Can MOOC programs improve student employment prospects?

Authors: Aboozar Hadavand[1], Ira Gooding[1], Jeffrey T. Leek[1]*

Affiliations:

[1]Johns Hopkins Bloomberg School of Public Health, Baltimore, MD 21205.

*Correspondence to: jtleek@jhu.edu.

Abstract: Massive open online courses (MOOCs) exploded into popular consciousness in the early 2010s *(1)*. Huge enrollment numbers set expectations that MOOCs might be a major disruption to the educational landscape *(2)*. However, there is still uncertainty about the new types of credentials awarded upon completion of MOOCs. We surveyed close to 9,000 learners of the largest data science MOOC program to assess the economic impact of completing these programs on employment prospects. We find that completing the program that costs less than \$500 led to, on average, an increase in salary of \$8,230 and an increase in the likelihood of job mobility of 30 percentage points. This high return on investment suggests that MOOCs can have real economic benefits for participants.

One Sentence Summary: A survey of the largest data science MOOC program shows improved salary and job mobility among completers.

Massive Open Online Courses (MOOCs) are recent developments in education. They take the form of online courses that are provided for free or at low cost and are open with no admission process. Growth in MOOC participation was so rapid that it was even faster than user growth on social media platforms such as Facebook *(3)*. Proponents argue that MOOCs are cheaper and more scalable than traditional college courses and can serve a wider variety of students with different needs and learning habits *(2)*.

However, the enthusiasm surrounding MOOCs has been tempered by early results on MOOC completion rates and learner populations *(4)*. Critics of MOOCs have highlighted high attrition rates among learners *(5)* and the fact that MOOCs tend to serve those who already have a college degree or above *(6)* as causes for skepticism. Moreover, it is unclear whether the non-degree credentials typically offered after completion of a MOOCs can serve as an alternative to a university degree or lead to tangible economic or career benefits for learners.

Research on MOOCs is still at an early stage. Although there is an increasing number of studies on learners' behavior and educational outcomes on MOOC platforms, to date, there is no study that quantifies the economic benefits of MOOCs to learners. We found only two qualitative studies on how MOOCs improve job prospects of participants. The first study found that 72% of survey respondents reported career benefits *(7)*. The findings are based on a survey of 52,000 individuals who had completed a Coursera MOOC. A second study looking at the impact of MOOCs on employability surveyed 441 learners who indicated they were motivated to take MOOCs for financial or employment-related reasons *(8)*. Both of these papers make no attempt to quantify the benefits.

We focus on studying and quantifying two potential economic benefits of taking a MOOC: increased earnings and job mobility. Our analysis is based on comparing completers and non-completers of the Johns Hopkins University (JHU) Data Science Specialization (DSS) on the MOOC platform Coursera. Launched in January 2012, Coursera is the most popular provider of MOOCs in the world with more than 25 million learners. Coursera partners with close to 150 universities across 29 countries to produce more than 2,000 MOOCs covering subjects ranging from computer science to philosophy. A typical course on Coursera includes recorded video lectures, graded assignments, quizzes, and discussion forums. Upon successful completion of certain courses or bundle of courses, students have the option to obtain a certificate from Coursera and the partner university.

The initial JHU data science courses on Coursera were created by three Department of Biostatistics faculty members in 2012. These courses reflected, to a large extent, material that was developed for and used in traditional courses at JHU. The offering of these courses, first as a combination of three courses and later as a combination of ten courses, coincided with Coursera's plan to offer “Specializations.” This collaboration led to the birth of the DSS on Coursera in 2014. There have since been more than 4 million enrollments for the entire program *(9)* and 13,119 learners have completed the entire Specialization.

Our study relies on two unique sources of data. First, we use data provided by Coursera, which tracks learner behavior on the Coursera website. Coursera provides user data for specific courses or programs only to the instructors and institutions involved in the creation of those courses. Coursera collects information on learners in five major categories: course content, demographics, learner progress, learner outcome, and forum participation.

