Unveiling the Impact of Within-Content Engagement Information: Evidence from a Natural Experiment on YouTube

Abstract

Digital content platforms increasingly display granular, within-content engagement signals across their interfaces, yet empirical evidence on their causal effects remains limited. We investigate the causal impact of this strategy, studying YouTube's engagement graphs—visual displays showing moment-by-moment user engagement throughout videos—on viewership, user satisfaction, and community engagement. Conceptually, engagement graphs present a tension between helping users find engaging content and potentially fragmenting viewing experiences. Using a dataset corresponding to over 121,000 YouTube videos, collected from February to April 2023, we address this empirical question using a novel identification strategy. We first reverse-engineer the platform's activation criteria, and then identify quasi-random variations in the duration between upload and eligibility across otherwise similar videos. Leveraging these variations, we adopt a difference-in-differences strategy with matched samples to obtain causal effects. Our findings show that enabling engagement graphs significantly increases content viewing, liking, and community engagement. Our heterogeneity analysis demonstrates that more informative engagement graphs (those with more engagement peaks) drive stronger treatment effects. Over time, engagement distributions evolve to become more concentrated around highlighted moments, suggesting potential observational learning among viewers. Beyond these demand-side effects, we also document strategic supply-side responses by examining whether content creators change their content supply decisions when engagement graphs become available. Our findings provide actionable insights for content creators, advertisers, and platform managers.

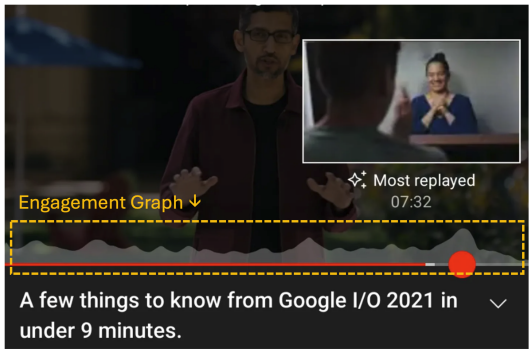
Keywords: Engagement graphs, natural experiment, YouTube, creator economy

1 Introduction

The rapid growth of digital content platforms has fundamentally transformed how users discover and consume content. These platforms employ numerous informational strategies to increase user engagement, such as recommendation systems and aggregate popularity metrics like view counts. Increasingly, they are offering more granular engagement information. A notable strategy for content platforms – including text (e.g., e-books), audio (e.g., Spotify), and video – is to show how other users engage with specific parts of the content. For instance, Facebook Live introduced engagement graphs in 2016 that display moment-by-moment volume of live comments and reactions during recorded streams (Lopez 2016), and Kindle's "Popular Highlights" feature marks frequently highlighted passages by other readers (Amazon 2025).

Despite the widespread adoption of such informational strategies, their empirical impact, particularly causal effects, are not well understood and deserve careful study. In this paper, we examine the impacts of YouTube's "engagement graphs," which visually display moment-to-moment user engagement levels throughout the duration of a video (see Figure 1), and investigate their effects on viewership, satisfaction, and community engagement. Beyond these demand-side effects, we also examine how content creators strategically respond to this new information environment by adapting their content production and monetization decisions.

Figure 1: The YouTube Engagement Graph



From a conceptual viewpoint, the provision of granular engagement information potentially benefits users. Videos, and content more broadly, often alternate between highly engaging moments and less compelling segments, leading to an uneven viewing experience. After selecting a video, users continually face the decision of whether to continue watching or abandon viewing, often with

incomplete information about potentially valuable upcoming content. Engagement graphs might encourage users to stay engaged if they foresee more interesting content ahead.

However, providing engagement graphs could function as a double-edged sword. Such engagement signals might disrupt viewing experiences by promoting fragmented consumption or causing users to skip seemingly less engaging sections that provide necessary context, thereby affecting narrative coherence. Content creators themselves have expressed concerns about whether providing this information might decrease overall user engagement for some types of content or even for all content.[1]

The above conceptual framework captures the demand-side of the platform ecosystem. On the supply side, content creators may also respond strategically to changes in the information environment. Understanding how engagement graphs affect creator supply decisions is important for platform strategy and the broader creator economy. Content supply represents a critical challenge for digital content platforms like YouTube, which shares 55% of ad revenue with creators and invests billions in creator funds to stimulate production (Mohan 2024). The introduction of engagement graphs creates new incentives that may influence creators' production decisions. Creators may increase or decrease overall output depending on whether the feature increases or decreases returns to content creation. Creators may also strategically reallocate effort toward content formats more likely to qualify for graph activation, potentially reshaping the platform's content landscape.

Thus, the overall ecosystem impact encompasses both demand-side effects and supply-side creator responses, making this an empirical question with implications for all stakeholders in the digital content ecosystem, including content creators, advertisers, and the platform.

