Algorithmic Recommendations and Earned Media: Investigating Product Echo Chambers on YouTube

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Abstract

'Echo chambers' in digital media, where a person is exposed to similar content through algorithmic recommendations, are often thought to increase digital polarization. Firms, however, may aim to replicate such echo chambers, to ensure that consumers are repeatedly exposed to their content. We investigate the viability of such a strategy in the context of the largest US charitable organizations on YouTube. Charities have limited resources and could benefit significantly from augmenting earned media impressions. Across two studies, we find that an algorithm recommends a video on a different topic not associated with the focal charity about 45% of the time. The algorithm frequently steers users to popular videos that are unrelated to the focal charity. This holds irrespective of whether individuals are logged into their YouTube accounts or not as well as independent of the sequence in which users view these videos. Moreover, we show that as a user follows a chain of recommendations provided by the platform to second, third, fourth and fifth recommendation, it becomes increasingly likely that the algorithm moves away from focal charity videos. Our results suggest that it is unlikely that organizations like charities can leverage echo chambers to generate earned media and that attempting to do so could side-track interested users.

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1 Introduction

Algorithmic recommendations in digital media can create echo chambers where individuals are exposed to content that reinforces their existing beliefs (Pariser, 2011). Echo chambers have been documented in topical areas such as politics, science and conspiracy theories where consumers often have strongly divergent views, look for content confirming their views, and platforms then may algorithmically recommend confirmatory content (Bessi et al., 2016; Boxell et al., 2017).

However, most digital content is more mundane, and includes information on commercial products or on charities. From a commercial perspective, the potential that echo chambers might exist for products or charities is attractive. If recommendation algorithms repeatedly expose a consumer to information from the same firm, that process could create valuable earned media impressions for firms or charities, reinforcing brands and increasing revenue.

It is unclear, however, whether such product echo chambers would emerge for non-polarizing commercial content. The platform's objective function may diverge from that of the firm and, as a result, the platform's algorithm may increase engagement by steering users towards the most popular videos – which may not necessarily be those offered by the focal firm. It may also direct users to videos on the same broad set of topics that are offered by other firms – in which case it may increase exposure in the category but not to a focal firm.

In this paper, we ask whether recommendation algorithms can lead to product echo chambers where consumers are repeatedly exposed to information by the same organization. In two related empirical studies, we collect data on videos that YouTube recommends watching. Individuals are instructed to watch specific videos posted by US-based charities on YouTube and then record which video the platform recommends next. We then use this information to evaluate whether such recommendations are likely to result in a product echo chamber.

We choose US charities as our empirical context because of the societal importance of non-profit marketing; in 2020, US donors gave $470 billion to charity, representing 2% of GDP. Given limits to the amount charities can spend on fundraising, their advertising expenditures are limited, which makes reaching out to potential donors through organic content particularly important.[1] Social media offers charities a unique opportunity to reach many consumers at a low – or zero – price. If social media such as YouTube leads to the emergence of product echo

[1]These restrictions are not legally binding, but it can harm the charity's reputation if they exceed certain thresholds. Charity Navigator, a leading charity assessment organization, suggests that a charity should spend less than 10% on fundraising. See also https://smallbusiness.chron.com/much-can-nonprofit-legally-spend-overhead-72388.html.

chambers whereby consumers learn in repeated videos from the same charity's channel about a cause, or alternatively about the same cause from different charities, such echo chambers may substantially benefit charities. In the data collection process, we use a list of the 100 largest charities in the US in 2019, based on a list a compiled by Forbes.[2] For each charity, we harvest URLs of the first five most popular videos listed on their channel. This serves as the base data for both studies.

In our first study, we asked 78 individuals on M-Turk to log into their YouTube account and watch a set of 10 randomly selected videos from 20 highly popular charity videos chosen from the most popular category of charities on YouTube. For each video they watched, they recorded the next video recommended by the YouTube algorithm. We then coded the content of each video into whether the video is about the same charity, on a completely different topic, about a competing charity, or a related topic but not about charities. We find that 57% of the time, the YouTube algorithm leads the user away from any video of the focal charity. That is for only 43% of occasions the algorithm recommends a video of the same charity. In fact, in 41% of instances, the algorithm recommends videos that are completely unrelated to charities or the topic of the focal video. This finding is not affected by the sequence in which users are shown charity videos. The pattern suggests that charities have at best an even chance of keeping a viewer watching their content after a user chooses an initial focal video. In general, the charitable videos that were recommended had fewer previous views than the non-charitable videos, suggesting at least some algorithmic subsidy towards charitable content.

However, Study 1 has a few limitations. First, the sample consists of very popular charity videos, potentially limiting the generalizability of the results. Second, users were logged into their YouTube accounts, implying that the algorithm used each user's past browsing behavior. Since most users do not regularly view charity videos, relative to more mainstream content, an algorithm emphasizing past viewing behavior might inhibit a product echo chamber for charitable content. Third, recent concerns around consumer tracking and privacy imply that platforms' ability to provide personalized recommendations may diminish in the near future. For example, Google announced in March 2021 that it will phase out third party cookies for advertising, as well as limit the tracking of individuals across the web and its incorporation in their products.[3] Thus, it is unlikely that platforms will continue to have access to detailed

[2]See the list here `https://tinyurl.com/msnetshx`
[3]See this article for some details `https://tinyurl.com/43su8rjh`

consumer browsing histories.

As a result, in our second study, we broaden our analysis to the largest 100 charities in the United States, covering a variety of causes ranging from homelessness to animal welfare. Data is collected anonymously by logging out of the YouTube accounts and going into incognito mode to prevent the platform from from tracking behavior and base recommendations on the past viewing history. For each of the charities, we identified the five videos listed first for their YouTube channel. We then recorded for each of these five focal videos the next video recommended by YouTube, as well as those recommended subsequently until we have followed the chain of recommendations to the fifth recommendation. This approach allows us to examine the patterns when a user follows the platform's chain of recommendations. Again, we measure whether a consumer watching a video is subsequently recommended a video from the same channel, from another charity or outside of the charitable context.

Analyzing the first video recommended following the focal video, we find that, in line with Study 1, in 44.6% of instances users are recommended a video on a completely different topic. In only 15% of instances is a video by the original charity recommended. Hence, contrary to our expectation, lack of tracking makes it less likely for a product echo chamber to occur. This decrease, relative to the 43% in Study 1, is offset by an increase in recommendations associated with videos that are in line with the topic of the focal charity but are not centered around charities. As we follow the chain of platform recommendations (i.e. go to the second, third, fourth, fifth recommendation), the algorithm becomes increasingly less likely to stay with the focal charity and a completely different topic is more likely to be featured.

We also analyze the characteristics of the recommended video. Consistent with Study 1, the prior views of a recommended video that focuses on a different topic are significantly higher than the views of a recommended video that comes from the same charity as the focal video. Finally, we demonstrate that it is the popularity of the focal video that could potentially lead to the creation of an echo chamber, since more popular charity videos lead to further recommendations from the same charity. Charity characteristics, captured by charity fixed effects, do not affect the probability of a video from the same charity being recommended by the algorithm.

In sum, our results demonstrate that despite concerns that algorithmic recommendations of content lead to the emergence of echo chambers that reinforce consumers' views, charitable institutions are unlikely to benefit from similar echo chambers. Algorithmic recommendations do not systematically recommend content from the same charity or on the same topic. To the extent that such effects exist, they largely dissipate after a user has viewed the first recommended video and continues to follow the platform's recommendations. From a charity's point of view this means that they are unlikely to benefit from earned media through algorithmic recommendations. At the same time, it suggests that consumers who wish to explore a topic should not rely on algorithmic recommendations, as these are likely to side-track them to completely different content.

This paper contributes to four different streams of the literature. First, we contribute to a literature on echo chambers on online platforms due to algorithmic optimization (Gentzkow and Shapiro, 2011; Bessi et al., 2016; Bakshy et al., 2015). These studies find mixed results while focusing on potentially polarizing political and science news (Munger and Phillips, 2020). Bakshy et al. (2015) find that in Facebook's news feed, individuals' choices played a stronger role in limiting exposure to broad content than algorithmic ranking. Flaxman et al. (2016) document that social networks and search engines are associated with an increase in the mean ideological distance between individuals but also with an increase in an individual's exposure to material from his or her less preferred side of the political spectrum. Yet, Bessi et al. (2016) focus on user comments left on YouTube and Facebook for videos related to science and conspiracy, and find that the vast majority of users are drawn to polarized content relatively quickly. To the best of our knowledge, we are the first to analyze the potential existence of 'product' echo chambers outside of the political context, and in particular to examine the perspective of the content producer on social media platforms. This is of importance to charitable organizations and sellers, especially startups, that wish to reach out to consumers through digital media but have limited advertising budgets to do so and thus need to rely on word of mouth. Our results relating to recommendations when users are logged in versus logged out can also shed light on the echo chamber phenomenon going forward, in the wake of regulations such as the GDPR and other industry initiatives to increase user privacy. Indeed, there is a recently proposed U. S. House bill that aims to limit the use of personalized recommendation by algorithms.[4]

Second, we contribute to a literature that analyzes whether digital platforms and the internet more generally can level the playing field. Aguiar and Waldfogel (2018) show how digitization has helped new product discovery and led to increased consumer surplus in the context of music.