Our second source of data is a survey that we sent to learners of DSS. Approximately 9,000 DSS learners responded to the survey. The survey includes questions on job market experience before and after completing the program, educational background, and other demographic variables. More specifically, we ask questions about employment status, occupation, income, the number of job changes since graduation from the program, and the probability of changing jobs in the future. The survey respondents were representative of the learners in DSS as shown in Table S2 in the Supplementary Materials. For instance, among our survey respondents the share of female learners is 31%, the share residing in the United States is 35%, the share who are employed full time is 64%, and the share with a master’s degree or above is 65%, while among general DSS learners on Coursera theses shares are 29%, 34%, 65%, and 61%, respectively. These two sources of data, i.e., the survey data and the Coursera data, were linked using the respondents’ user IDs.

The survey was sent to all of the learners who interacted with the most popular course in the Specialization, *R Programming*. Interaction is defined as clicking on the course, reading the course description, pre-registration, or enrollment. As shown in Panel (A) in Fig. 1, a total of 297,372 learners have interacted with the *R Programming* course since 2015 out of which 57,993 enrolled in the course, 55,360 completed at least one course-item (a lesson, quiz, or exercise), and 29,465 completed the entire course. Panel (B) summarizes the main demographic questions on our survey and how it compares to the learners of DSS on Coursera.

The main challenge in program evaluation studies using observational data is endogeneity (or self-selection) issues. In the case of MOOC program evaluation, we are not aware of the unobserved inherent differences between those who complete the program and those who don't. Individuals who complete a training program are by definition different from those who don't complete. These differences, if they influence the response, may discredit causal comparisons of outcomes by treatment status, even if one controls for the observed covariates. In the absence of experimental designs, there are various ways we could employ to analyze the effectiveness of the program using observational data. As a result, standard methods such as ordinary least squares, which are based on covariate adjustment are not sufficient *(10)*.

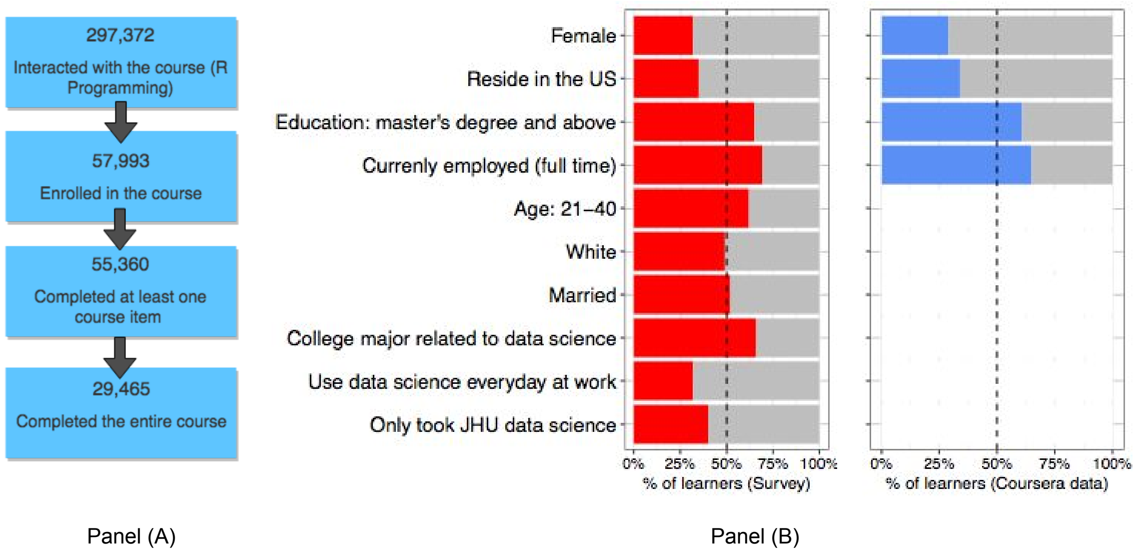

Fig. 1. Panel (A) shows the number of learners with different levels of interaction with the course R Programming. Panel (B) summarizes the share of survey respondents (left) and the share of Coursera learners (right) in various demographic and educational group. Demographic data on Coursera is only available in gender, geography, education, and employment status domains.

