Response Letter to Senior Editor Feedback on Manuscript MKSC-2025-0013

Dear Senior Editor Tucker,

Thank you for your thoughtful feedback by email on June 4, 2025, directing us to focus on the substantive contribution of the paper. Based on your feedback, we submit both a revised introduction and a response letter with a detailed proposal for additional analyses (this document) to strengthen the paper's contribution. These proposed analyses require substantial new data collection and additional empirical work that we have not yet conducted, as recommended by the senior editor. We have therefore refrained from speculating on the results of the analysis. We present research plans in this response letter for the editors to evaluate the potential additional contribution. We have made targeted revisions to our introduction to appropriately position these additional contributions while maintaining focus on our previously established demand-side results.

Our proposed plans include the following:

1. **Creator Content Supply Decisions** - We propose examining whether content creators change their content supply decisions when engagement graphs become available to their audiences. We are enthusiastic about adding this to improve the contribution of the paper, positioning also around the creator economy.

2. **Other Potential Analyses** - We offer these as suggestions in case the editors think they would be important to further improve the contribution. We could examine:

   (a) creator response in sponsorship decisions (supply side)

   (b) heterogeneity across different engagement patterns (demand side)

   (c) heterogeneity across different content categories (demand side)

Below, we provide detailed plans for each proposed analysis. We welcome feedback on these proposals and are prepared to implement the analyses that you believe will most strengthen the manuscript's contribution.

1 Creator Content Supply Decisions

Research Context: Our main analysis has documented the demand-side effects of the YouTube engagement graph feature on users. However, as YouTube operates as a two-sided platform, content creators could also respond strategically to this informational change. To provide a more comprehensive view of engagement graphs' impact, we propose a new supply-side analysis, examining whether and how content creators change their content supply decisions when engagement graphs become available.

Contribution in Literature: Empirical evidence on creators' content supply decisions remains very limited.[1] A few exceptions include Zeng et al. (2023) on social nudges' impact on video supply and Qian and Xie (2025) on star creator exit effects on Twitch.tv. However, no prior work examines how platform's provision of granular engagement information causally impacts creators' supply decisions and viewers' demand decisions. We therefore believe that this supply-side analysis would be a valuable addition to this literature.

Motivation: 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).

Our demand-side results demonstrate that engagement graphs increase viewer engagement, creating higher returns for qualifying content. This effect generates an incentive for creators to produce more qualifying content that can benefit from the feature. However, creators face uncertainty about which specific videos will meet the platform's eligibility criteria for receiving engagement graphs, because they may not know the criteria, nor can they perfectly predict the performance of each video.

This uncertainty creates two potential responses. Creators may increase their overall production volume as a portfolio strategy since producing more content increases their chances of creating videos that qualify for engagement graphs. Alternatively, creators may attempt to

[1] However, there are game-theoretical analyses (e.g., Amaldoss et al. 2021, Ren 2024, Qian and Jain 2024).

learn the platform's implicit performance standards by observing which of their videos receive the feature, then strategically focus their limited resources on producing content with greater performance potential that is more likely to qualify.

Both responses could increase the supply of high-performing content, but through different mechanisms: volume increases versus performance concentration. The latter strategy, however, may come at the expense of more experimental or diverse content, potentially increasing performance inequality within creators' video portfolios as they reallocate effort toward their most promising content types.

These conceptual arguments above lead us to the following empirical questions.

Research Question: Do creators increase their content supply (or high-performing content supply) after their videos begin receiving engagement graphs? Does engagement graph availability increase performance inequality within creators' video portfolios?

Methodology: In May 2022, YouTube launched the engagement graph feature, and applied it retroactively to all eligible videos uploaded before the launch date. This retroactive activation by YouTube created differential exposure to engagement graphs across creators: creators whose pre-rollout (before May 2022) video portfolios contained a higher proportion of videos meeting the eligibility criteria suddenly found more of their existing content equipped with engagement graphs, while creators with fewer qualifying videos experienced substantially less exposure to the new feature.

We plan to leverage this variation to measure *treatment intensity* as the proportion of each creator's videos from the one-year pre-rollout period (May 2021-May 2022) that received engagement graphs at the time of platform-wide feature rollout. We will employ a difference-in-differences design comparing creators with high versus low treatment intensity before and after the May 2022 feature rollout. This approach controls for creator-level time-invariant unobservables and common temporal shocks, and is established in recent work examining platform-wide feature rollouts where all firms are simultaneously impacted by one policy shock (Aridor et al. 2025; Hui et al. 2025).[2]

[2]Following Aridor et al. (2025), who study the impact of Apple's App Tracking Transparency on e-commerce firm revenues, we plan to implement two complementary estimators: (1) a median split DiD estimator, and (2) the heterogeneous adoption design (HAD) estimator by de Chaisemartin et al. (2024). In this proposal, we only focus on the median split DiD estimator and use it as our primary model specification.

Primary Model Specification (Median Split DiD):

$$Y_{it} = \sum_t \beta_t(Month_t \times HighExposure_i) + \alpha_i + \kappa_t + \epsilon_{it}$$

where $HighExposure_i$ is an indicator variable equal to 1 for creators whose treatment intensity (percentage of pre-rollout videos receiving engagement graphs) is above the median across all creators in our sample, and 0 otherwise. α_i denotes creator fixed effects, and κ_t denotes month fixed effects. We plan to focus on the following outcome variables, Y_{it}: (1) the number of videos uploaded per creator-month, (2) the number and proportion of successful videos (passing 50k views in three months) uploaded per creator-month, and (3) the number and proportion of unsuccessful videos (below 10,000 views in three months) uploaded per creator-month.