[4]See the draft bill here: `https://tinyurl.com/kjnhnd34` and related discussions on Twitter here `https://tinyurl.com/2czancm7`.

Relatedly, Petrova et al. (2020) demonstrate how social media helps new politicians raise money to reduce the incumbency advantage in US politics. At the same time, as platforms gain market power, there is increasing evidence that platform rankings play a significant role in user decisions (Ursu, 2018; Aguiar and Waldfogel, 2019). Our results on the lack of a product echo chamber for less popular content on YouTube raise the concern that rather than leveling the playing field between different organizations, social media algorithms might treat content preferentially that comes from more popular organizations and that focuses on a subset of topics (e.g. more entertaining content). Our results therefore point to a mismatch in the objective function of the platform and that of the organization whose content is being hosted. This is problematic since these organizations are typically financially constrained and do not command large marketing budgets.

Third, we contribute to a stream of marketing research on the role of social media platforms for firms. Smith et al. (2012) analyze the role of brands in user generated content across different social media platforms and find that YouTube is focused on broadcasting the self, and brands play mainly a supporting role. In their analysis of firms' 'social media listening', Schweidel and Moe (2014) find that inferences from social media content best account for more than a single venue and cannot ignore differences across venues. Ma et al. (2015) focus on customers' complaints and compliments on social media. They demonstrate that a firm responding to complaints may improve the customer's relationship with the firm but also raise expectations, encouraging more complaints. This stream of literature focuses on brand-related content generated by consumers, but we ask how an organization can use social media to actively reach out to consumers. Our conclusion is that trying to do so by relying on recommendations through a platform's algorithm may be difficult for the vast majority of organizations, unless perhaps the content attracts unusually large crowds.

Finally, we contribute to the literature on non-profit marketing. This strand focuses on how different types of content messages can increase donations to charities (Sudhir et al., 2016; Munz et al., 2020; Tsiros and Irmak, 2020). Sudhir et al. (2016) shows that donors have sympathy biases that can be leveraged to increase donations while Munz et al. (2020) show that matching donor and recipient name on the basis of name and demographics can lead to higher donations. Our paper attempts to evaluate how charities can leverage earned media since there are restrictions on how much a charity can spend on advertising. Our results are pessimistic: We show that it will be hard for charities to create an echo chamber on a platform like YouTube whose algorithm shows a clear preference for mainstream or popular content. We hope these results will encourage charities to not rely on algorithmic recommendations, but instead to seek out alternate sources of traffic.

2 Study 1

2.1 Empirical Setting and Design

The objective of Study 1 is to collect evidence on whether product echo chambers can arise for videos posted by charities. Specifically, we aim to understand whether a consumer who watches a video posted by a charity on YouTube receives as a recommendation by the platform a further video by this charity or, alternatively, other kinds of videos to watch next. If the YouTube algorithm were to recommend to the consumer a video by the same charity, that could help the charity reinforce its brand with the consumer, with potentially positive effects on donations. In defining a 'product echo chamber', we focus on YouTube recommendations that lead to videos of the same charity relative to content posted by other channels.

As a first step in the data collection process, we identify the YouTube channels of the 100 largest charities in 2019 based on a list compiled by Forbes.[5] For each charity, we harvest URLs of the first five most popular videos listed on their channel. This serves as the base data for both Study 1 and Study 2. For Study 1, in particular, we focus on the 20 most popular videos in the most popular charity category on YouTube, based on the average number of views per video on YouTube. The most popular category is that of 'International' charities which includes videos from organizations such as the United States Fund for UNICEF, World Vision or International Rescue Committee. The most popular video in this list is a video by the Carter Center on guinea worm eradication, and has over 17 million views. The median number of views for a charity in this list is 884,328 and the mean is over two million, implying that these videos are relatively popular.

For the study, we recruited 78 individuals on Amazon Mechanical Turk.[6] We initially asked participants a number of questions with respect to their YouTube viewing patterns and their behavior relative to charities. Specifically, we asked how often they view videos on YouTube and

[5]See the list here https://tinyurl.com/msnetshx and details on the methodology here https://tinyurl.com/dbph6dxk.

[6]The target number of individuals was 75 but we received 78 complete responses and hence, we use the full set of respondents.

how often they view charity videos on YouTube. The options given were daily, weekly, monthly, less than once a month or never. Our sample consists of individuals who use YouTube frequently. 64% of participants watch YouTube every day, while 34% of individuals use YouTube at least once a week though not every day.

Each participant was then asked to watch ten videos that were selected at random from the set of 20 videos. Individuals were instructed to log into their YouTube account before starting the survey. After watching each video, participants were asked to record the URL of the video that YouTube recommended to watch next. Specifically, this referred to the thumbnail for the video displayed on the top right-hand side and marked as "Up Next" as shown in Figure 1. Participants were also asked to record the number of video views displayed on the site. After recording the data, participants were asked to watch the next video until they had finished watching ten videos and recording the associated information.

Thus, this procedure created a data set that records the recommendations made by the algorithm for a total of 780 views of the focal videos, across 78 different individuals. As Table 1 indicates, the mean number of views across recommended up-next videos is about 4.4 million.

We then asked a research assistant to categorize similarity between each focal and up-next video. An up-next video was categorized as (1) being from the same charity, (2) being from a competing charity, (3) covering a related topic but not about charities or (4) covering a completely different topic (and being unrelated to charities). We carried out an audit of the classification undertaken by the research assistant, and found that the exercise was competently done.

The aim of Study 1 is to understand whether product echo chambers can arise for the most popular charity videos. Having individuals being logged into their YouTube accounts allows the algorithm to track what individuals are watching otherwise, and optimize recommendations accordingly. Thus, this setup reflects the type of recommendations consumers would receive in real life when a platform has access to their actual viewing history.

2.2 Results for Study 1

Figure 2 captures the main result of Study 1. Strikingly, it shows that about 57% of the time, captured by the red bar, the YouTube algorithm recommended a video that was not posted by the original charity. In Figure 3, we take a disaggregated look at the videos that were recommended by the algorithm but were not posted by the focal charity. The algorithm recommends a video on an entirely different topic in 41% of instances. This number is neither economically not statistically different from the 43% of instances when the focal charity's video is recommended (p=0.43). The algorithm also recommends a video by a competing charity 7% of the time, a pattern that indicates that positive spillovers between charities rarely happen. Finally, in 13% of the time, the algorithm leads the viewer to a video that is on a related topic but not posted by a charity. This general pattern may be related to consumers' browsing history in that users rarely watch charity videos on YouTube. Figure 5 demonstrates that the vast majority of users (over 85%) view charity videos on YouTube either never, or less than once a month.

Overall, the fact that in almost 60% of instances, viewers are led away from the charity's channel, suggests that it would be difficult for a charity to create a product echo chamber. This may well be a result of past viewing behavior of users, as 86% report viewing charity videos less than once a month.[7]

We then explore the popularity of individual videos based on the number of views our data record. We find that recommended videos that had been posted by the focal charity are significantly less popular than recommended videos for an entirely different topic (430,418 views for focal charity vs. 1,047,066 views for a completely different topic with p<0.01). Figure 4 summarizes this pattern. This suggests that when the algorithm does not show an up-next video posted by the focal charity, it gravitates towards highly popular videos. When we look at median views, the results are qualitatively similar. This should alleviate any issues about outliers, that is, videos with an exceptional large number of views, driving the results. Column (1) in Table 2 demonstrates that the number of a video's prior views recorded by YouTube has a significant effect on this recommendation. We then show that this result holds even after accounting for the sequence in which a survey participant views the video in Columns (2) and (3) of Table 2. These results still hold if we use dummy variables rather than capturing the sequence in which videos are shown as a linear variable. This is surprising, given that such seeding should generate an echo chamber.

