The Impact of Engagement with User-generated Content in Online Discussion Forums

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Abstract

Many online platforms that offer a core product for consumption also provide a space for the creation and consumption of user-generated content (UGC). Conditional on such an arrangement, we study whether a user's engagement with UGC has an impact on their engagement with the core product using a novel dataset from Coursera, a popular online education platform. Coursera provides its core product in the form of course material embedded within lecture videos and supplementary readings and provides a space for UGC creation and consumption via discussion threads about course materials on a discussion forum. We leverage the exogenous variation in the forum home page as a shifter of a user's propensity to engage with UGC (i.e., the discussion forum). This allows us to identify the causal effect of that user's engagement with UGC on their engagement with the core product and their mastery of the content covered in that course segment. Our analysis suggests that, on average, a 10% increase in a student's UGC engagement increases that student's engagement with the core product by 4.18% and performance by 0.34%. We conduct multiple robustness checks to ensure that our findings are robust to modeling choices. Our findings for this platform suggest that users tend to view UGC and the core product as complements. In the specific context of online education platforms, our results suggest that discussion forums bolster student engagement with the course content as well as their learning.[1]

[1]We thank seminar participants at the Department of Marketing and the Department of Economics at the University of Michigan, and attendees of the Marketing Science Conference, Chicago 2022. This paper has also benefited substantially from thoughtful comments made by Jessica Fong and Justin Huang. All errors are our own.

INTRODUCTION

Many online platforms, in addition to the main product that they offer, also provide the space for creation and consumption of user-generated content (UGC), usually in the form of discussion forums. For example, news platforms provide curated information on current events and present opinion pieces in the form of editorials. These constitute the main product that the news platforms offer to their users. At the same time, they also allow users to post their comments and elicit reactions from their peers (a form of UGC) in their discussion forums. Other examples where the core product and UGC coexist include social news aggregation websites such as Reddit, online gaming platforms (e.g., Gaia and Zapak), fitness websites (e.g., Bodybuilding.com and MyFitnessPal), and online education platforms (e.g., Coursera, EdX, Udemy, etc.).

In light of the coexistence of the core product and UGC within the same platform, a natural question that arises is whether the two types of content are complements or substitutes. On the one hand, engagement with user-generated content can enhance the value derived from the main product and vice versa. This would render the two types of content as complements. On the other hand, consumption of one type of content could potentially distract users from consuming the other content, probably because they compete for the same available time (or other resources), thereby making them substitutes. Therefore, in contexts such as media consumption and online education where both effects are likely to occur, the direction of the relationship is ambiguous. If the core product and UGC are complements (substitutes), increasing user engagement with UGC will increase (decrease) their engagement with the core product. This can have downstream implications for the value that users derive from the core product, and consequently, their retention.

In this paper, we ask whether engagement with UGC has a spillover effect on that user's engagement with the core product. If such spillover effects exist, their direction (i.e., positive vs. negative) would tell us if users view the two types of content as complements or as substitutes. We perform our empirical analysis using data from the online education platform, Coursera. Education platforms such as Coursera collaborate with academic institutions and industry partners to offer online courses, which constitute their core product. At the same time, these platforms also provide access to UGC in the form of forums where participants can browse the discussions of past students and participate in discussions with their peers while learning.

On online education platforms, on the one hand, increasing engagement with the discussion forums can potentially foster social learning and thus enhance the value that participants derive from these courses. This, in turn, will have positive implications for the platform in the form of higher user retention. On the other hand, engaging with the discussion forum could take participants' attention away from the core course material. Furthermore, from a supply perspective, managing these discussion forums for each course, at a time when the number of courses offered on these platforms is exploding, can be expensive for platforms. There is also a debate about whether the value of discussion forums can be realized given the technical architecture of forums on online education platforms. For example, Thomas (2002) suggests that the typical nonlinear branching structure of online discussions may be insufficient for the realization of truly conversational modes of learning that is the main source of effectiveness of discussion forums. Hill (2013) echoes this critique by finding that most MOOC discussion forums are distracting as they have dozens of indistinguishable threads and offer no way to link between related topics and that such discussion forums can be barriers to engagement. Understanding how a given participant's engagement with UGC affects their engagement with the course content will shed light on the relationship between the two forms of content. If the two forms of content are perceived as complements (substitutes), increasing engagement with one would increase (decrease) engagement with the other. Answering our research question will help resolve the ongoing debate about the value of engagement with UGC in online courses.

However, isolating the relationship between user engagement with UGC and the core product (educational material in our context) using observational data is likely to be challenging for several reasons. First, users are likely to be different in terms of their level of motivation as well as their ability to master the course material. These differences can influence engagement with both types of content and therefore render them correlated. Second, courses (as well as different modules within a course) may differ in terms of the level of engagement that they require from their users. These differences can result in users spending more time in both types of content in some courses (or in some modules within a course) and less in others. Third, the overall proficiency of the users with respect to the educational content as well as in navigating the various learning objects might evolve over time. Similarly, the courses as well as the modules within these courses may have evolved over time in a way that would have influenced the benefit from joint consumption of the two types of content. The three factors noted above can induce correlation between the consumption of the two types of content. Separating this correlation induced by user heterogeneity, course design, and accumulated experience from the causal relationship that we seek to uncover can be challenging. Finally, even if we can control for these correlated unobservables that drive engagement with both types of content, it might be difficult to isolate the direction of causality, i.e., did engagement with UGC drive engagement with the course material (i.e., the main product) or vice versa?

We perform our empirical analysis using granular clickstream data from ten courses offered on the Coursera platform. Our data span 63 months from January 2015 through March 2020. During this period, each course had several cohorts of students. Furthermore, each course is broken down into multiple modules (average of approximately 8 modules per course), with each module having its own course material (i.e., the main product) and discussion forum (i.e., UGC). For each user, our data enable us to infer the time that they spent on the educational material as well as on the discussion forums at the module level. The granularity of these data allow us to include a rich set of fixed effects that account for several confounders in the analysis; they control for cross-sectional differences (i.e., between users, courses, and modules within a course) as well time-varying factors (e.g., changes in course content, differences across cohorts etc.) that may induce correlation between engagement with the two types of content.

In order to isolate the causal effect of user engagement with one type of content on their engagement with the other type of content (i.e., pin down the direction of the causal effect), we need an exogenous variable that will have a direct effect on the former but not the latter. We exploit a unique aspect of the discussion forums to help with this identification. In particular, the discussion forums list multiple threads in order of the recency in the activity on each thread. As a result, the threads on the home page for the discussion forum for a module can change over time based on which threads saw activity recently. Thus, two users visiting the forum a few minutes apart could see different sets of threads listed and ordered on the home page. We show that the propensity among users to click on the discussion threads within a forum (a metric of engagement with UGC) increases with the number of views of the threads listed on the first page. We refer to the number of views for the threads on the first page of the discussion forum as the view index. Since the threads that are displayed on the home page and the order in which they are listed can be considered as being assigned at random given the specific arrival time of a user, we use the view index as an exogenous shifter of the user's propensity to engage with the discussion forum (i.e., the UGC). At the same time, this variable should not have a direct effect on their engagement with the course material (i.e., the main content) for that module.

Our results suggest that engagement with discussion forum (i.e., UGC) increases the marginal utility from the consumption of the course material (i.e., the main product). On average, a 10% increase in engagement with UGC increases engagement with the main product by 4.18%. Therefore, users view UGC and the main product as complements. Furthermore, our results suggest that a given user's engagement with UGC has a positive impact on their performance within the course. On average, a 10% increase in engagement with UGC increases student performance by 0.34%. Overall, these results imply that, in the context of MOOC platforms, having a vibrant discussion forum (i.e., UGC) can help in increasing user engagement with the course material (i.e., the main product) as well as their performance in these courses. Therefore, MOOC platforms ought to internalize this benefit of discussion forums while making their design decisions.

The explosion of UGC has made managing it a big challenge for content-based platforms. The borderless nature of discussion forums means that it can be hard to avoid the less useful content embedded within (Sunyer, 2014). Propelled by such concerns, some news websites (eg: Recode, Reuters, The Week, Mic, The Verge, Popular Science, Radio New Zealand, etc.) are drastically reducing support for UGC stating that it is not their primary product and that moderating it poses a major challenge ((Ellis, 2014); (Goujard, 2016)).

Note that the coexistence of different forms of content, the core product and UGC is not a unique feature of the institutional setting explored in this study. Rather, in today's online platforms across a variety of industries such as gaming, fitness, mass media, etc., the core product often co-exists with UGC. Therefore, by exploring how consumers perceive the two forms of content when they coexist, our research has potential managerial implications beyond online education.

The rest of the paper is organized as follows: First, we will discuss the related literature. Second, we will describe our dataset and discuss our research design in greater depth. Next, we will present our empirical analysis, discuss the results and robustness checks. Finally, we will conclude with the implications of our findings and the limitations of our study.

RELATED LITERATURE

Firms are interested in increasing user engagement with their content because it has implications for retention and monetization. The extant literature has studied the drivers of user engagement with content in many contexts, ranging from entertainment, news, gaming, social media, and online education. Depending on the context, engagement can be measured in several ways such as time spent in actively consuming the content, commenting on various aspects of the content, and sharing the content with others. We discuss what we know from the literature regarding drivers of user engagement with content. Given that our empirical investigation is in the context of online education, we discuss the literature corresponding to this setting separately.

Drivers of User Engagement

A natural way to increase engagement is by modifying the way content is designed. In the context of social media platforms, design can play an important role in driving engagement with the content posted by a brand. For example, Lee et al. (2018) find that content related to brand personality, such as humor and emotion are associated with higher engagement. On the other hand, messages with informative content such as price and deals is associated with lower engagement when present in isolation. However, when the informative content is presented along with brand personality-related attributes, the engagement is higher. In a similar vein, Li and Xie (2020) find that the mere presence of image content in branded posts on Twitter affect user engagement. In addition to influencing engagement with the content posted by brands, design features can also drive peer influence. For example, using a randomized field experiment, Aral and Walker (2011) show that by designing viral features into products and marketing campaigns, firms can generate economically identifiable peer influence and contagion effects.

Researchers have also reported the role of product design in driving user engagement in contexts other than social media. In the context of multiplayer video games, Huang et al. (2019) show that matching players in game rounds can be an effective tool for increasing their engagement. Gu et al. (2022) study the impact of crowdsourcing features on user engagement in the context of a mobile gaming app. The authors report that giving users the opportunity to submit content increases their engagement and retention by empowering users to control their product experience. On the other hand, allowing users to access crowdsourced content does not have a significant effect on engagement, although it does improve retention. However, the authors find that allowing users to submit content as well as access crowdsourced content lowers engagement. Therefore, the ability to submit and access content are not complements.