A method for adjusting for pre-treatment variables has been proposed by *(11)* that is based on calculating the conditional probability of receiving the treatment, also known as a Propensity Score (PS), given pre-treatment variables. Propensity-score based methods are advantageous to standard regression methods since they (a) work as dimension reduction tools since they reduce multiple covariates into one propensity score, which is an important feature when there are a large number of pretreatment covariates *(12)*, (b) make it clear when it is and it is not possible to separate the effect of the treatment from the effect of other covariates *(13)*, (c) do not require a formal model of the response (outcome) variable, which reduces potential biases caused by misspecification such as multicolinearity *(14)*, and (d) do not extrapolate beyond observed data *(13)*. Propensity-score based methods are becoming more popular in program evaluation analyses using observational data. Various studies use propensity-score based methods to examine the effect of educational or job training programs *(15–19)*.

We perform a propensity score weighted analysis to estimate the causal effect of course completion on incomes. A more detailed explanation of our method can be found in the Supplementary Materials. Panel (A) in Fig. 2 shows the distribution of post-completion income for three different groups for the top ten countries based on the share of respondents in our sample: those who did not complete any of the courses, those who completed between one to five courses, and those who completed more than five courses. We have resampled the survey population using the PS weights.

To better understand the effect of the program on incomes, we perform a regression analysis using the PS weighted sample. We then regress post-completion income on demographic covariates, education, and country of residence. Detailed regression results are in Table S4 in the Supplementary Materials. If we set the treatment threshold at 50 percent of the courses (completing at least 5 out of 10 courses), the average increase in income due to participation in the program is \$4,840 [95% CI = (\$742, \$8,937), P = 0.020]. All values are in U.S. dollars.

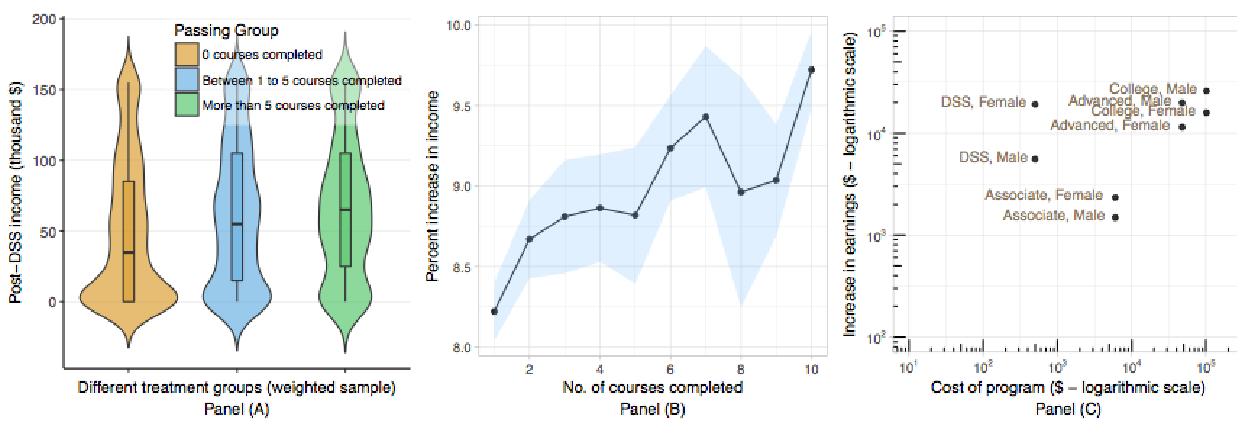

Fig. 2. Panel (A) shows the propensity-score weighted and resampled distribution of income in dollars for the top ten countries in the sample for three different groups: those who did not pass any courses, those who passed between 1-5 courses, and those who passed more than five courses. Panel (B) shows the percentage increase in income for every additional course in the Specialization as well as the 95 percent confidence interval for the top ten countries in the sample. Panel (C) compares DSS to other degrees and certificates in terms of costs and benefits of each program for men and women. See Supplementary Materials for how the numbers on the graph are calculated.

To better analyze different levels of course completion on income, we exploit a recent generalization of binary treatment propensity score models. Following the approach in *(20)*, we estimate propensity scores for each course completion level (zero percent to 100 percent). After calculating the propensity score, we regress post-completion income on the number of courses passed as a continuous variable, the propensity score, and other covariates including education level, gender, age, race, a categorical variable for college major, and country of residence. We find that the coefficient on the number of courses completed is \$823 [95% CI = (-\$10, \$1,650), P = 0.053], which means that for every additional course completed in the Specialization, on average, income goes up by \$823. Panel (B) in Fig. 2 shows the percentage increase in income for every additional course in the Specialization as well as the 95 percent confidence interval. As it can be seen from the plot, most of the increase in income happens in the first quarter of the Specialization *(21)*.