In sum, Study 1 demonstrates that after a user viewed a particular video by a charity, there is a high chance that the user is next recommended to watch a video that has not been

[7]Note that while the effect appears less pronounced for those who view charity videos somewhat more often, broadly similar patterns persist. Appendix Figure A.1 compares whether the patterns are similar for the 14% of users who report they view charity videos monthly or weekly. We find that viewers who more frequently watch charity videos are also more frequently recommended a video of either the same charity or a video on the related topic, even if this is not by a charity. This difference is not statistically significant (p=0.17), possibly due to the small share of users regularly viewing such videos.

posted by the charity. In fact, on average the likelihood of being recommended a completely unrelated video is as high as being recommended a video by the same charity. Even if during the course of the study the user has already watched, as instructed, several other videos posted by charities, there is still a high chance that the user is recommended a video other than posted by a charity. Thus, the results suggest there is no consistent echo chamber that might benefit charities in their marketing. However, Study 1 has a few limitations. First, the sample consists of very popular charity videos, potentially limiting the generalizability of the results. Second, users were logged into their YouTube accounts, implying that the algorithm used each user's past browsing behavior. Since most users do not regularly view charity videos, relative to more mainstream content, an algorithm emphasizing past viewing behavior might inhibit a product echo chamber for charitable content. Third, recent concerns around consumer tracking and privacy imply that platforms' ability to provide personalized recommendations may diminish in the near future. For example, Google announced in March 2021 that it will phase out third party cookies for advertising, as well as limit the tracking of individuals across the web and its incorporation in their products.[8] Thus, it is unlikely that platforms will continue to have access to detailed consumer browsing histories. In order to account for these issues and provide a broader set of insights, we implement Study 2.

3 Study 2

3.1 Empirical Setting and Design of Study 2

We aim to broaden our results from Study 1 that YouTube is unlikely to provide consistent product echo chambers for charitable organizations along three dimensions. First, we enlarge the sample of charity videos to ensure that our findings in Study 1 are not driven by small sample size, or by the fact that the videos included were all highly popular. Second, we aim to focus on a setting where recommendations are not influenced by past browsing history. Third, while Study 1 sheds light on the up-next recommendation following a user's viewing of a chosen focal video, it abstracts from the typical behavior of users that continually follow a platform's recommendations.[9] In Study 2, we aim to mirror the behavior of such users who follow the platform's recommendation across a sequence of multiple videos. Such a setup is relevant as

[8] See this article for some details `https://tinyurl.com/43su8rjh`

[9] See, for example, `https://qz.com/1178125/youtubes-recommendations-drive-70-of-what-we-watch/` that report that 70% of the time users watch YouTube videos these are based on the platform's recommendations

only this structure would create a strong product echo chamber.

We hire a research assistant to view videos and collect data in a broadly similar fashion as in Study 1. In order to abstract from their past browsing histories, we request the research assistant to log out of their YouTube account and choose incognito mode. As mentioned previously, a reason for the lack of echo chambers in Study 1 could be that individuals are logged into their accounts which biases the algorithm against niche content such as charity videos that are likely viewed more rarely. Logging out and choosing the incognito setting ensures that the algorithm is not basing its recommendations on past browsing behavior.[10] Given this feature of Study 2, we expect that the YouTube algorithm will be less likely to recommend content that would be of interest to the user given their past browsing behavior and thus would work in favor of creating a product echo chamber, relative to Study 1.

As a result, in our second study, we broaden our analysis to the largest 100 charities in the United States, covering a variety of causes ranging from homelessness to animal welfare. Data is collected anonymously by logging out of the YouTube accounts and going into incognito mode to limit the algorithm from tracking behavior. For each of the charities, we identified the five videos listed first for their YouTube channel. We then recorded for each video the next videos recommended by YouTube and repeat this procedure for the following videos. This approach allows us to examine the patterns when a user follows the platform's chain of recommendations. Again, we measure whether a consumer watching a video is subsequently recommended a video from the same channel, from another charity or outside of the charitable context.

Analyzing the first video recommended following the focal video, we find that, in line with Study 1, in 44.6% of instances users are recommended a video on a completely different topic. In only 15% of instances is a video by the original charity recommended. Hence, contrary to our expectation, lack of tracking makes it less likely for a product echo chamber to occur. This decrease, relative to the 43% in Study 1, is offset by an increase in recommendations associated with videos that are in line with the topic of the focal charity but are not centered around charities. As we "go down the rabbit hole", i.e. to the second, third, fourth, fifth recommendation, the algorithm becomes increasingly less likely to stay with the focal charity and a completely different topic is more likely to be featured.

To ensure that we are not limited to a small sample of YouTube videos, we broaden our

[10] See here for some details about how incognito mode works on YouTube `https://support.google.com/youtube/answer/9040743?hl=en`

analysis to the full list of YouTube video URLs collected. This means we use videos from the 100 largest charities in the US based on a list compiled by Forbes. For each charity, we look at the first five most popular videos listed on their channel.

Relative to Study 1, we also extend the number of recommended up-next videos recorded using a procedure that mimics the behavior of a consumer who watches a stream of YouTube videos as recommended by the algorithm. Specifically, when watching each focal video the research assistant records the URL of the first recommended up-next video as well as the number of views that video has accumulated. The key difference to Study 1 is that the research assistant then watches this up-next video and again records the same data for the next recommended up-next video. The research assistant follows this procedure until they have recorded a sequence of five recommended up-next videos. This design implies that for each charity we collect up to 25 pairs of focal and up-next videos.[11] Thus, this process allows to track how algorithmic recommendations play out over a longer sequence. Given the results of Study 1, we expect that the likelihood that a video not by the original charity will be recommended increases with each step. At the fifth recommendation, we expect it will be very rare for a user to still be recommended a video by the focal charity.

The mean number of views is about 1 million for the sample of focal videos in Study 2, with the median of 138,834 views being significantly lower than for Study 1. This is not surprising as we broadened the set of focal videos to include less popular ones. On average, the popularity of recommended up-next videos is similar to Study 1 – we record again an average of over 4 million views, as panel (b) of Table 1 indicates. Similar to Study 1, we code similarities between each focal video and each of the up-next videos. We record whether, relative to the focal video, the recommended up-next video (1) comes from the same charity, (2) comes from a competing charity, (3) covers a related topic but not about charities or (4) covers a completely different topic (unrelated to charities).

3.2 Results for Study 2

Figure 6 displays results for Study 2 where we focus only on the first up-next video recommended following the focal video to enable us to compare results to Study 1. Strikingly, and in line with Study 1, we find that in 44.6% of instances users are recommended a video on a completely

[11] This procedure should lead us to have 2500 observations in the data. We end up with 2460 in particular because one charity only has one video on its page (Midwest Food Bank). For a few other focal charity videos, we find that their up-next videos result in broken or expired links, making them unsuitable for content analysis.

different topic. The corresponding share in Study 1 was 41%. In only 15% of instances is a video by the original charity is recommended. This magnitude is statistically and economically different from the probability that a completely different topic is recommended ($p<0.01$). It is also much smaller than the 43% found in Study 1. Thus, contrary to expectations, switching off tracking of an individual's browsing behavior does not make it more likely for a product echo chamber to occur. This decrease is offset by an increase in recommendations associated with videos that are in line with the topic of the focal charity but are not centered around charities.[12]

Recall, though, that in Study 2, we mimicked a user's behavior who follows a stream of five up-next video recommendations. Figure 7 shows how the proportion of recommended videos of the same charity and different topics varies by the position of the up-next video in the sequence of recommendations. As we move along the stream of recommendations, the algorithm becomes less and less likely to recommend a video from the same charity, and more and more likely to recommend a video on a completely different topic. After the fifth recommended up-next video, there is only a 3.5% chance of the recommended video being from the original charity.

The pooled analysis in Figure 8 that combines all up-next video recommendations recorded in Study 2 shows that the propensity to take the user away from charity videos increases to over 65% for all up-next videos in our sample. The algorithm leads the user to another video from the same charity about 7% of the time. This difference in recommending a different topic is statistically significant ($p<0.01$). Approximately 20% of the time, the algorithm leads the user to a related topic, but not one that is posted by the focal charity on its YouTube channel. In line with the pattern in Study 1, in Figure 9 we also find that recommended up-next videos that have a completely different topic have a significantly higher number of views than those that are from the same charity.

Finally, we dig deeper into the factors that might lead to a user being steered away from the focal charity's videos to a completely different topic. Column (1) of Table 3 confirms that the further we move along the sequence of up-next recommendations, captured by a higher number (recommendation 2, recommendation 3 etc.), the higher is the probability that the algorithm steers the user to a different topic. This confirms the descriptive evidence provided above. The negative and statistically significant coefficient in Column (2) implies that the higher the views

[12]To rule out that simply the broader set of videos in Study 2 lead to a difference in patterns between Study 1 and Study 2, we display in Figure A.2 the Study 2 results for only the videos that were also included in Study 1, again focusing on only the first up-next recommendations. Figure A.2 shows that the patterns indeed appear to be due to a lack of browsing history, rather than to the broader set of videos included in Study 2.

on the focal charity's video, the higher is the probability of not being taken to a different topic. This suggests that the main factor that allows for a semblance of a product echo chamber is the popularity of the focal video itself. On the other hand, Column (3) shows that up-next recommendations that are popular are significantly more likely to be of a completely different topic. Column (4) demonstrates that these results hold and are reinforced when we include all three variables in one estimation. Column (5) demonstrates that they continue to hold when we include fixed effects for the charity that posted the focal video so that the estimation of all other coefficients relies only on within-charity variation. This suggests that our findings are a result of the characteristics of the videos rather than of the characteristics of the particular charities.