In addition to product design, the literature has also documented the effect of the elements of the marketing mix, such as pricing and promotions, in driving user engagement. In the context of online newspapers, Pattabhiramaiah et al. (2019) show that the implementation of paywall by the New York Times in 2011 resulted in a decrease in user engagement. In the context of social media, marketers routinely use influencers to increase user engagement for their products and related postings. In this context, Valsesia et al. (2020) show that, conditional on having many followers, influencers who follow few others are more effective in generating user engagement than those who follow a large number of other users. While these interventions consider actions taken by firms, researchers have also investigated the effect of UGC in driving engagement with the brand. For example, Hartmann et al. (2021) study the effects of two types of selfie images on social media on engagement - consumer selfies and brand selfies. The authors find that while brand selfies increase engagement with the brand, consumer selfies increase engagement with the sender. Their findings have implications for managers seeking to use consumer selfies on social media to increase engagement with their brands. Still in the context of UGC, Ksiazek et al. (2016) study the generation of UGC, which can also be viewed as a metric of engagement. The authors study how the exposures of YouTube news videos are associated with the number of user-content and user-user interactions generated by such videos. They find that an increase in a video's exposures is associated with an increase in the number of comments received by that video (UGC in the form of user-content interactions). In contrast, a decrease in a video's exposures is associated with an increase in the number of conversations among users in the comments section of that video (UGC in the form of user-user interactions).

In recent years, organizations have explored ways to enrich the user experience by developing platforms (websites) through which users generate and contribute content (Di Gangi and Wasko, 2009). As a result, researchers have tried to understand the consequences of customer engagement with UGC residing on these platforms in a variety of different contexts. In the context of politics, Houston et al. (2013) find that tweeting while watching a presidential debate was related to participants reporting more favorable attitudes about the democratic candidate, paying more attention to the debate, and perceiving debates to be more important. However, such behavior was not related to enjoying the debate more. Berman et al. (2019) shed further light on these findings in subsequent research that shows that sharing content on Twitter during an election debate is positively associated with engagement with the live event among sharers.

In addition to the association between UGC creation and engagement, researchers have also studied the relationship between the recognition of the UGC created by a user and their subsequent engagement with the platform. For example Lu et al. (2022) study the effect of users receiving badges for posting UGC. They find that users increase their content generation, but decrease their content consumption immediately after receiving a digital badge. However, the authors report enduring positive effects on content generation and consumption as a result of badging. In a similar study, Huang et al. (2022) conduct a field experiment to study the relationship between the attention and recognition that a user's content receives on their subsequent engagement with the platform. The authors report that increasing the attention and recognition for a user's content can increase their engagement with the platform. Together, these results suggest that being recognized by their peers or the platform for their contribution can be an effective lever in increasing their engagement with the platform.

Drivers of User Engagement in Online Courses

Despite their promise to revolutionize education, online courses have fallen short on account of low user engagement and completion rates (Khalil and Ebner, 2014; Koller et al., 2013;

Onah et al., 2014). As a result, there is a growing body of research investigating the drivers of user engagement in online education. Given that online courses are open to all learners, they attract a wide variety of participants, who differ considerably in terms of their ability and motivation. Banerjee and Duflo (2014) find that the ability of students to stay organized and force themselves to complete tasks on time is an important determinant of student engagement and performance. In addition, as Lu et al. (2022) document, participants in online courses differ considerably in terms of their learning styles. Therefore, some of the deficiencies in the effectiveness of online courses can be traced back to the characteristics of their participants. Although these intrinsic traits of participants may seem to be immutable, Patterson (2018) shows that they can be altered using behavioral interventions. Using a randomized control trial, Patterson (2018) shows that tools like commitment devices can increase student engagement in online courses.

As with the literature on the drivers of user engagement with content, researchers have also considered the link between course design and engagement. In one of the early studies on online courses, Conrad (2002) performed a descriptive investigation of the correlates of engagement. The author found that the experience in the first class or the beginning of an online course will contribute to the sense of well-being and engagement among learners. More recently, using video data from online education platforms such as Masterclass and Crash Course, Zhou et al. (2021) show that basic video characteristics (e.g., length, speaking rate, etc.), instructor's emotion and physical characteristics, and visual aesthetic features (e.g., brightness, warm hue proportion, clarity, etc.) are important predictors of engagement. Although they fall short of claiming this relationship to be causal, their results suggest that online education platforms could potentially increase engagement by adjusting the design of course videos. Extant research studying the effect of gamification as a driver of user engagement has also reported some interesting findings. While Hamari et al. (2014) reveal positive effects of gamification, Van Hentenryck and Coffrin (2014) suggest that one-size fits all style gamification programs may be perceived as annoying and can even induce users to abandon the learning platform.

In addition to content design, online education platforms and the courses therein can influence engagement using other levers that are not directly related to the content itself. For example, Goli et al. (2022) demonstrate that the mere act of paying for an online course can trigger the sunk cost effect and therefore increase the engagement of participants. Therefore, they suggest that pricing can potentially serve as a useful tool to increase engagement in online courses. Closer to our research context, researchers have also studied the relationship between participation in the discussion forum and engagement with the course content. Using an experiment that nudges users to share ideas on forums, Narang et al. (2022) examine how content sharing on the discussion forums in online courses affects the engagement of content "creators". Using a similar experimental design where users are nudged to visit the discussion forum, Zhang et al. (2017) study how engagement with content on the forums affects the quiz completion rates and performance of content "consumers" in online courses. The idea behind both these studies is that the randomly assigned nudge to engage with the discussion forum will result in increased engagement, which, in turn, can impact engagement with content.

Similar to Narang et al. (2022) and Zhang et al. (2017), our investigation is related to the idea of increasing engagement with the discussion forum and its consequence on consumption of the course material. However, our approach differs from Narang et al. (2022) and Zhang et al. (2017) by studying the effect of exogenous variation in the intrinsic attractiveness within the discussion forum once the participant has visited the forum. In general terms, there are two ways to increase engagement with the discussion forum: (a) nudging them to engage with the forum and (b) improving the attractiveness of the content within the forum. The experimental design employed by Narang et al. (2022) and Zhang et al. (2017) demonstrates the effectiveness of (a) on engagement. Our approach complements this by considering the influence of (b) in driving engagement. Therefore, while their approach sheds light on the effect of nudges to participate in the discussion forum, our approach has implications for the design of the forum to increase participation therein. Hence, our approaches can be viewed as complementing each other.

DATA DESCRIPTION AND MODEL-FREE EVIDENCE

We will first present a brief description of the data used in our analysis and present some summary statistics. Next, we will provide descriptive evidence for our thesis that engagement with UGC can have consequences for engagement with course material and performance. Finally, we will discuss the challenges in inferring the causal relationship between a user's engagement with the forum and their engagement with the course material.

Data Description

Our data come from ten "on-demand" courses offered by a large public university on Coursera. The observation period in our study is from January 2015 to March 2020. During this period, the courses in our panel did not undergo any major modifications, either in terms of content or structure. A total of 48,127 students participated in these courses.

On this platform, participants consume the course content in a self-paced manner. Thus, unlike in a regular classroom setting, each enrolled student progresses through a given course at their own pace. Each course is structured as a collection of modules. Within each module, students are expected to complete a set of lecture videos and some supplementary readings and activities. Once participants have completed the course material for that module, they take one or more assessments based on the topics covered in that module. In addition, each module has its own discussion forum where participants can discuss and ask questions about the course material covered in that particular module by either creating their own threads or by adding to existing threads. In addition, participants can merely engage with existing threads. We present the typical structure of a course offered on this platform in Figure 1.

Our dataset is longitudinal because we observe how an enrolled student progresses through

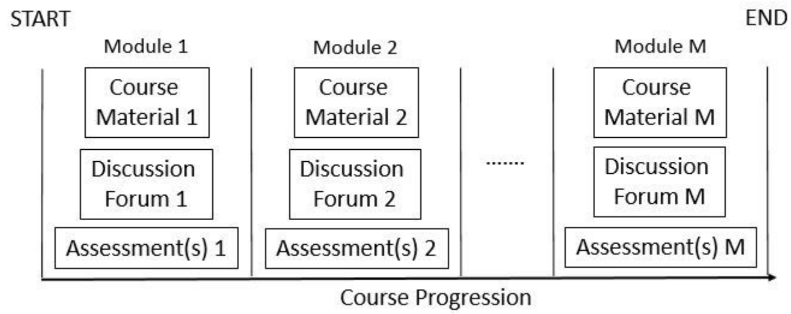


Figure 1: Course Structure on Coursera

the various modules within a course. We use two kinds of data in our empirical analysis. The first kind is the click stream data, which enable us to track the time spent by each student on the course material (i.e., the main product) corresponding to the various modules within the course. As noted above, each module has its own course material and discussion forum. The course material come in the form of lecture videos, readings, and other activities. In the discussion forum (i.e., the UGC), participants can engage in three different ways: (a) starting new threads, (b) adding to existing threads, and (c) consuming content in the existing threads. The click stream data allow us to infer the time spent by each student in accessing content in the module-specific course material. We use this time spent by each participant in consuming content as a measure of engagement. With regards to the discussion forums, we use the number of discussion threads that a user clicked (i.e., (c) above) as a metric of their engagement.[2]

The second kind of data we use include information on each participant's performance. For each participant, in every module, we observe their performance in the assessments for that module. For modules that have multiple assessments, we compute student performance as a weighted average of the grade in each assessment. Together, the two kinds of data give us three key metrics that are related to a student's experience with the course: (a) engagement with the course material (i.e., the main product), (b) engagement with the forum (i.e., the UGC), and (c) their performance in the course. As discussed above, our objective is to

[2]Subsequently, we verify the robustness of the results by modifying the metric to include all three modes of engagement, i.e., (a)-(c). The result of this robustness check is reported in Appendix C.

isolate the causal effect of (b) on (a), and subsequently on (c).

Among the 48,127 students, 7,874 students (16.35%) contemporaneously visited the discussion forum during their course journey at least once.

Summary Statistics

We present the summary statistics that describe the distribution of the key pieces of information across the ten courses in Table 1. The first two rows represent the characteristics of the courses. The information in Table 1 suggests that a typical course has about 7.6 modules and 4812 students enrolled. However, there is considerable heterogeneity across courses on both these dimensions. The remaining rows reflect different aspects of user behavior within these courses in terms of their (a) engagement with the course material (i.e., the main product), (b) engagement with the discussion forum (i.e., the UGC), and (c) completion of the course and performance therein.

