Improving Engagement and Learning in Massive Open Online Courses (MOOCs)

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Executive Summary

An increasing number of Massive Open Online Courses (MOOCs) are available to learners across the globe. While enrollment rates are high for such courses, the engagement and completion rates remain low. J-PAL has conducted several experiments to study the gap between enrollment and engagement in online courses. This report presents the results of our most recent experiment, where information on weekly class performance is provided to a random subset of students. Our hypothesis is that knowledge of peer performance is a motivating factor and can lead to greater engagement in the course and higher overall grades. A number of measures are used to determine engagement using data made available by edX. Results indicate that the intervention did not have a significant impact on the number of modules completed or the final score obtained in the course. This report also delineates Type 0 dropouts (those who never intend to complete the course) from Type 2 dropouts (those who intend to complete the course, but fail to do so) using edX’s improved data templates. Finally, the report recognizes some limitations for the study and provides some ideas for future research in this space.
1. Introduction and Motivation

Massive Open Online Courses (MOOCs) have seen huge growth in the past several years. For example, edX, a MOOC platform, currently offers over 570 courses across various streams of knowledge, ranging from engineering and other sciences to humanities and art. Enrollment rates, for most of these courses, is quite high. However, enrollment does not always translate into active engagement or course completion. Onah et al. (2014) find that completion rate in MOOCs is below 13%, significantly lower than for traditional in-person classes. Additionally, the Harvard Gazette reports that certification rates for online courses in computer science and technology related fields are typically lower than the rates for humanities and social science courses. While technically true, there is little reason to believe that those who enroll in free online courses are similar to those who enroll residential programs that have a fee. Since it is virtually costless to enroll into a free online course, there’s reason to believe that a large proportion of enrollees have little intention of, or commitment to, completing the course.

As a starting step towards understanding the gap between enrollment and engagement in an online course, J-PAL identified three types of dropouts:

- Type 0: This type comprises of enrollees who register in the course to browse the material, but never intend (or are unlikely to put in the effort) to complete.
- Type 1: This type includes enrollees for whom the course may not be appropriate. They may sign up only to realize during the first week that the course does not meet their learning objectives.
- Type 2: This group is made up of enrollees for whom the course material is in line with their requirements, and who intend to complete it, but face small barriers that inhibit them from doing so.

Table 1 summarizes the three categories. Our analysis focuses on Type 0 and Type 2 dropouts.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Type 0</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Course appropriateness</td>
<td>?</td>
<td>X</td>
<td>✓</td>
</tr>
<tr>
<td>Intention to complete</td>
<td>X</td>
<td>?</td>
<td>✓</td>
</tr>
<tr>
<td>Completion</td>
<td>X</td>
<td>X</td>
<td>?</td>
</tr>
</tbody>
</table>

In our earlier reports, we have cited several issues that might inhibit Type 2 enrollees from successfully completing a course and earning a certificate. Some of these challenges include disorganization (Banerjee and Duflo, 2014), discouragement when learning objectives are imprecise (Seaton et al., 2012) and course quality (length of videos, clarity of assessments etc.).

Apart from this, the online platform may not be user-friendly. Often times, a platform’s services may not be utilized by an enrollee, as information may not be organized in a suitable manner. For example, the course landing page on edX has several ‘tabs’, including one titled “Schedule” (See Figure 1). The Schedule tab has detailed information on lecture releases and submission deadlines. While it is easy to assume that students would browse all tabs before they start the course, the discussion forums tell a completely different story. Our teaching assistants spend substantial time responding to students seeking submission extensions because they were not aware of the due dates.
In order to understand Type 2 dropouts, J-PAL has tried several experiments in the past, including providing a baseline assessment and offering downloadable iCalendars with recommended deadlines. Thus far, we have not had much success in unpacking the black box between enrollment and engagement.

Figure 1: Course Landing Page – Schedule

In the last run of JPAL 101x: Evaluating Social Programs, we continued our endeavor to understand ways in which we can improve engagement and learning. JPAL 101x is an online version of JPAL’s flagship ‘Executive Education’ course that offers an insight into designing randomized evaluations and executing them in the field. The course comprises of videos interspersed with lecture sequence finger exercises, and case studies. There is also a baseline and final assessment. The finger exercises are designed to help students stay engaged with the video lectures. These questions are largely multiple choice and related to the short videos directly preceding them. The case studies involve thinking through the concepts and issues raised in the lecture sequences.