Overall, Study 2 reinforces the findings of Study 1 regarding the absence of a consistent product echo chamber on YouTube across a larger number of charities. It also demonstrates that as a user follows a stream of algorithmic recommendations provided by the platform, the ability for the original charity to continue reaching the user diminishes significantly.

Taking the results from Study 1 and 2 together, it also shows that the YouTube algorithm recommends popular content irrespective of whether an individual is logged into their account or not. In fact, product echo chambers in the case of charities are less likely with limited tracking, which implies that legislation or managerial policy that limits tracking might hurt the ability of important organizations such as charities and other non-profits to reach consumers at a lower cost.

4 Conclusion

In this paper we study the prevalence, or lack thereof, of echo chambers associated with video recommendations on YouTube. We analyze the 'up-next' video recommendations provided by the YouTube algorithm for the most popular videos on the YouTube channel of the largest charities in the US. We carry out two studies to find that in about 45% of instances, the algorithm leads the user away from any topic associated with the focal video or charity. This holds irrespective of whether individuals are logged into their accounts (Study 1) or not (Study 2). This also holds irrespective of the sequence in which users are shown these videos as seen in Study 1. Moreover, in Study 2, we show that as a user follows the platform's chain of recommendations to the second, third, fourth and fifth recommendations it becomes with each step increasingly likely that the algorithm moves away from video content posted by the focal charity.

Overall, these results suggest that there is a limited echo chamber phenomenon for products that do not intend to polarize the viewers. Indeed, there might be a mismatch in the objective function between the platform and the firm, since the algorithm might steer users towards the most popular content. We see this in our data with the algorithm leading users to videos of completely different topics that are highly popular in terms of views. Our results imply that important institutions such as charities are unlikely to benefit from earned media through algorithmic recommendations. Moreover, we demonstrate that in such 'mundane' contexts algorithms might side-track users and lead them to completely different content.

There are, of course, limitations to our study. First, we focus on a broad set of US charitable organizations, a context we believe matters particularly as charities are often severely constrained in the share of their budget they can spend on marketing, emphasizing the need to organically gain user attention online. We expect our results to hold similarly for other empirical contexts where firms offer factual or informative content to promote their products that does not typically attract unusually large crowds. Since, however, our data is limited to charities, we have no direct evidence of the extent to which this applies to other sectors. Second, our results apply to the specific empirical context during which the data was collected. In Study 2, ensuring that a user is not tracked allows us to proxy for the possible implication of phasing out third-party cookies and the limiting of individual-level tracking. However, we are unable to predict how platforms such as YouTube may further develop their recommendation algorithms in response to the more limited data available to them, which might affect future recommendations. Third, while our results apply to the large majority of users who rarely view charitable videos, it is possible that those who organically and repeatedly engage with charitable videos online may face somewhat different recommendations. Notwithstanding these limitations, our insight based on the result from two converging studies demonstrate that it is difficult to create product echo chambers with informative content across a large number of videos on YouTube. We believe that these insights are important for charitable organizations, and more generally firms, that wish to gain exposure through informative video content online. We encourage such organizations to not rely on platform recommendations but instead try and actively promote their content.

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Table 1: Summary Statistics

VARIABLES	Obs.	Mean	Std. Dev.	Min.	Max.
		Summary Stats for Study 1			
Focal Video Views	20	1950745	3805517	325189	17463467
Upnext Video Views (All)	780	4401230	2065658	65	360718178
Upnext Video Views (Different Topic)	311	1047066	3170989	214	360718178
Upnext Video Views (Same Charity)	350	430418.2	2140276	65	17463467
Focal Channel Subscribers	8	14502.5	10409.11	1860	31200
		Summary Stats for Study 2			
Focal Video Views	496	1106829	4177656	46	72422477
Upnext Video Views (All)	2,439	4262702	26941670	18	728239678
Upnext Video Views (Different Topic)	1611	5867990	3281253	18	728239678
Upnext Video Views (Same Charity)	172	159628.8	505795.4	40	5437386
Focal Channel Subscribers	99	42265.4	199314.2	10 1932851	

Table 2: Heterogeneity in Recommendations: Study 1

	(1)	(2)	(3)
VARIABLES	Different Topic	Different Topic	Different Topic
Log(Upnext Video Views)	0.477***		0.478***
	(0.0373)		(0.0377)
Sequence		0.0162	0.0263
		(0.0261)	(0.0324)
Observations	761	761	761

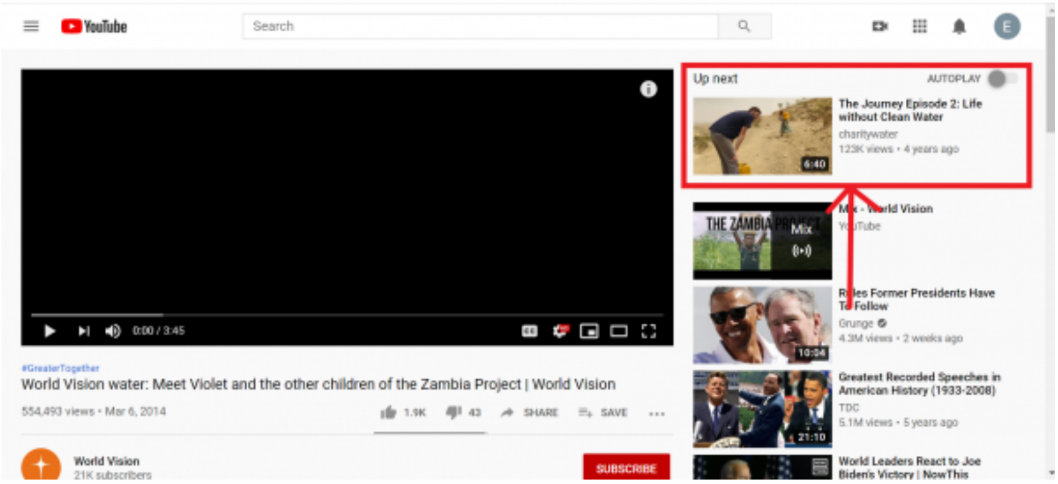
The dependent variable is the probability of whether the up-next video is a different topic relative to the focal video. The unit of observation is focal video-upnext video. Robust standard errors in parentheses clustered at the individual level. * $p < 0.10$, ** $p < 0.05$ *** $p < 0.01$.

Table 3: Factors Steering User Away from Focal Topic: Study 2

VARIABLES	(1) Different Topic	(2) Different Topic	(3) Different Topic	(4) Different Topic	(5) Different Topic
Upnext Position	0.388***			0.461***	0.525***
	(0.0301)			(0.0337)	(0.0411)
Log (Focal Video Views)		-0.0945***		-0.176***	-0.226***
		(0.0332)		(0.0355)	(0.0647)
Log(Upnext video views)			0.267***	0.314***	0.271***
			(0.0321)	(0.0345)	(0.0243)
Charity FE	N	N	N	N	Y
Observations	2,440	2,440	2,241	2,241	2,047