Table 1: Descriptive statistics across the ten courses

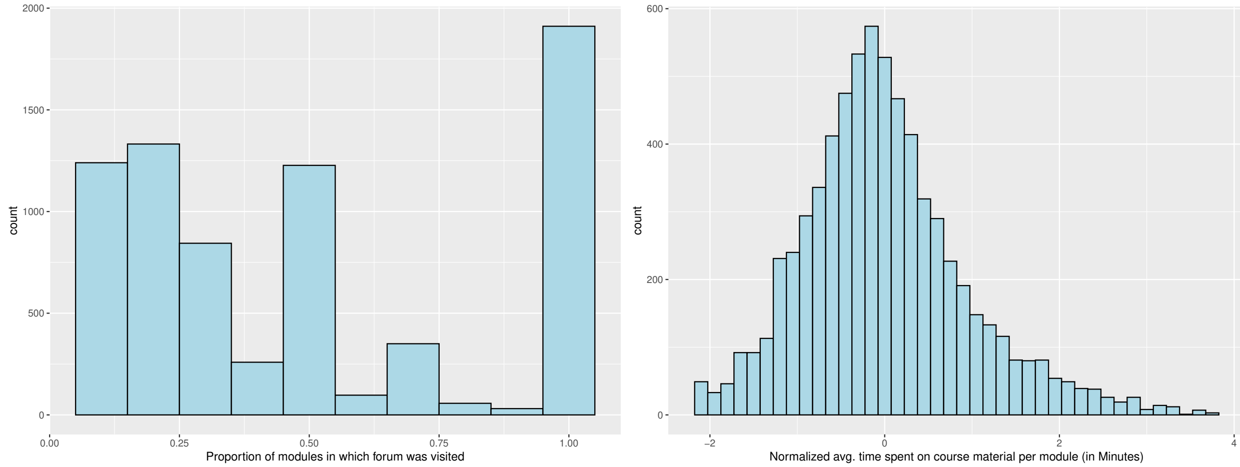
Statistic	Mean	Std. Dev.	Min	Max
Number of students	4,812.700	5,278.634	653	14,519
Number of modules	7.600	2.875	4	12
Avg portion of course completed	0.390	0.121	0.179	0.601
Avg Time spent on content per module (in minutes)	125.122	45.755	77.129	218.160
Number of Forum Visitors	787.400	1,036.310	57	3,081
Number of Thread Viewers	532.800	742.315	19	2,267
Percentage of students completing the course	17.5	9.1	3.2	32.3
Average overall course grade (out of 100)	38.104	13.832	17.872	57.301

With regards to user engagement with the course material (i.e., the main product), a typical student spent a little over two hours (125 minutes) per module. For engagement with UGC, we find that an average of 787.4 students (16.4% of those registered in the course) visited the discussion forum corresponding to at least one of the modules within the course. Of those who visited discussion forum, an average of 532.8 (67.6% of those who visited the forum) clicked on at least one of the threads and viewed the content therein.

The final two rows of Table 1 shed light on the course completion rates and the performance of participants within the course. These summary statistics reveal that only about 17.5% of participants taking a course ended up completing it. There is considerable heterogeneity across courses, ranging from a low completion rate of 3.2% for some courses to a high of 32.3%. Similarly, the average grade for the participants was 38.104%, with a range of 17.872% to 57.301% across courses. Together, the data in Table 1 highlight the fact that courses differ considerably in terms of their design, student engagement with the course material and the discussion forum, and their performance in the course.

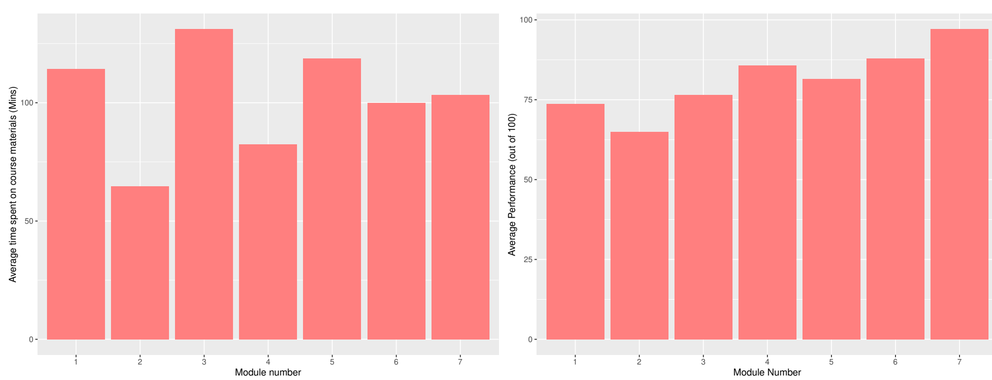
Let us now take a closer look at the distribution of some of the key metrics across individuals and modules within courses. First, we consider heterogeneity across individual users in terms of their engagement. We consider users that had at least one engagement with the forums and present the distribution of the proportion of modules within a course where each user visited the discussion forum in Figure 2a. The information in these figures suggests that there is considerable heterogeneity across users in terms of their propensity to engage with the discussion forum as well as the course material as shown in Figure 2b. In particular, while some users consistently engage with the discussion forum, others are largely dormant. This heterogeneity in engagement across users is probably driven by differences in their intrinsic motivation to engage and/or in their ability to master the material.

Next, we consider how the engagement metrics vary across modules within a course. In Figure 3, we present this information for one course in our data. Once again, the data suggest that modules within a course differ considerably in terms of the amount of time participants spend in consuming course material, visiting the discussion forum, and in viewing threads in the discussion forum and engaging with the user generated content. This heterogeneity is probably attributable to differences in the need for engagement (i.e., due to the nature of the course material) or to the ability of the material to foster engagement (i.e., due to design). As we discuss subsequently, we need to control for such heterogeneity across individuals and modules while parsing out the causal effects of interest.

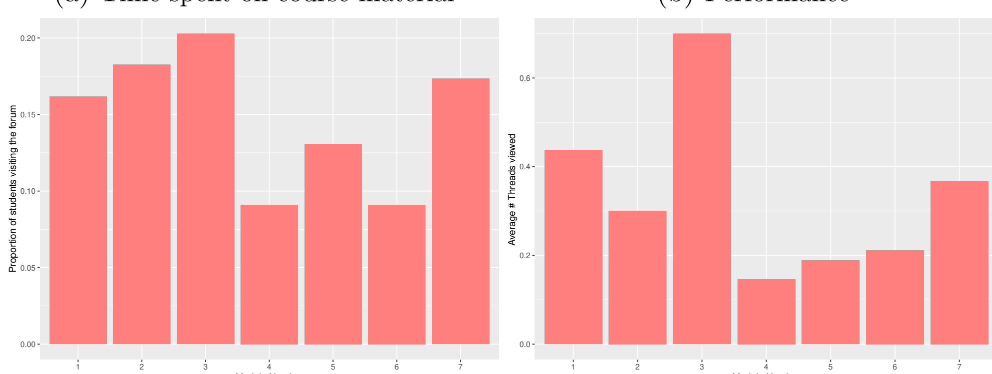


(a) Discussion forums (b) Course material

Figure 2: Users differ in terms of their intrinsic tendency to engage with course discussion forums and material.



(a) Time spent on course material (b) Performance



(c) Portion of students visiting the forum (d) Threads viewed

Figure 3: Variation in engagement with the core product, UGC, and performance across different modules within a given course.

Lastly, we also consider how student behavior and outcomes evolve over the life cycle of a course. In Figure 4, we present this information for one module within a course as a function of its age (the x-axis). For this particular module, the data suggest that the engagement metrics and course outcomes increase with the age of the course. This evolution could possibly be attributed to growing proficiency in navigating online courses among learners. In our empirical analysis, we control for such potential confounding due to the age of the course.[3]

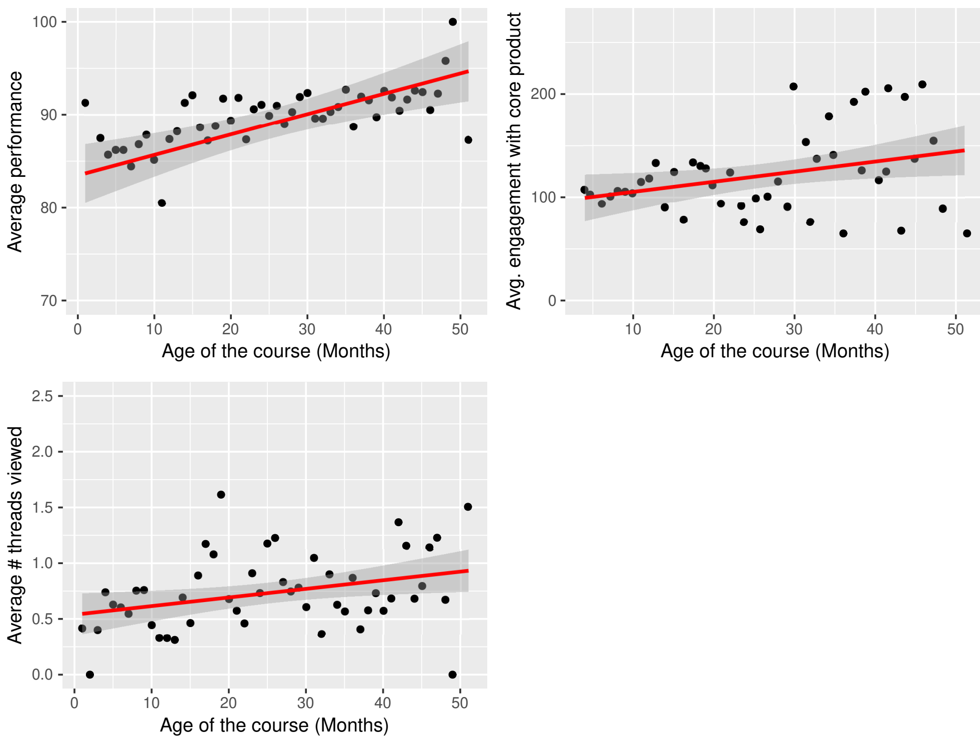


Figure 4: Student behavior and outcomes within one course evolve over time

Model-Free Evidence

As noted in the introduction, our objective is to assess if engagement with UGC (i.e., the discussion forum) has an effect on engagement with the main product (i.e., the course mate-

[3]Another explanation is that the design of the course changed over time in such a way that it fostered greater engagement and also resulted in higher performance. While this explanation does not invalidate our identification strategy, we did verify that the courses used in our study did not undergo any major design changes.

rial). As a first cut analysis, we investigate if there is a difference between users who engage with the discussion forum vs. those who do not in terms of their engagement with the course material. To this end, we first consider these outcomes at the course level. In Figures 5, we compare the engagement and performance for two groups of users: those who visited the discussion forum at least once during the course vs. whose who did not. These data suggest that, on average, those who visited the discussion forum spent more time with the course material and also performed better in terms of learning outcomes.

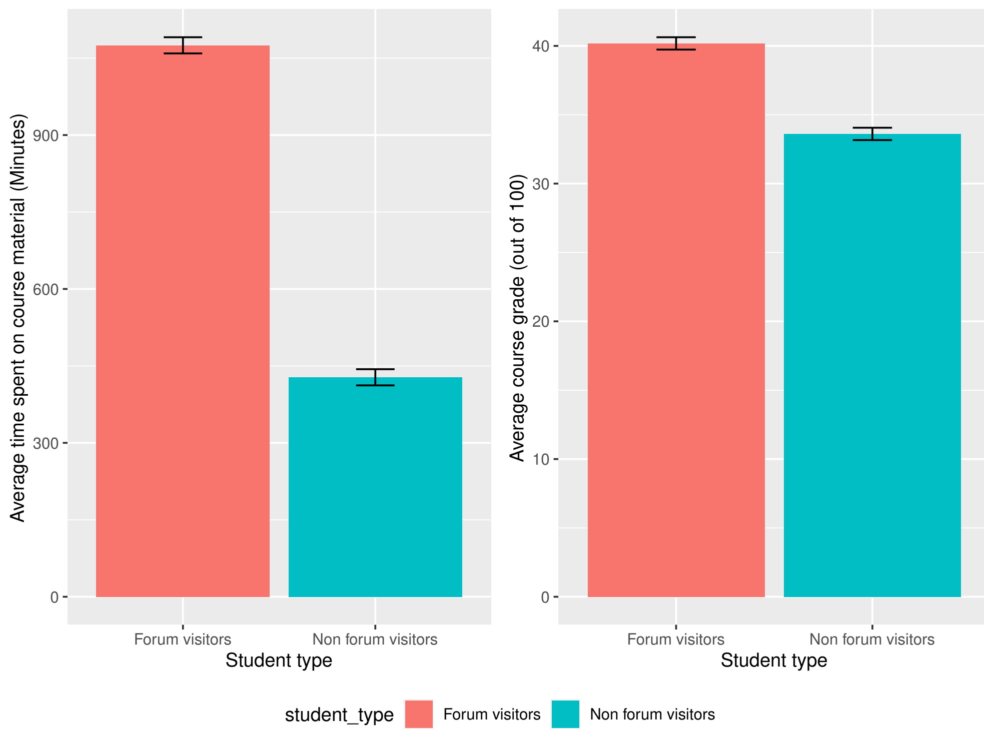


Figure 5: Relationship between engagement with the discussion forum and time spent on the material and performance at the course level.