Akin to the last experiment conducted on JPAL 101x, we tried to explore how the in-built functions within edX can be used to encourage course completion. For example, guiding students to the ‘Progress’ tab (See Figure 2), where a student can track his/her grade through the course.

Figure 2: Course Landing Page – Progress

In the last experiment, we only directed students to the progress tab without providing any benchmarks to help them gauge their performance vis-à-vis their colleagues in the course. Our research proposes to understand whether providing information on the weekly class average grades encourages course completion and learning. Finally, we also explore how many Type 0 dropouts enrolled in the course.

This report is organized as follows: Section 2 describes the experiment set-up, Section 3 provides the analysis and Section 4 provides the conclusion.
2. Experiment Set-up

We implement a randomized experiment, where the treatment group is provided information on weekly class performance. Randomization is done at the individual level using the cohort feature on edX. When enabled, the cohort feature randomly assigns enrollees into treatment or control as soon as they open a course page.

Until its fall 2016 round, JPAL 101x was set up such that modules are released each week, but the deadline to complete all assignments for each module is the last day of the course. This system was not suitable for our experiment, which required sharing weekly scores with the treatment group. So, for this round of the course we set up weekly deadlines for all students. Lectures were released every Wednesday and the respective finger exercises and case studies were due the following Tuesday. We ensured that both the treatment and control group were notified of the deadlines in every communication we shared with them.

The information on class performance (average scores and completion) was provided through emails sent via edX. The treatment group received an email at the start of every lecture week i.e. every Wednesday, with the following information (See Figure 3):

- The modules released with their submission deadline
- Class average and top score for the finger exercises and case studies released in the previous week
- Link to the Progress tab [hyperlink to progress tab within the MOOC platform]

**Figure 3: E-mail sent to Treatment group in Week 2**

The Control group received an email at the start of every week, detailing the modules released and their submission due dates, as illustrated in Figure 4.

It is important to note here that the ‘Progress’ tab is available to all learners. We directed the Treatment group assuming that learners do not fully explore all features of the platform. Our original experiment intended to randomize the submission deadline dates. Unfortunately, edX does not offer a feature where we can offer different deadlines across participants, so we were unable to proceed further.
3. Data, Analysis and Results

The data for our analysis comes from five different sources. The details of the dataset, its contents and the data source is listed in Table 2.

Table 2: Datasets used in the analysis

<table>
<thead>
<tr>
<th>Data</th>
<th>Contents</th>
<th>Source</th>
<th>Unique identifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student meta data</td>
<td>Per student profile and course engagement data</td>
<td>IRX</td>
<td>User name</td>
</tr>
<tr>
<td>Grade report</td>
<td>Grade per student/question</td>
<td>edX course page</td>
<td>User name and User ID</td>
</tr>
<tr>
<td>Entrance survey</td>
<td>Student aspirations from the course</td>
<td>IRX</td>
<td>Anonymized ID</td>
</tr>
<tr>
<td>Exit survey</td>
<td>Student feedback on the course</td>
<td>IRX</td>
<td>Anonymized ID</td>
</tr>
<tr>
<td>Anonymized IDs</td>
<td>Used for merging data sets</td>
<td>edX course page</td>
<td>User ID and Anonymized ID</td>
</tr>
</tbody>
</table>

Note: IRX is the data management wing on edX that complies data across courses and shares them with the respective course teams.

The datasets contain unique identifiers that can be used to merge them into one master data file for analysis. Most of our study uses the student meta data and the grade report. Though the entrance and exit survey data contain useful information, there are usually low responses since both surveys are not mandatory.

Given the existing understanding that MIT has with edX, additional informed consent was not required from users. All necessary IRB exemptions were obtained before the study launch and confidentiality clauses were duly maintained during analysis and reporting.

The analysis is divided into four parts. We briefly discuss Type 0 dropouts and then measure the effect of the treatment on course engagement and learning. Finally, we test if the treatment has any impact on weekly course completion. Note that parts two and three is similar to the analysis provided in our previous report.
3.1 Attrition

Our earlier report provided a comparison including zero and non-zero grades because we were unable to distinguish between Type 0 and Type 2 dropouts. To recap, edX’s data management system was such that the grade for a particular question was assigned as zero if (a) the student actually received a score of zero for the said question or (b) the student did not attempt the question. Following several negotiations, edX was able to revise the grade report such that if a student did not attempt a question, his/her score was recorded as “Not Attempted” and not zero. This opened doors for us to invest in categorizing Type 0 dropouts more effectively.