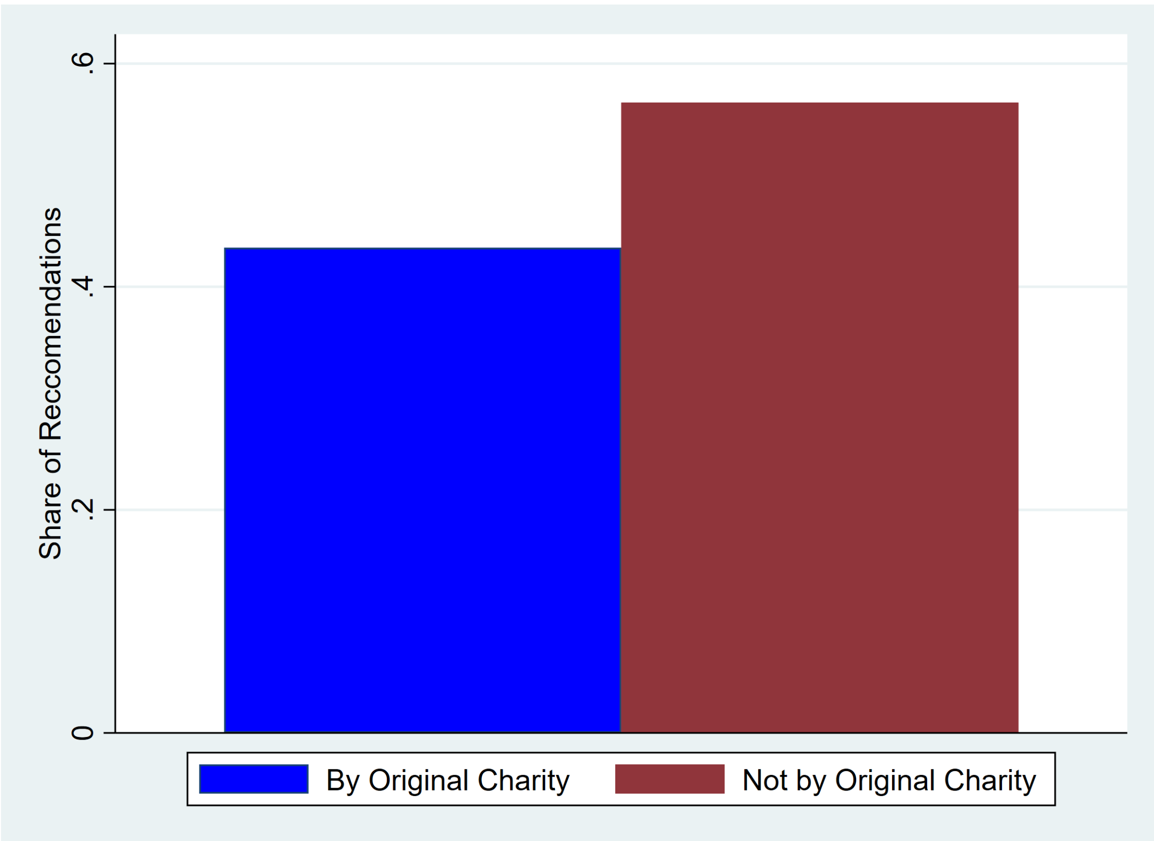
The dependent variable is the probability whether the up-next video is a different topic relative to the focal video. The unit of observation is focal video-upnext video. Robust standard errors in parentheses clustered at the charity level. * $p < 0.10$, ** $p < 0.05$ *** $p < 0.01$.

Figure 1: Upnext Videos on YouTube



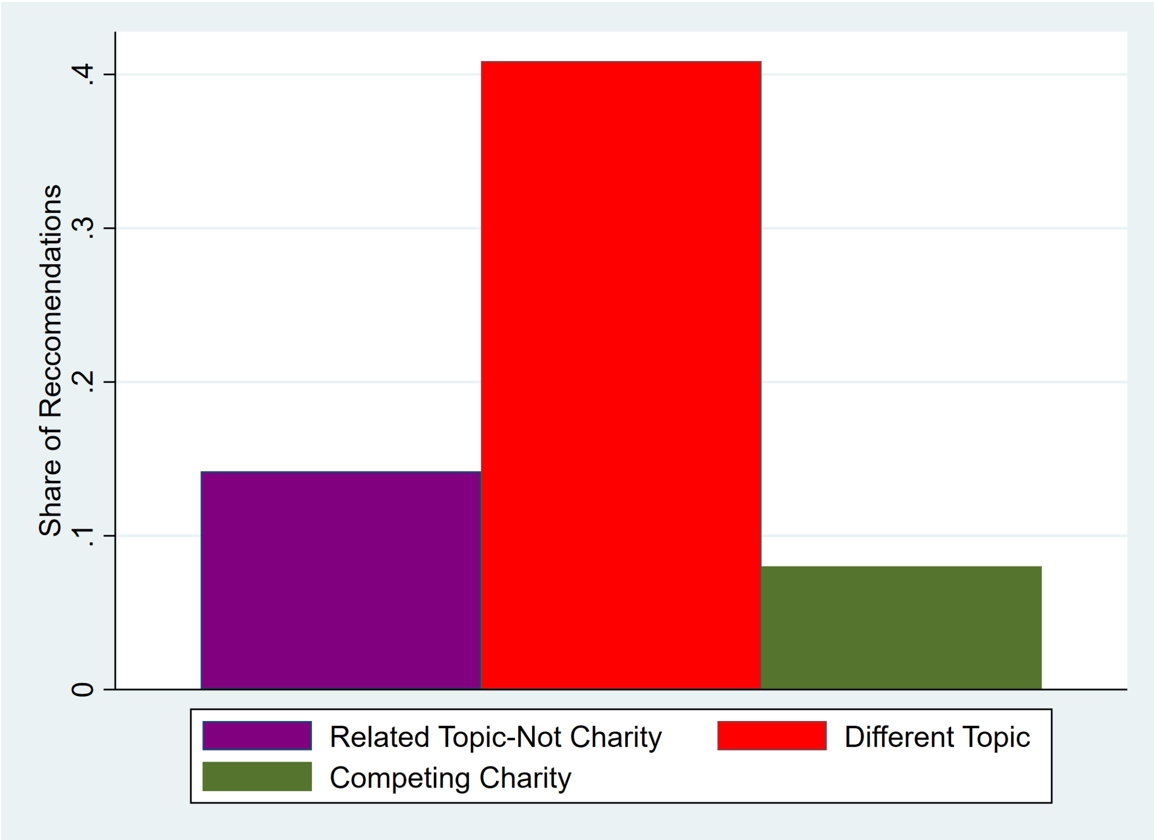
The figure shows how the upnext videos look within the YouTube interface.

Figure 2: Distribution of Topics for Upnext Videos: Study 1



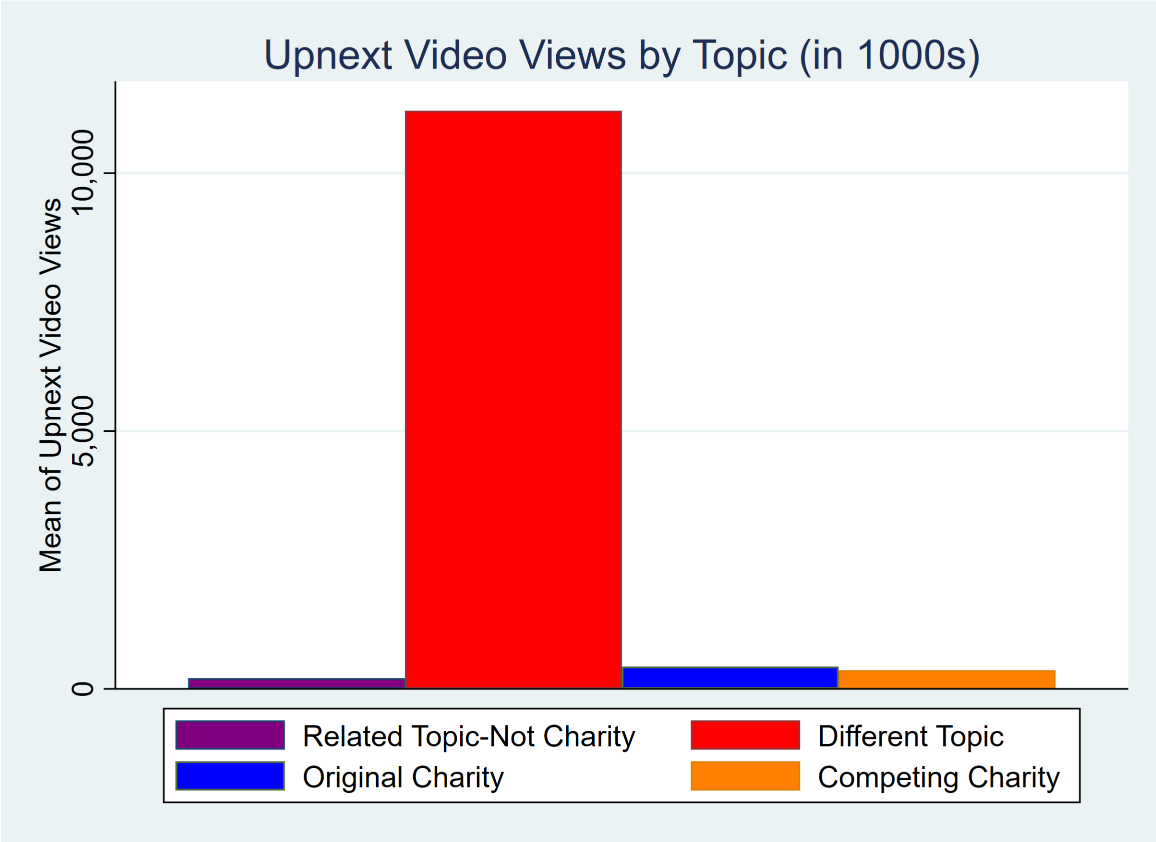
The figure shows the distribution of video topics of upnext videos in Study 1. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity. Not related to original charity is a video that is not about the focal charity or associated with the charity's channel.