We extend this analysis by considering engagement with the discussion forum at the module level. This will help us assess the contemporaneous relationships between forum engagement and engagement with the course material and performance. Furthermore, we distinguish between three levels of engagement with the discussion forum pertaining to a course module: (a) did not visit the discussion forum, (b) visited the discussion forum, but did not view any of the threads, and (c) visited the discussion forum and viewed at least one thread. We present the results from this analysis in Figure 6. Once again, we observe that those who actively engaged in the discussion forum corresponding to a module (by clicking on individual threads in the forum) were significantly more engaged with the course material than the other two groups of users. Interestingly, users who visited the discussion forum, but did not engage with the content were also more engaged than their peers who did not visit the discussion forum. We find a similar pattern when we consider performance within the module, although the differences are muted.

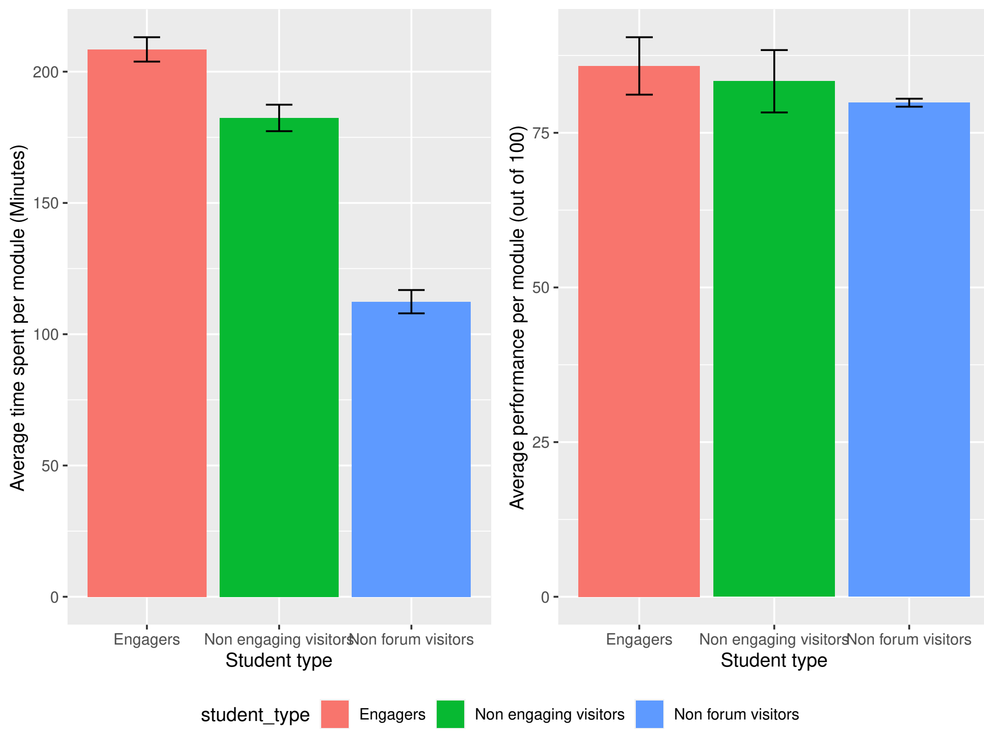


Figure 6: Relationship between engagement with the discussion forum and time spend on the material and performance at the course level.

While it is tempting to interpret these patterns as evidence of the causal effect of engagement with the discussion forum on engagement with the course material and performance, we need to be careful about drawing such a conclusion for several reasons. First, recall that the patterns in Figure 2a presented earlier revealed that while some users actively engaged with the discussion forum, others were largely dormant. Such heterogeneity might arise due to differences among students in terms of their level of motivation as well as their ability to master the content. If users who were more active in the discussion forum were also systematically more engaged with the course material, then the observed correlation between these modes of engagement is probably attributable to these intrinsic differences, rather than to a causal relationship between them.

Second, in addition to heterogeneity across individuals, we also documented systematic differences across courses as well as modules within a course. For example, courses (as well as different modules within a course) may differ in terms of the level of engagement that they require from their users or in terms of the extent to which they foster engagement. These differences can result in users spending more time on both types of content in some courses (or in some modules within a course) and less in others. As we discussed earlier, the information in Figure 3 provided some evidence of such heterogeneity across modules within a course, probably because of the nature of the content. We need to control for these differences before isolating a causal relationship.

Third, as we saw in Figure 4, the overall proficiency of the users with respect to the educational content as well as in navigating the various learning objects might have evolved over time. Similarly, the courses as well as the modules within these courses may have evolved over time in a way that would have influenced the benefit from joint consumption of the two types of content. These require us to control for the evolution of each course and its modules over time. Finally, even if we can control for these correlated unobservables that drive engagement with both types of content, it might be difficult to isolate the direction of causality, i.e., did engagement with UGC drive engagement with the course material (i.e., the main product) or vice versa? In the next section, we will discuss our approach to addressing these challenges with a combination of a rich set of fixed effects and an instrumental variable approach to isolate the causal relationship between user engagement in the discussion forum and the course material.

EMPIRICAL ANALYSIS

In this section, we first present a simple regression model to illustrate the relationship between UGC and course material consumption more formally. Subsequently, we present an instrumental variable that relies on exogenous variation in the forum rankings that will help us establish a causal link between consumption of UGC and the course material.

Model Specification

Our goal is to understand if engagement with UGC, i.e., discussion forums, could increase consumption of course material and also improve students' performance. We consider the following regression model:

$$sinh^{\text{-1}}(\mathbf{Y}_{icm}) = \alpha \cdot \mathbf{V}_{icm} + \beta \cdot sinh^{\text{-1}}(\mathbf{E}_{icm}) + \eta_{cmw} + \eta_i + \epsilon_{icm}, \tag{1}$$

where i, c, w and m index individual, course, week, and module, respectively. $\mathbf{Y}_{icm}$ is an outcome of interest, that is either time spent on module m of course c by individual i, or individual's i performance within module m of course c. $\mathbf{V}_{icm}$ is a dummy that indicates if individual i visited module m's forum from course c. $\mathbf{E}_{icm}$ is the number of threads user i clicked on during module m of course c. Finally, η_i and η_{cmw} are user and course-module-week fixed effects. These fixed effects absorb the persistent differences across different users, and also non-parametrically control for the evolution of content available on the course forums as the material ages.

The parameter of interest (β) aims at measuring the marginal effect of $\mathbf{E}$ on $\mathbf{Y}$, that is the percentage change in course material consumption as a result of a percent shift in engagement with UGC. This is typically achieved using a log-log specification. However, since our outcome ($\mathbf{Y}_{icm}$) and independent variable $\mathbf{E}_{icm}$ do obtain zero as a value, we use the inverse hyperbolic sine (IHS) function:

$$sinh^{-1}(y) = \log\left(y + \sqrt{y^2+1}\right).$$

The IHS transformation alleviates the influence of outliers and the zero-inflation concern that is associated with adding an arbitrary value to the dependent variable while conducting inference, see Bellemare and Wichman (2020), Burbidge et al. (1988), Jayachandran et al. (2017), and Johnson (1949), for more discussion on IHS and Bahar and Rapoport (2018), Clemens and Tiongson (2017), and McKenzie (2017) for a few of its applications.[4]

Our objective is to use the variation in the data to measure the causal effect of UGC consumption on consumption of the core product, which is measured by β in model (1). Note that our data is at user-module-course level. There are a number of different factors that could create spurious correlations between UGC consumption and consumption of course material in each module. Below we list these issues along with our proposed solution:

- **Unobserved user heterogeneity:** Students could vary across different dimensions such as their intrinsic motivation or ability. These cross-sectional differences could affect their engagement with both UGC and course content. We use user fixed effects to absorb the effect of these confounds.

- **Unobserved course-module heterogeneity:** Different modules within a course may require different levels of time investment and engagement. These factors could be correlated with both engagement with UGC and time spent watching lectures. Furthermore, course forums are shared across student cohorts. This means that as time passes by more content is added to the forums that could affect user engagement with course forums. We employ course-module-week fixed effects to control for confounds such as module difficulty or time varying content of the forums.

- **Reverse causality:** Exposure to lectures could induce students to then engage with

[4] In the online appendix B we explain how to convert the coefficients β to elasticities.

course forums to resolve questions or ambiguities that arise during the lectures. This would mean that OLS estimates from specification 1 could be biased due to the spurious correlation that is caused by the effect of content consumption on engagement with UGC. Note that including user and course-module-week fixed effects does not solve this issue. To address this endogeneity issue we use an instrumental variable which we introduce in the next section.

We present the OLS estimates for specification (1) in Table 2. The effect of user engagement with the forum on time spent on lectures, see columns (1)-(3), shrinks as we include more granular fixed effects, The effect on time spent attenuates from 0.243 to 0.042, which means that unobserved user heterogeneity and course-module differences do indeed bias the estimates, and including these fixed effects absorbs the effect of confounds that vary at user, and course-module-week level. The effect of UGC consumption on performance, however, remains similar as we include finer fixed effects, see columns (4)-(6). Nevertheless, these estimates may still be biased because of the reverse causality issues discussed above. In the next section, we employ an instrumental variable approach to address this issue.

Table 2: The effect of user engagement with course forums (OLS estimates)

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engagement with forum (β)	0.243***	0.053**	0.042**	0.011**	−0.002	0.012**
	(0.018)	(0.022)	(0.019)	(0.005)	(0.006)	(0.005)
Visited forum (α)	1.456***	0.668***	0.483***	0.009	0.044***	0.030***
	(0.035)	(0.035)	(0.030)	(0.009)	(0.010)	(0.008)
Constant	3.788***			5.085***		
	(0.017)			(0.003)		
User FE		X	X		X	X
Course-Module-week FE			X			X
Observations	115,036	115,036	115,036	115,036	115,036	115,036
R^2	0.037	0.671	0.744	0.0001	0.581	0.647
Adjusted R^2	0.037	0.569	0.664	0.0001	0.451	0.537

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

Instrumental variable regressions

While cross-sectional differences across users and modules can be absorbed using high dimensional fixed effects, the reverse causality issue discussed above requires us to use exogenous variation that affects forum usage but does not directly impact course material consumption. As discussed in the "Drivers of User Engagement in Online Courses" section, there are two approaches to increase user engagement with course forums: (a) nudging users to engage with forums, and (b) improving the attractiveness of the content within the forum. Previous research by Narang et al. (2022) and Zhang et al. (2017) have relied on experimental variation to demonstrate (a), however, our approach differs from these papers as we study the effect of exogenous variation in the intrinsic attractiveness within the discussion forum once the participant lands on the forum page. In particular, we employ an instrumental variable that shifts user engagement with the forum threads by shifting forums' attractiveness.