In this paper, we investigate the following research questions. First, we examine how providing engagement graphs causally impacts user viewing (views), satisfaction (likes), and community engagement (commenting activities). Second, related to the content creators' concern, we examine two related questions: how the effects of enabling engagement graphs are heterogeneous across content types, and how the informativeness of the engagement graph distribution impacts user response. Third, complementing these causal investigations, we descriptively detail the temporal evolution of engagement distributions, and examine whether viewer attention patterns over time

[1]For example, YouTube creator LaterClips expressed their concerns in video "YouTube's 'Skip To The Good Part' Feature Is Dangerous..." (LaterClips 2022).

become more evenly distributed or increasingly concentrated around highlighted moments. Finally, we examine how content creators adapt their production decisions when audiences gain access to engagement graphs.

Several empirical challenges complicate the identification of causal effects in this setting. First, engagement graphs may be selectively activated by the platform for videos that have certain characteristics or performance patterns, creating potential selection bias. Second, the timing of activation might correlate with unobserved factors affecting video performance, making it difficult to isolate the causal impact of the feature. Understanding these activation patterns is crucial for developing a credible identification strategy. We address these challenges using a novel identification strategy that exploits YouTube's batch processing approach to engagement graph activation. Using a dataset of over 121,000 YouTube videos collected from February to April 2023, we first reverse-engineer the platform's activation criteria to account for the platform's selection. Next, we identify and leverage quasi-random variations in the duration between upload and eligibility across otherwise similar videos, created by a batch processing implementation decision made by the platform. These institutional details provide a natural experiment setting for causal inference, allowing us to use a difference-in-differences strategy with matched samples to estimate the causal effect of engagement graphs.

Our analysis yields several key findings. First, we document that engagement graphs significantly increase user engagement. Our analysis focuses on the first two weeks after video upload. Treated videos experience a 7.9% increase in new views (recorded when a user watches at least 30 seconds of a video cumulatively) per period after receiving the engagement graphs. Since users cannot observe the presence (or absence) of an engagement graph before starting to watch a video, this is best seen as a retention effect. This effect is particularly meaningful given that creators commonly report losing 30-40% of viewers within the first 30 seconds of their videos (Reddit 2023), highlighting how engagement graphs may help address this prevalent early abandonment problem. Engagement graphs also lead to a 9.2% increase in new likes per period and an average of 3.19 additional comments per period for treated videos. When aggregating these effects across post-treatment periods, they contribute approximately 1% to total two-week views and likes, and 3% to total two-week comments. These effects translate into meaningful economic value—generating an estimated \$22-\$67 in additional advertising revenue per treated video for content creators.

Our analysis of comment content using state-of-the-art large language models reveals that engagement graphs do not significantly affect sentiment or depth of engagement in the comments. This suggests the feature promotes broader participation in discussions without altering the qualitative nature of the discussions.

Second, our examination of treatment effect heterogeneity reveals that more informative engagement graphs are more effective in driving engagement. All else equal, videos with engagement graphs having one standard deviation more peaks than the mean enjoy 4.5% more new views, 4.0% more new likes, and 0.736 more new comments per period after treatment. These effects are significant while controlling for video length and channel popularity, suggesting that information richness—not video or creator characteristics—drives the heterogeneity.

Lastly, our descriptive analysis of temporal patterns reveals that over time, engagement graphs become more unequally distributed with fewer, more pronounced peaks, indicating that users increasingly focus their attention on highlighted moments. A likely explanation for this is through observational learning, where viewers herd towards the highlighted moments, although alternative explanations might be at play as well.

Our findings yield actionable insights for content creators, the platform, and advertisers. To structure these implications, we first outline each stakeholder's decision authority and then provide targeted strategic recommendations based on our findings (summarized in Table 1). First, content creators can monetize their videos by enabling ads. For longer videos, creators can turn on mid-roll ads that play during their video. They determine both the ad load (total number of mid-roll ad slots) and the mid-roll ad placement (precise locations within the video). These settings can be modified anytime. Second, advertisers can target specific YouTube channels, or even specific videos, when configuring their ad campaigns, and choose whether their ad is skippable or non-skippable. Finally, YouTube executes the actual ad delivery by balancing ad supply and demand.

For content creators, our findings suggest they should dynamically manage their monetization-engagement tradeoff. Higher ad loads generate more revenue, but can potentially diminish viewer engagement, creating an inherent tradeoff between monetization and engagement. Given our finding that engagement graphs increase views, likes, and comments, creators should incorporate these effects into their monetization strategy. For instance, creators may find it beneficial to reduce ad load to accelerate reaching the 50,000-view threshold, then strategically increase ad load post-

activation to capitalize on heightened engagement driven by the engagement graph. Such a dynamic approach is likely to be better than a strategy that is constant over time. Second, given our finding that viewership increasingly shifts towards the highlighted segments, creators could position mid-roll ads immediately before these high-engagement segments to maximize ad exposure and revenue by connecting with users when they are more engaged. Finally, creators of videos exhibiting multiple engagement peaks – which enjoy stronger treatment effects – could implement more sophisticated ad strategies, placing more mid-rolls before various highlighted segments to leverage increased viewer engagement.