Figure 3: Distribution of Topics for Upnext Videos: Study 1



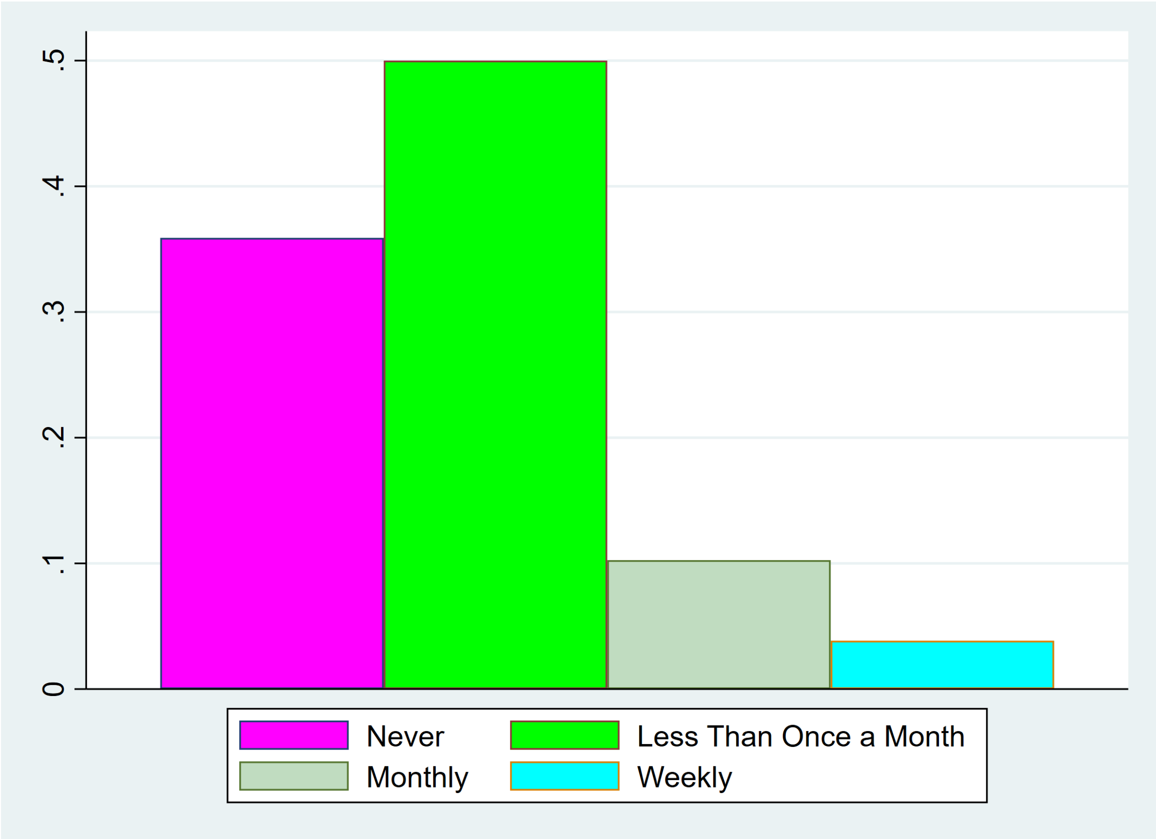
The figure shows the distribution of video topics of upnext videos in Study 1. Related topic-not charity is if the video is about the topic in the focal video but doesn't mention any charity. Competing charity is if the the video is hosted by or is about another charity than the focal one. Different topic refers to the upnext video being about a completely different topic relative to the focal video.

Figure 4: Mean Upnext Video Views by Topic: Study 1



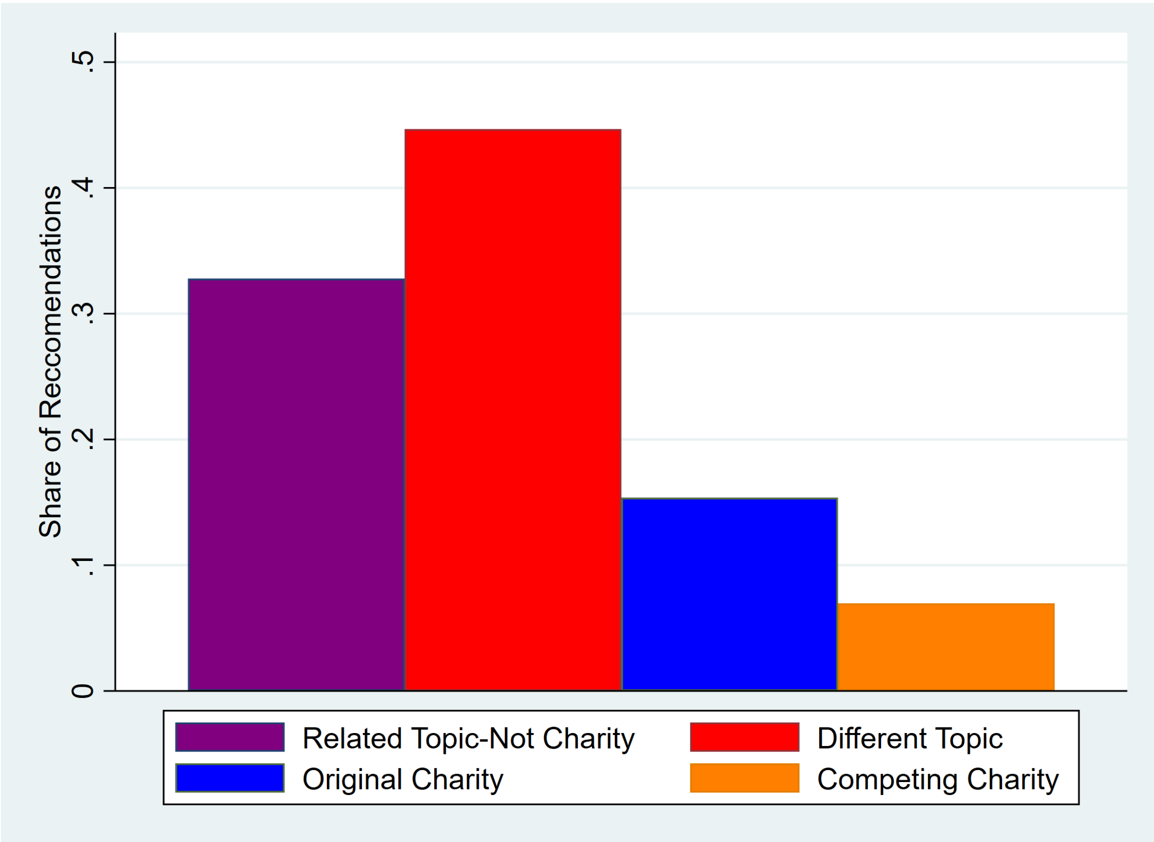
The figure shows the mean of upnext video views by the topic of the upnext video for Study 1. The number of views is scaled down by 1000 for legibility. These videos are exactly the same as those that are used in Study 1. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity. Related topic-not charity is if the video is about the topic in the focal video but doesn't mention any charity. Competing charity is if the the video is hosted by or is about another charity than the focal one. Different topic refers to the upnext video being about a completely different topic relative to the focal video.