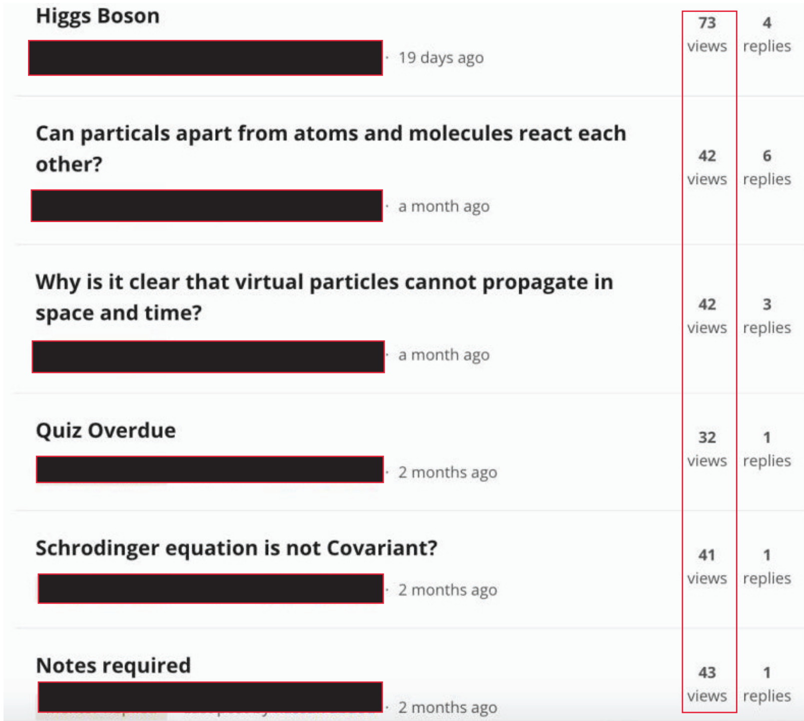


Figure 7: Forum Home Page for a module

Definition of ViewIndex

Each module in a given course has a separate discussion forum where students can discuss the course material covered in that particular module. Once students visit a discussion forum within a module, they are greeted by its home page which consists of a set of discussion threads. The threads on the homepage are sorted by activity recency, i.e., the thread with the most recent activity (post or comment) bubbles up to the top of the list. The discussion threads list is paginated, with at most fifteen threads per page. The number of user thread views for each thread in the forum is reported on the forum page, see Figure 7 for an example.

Our goal is to construct a metric that shifts each student's engagement level with a given module's forum. As mentioned above, the rank ordering of items in the forum changes as a new thread is created or new posts/comments are added to an older thread. Hence, users who arrive at the same forum's homepage for a module could face a different set of threads as the forum evolves. Let $\mathcal{F}_{icm}$ be the set of threads that appear on the first page of the forum m when user i from course c first visits it. Also, let $v_{icm}^{(t)}$ be the number of views for thread t at the time where user i visits the forum's homepage for module m in course c, e.g., see Figure 7. Define ViewIndex as follows:

$$\mathcal{I}_{icm} = \frac{1}{1000} \sum_{t \in \mathcal{F}_{icm}} v_{icm}^{(t)}. \tag{2}$$

This metric is defined only for students that visit a module-course's homepage and captures the student's first impression of other students' engagement level with a given module's forum. It is the sum of impressions (measured in thousand views) that threads listed on a given module's forum homepage received when the focal student visited that module's forum for the first time while learning that module.

ViewIndex as an instrument

To understand how ViewIndex evolves, we present the time series of this measure for one module within a course in our panel in Figure 9a. Initially, ViewIndex evolves slowly, and then we see sharp discontinuous drops/jumps in the time series plot. Sharp drops (jumps) in ViewIndex, see point A/B in Figure 9a, indicate that a thread with a high number of views has just left (entered) the forum home page. These drops and jumps in ViewIndex are due to changes in the composition of threads presented on the homepage and are due to a thread creation or activity in one of the threads that was not on the homepage. This variation in the composition of threads on the homepage and the resulting changes in ViewIndex is the main source of exogenous variation used in our study.

Our goal is to use ViewIndex as an instrument that shifts forum's attractiveness and thereby affects user engagement with the forums. There are three concerns than one might have about using ViewIndex as an instrument that shifts forum's attractiveness:

- **Peer effects:** One might be concerned that ViewIndex may reflect the extent of peer activity which could induce students to directly increase their engagement with the course material through peer effects. We rule this mechanism out in the online appendix A. The idea is to use the variation in ViewIndex across students who visit a forum's homepage but do not click on any threads. If this instrument is indeed signaling activity by peers, students who don't engage with the threads must be treated as well and higher ViewIndex would be associated with an increase in user engagement with course content which is not the case in our data.

- **Trends and spurious correlations:** While the discontinuous jumps/drops in ViewIndex present a source of exogenous variation, ViewIndex tends to have an increasing trend as the course ages which could be correlated with other confounds that could impact students' engagement and performance. For instance, the students who enroll later on could be systematically different from those who enrolled in the course when it was relatively new on the platform. Thus, the age of the course on the platform has the potential to confound our empirical analysis. To address this issue we use two sets of fixed effects: (a) user, and (b) course-module-week fixed effects. The user fixed effects address the user selection issue and ensures that we are relying on within user variation. The time-varying course-module-week fixed effects subsume seasonalities or other time-varying factors and ensure that we rely on within week variation when investigating the effect of ViewIndex on user engagement. Figure 9b shows that the fixed effects were effective in absorbing the general trend in ViewIndex (see Figure 9a) and the identification would rely in the changes in detrended View index in Figure 9b.

- **Sequential interactions and aggregation:** Note that our data is aggregated at the user-course-module level, meanwhile ViewIndex is calculated based on the first visit of each individual to a forum's homepage. Therefore, ViewIndex is essentially shifting the engagement level for the first visit within each module. Since visiting a forum page could prompt users to consume course content, and consuming course content can induce users to return to forums to seek help regarding course content,

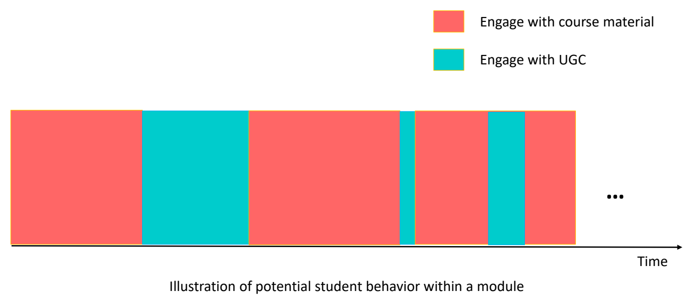
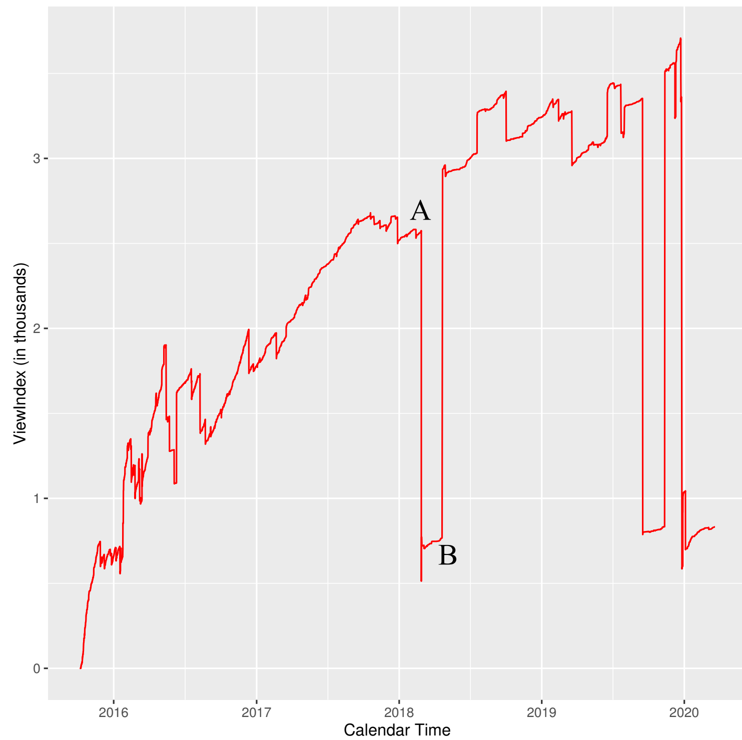


Figure 8: Sequential interactions

aggregating forum engagement and course material consumption to module level could violate the exclusion restrictions and bias our estimates, see Figure 8 for illustration. To allay these concerns, in the online appendix D we repeat the analysis for the set of observations with a single visit to the forum's homepage and show that our results remain robust.

In the subsequent sections, we present the results from the first-stage regressions, and then discuss the estimates from the second-stage regressions.



(a) ViewIndex

(b) Residual ViewIndex

Figure 9: The top panel shows the Evolution of ViewIndex for a discussion forum. The discontinuous jumps in ViewIndex are driven by changes in the composition of threads on the first page. For example, at point (A) a new thread bubbles up and another thread with large number of views exits the homepage. In contrast, at point (B) a thread with a high number of views enters the forum home page because of an activity (post/comment) by a user. The bottom panel displays the residualized ViewIndex and demonstrates that the general increasing trend is absorbed by our time-varying fixed effects.

First-stage regressions

In this section, we present the first-stage regression specification and discuss the estimates from the first stage. We consider the following specification:

$$sinh^{\text{-}1}(\mathbf{E}_{icm}) = \tilde{\alpha} \cdot \mathbf{V}_{icm} + \tilde{\beta} \cdot \mathbf{V}_{icm} \cdot \mathcal{I}_{icm} + \eta_{cmw} + \eta_i + \epsilon_{icm}, \tag{2}$$

where i, c, and m index users, courses, and modules, respectively. $\mathcal{I}_{icm}$ is the ViewIndex and is defined for users where $\mathbf{V}_{icm} = 1$ and captures the state of the forum when the user first visits a forum's homepage. The rest of the parameters and fixed effects are defined similar to specification (1). Moving from left to right in Table 3 we progressively add fixed effects and report the estimates from (2). The estimate for β is 0.024 and it suggests that a higher value for the forum's homepage ViewIndex is associated with more clicks on threads in that forum. Once we add user fixed effect the coefficient grows to 0.038 and changes marginally to 0.039 as we include course-module-week fixed effects. [5]

Our results in Table 3 show that ViewIndex does indeed shift users' engagement with forums. Furthermore, the positive effect of ViewIndex on forum engagement supports the mechanism that larger number of impressions in the homepage threads do reflect content relevance/attractiveness and increase engagement with the threads. Finally, our findings show that the results remain stable after we include granular fixed effects to control for confounds that could affect the analysis. In the "robustness checks" section, we provide more support for validity of this instrument using a set of placebo tests.