According to Coursera, course completion is defined as completing all graded assignments for the courses in the Specialization. In fact, if the learner does not finish all the assignments, they will not receive a certificate from JHU. We test whether there is any *sheepskin effect*, also referred to as a *signaling effect*. The sheepskin effect states that employees with a credential will have higher earnings than those with the same training but no credential *(22)*. In our Coursera dataset, for each learner in each course, we can see how many items of the course they have passed. We use this to compute a non-binary course completion rate that captures the percentage of items within a course a learner has completed. Aggregating this across all courses creates a new continuous outcome that is the fraction of the Specialization completed by a student. Using the same method by *(20)*, we find the coefficient on the share of courses passed as \$85 [95% CI = (\$5, \$165), P = 0.036], reflecting the increase in income for every percentage point progress throughout the Specialization. This means that for every 10 percent progress (roughly equivalent to one course), income increases by \$850, which is similar to when we only looked at binary course completion, which suggests that there is a limited signaling effect from completing the courses. We use the same covariates as the previous regression.

We further consider whether completing MOOCs has any impact on job mobility in addition to the effect on earnings. Even if taking MOOCs does not lead to an increase in income, it could potentially lead to a change in career path or promotions. We asked learners whether they had changed jobs or gotten promoted since completion of DSS. We then fit a model to evaluate the association between DSS completion and the probability of changing jobs. Our results show that controlling for learner characteristics, for every course passed the chances that the learner has changed job since completion goes up by 3 percentage points [95% CI = (2.4, 4.7), $P < 1 \times 10^{-3}$]. Therefore, on average, completion of the entire DSS increases this likelihood by 30 percentage points.

Similar to most studies on return to education, our analysis suffers from biases caused by unobserved characteristics, such as innate abilities *(23)* that were impossible for us to measure in a survey. Second, DSS does not represent a typical MOOC. The high demand for data scientists makes the market for data scientists unique *(24)*. Despite this, we show in Table S2 in the Supplementary Materials that those who enrolled in DSS replicate an average learner on Coursera or similar platforms regarding demographics (outside of gender) and educational backgrounds. Third, learners were asked to report their income in the year following the completion of the courses from DSS. Thus, this only represents an estimate of the short-term earning and job mobility benefit of MOOC completion.

Here, we have studied the effectiveness of one of the most extensive and most popular data science programs offered online. Our analysis is the first attempt to measure the economic benefits of MOOC programs. The results point to positive and significant benefits of taking DSS MOOCs. College credentials are still highly regarded and employers are still not confident that

MOOC credentials greatly vouch skills *(25)*. However, on the employees' side, we find that a significant share of our respondents mention acquiring MOOC certificates on their LinkedIn profiles (69%), on their resumes (66%), during a job interview (41%), to their colleagues (40%), and to their managers (36%).

Despite having a low completion rate similar to other MOOCs, the number of completers of the DSS program (13,119) outweighs the number of master's degrees in statistics and biostatistics conferred in a given year in the United States (2,486) *(9)*. This high graduation rate reflects the accessibility of MOOCs given that they are provided at a meager cost. The certificate program, on average, costs less than $500 *(26)*. In comparison, we estimate that the cost of a master's program in data science or analytics averages $53,300 for a total of two years. Panel (C) in Fig. 2 compares DSS to college degrees and other certificates in terms of costs and benefits of each program for men and women. Given costs, DSS ranks among the highest in terms of the return on investment. In addition to the high return on investment, DSS is available to anybody around the world. In fact, one out of every four learners in the DSS program is from a lower-middle income or low-income country. MOOCs may not have disrupted traditional college programs, but our results indicate they may be a positive and economically viable supplement for people without the access or means to enroll in traditional programs.

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Supplementary Materials:

Materials and Methods

Supplementary Text

Figures S1-S4

Tables S1-S6

Appendix S1

External Databases S1

References (*27-31*)