In our analysis, we consider Type 0 dropouts as those who did not attempt even a single question in the course. By this definition, we found that over half of the total enrollees were Type 0 dropouts.

The attrition patterns between treatment and control is provided in Figure 5.

![Figure 5: Weekly Attrition Rates for JPAL 101x](image)

As seen in Figure 5, attrition is the highest during Week 1, which mainly comprises Type 0 dropouts. Since our intervention began only in Week 2, we cannot attribute the difference in attrition among treatment and control during week 1 to our experiment. From Week 2 onward, the dropout rates continues to be higher for the control group. However, this difference is not statistically different.

Our sample size for the analysis, excluding the Type 0 dropouts, stands at 242 for the Treatment group and 268 for the Control group.
3.2 Course Engagement

Course Engagement or CE is measured using three variables – (i) Number of days the learner was active on edX, (ii) Number of modules completed by a student, and (iii) Number of videos played by a student. Table 3 provides the regression results.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of days active</td>
<td>No. of modules completed</td>
<td>No. of videos played</td>
</tr>
<tr>
<td>Treatment</td>
<td>1.207</td>
<td>-0.00683</td>
<td>26.99</td>
</tr>
<tr>
<td></td>
<td>(0.764)</td>
<td>(0.347)</td>
<td>(21.25)</td>
</tr>
<tr>
<td>Constant</td>
<td>11.03***</td>
<td>7.034***</td>
<td>145.2***</td>
</tr>
<tr>
<td></td>
<td>(0.532)</td>
<td>(0.242)</td>
<td>(14.79)</td>
</tr>
</tbody>
</table>

Observations 462 462 462

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

The hypothesis here is that awareness of class performance encourages students to stay-on in the course and complete more modules and view more videos. However, we do not see any significant impact of the intervention on course engagement.

3.3 Course Learning

Course Learning (CL) is measured using the final grade received by the learner in the respective course. Our hypothesis here is that knowledge of class averages for each week fosters a sense of completion leading to better grades among the treatment group.

Figure 6: Effect of Treatment on Course Learning

Note: For a regression to be significant, the coefficient has to be significantly different from zero. In other words, the errors bars, which represent 95% confidence intervals, should not pass through the red line.
As seen in Figure 6, the grades for the treatment group are not significantly different from the grades obtained by the control group. Thus, providing information on weekly class performance does not seem to impact the overall grade.

3.4 Weekly Completion

The final component of our analysis looked at the week on week completion rates by treatment status. Here, the assumption is that receiving weekly performance reports leads to better engagement and completion of weekly deadlines. We use an ordered logit model here, where the dependent variable (i.e. Weekly course completion) is defined as per Table 4. Results are provided in Figure 7.

<table>
<thead>
<tr>
<th>Value</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>If the student did not attempt any of the assignment questions for the given week (this excludes Type 0 dropouts)</td>
</tr>
<tr>
<td>1</td>
<td>If the student has completed at least one of the following – (a) all the finger exercises for one lecture released in the week or (b) one of the case studies released in the week</td>
</tr>
<tr>
<td>2</td>
<td>If the student has attempted all the assignments released during a given week</td>
</tr>
</tbody>
</table>

Figure 7: Weekly Course Completion

Note: For a regression to be significant, the coefficient has to be significantly different from zero. In other words, the errors bars, which represent 95% confidence intervals, should not pass through the red line.

As evident from Figure 7, the weekly course completion rates are not significantly different between treatment and control. Overall, providing weekly emails on class performance does not seem to encourage Type 2 dropouts to continue the course.
4 Conclusion

The analysis does not detect any impact of the intervention on outcomes of interest. In our last report, we indicated that since the level of Type 0 dropouts is high, we are left with a sample size that does not have enough power to underpin the results. This is probably true for this round as well. That said, we also need to ask a more fundamental question here – do students check emails that come from edX? It just may be the case that our implementation technique is flawed. We plan to both continue this experiment for future rounds of the course as well as identify other ways in which we can share progress information with a sub-set of students via edX.
References