Figure 5: Intensity of Viewing Charity Videos on YouTube: Study 1



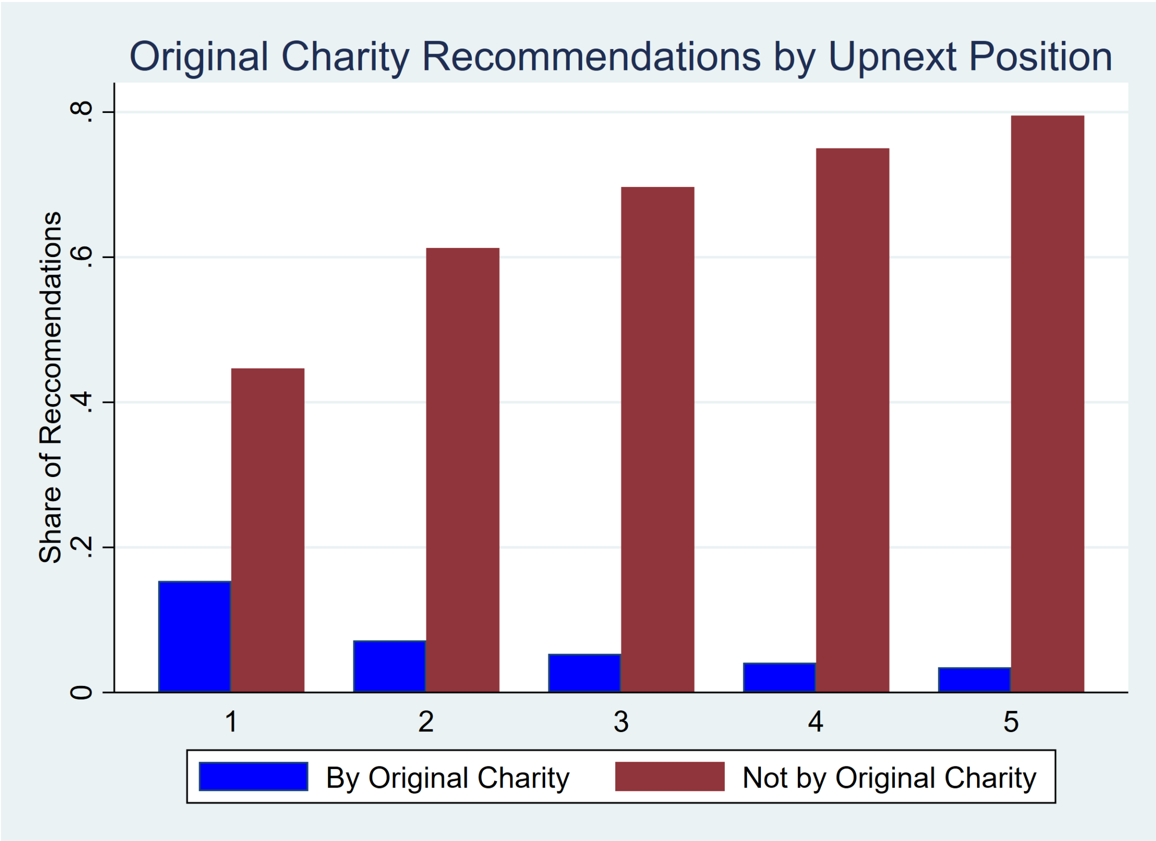
The figure shows the distribution of users' responses to the question about their charity viewing behavior on Youtube.

Figure 6: Distribution of Topics for First Upnext Video: Study 2



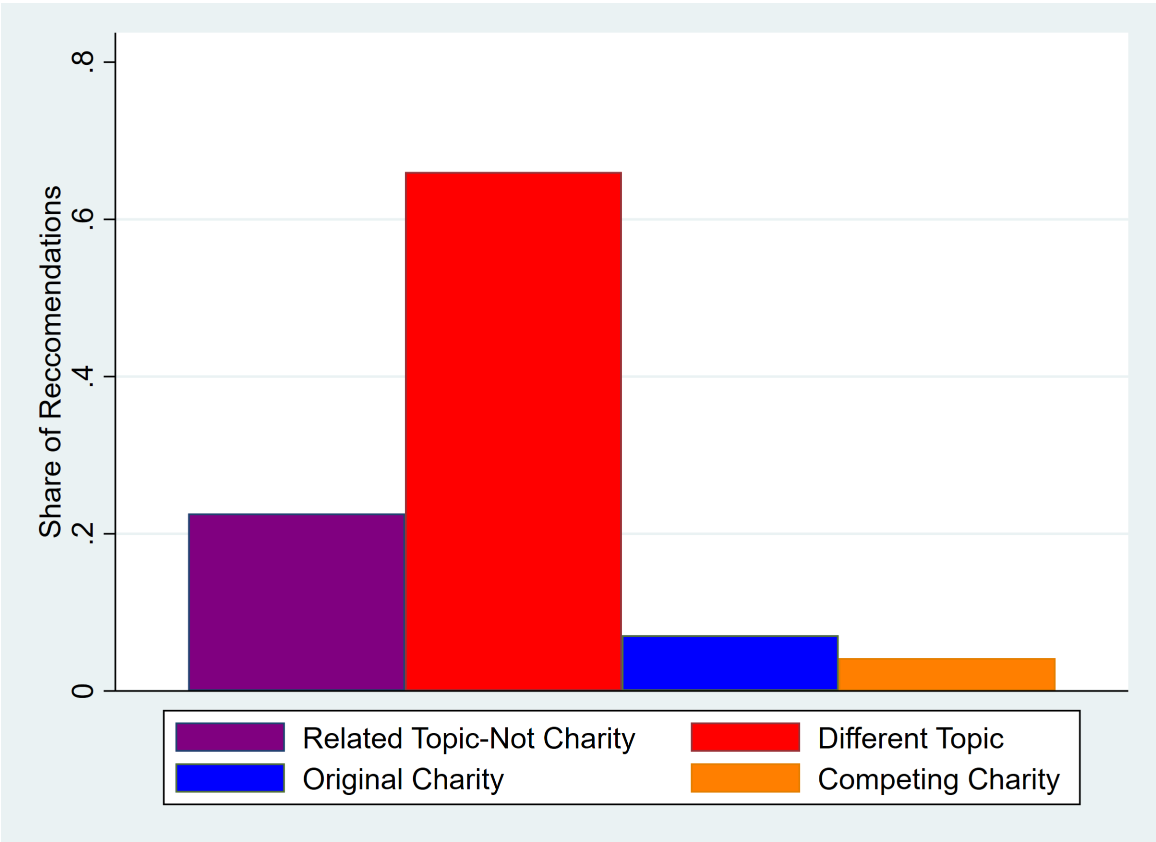
The figure shows the distribution of video topics of only the first upnext videos in Study 2. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity. Related topic-not charity is if the video is about the topic in the focal video but doesn't mention any charity. Competing charity is if the the video is hosted by or is about another charity than the focal one. Different topic refers to the upnext video being about a completely different topic relative to the focal video.

Figure 7: Original Charity recommendations by Upnext Position: Study 2



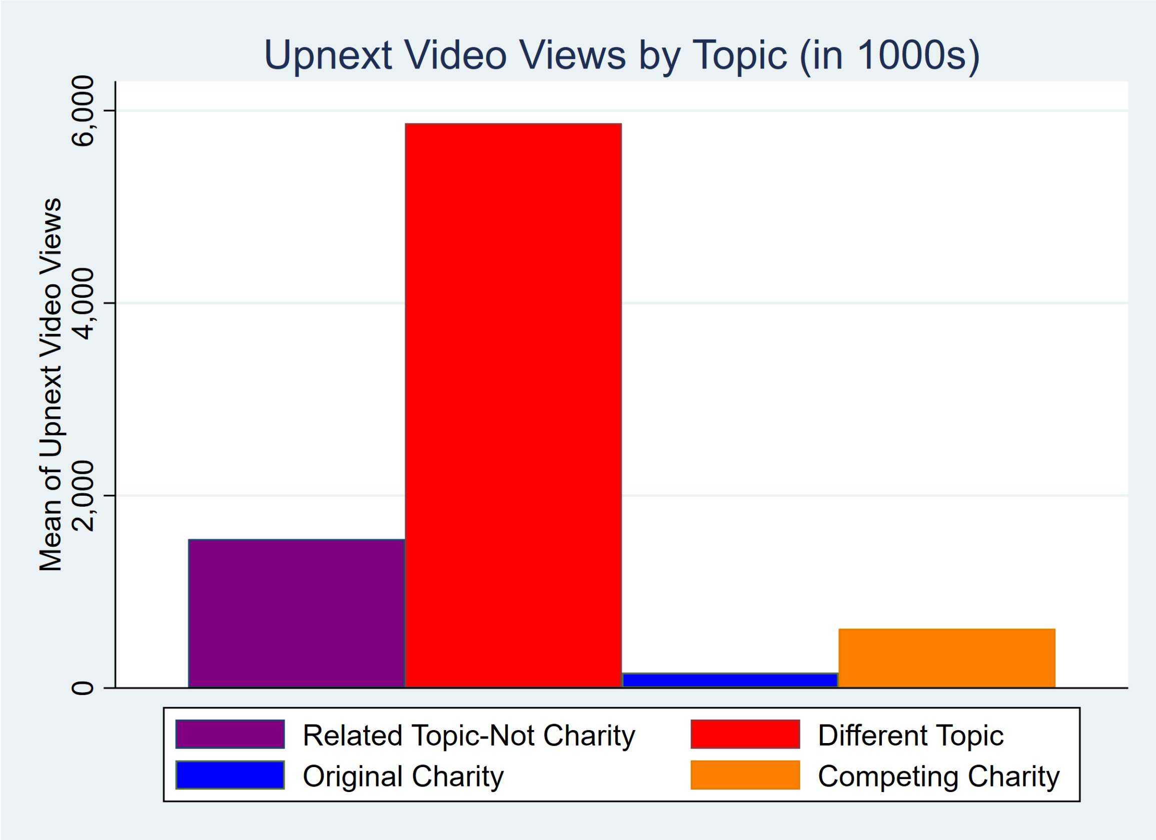
The figure shows the the share of recommendations for Original charity videos by upnext position in Study 2. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity.