For the YouTube platform, our findings reveal a monetization opportunity through potentially offering early access to engagement graphs as a premium creator feature. This would generate additional revenue streams for the platform while providing value to creators seeking a competitive advantage in the attention economy. This would be similar to airlines offering gold status for purchase when customers are close to qualifying (Schlappig 2025). More broadly, our supply-side findings reveal that engagement graphs may generate organic content supply growth without direct platform investment in creator incentives or subsidies, an effect that extends beyond the direct viewer engagement benefits.

For advertisers, first, they should experiment and understand the impact of advertising in videos having a flat v.s peaky engagement graph. Second, since videos with a greater number of engagement peaks enjoy stronger treatment effects, advertisers should incorporate that knowledge into their strategic content selection.

For researchers, whereas previous studies typically focus on how product-level popularity signals influence discrete consumer choices among alternatives, our setting allows us to observe how segment-level popularity information affects engagement with the entire content video. This provides unique insights into whether such granular signals can "increase the pie" of overall engagement rather than merely redistributing engagement across competing options. Second, our empirical strategy demonstrates how careful analysis of institutional mechanics may reveal useful variation or natural experiments for causal inference in platform settings. This approach offers a valuable alternative for researchers studying digital platforms where traditional randomized experiments may be impractical or infeasible.

Our research makes several important contributions to the literature on digital platforms and

user engagement. First, we provide novel causal evidence on how fine-grained, moment-by-moment engagement signals affect user behavior, extending beyond traditional aggregate popularity metrics. Second, our methodological approach leverages platform-specific institutional details to recover a natural experiment, providing insights on how researchers can identify causal effects in complex platform settings where randomized experiments are often infeasible. Third, we document how these granular signals not only reshape immediate viewing decisions but also influence broader engagement dimensions including satisfaction and community participation. Fourth, we uncover important heterogeneity across content types while documenting the temporal evolution of engagement patterns, revealing how information richness—rather than merely content characteristics—drives differential responses. Finally, we provide novel evidence on supply-side creator responses to platform information provision features, addressing an understudied area in the creator economy literature by examining how creators strategically adapt their content supply decisions when granular engagement information becomes available to audiences. Collectively, these contributions advance our understanding of information provision in digital ecosystems and offer actionable strategies for multiple stakeholders in the content creation value chain.

Table 1: YouTube Advertising Ecosystem: Decision Authority and Strategic Recommendations

Entity	Decision Authority	Strategic Recommendations
Content Creators	• Allow monetization (channel-level) • Enable pre-roll and post-roll ads (video-level) • Set mid-roll ad load and placement* (video-level) • Content production	• Dynamically manage the monetization-engagement tradeoff: less *ad load* before engagement graph activation and more after • Place mid-rolls immediately before high-engagement segments • For videos with more peaks: can afford higher ad load
Advertisers	• Ad format (skippable/non-skippable) • Targeting options (e.g., specific creators/videos, audience demographics) • Budget and bidding strategy	• Incorporate knowledge of the estimated heterogeneity effects into channel/content selection strategies • Experiment and understand the ad effectiveness in videos having a flat v.s. peaky engagement graph
YouTube	• Execute the actual ad delivery • Personalize which specific ads are shown to which viewers • Platform feature development and rollout strategy	• Offer early access to engagement graphs as a premium feature for content creators • Leverage organic content supply growth generated by engagement graphs without direct creator subsidies

* Mid-roll ads are only available for videos longer than 8 minutes.

References

Amazon (2025). Kindle app updates. Accessed: 2025-04-28. https://www.amazon.com/Kindle-App-Updates/b?ie=UTF8&node=11627044011.

LaterClips (2022). Youtube's 'skip to the good part' feature is dangerous... Accessed: 2025-04-28. https://www.youtube.com/watch?v=QgXnhxwSwIY.

Lopez, N. (2016). Facebook's new live video graph could help you find the interesting bits. Accessed: 2025-04-28. https://thenextweb.com/news/facebook-live-video-getting-soundcloud-like-reactions-feature.

Mohan, N. (2024). Letter from the YouTube CEO: 4 big bets for 2024. YouTube Blog. Accessed July 31, 2025.

Reddit (2023). What is considered good viewer retention? Accessed: 2025-04-28. https://www.reddit.com/r/PartneredYoutube/comments/13mf946/what_is_considered_good_viewer_retention/.

Schlappig, B. (2025). Buy up to american airlines elite status for 2025: Offers now live. Accessed: 2025-04-28. https://onemileatatime.com/deals/buy-american-airlines-status/.