[5] Using a procedure similar to the one shown in *Appendix B* but for an IHS-linear specification instead of an IHS-IHS specification, we translate the parameter estimate into an elasticity estimate and find that on average, a 1 unit increase in ViewIndex (i.e., 1000 additional views for threads on the forum home page) increases the number of threads viewed by 125.36%

Table 3: The effect of ViewIndex on user engagement with the thread on a course forum.

	Dependent variable		
	$\sinh^{-1}$(Engagement with forum)		
	(1)	(2)	(3)
Visited forum x ViewIndex ($\tilde{\beta}$)	0.024***	0.038***	0.039***
	(0.007)	(0.008)	(0.008)
Visited forum ($\tilde{\alpha}$)	1.080***	0.949***	0.943***
	(0.019)	(0.019)	(0.018)
User FE		X	X
Course-Module-Age FE			X
Observations	115,036	115,036	115,036
R^2	0.525	0.721	0.723
Adjusted R^2	0.525	0.635	0.637
F-statistic on the excluded instrument	11.337	22.762	23.484

Note: *p<0.1; **p<0.05; ***p<0.01
All standard errors are clustered at user level.

Second-stage regressions

We now re-estimate (1) using ViewIndex as an instrumental variable for engagement with the forum $sinh^{-1}(\mathbf{E}_{icm})$. The estimates from this analysis are displayed in Table 4, which are the counterparts to the OLS estimates reported in Table 2. Moving from left to right, we progressively add more granular fixed effects. Our preferred specifications for the effect on time spent on course material and performance are models (3) and (6), respectively — both of these include fixed effects by user and course-module-week. Using the procedure in appendix B to convert these estimates to elasticity, we find that a 10% percent increase in engagement level with forum content increase time spent on course material and performance by 4.18% and 0.34% percent, respectively. The IV estimates for the effects of engagement on course content consumption and performance are statistically different and significantly larger than the OLS estimates documented in Table 2, which suggests that high-dimensional fixed effects in (1) were not adequate for addressing the endogeneity issues discussed above.

Table 4: The effect of user engagement with course forums (IV estimates)

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engagement with forum (β)	4.935***	0.728***	0.524***	4.562***	0.043***	0.042***
	(0.062)	(0.029)	(0.025)	(0.057)	(0.008)	(0.007)
Visited forum (α)	−5.418***	−2.382***	0.496	−0.663***	−0.347***	0.020
	(2.100)	(0.729)	(0.317)	(0.220)	(0.123)	(0.089)
Constant	3.788***			5.085***		
	(0.017)			(0.003)		
User FE		X	X		X	X
Course-Module-Week FE			X			X
Observations	115,036	115,036	115,036	115,036	115,036	115,036
R^2	−2.542	0.668	0.742	−0.072	0.563	0.647
Adjusted R^2	−2.542	0.564	0.662	−0.072	0.427	0.537

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

Identification Strategy

Our identification strategy hinges on two premises:

- The *precise* time a user lands on a given module's forum homepage is "as good as random."
- The state of a given module's forum, captured by the ViewIndex, fluctuates by virtue of the forum sorting rule and this sorting rule generates exogenous variation in the set of topics a user faces, see Figure 9.

Using a similar identification strategy, Donnelly et al. (2021) and Levin et al. (2017) have leveraged randomness in customers' arrival time in a supermarket that changes prices on Tuesdays and high-frequency shifts in prices of gasoline to identify price elasticities in each context. In our case, the composition of threads available on a forum's homepage could change discontinuously as new threads bubble up or old ones get updated by the users. This means that the set of threads available on the homepage of a module's forum for two users who arrive within a short time period of one another could be different.

To capture the exogenous variation in the composition of threads on the forum homepage we define ViewIndex. In essence, ViewIndex is a metric that gauges the attractiveness of threads on the forum's homepage at any point in time. As demonstrated in Figure 9, this metric could change dramatically as the composition of the threads changes due to the platform's sorting rule. We argue that conditional on the fixed effects used in our analyses ViewIndex qualifies as a valid instrument for user engagement. First, note that detrended ViewIndex (Figure 9b contains exogenous variation that is caused due to the changes in the set of threads on the homepage as threads enter/exit the page. To qualify as a valid instrument, ViewIndex must satisfy the following conditions: i) relevance: ViewIndex, i.e., a given student's first impression of other students' forum usage, must be correlated with that student's forum usage, and ii) exclusion: ViewIndex must affect the focal student's engagement with course material and the focal student's performance only through its effect on the focal student's UGC engagement. Our results in Table 3 show that this instrumental variable is indeed relevant and as expected higher ViewIndex led to higher engagement with the forum. In the robustness checks and online appendices, we present more evidence ruling out other plausible channels through which ViewIndex can affect engagement with the course material and outcomes.

ROBUSTNESS CHECKS

In this section, we discuss further examination of the results presented in the previous section

Selection bias due to attrition

Not every enrollee in the course completes the course. A lot of students drop out on MOOC platforms. Once a student drops out, we don't observe their behavior. Thus, the parameter estimates obtained from our econometric model fitted on the full sample will reflect both changes in the composition of the sample and changes in the behavior of students. The research objective of the paper is to document findings based on changes in behavior rather than findings based on the changes in the composition of the sample.

We assess the sensitivity of our results to changes in the composition of the sample by estimating our model on subsamples stratified by the course completion rate. Specifically, we fit our model on the sample of students who completed at least 10% of the course, fit the model on the sample of students who completed at least 20% of the course, and so on and so forth. The idea is that if the parameter estimates of our model are reflecting changes in behavior, then the results should persist across these subsamples. Tables 5 and 6 report the results from estimating the model on different subsamples stratified by the course completion rate. The results persist across the different subsamples, which suggests that parameter estimates reflect changes in behavior rather than changes in the composition of the sample.[6]

Weak Instruments

Researchers are increasingly recognizing that weak instruments can lead to incorrect inferences (Bound et al., 1995; Nelson and Startz, 1988; Rossi, 2014; Stock et al., 2002). To assess whether ViewIndex suffers from problems of being a weak instrument, we checked the F-statistic on this excluded instrument and find that they range between 12.16 and 23.48 across subsamples stratified by the course completion rate (See Tables 5 and 6). This first-stage F-test for ViewIndex suggests that the instrument has power and does not suffer from the problems of being a weak instrument.

[6] Each module consists of course items such as lecture videos, supplementary readings, etc. Completion rate is computed using course progress data as the percentage of course items completed by the student.

Table 5: Estimation of second stage equation on subsamples stratified by the course completion rate for time spent on course material

	Dependent variable									
	$\sinh^{-1}$(Time spent on course material)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Engagement with forum (β)	0.524***	0.496***	0.469***	0.450***	0.444***	0.435***	0.430***	0.417***	0.403***	0.416***
	(0.025)	(0.024)	(0.024)	(0.026)	(0.027)	(0.028)	(0.030)	(0.031)	(0.033)	(0.036)
Visited forum (α)	0.496	0.569*	0.595	0.416	0.246	−0.156	−0.136	−0.165	−0.262	−0.472
	(0.317)	(0.337)	(0.401)	(0.450)	(0.400)	(0.515)	(0.551)	(0.593)	(0.671)	(0.984)
User FE	X	X	X	X	X	X	X	X	X	X
Course-Module-Age FE	X	X	X	X	X	X	X	X	X	X
Observations	115,036	107,438	90,291	80,306	72,945	67,292	61,613	54,853	45,690	34,139
R^2	0.742	0.724	0.659	0.639	0.630	0.627	0.629	0.636	0.652	0.668
Adjusted R^2	0.662	0.648	0.588	0.577	0.574	0.576	0.580	0.590	0.609	0.628
F-statistic on the excluded instrument	23.48	20.88	13.98	12.16	13.55	14.77	15.81	16.68	17.19	18.34

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

These are estimates from the second stage of the model for engagement with the course material for different subsamples stratified by the course completion rate

Table 6: Estimation of second stage equation on subsamples stratified by the course completion rate for performance

	Dependent variable									
	$\sinh^{-1}$(Performance)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Engagement with forum (β)	0.042***	0.044***	0.036***	0.023***	0.019***	0.016**	0.010*	0.011*	0.008	0.006**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)
Visited forum (α)	0.020	0.006	0.063	0.212*	0.204**	0.179**	0.179**	0.146*	0.188**	0.125
	(0.089)	(0.094)	(0.104)	(0.109)	(0.086)	(0.088)	(0.086)	(0.080)	(0.094)	(0.093)
User FE	X	X	X	X	X	X	X	X	X	X
Course-Module-Age FE	X	X	X	X	X	X	X	X	X	X
Observations	115,036	107,438	90,291	80,306	72,945	67,292	61,613	54,853	45,690	34,139
R^2	0.647	0.618	0.593	0.595	0.600	0.602	0.601	0.628	0.597	0.561
Adjusted R^2	0.537	0.512	0.507	0.525	0.540	0.547	0.548	0.580	0.547	0.508
F-statistic on the excluded instrument	23.48	20.88	13.98	12.16	13.55	14.77	15.81	16.68	17.19	18.34

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

These are estimates from the second stage of the model for performance for different subsamples stratified by the course completion rate

Validity of the exclusion restriction

The exclusion restriction requires that ViewIndex must affect a forum visitor's engagement with course material and performance only through its influence on the forum visitor's engagement with UGC. There should not be a direct effect of ViewIndex on the dependent variables. We conduct some additional analysis to assess the validity of the exclusion restriction in our setting.

We conjecture that two behavioral mechanisms can drive the effect of ViewIndex on engagement with UGC. First, observing a high ViewIndex can improve the focal student's perception of the quality of UGC available in the forum. This improvement in the perceived quality of UGC can make the focal student engage more with the UGC, i.e., view more discussion threads. Let us call this mechanism the quality account. Second, observing a high ViewIndex can awaken the focal student's competitive streak. This awakening of the competitive streak can then make the focal student engage more with the UGC, i.e., view more discussion threads. Let us call this mechanism the competition account.

If the competition account is the dominant driving force behind the effect then that will only serve to aggravate concerns regarding the validity of the exclusion restriction because a direct effect of the instrument on the dependent variables becomes more likely under this mechanism. While it is challenging to completely rule out the possibility of such a peer spillover leading to a direct of ViewIndex on engagement with course material and performance, we conducted additional analysis to determine whether the competition account is the dominant mechanism in our setting.