Figure 8: Distribution of Topics for All Upnext Videos: Study 2



The figure shows the distribution of video topics of all upnext videos in Study 2. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity. Related topic-not charity is if the video is about the topic in the focal video but doesn't mention any charity. Competing charity is if the the video is hosted by or is about another charity than the focal one. Different topic refers to the upnext video being about a completely different topic relative to the focal video.

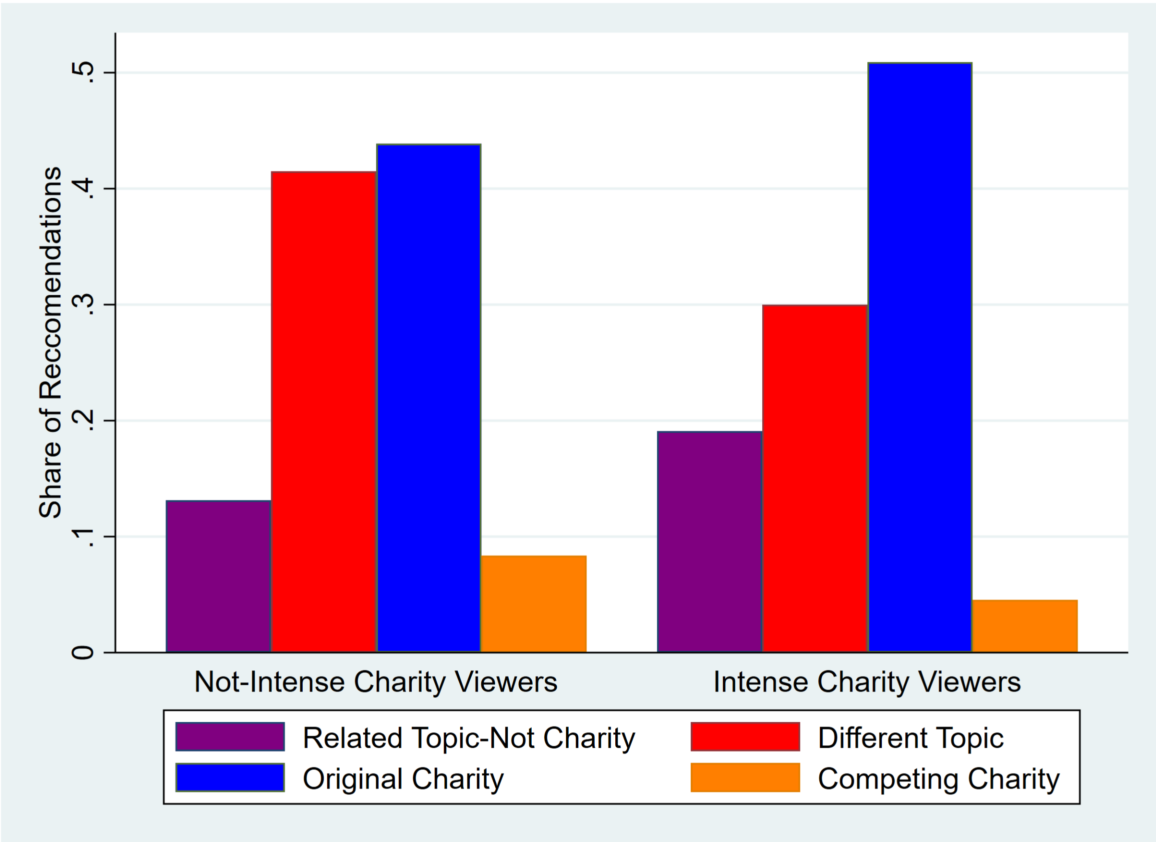
Figure 9: Mean Upnext Video Views by Topic: Study 2



The figure shows the mean of upnext video views by the topic of the upnext video for Study 2. The number of views is scaled down by 1000 for legibility. These videos are exactly the same as those that are used in Study 1. Original charity is when the video is hosted by the channel of the original charity or is explicitly about the charity. Related topic-not charity is if the video is about the topic in the focal video but doesn't mention any charity. Competing charity is if the the video is hosted by or is about another charity than the focal one. Different topic refers to the upnext video being about a completely different topic relative to the focal video.

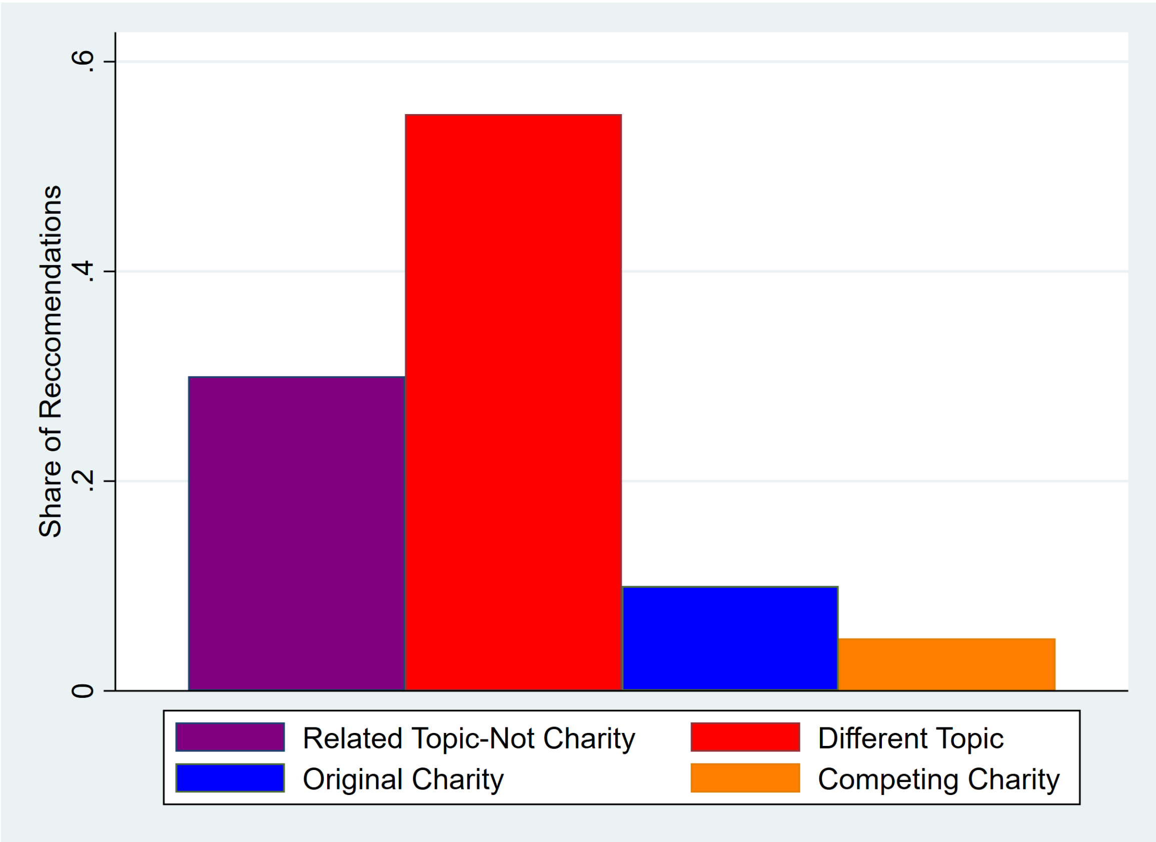
Online Appendix

Figure A.1: Charity Video Viewers vs. Others: Study 1



The figure shows the distribution of video topics of up-next videos in Study 1 by type of user. An 'intense' charity viewer is someone who reports watching charity videos on YouTube at least once a month, while a 'non-intense viewer' is one who either never watches such videos or less than once a month. 'Related topic-not charity' is if the video is about the topic in the focal video but does not mention any charity. 'Competing charity' is if the the video is hosted by or is about another charity than the focal one. 'Different topic' refers to the up-next video being about a completely different topic relative to the focal video.

Figure A.2: Distribution of Topics for First Up-next Video of Focal Videos used in Study 1: Study 2



The figure shows the distribution of video topics of only the first up-next videos for focal videos used in Study 1 and in Study 2. The distribution is based on the data collected as part of Study 2. 'Original charity' is when the video is hosted by the channel of the original charity or is explicitly about the charity. 'Related topic-not charity' is if the video is about the topic in the focal video but does not mention any charity. 'Competing charity' is if the the video is hosted by or is about another charity than the focal one. 'Different topic' refers to the upnext video being about a completely different topic relative to the focal video.