitivity if we consider the differences between the student populations in the MOOC versus the on-campus course. INAF-523 is an upper level international economics course in the School of Foreign Service, only open to junior and senior undergraduates, and graduate students. On the other hand, the MOOC has no barriers to entry, allowing anyone in the world with an internet connection to enroll. Although most registered students already have bachelor's degrees, we don't know how much experience in economics-related topics they might have. Thus the MOOC population probably resembles more closely the introductory-level populations where we see gender discrepancies in economics, while the INAF-523 population contains the females who in fact have "persisted" to the point of being able to enroll in an upper level class. Rask notes, "women who continue beyond introductory economics do, on average, better in their economics courses than men who continue" (Rask 2008). Similarly, the mean grade for female students in INAF-523 was slightly (but not significantly) higher than that of male students.

Chapter 6: Results & Implications for the Future

Summary of Results

I investigated three aspects of GeorgetownX's MOOCs: completion, intention, and gender achievement gaps. In general, the courses are serving populations of already-educated learners, and many enrolled students (around a third) never even log in to the courses they sign up for. Intention does matter: students who say they want a certificate have much higher certification rates than

[14] 2005 and 2006 were omitted from the dataset for unintentional reasons

the general population (22% vs. 4% in INFX523-01x: Globalization). I also found two opposing self-selection effects among students who opted to take the pre-course survey, which measured intention: respondents were more likely both to earn a passing grade and to drop out of the course in the first week.

In applying the theory of grade sensitivity to the online setting, I found that low-achieving female students were significantly less likely than their male counterparts to keep logging in, or passively complete, the course. Yet among high-achievers, this gender discrepancy did not exist.

Access to Education

As illustrated in all six MOOCs, the overwhelming majority of GeorgetownX students already have some kind of postsecondary degree. Thus, from the perspective of both institutions (e.g. Georgetown) and platforms (e.g. edX), we should reconsider the fundamental goals of MOOCs in terms of widening access to higher education. Are these courses meant to democratize higher education, or simply serve interested learners who already have traditional credentials? In some ways, the goals of member institutions and MOOC platforms may not align perfectly. The first goal listed on edX's "About" page is to "Expand access to education for everyone." Conversely, on its "About the edX Partnership" page, Georgetown states its goals for the MOOCs with a more internally-focused set of priorities: "Georgetown's primary commitment remains providing the best possible education to our students, and participation in edX gives our community access to new tools and technologies that will support innovation among our faculty to enrich the ways our students interact with course material, with faculty and each other in class discussion."[15]

Improving the MOOC experience

In order to improve MOOCs, universities must first decide on the goal, or set of goals, which MOOCs should work toward. If these goals include spreading higher education to those who would not otherwise have access, then much work remains. Clearly, MOOCs serve a population of mostly highly educated learners. Looking within the individual course experience, MOOC creators may be able to find clever, technology-based interventions for supporting students at particular risk of dropping out, such as low-performing female students in economics courses (other sub-populations can surely be identified by investigating other courses in more depth). Of course, because not all students intend to complete a MOOC, interventions should be tiered on student intention level (either stated in a survey

[15] edX "About": https://www.edx.org/about-us ; Georgetown "About the edX Partnership" page: https://itel.georgetown.edu/about-the-edx-partnership/ga=1.205376208.1544220068.1406484905

or predicted via an algorithm using student demographics and/or initial click data in the course).

Conducting Further Research

For research purposes, Georgetown should reevaluate its pre- and post-course survey methodology. At least for INFX523-01x, we saw a much lower response rate than other institutions (13.8% vs. HarvardX's average of 28%, Reich 2014), and garnering more survey responses would help us better understand the students we serve.

Many questions remain unanswered regarding gender differences in MOOC performance. In this paper, I have taken a very specific look at gender differences in an international economics MOOC, but I have not come close to an exhaustive analysis of gender and performance in online education. Many questions remain, For example: Why are female students more likely to sign up for a course and then never log in? Why do female students have a shorter duration between a course's start and their last login?

I conducted my research using relatively basic course performance data. For future work, I would recommend that researchers with greater technical expertise delve more deeply into click-level course usage data for Georgetown's MOOCs. Through this more precise work, we could get an even better perspective on how to structure interventions or support students in achieving their educational goals. Importantly, more detailed click-level data could clarify some of the gender differences I've discussed in this paper. It might even be possible to research instantaneous reactions to receiving high or low grades with more precision than week-to-week grades and date of last click allowed me to estimate.

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