Figure 10 shows that there are three types of students within a given module. We extract the subsample of those students who visited the forum but did not click on any threads. Students present in this subsample, by definition, did not engage with the UGC available on the forum as engaging with UGC requires a student to open a thread and browse through the discussion within the thread. Thus, for this subsample, observing a systematic

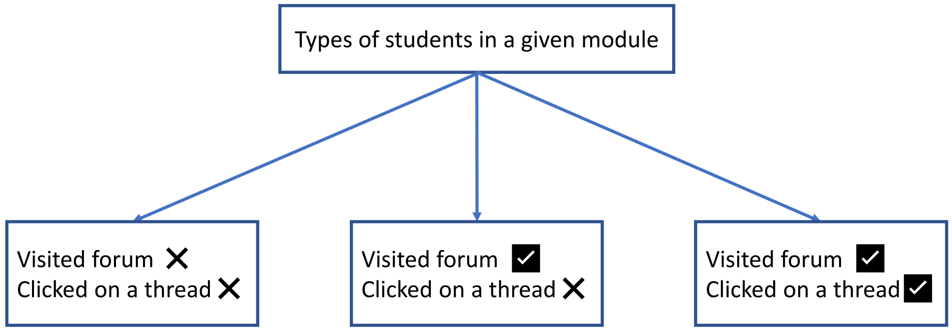


Figure 10: Types of students within a course module

relationship between ViewIndex and the dependent variables will raise concerns about the validity of the exclusion restriction because a direct effect of ViewIndex would then be the most likely explanation for a systematic relationship between the instrumental variable and dependent variable in this subsample.

In *Appendix A*, we report the result from the estimation of our model for the subsample of students who visited the forum but didn't engage with any UGC by clicking on threads. The result suggests that there is no systematic relationship between ViewIndex and the dependent variables for this subsample. This alleviates our concern regarding the validity of the exclusion restriction.

Placebo Test

We conduct a placebo test to demonstrate that the effect of ViewIndex on engagement with forum threads in the first-stage regressions stems from the differences in the state of the forum at the precise time a user visits the forum homepage rather than the result of trends or a common shocks that are not absorbed of our fixed effects. To that end, we construct a set of *placebo instruments* by permuting ViewIndex across students within each course-module-week group in our panel, and we re-estimate the first-stage regression (2). We repeat this exercise with placebo instruments 1000 times and plot the coefficients from the first stage regression with placebo instruments in Figure 11. Comparing the magnitude of

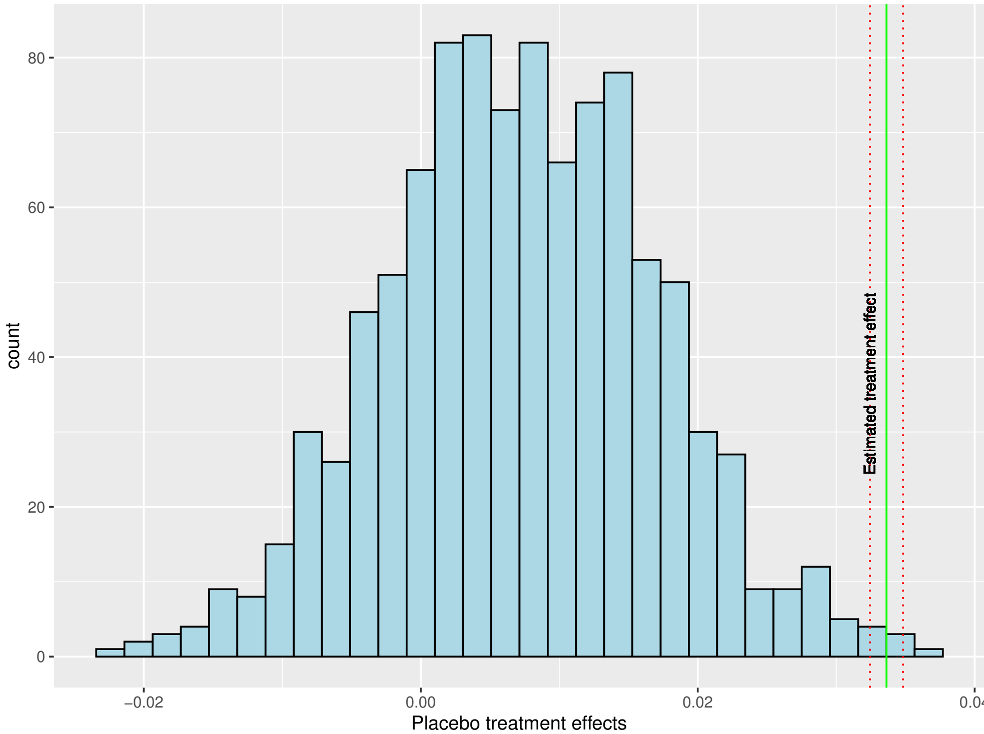


Figure 11: Placebo Test Result

the coefficient with the actual instruments and the placebo ones in Figure 11 suggests that it is very unlikely that the estimated treatment effect of ViewIndex is a result of random chance or common trends/shocks within a given module-week. [7]

DISCUSSION AND CONCLUSION

In this section, we conclude by summarizing the main results from our analysis, discussing the implications of our findings, and highlighting the limitations of our study.

Managerial Implications

In this paper, we investigated how engagement with UGC affects student behavior and outcomes on a popular online education platform. Our study finds that a good first impression

[7]Because our observation of the forum state is linked to students' arrival at a module, the permutation of ViewIndex across students within a course-module-week still happens in a non-uniform manner. As a result, the mode of the distribution of placebo coefficients isn't exactly at zero.

of others' engagement with the available UGC increases one's engagement with UGC. Thus, the popularity of UGC matters for engagement. So, nudging users to visit the forum might not be the only lever that platforms have for increasing engagement with UGC. This has potential implications for the design of discussion forums.

Using popularity of UGC as an exogeneous shifter of engagement with UGC, this study also finds that engagement with UGC positively affects engagement with the core product and student performance. So, platforms need to view the discussion forum as a tool for increasing engagement. This runs counter to some current practices where some online education and other media consumption platforms are reducing support for discussion forums. In contrast, our study suggests that conditional on the existence of a forum, firms should not only encourage students to visit discussion forums but should also strive to improve the attractiveness of the discussion forums in hopes of improving course engagement and performance. (See table 7). The results from this study suggest that it behooves online education firms to consider redesigning their platform in a manner that encourages joint consumption of the two types of content on their platforms. At the very least, MOOC platforms must incorporate this benefit of discussion forums to inform their decision of whether to continue or discontinue support for discussion forums.

Our finding that the discussion forum and the main content tend to be viewed as complements by users has some potential implications for content platforms, including those beyond the context of online education. In particular, our results seem to suggest that having a thriving discussion forum could be a potential tool that platforms such as Netflix can use to keep their users engaged with their main content. However, we acknowledge that our data do not include instances where there is entry/exit of UGC. Therefore, while our study can provide insights about the effect of content presentation on the utilization of UGC forums, it cannot comment on the value of having these forums per se.

This study also highlights the importance of the default ranking algorithm. Using recency as the default ranking algorithm can result in random fluctuations in the information that is most readily accessible to consumers. Future research can investigate the desirability of such random fluctuations in the most readily accessible information for different stakeholders. A potential unintended negative consequence of recency as a thread ranking algorithm is that when lots of new threads are created, the forum home page consists of threads with a very small view count as views accumulate slowly over time. As a result, although fresh content may have just been supplied to the forum, a weak signal regarding the popularity of UGC can discourage users from engaging with the UGC. Thus, future research can investigate a potential trade-off between the freshness of content and the popularity of content in driving engagement with the content.

It is also worth exploring whether regulators should control the information that online platforms provide regarding the popularity of content. A recent study by (Fu 2020) explores the effect of disclosing historical sales information on consumers' search decisions when they search across vertically differentiated products with incomplete information about product qualities. The study finds that disclosing sales information can asymmetrically benefit high-selling products since they are more attractive to the consumer due to their revealed popularity. This creates a positive feedback loop. This positive feedback loop allows the short-run popularity of a product to persist in the long run which further leads to concerns about the fairness of competition in the online market when sellers can influence the temporary popularity of their products. The existence of such effects propounds the need to study the need for regulation of the control that online platforms have over the provision of content popularity signals.

Table 7: Summary of the main result

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	OLS estimate	IV estimate	Elaticity estimate	OLS estimate	IV estimate	Elasticity estimate
Engagement with forum (β)	0.042***	0.524***	0.418	0.012***	0.042***	0.034
	(0.019)	(0.025)		(0.005)	(0.007)	

Note: All standard errors are clustered at user level. *p<0.1; **p<0.05; ***p<0.01

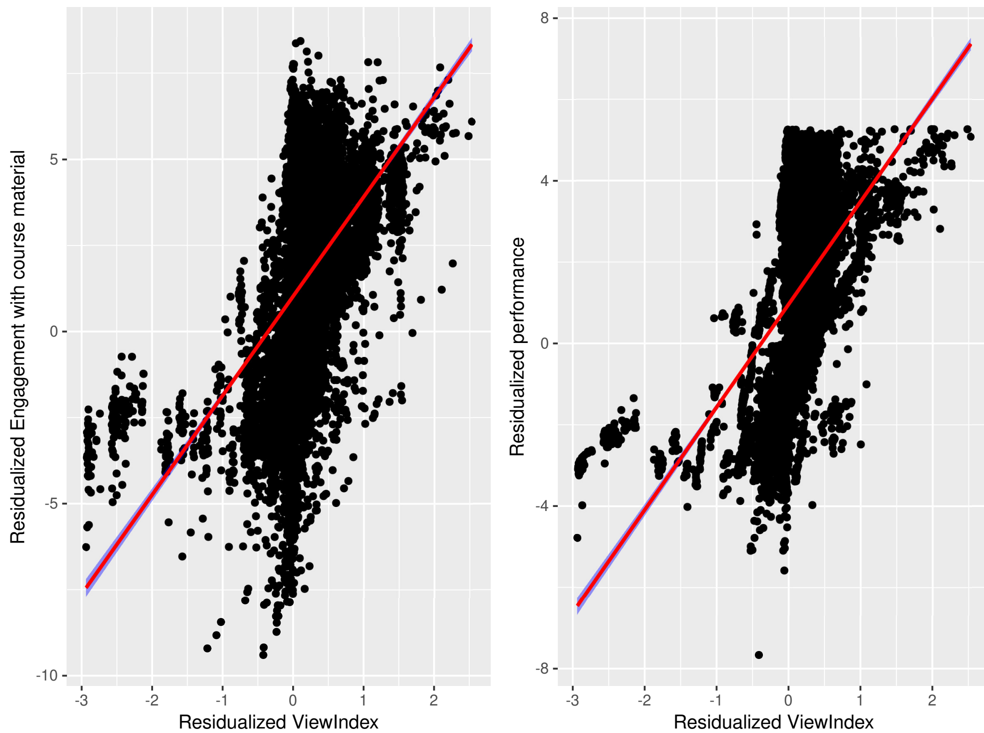


Figure 12: Effect of ViewIndex on engagement with course material and performance. Due to module-specific heterogeneity and potential confounding due to the age of the course, a scatter plot with raw data will not provide a clear picture regarding the relationship between ViewIndex and the dependent variables of interest. Thus, to get a clearer picture, we residualized ViewIndex and the outcome measures by the course-module-week fixed effects for the observations where a forum was visited to construct this scatterplot.

Future research can investigate the extent to which these findings and policy implications regarding the organization of content differ in other contexts. The benefits and costs of nudging users to access UGC and improving the UGC that's readily accessible can have different implications in other contexts. There can also be potential interaction effects of these two treatments awaiting their discovery. These lines of inquiry can provide useful knowledge to inform firms about the non-trivial decision of whether or not to support discussion forums as well as how to manage their customers' use of the UGC available on their online platforms.

Limitations

Our study suffers from a few limitations. First, as noted earlier, our study has abstracted away from potential substitutability or complementarity across modules and has just focused on contemporaneous engagement with UGC. A perfectly plausible hypothesis is that engagement with the previous module's UGC in the current module affects performance and engagement with course material in the current module. However, we focus on the consequences of engagement with the current module's UGC on behaviors and outcomes in the current module. Future research can investigate such potential substitutability or complementarity across different periods in the customer journey. Research along these lines can inform principles that should govern the optimal design of discussion forums.

Second, since we don't control for the endogeneity of the decision to visit the forum, we need to view the quantifications as suggestive. Nevertheless, the evidence that students who were induced to engage more with UGC due to exposure to a better forum (a forum with a higher ViewIndex), also engaged more with the course material and performed better, reassures us that UGC engagement positively affects both engagement with the core product and performance. This interpretation of our results is valid because a student's decision to visit a module's forum while learning that module is uncorrelated with the state of that module's forum at the time of that student's first forum visit. This is because every module has a separate forum and the state of a given module's forum is only known to the student after they have visited that module's forum.

Third, to leverage the panel nature of our dataset and use individual fixed effects to control for unobservable heterogeneity, we have to assume that the student-module match is fixed within a course. Finally, we are unable to comment on the value of the discussion forum itself as we only have data from a world where discussion forums exist. We do not have access to data on student behavior and outcomes from a world where discussion forums don't exist or where student access to the discussion forum was randomly manipulated. Such a dataset can be very useful in understanding the value of discussion forums and the boundary conditions of when having a discussion forum is desirable and when that isn't the case. Access to a dataset where discussion forums didn't exist can provide clean comparison groups to generate additional insights regarding the value of discussion forums. This knowledge can be useful to inform online platforms' content design policies.

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Appendix A - Ruling out peer effects

In our analysis in the body we showed that ViewIndex does shift users' engagement with forum content. However, one threat to our analyses is that ViewIndex may reflect the extent of peer activity in a given course module. This activity could induce students to directly increase their engagement with the course material through peer effects. In this appendix, we use the variation in ViewIndex across students who visit a forum's homepage but do not click on any threads to rule this mechanism out. If this instrument is indeed signaling activity by peers, students who don't engage with the threads must be treated as well and higher ViewIndex would be associated with an increase in user engagement with course content.

To investigate this, we consider two sets of observations:

- User-course module-week tuples where the user visited forum's homepage and clicked on at least one thread.

- User-course module-week tuples where the user visited forum's homepage but did not click on any thread.

We show the results from estimating the reduced form regression on the first sample in Table 8. Subsequently, we present the results from estimating the reduced form regression in the second subsample in Table 9. The estimates reported in columns (3) and (6) of tables 8-9 demonstrate that (a) the instrument does shift the outcomes in the case where users engaged with the forum, and (b) the instrument does not have an effect when users did not click on threads but visited forum's homepage. This observation means that mere exposure to a forum's homepage with higher ViewIndex cannot lead to higher engagement with course content through peer effects.

Table 8: Effect of the instrumental variable on the dependent variables in the full sample of forum visits

	Dependent variable:					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
ViewIndex	0.254***	0.162***	0.126***	0.147***	0.067**	0.025***
	(0.010)	(0.020)	(0.036)	(0.020)	(0.032)	(0.005)
Constant	5.272***			5.083***		
	(0.031)			(0.008)		
User FE		X	X		X	X
Course-Module-Age FE			X			X
Observations	27,880	27,880	27,880	27,880	27,880	27,880
R^2	0.023	0.710	0.816	0.003	0.763	0.843
Adjusted R^2	0.023	0.232	0.501	0.002	0.371	0.575

Note: *p<0.1; **p<0.05; ***p<0.01
All standard errors are clustered at user level.

Table 9: No evidence of violation of exclusion restriction in the subsample of forum visits where no thread was viewed

	Dependent variable:					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
ViewIndex	0.179***	0.140**	0.024	0.014***	−0.045***	−0.029
	(0.016)	(0.065)	(0.072)	(0.001)	(0.015)	(0.016)
Constant	4.990***			5.069***		
	(0.050)			(0.011)		
User FE		X	X		X	X
Course-Module-Age FE			X			X
Observations	2,825	2,825	2,825	2,825	2,825	2,825
R^2	0.026	0.920	0.956	0.0002	0.739	0.957
Adjusted R^2	0.025	0.426	0.612	−0.001	0.245	0.652

Note: *p<0.1; **p<0.05; ***p<0.01
All standard errors are clustered at user level.

Table 10: The effect of user engagement with course forums in the full sample of forum visits (IV estimates)

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engagement with forum (β)	4.935***	0.728***	0.534***	4.562***	0.043***	0.046***
	(0.057)	(0.029)	(0.025)	(0.057)	(0.008)	(0.007)
Constant	4.428***			5.100***		
	(0.034)			(0.006)		
User FE		X	X		X	X
Course-Module-Week FE			X			X
Observations	27,880	27,880	27,880	27,880	27,880	27,880
R^2	−2.456	−0.696	0.652	−0.433	0.330	0.584
Adjusted R^2	−2.456	−1.113	0.565	−0.433	0.164	0.481

Note: *p<0.1; **p<0.05; ***p<0.01
All standard errors are clustered at user level.

Finally we present, the 2SLS results using the first subsample in Table 13, that is user-module-week tuples where the forum was visited and at least one thread was clicked on, and computed the elasticities similar to those calculated for estimates in Table 4. The results are similar to those obtained using the full sample. On average, a 10% increase in a student's UGC engagement increases that student's engagement with the core product by 3.62% (versus 4.18% for the full sample) and performance by 0.26% (0.34% for the full sample).

Appendix B - Elasticity calculation

In this appendix, we illustrate how we translate our parameter estimates into elasticity estimates

Consider a regression of the form,

$sinh^{-1}(y) = \alpha + \beta * sinh^{-1}(x) + \epsilon$

After estimating such a regression, to compute elasticities, we need to compute the derivative. To compute the derivative, we need recover the left hand side. To recover the left hand side, we revert the IHS transformation by applying the hyperbolic sine transformation on both sides.

Therefore,

$y = sinh(\hat{\alpha} + \hat{\beta} * sinh^{-1}(x) + \hat{\epsilon})$

To compute the derivative in IHS-IHS models, we can apply the chain rule of differentiation to obtain,

$\frac{\hat{dy}}{dx} = \frac{\hat{\beta} * cosh(\hat{\alpha} + \hat{\beta} * sinh^{-1}(x) + \hat{\epsilon})}{\sqrt{x^2+1}}$

Since the argument inside the cosh function is $sinh^{-1}(y)$,

$\frac{\hat{dy}}{dx} = \frac{\hat{\beta} * cosh(sinh^{-1}(y))}{\sqrt{x^2+1}}$

Since hyperbolic functions satisfy the fundamental identity: $cosh(t)^2 - sinh(t)^2 = 1$,

$=> cosh(t)^2 = 1 + sinh(t)^2$,

$=> cosh(t) = \sqrt{1 + sinh(t)^2}$,

Now, we can compute the derivative as,

$\frac{\hat{dy}}{dx} = \frac{\hat{\beta} * \sqrt{1 + sinh(sinh^{-1}(y))^2}}{\sqrt{x^2+1}}$

Since $\sinh(\sinh^{-1}(t)) = t$,

$\frac{\hat{dy}}{dx} = \frac{\hat{\beta} * \sqrt{1+y^2}}{\sqrt{x^2+1}}$

Now, we can compute the elasticity as,

$\frac{\hat{dy}}{dx} * \frac{x}{y} = \frac{\hat{\beta} * \sqrt{1+y^2}}{\sqrt{x^2+1}} * \frac{x}{y}$

Notice that the elasticity will be undefined when y=0. Hence, following the practice in the extant literature using IHS transformations, we report the average elasticity estimates for the forum visitors in our sample.

Appendix C - Using alternative measures for forum engagement

In this appendix, we report the results from estimating our model using an alternative measure of engagement with UGC. This alternative measure is computed as the sum of both consumption of UGC and creation of UGC. Although this measure weighs consumption and creation of UGC equally, we find that the results using this measure of engagement with UGC are similar to the results obtained using just the consumption of UGC as the measure of engagement with UGC.

Table 11: The effect of ViewIndex on user engagement on course forum.

	Dependent variable		
	$\sinh^{-1}$(Engagement with forum)		
	(1)	(2)	(3)
Visited forum ($\tilde{\alpha}$)	1.130***	0.957***	0.940***
	(0.019)	(0.019)	(0.019)
Visited forum x ViewIndex ($\tilde{\beta}$)	0.010	0.041***	0.045***
	(0.007)	(0.008)	(0.008)
Constant	0.000***		
	(0.000)		
User FE		X	X
Course-Module-Age FE			X
Observations	115,036	115,036	115,036
R^2	0.459	0.711	0.730
Adjusted R^2	0.459	0.622	0.646
F-statistic on the excluded instrument	1.893	24.572	29.703

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

Table 12: The effect of user engagement with course forums (IV estimates)

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engagement with forum (β)	4.753***	0.721***	0.521***	4.397***	0.043***	0.042***
	(0.058)	(0.029)	(0.024)	(0.054)	(0.008)	(0.007)
Visited forum (α)	−15.871	−2.246***	0.500*	−1.662	−0.330***	0.022
	(12.680)	(0.676)	(0.278)	(1.232)	(0.116)	(0.078)
Constant	3.550***			5.063***		
	(0.172)			(0.017)		
User FE		X	X		X	X
Course-Module-Age FE			X			X
Observations	115,036	115,036	115,036	115,036	115,036	115,036
R^2	−4.186	0.668	0.742	−0.577	0.581	0.647
Adjusted R^2	−4.186	0.565	0.662	−0.577	0.451	0.537

Note: *p<0.1; **p<0.05; ***p<0.01

All standard errors are clustered at user level.

Appendix D - Sequential interactions with forum's content

In this appendix, we try to assess the sensitivity of our parameter estimates to potential violations of the exclusion restriction stemming from sequential interactions with the forum within a module. We do this by estimating our model on the subsample of forum visits, where the forum was visited on a single day. As we don't know the stickiness of the first exposure to the forum, this subsample aids in assessing the robustness of the results to potential violations of the exclusion restriction stemming from sequential interactions with the forum within a module.

Table 13: The effect of user engagement with course forums (IV estimates)

	Dependent variable					
	$\sinh^{-1}$(Time spent on course material)			$\sinh^{-1}$(Performance)		
	(1)	(2)	(3)	(4)	(5)	(6)
Engagement with forum (β)	8.657***	0.830***	0.630***	0.820***	0.056***	0.055***
	(3.130)	(0.042)	(0.036)	(0.317)	(0.011)	(0.010)
Constant	4.361***			5.102***		
	(0.037)			(0.007)		
User FE		X	X		X	X
Course-Module-Age FE			X			X
Observations	25,916	25,916	25,916	25,916	25,916	25,916
R^2	−19.576	0.364	−11.260	−2.351	0.803	0.544
Adjusted R^2	−19.579	−0.973	−38.281	−2.352	0.390	−0.461

Note: *p<0.1; **p<0.05; ***p<0.01
All standard errors are clustered at user level.