Data Collection: This analysis will require us to obtain a completely new dataset. To examine whether creators change their content supply when engagement graphs become available, we need a panel dataset of active creators with sufficient variation in treatment intensity and observable content production patterns. Our proposed data construction process involves three steps:

1. Identify creators across content categories, focusing on creators in the medium-subscriber range (e.g. 1 million subscribers) where we expect meaningful treatment variation;
2. For the above creator list, collect comprehensive posting histories and video metadata spanning May 2021 to May 2023 (12 months before and after the feature rollout), retaining only creators with active posting histories pre-rollout;
3. Use Internet Archive snapshots to obtain historical view counts at the feature rollout, then calculate treatment intensity as the percentage of each creator's pre-rollout videos that received engagement graphs (proxied by videos exceeding 50K views at rollout, since historical engagement graph status is not directly observable).

Expected Sample: 3,000-5,000 creators depending on data quality, which will involve collecting and processing data for potentially millions of individual videos.

Feasibility Note: We have tested the feasibility of data collection using the YouTube Data API and web scraping on a small sample of content creators, and we are relatively comfortable that we would be able to collect data for a well-powered analysis. Some uncertainties remain regarding ensuring sufficient variation in treatment intensity across creators to support robust statistical inference, among creators with adequate posting consistency in our target timeframe.

Implications: Testing these hypotheses has significant implications for platform strategy and content creator economy. If creators indeed produce more content or higher-quality content generating greater engagement, it demonstrates that the engagement graph feature can generate organic content supply growth without direct platform investment in creator incentives or subsidies. The increased content supply may also strengthen the platform's competitive position against rival platforms. If within-creator content performance inequality increases without an increase in overall supply, it may indicate that creators strategically reallocate their production efforts toward content formats more likely to receive engagement graphs, potentially at the expense of more experimental or diverse content.

Implications of Potential Null Effects: If we find no significant changes in creator content supply decisions, this would also provide valuable insights, documenting that engagement graphs can effectively boost viewer engagement but not change content creators' supply decisions. This suggests content creators may have established production routines that are relatively insensitive to incremental changes in engagement feedback mechanisms. For platform managers, this would highlight the limits of indirect supply-side incentives and underscore the continued necessity of direct interventions such as revenue sharing to influence creator behavior and stimulate content supply growth.

2 Other Potential Analyses

We list multiple potential analyses that could be interesting to explore. We would appreciate guidance from the editorial team on whether it would be required to complete them to ensure the paper meets the bar for contribution.

(A) Supply-Side Creator Response - Sponsorship Decisions

Motivation: For creators, beyond ad revenue obtained from the platform, brand sponsorships represent a critical monetization channel. Sponsored segments are often observed to generate lower viewer engagement and appear as distinct dips in engagement patterns. Engagement graphs are likely to make these low-engagement promotional segments more transparent and skippable to viewers, potentially reducing the effective reach of sponsored messages and creating strategic pressure for creators to reduce their reliance on sponsorships.

Research Question: Do creators change their sponsorship decisions after their videos begin receiving engagement graphs?

Methodology: We plan to identify video sponsorship status and locate sponsored segments within videos using natural language processing techniques applied to video descriptions and time-coded transcripts, an approach established in the literature (e.g., Cheng and Zhang 2024, Lam 2024).

We will examine whether creators change their sponsorship decisions when engagement graphs make these engagement gaps visible to viewers. Using the same difference-in-differences framework as in Analysis 1, we would examine changes in the number of sponsored videos per creator-month before and after treatment for creators with high vs. low engagement graph exposure.

Data Collection: Again, analyzing creator response would require constructing a new creator panel dataset. We would build on Analysis 1's creator panel with additional transcript data and sponsorship identification. Given expected low sponsorship rates (discussed in "Feasibility Concerns" below), we plan to oversample creators in high-sponsorship categories (such as gaming, technology, lifestyle) and potentially extend the sample size. We plan to extract video descriptions and time-coded transcripts via web scraping on all historical videos, applying NLP techniques following established methods to identify sponsored segments.

Expected sample: 5,000-10,000 creators depending on data quality. Please refer to "Feasibility Concerns" below for a discussion of challenges faced in this analysis.

Implications: Investigating this question has important implications for creator economy regulation. If the effect of engagement graphs on sponsorship frequency is negative, it means the feature creates spillover effects on external revenue streams beyond the platform's direct control, affecting the creator-brand partnership markets that arguably compete with YouTube's own advertising ecosystem.

Feasibility Concerns: This analysis may face challenges due to low frequency of sponsored content. Cheng and Zhang (2024) reports that approximately 7% of videos contain sponsorships among top YouTube influencers, with likely lower rates among smaller creators. However, our research design requires meaningful variation in engagement graph treatment intensity, which necessitates including creators across different subscriber tiers rather than focusing solely on mega-influencers (as is common in other studies). We cannot predetermine how many creators will satisfy our joint criteria for (i) treatment intensity variation, (ii) sponsorship activity, and (iii) posting consistency. Given these constraints, we view this as a high-risk analysis where feasibility cannot be guaranteed (the feasible sample may prove insufficient for reliable statistical inference) even after substantial investment in data collection.

(B) Demand-Side Heterogeneity - Content Pattern

Our demand-side results demonstrate that engagement graphs increase viewership and other engagement metrics, but this aggregate effect likely masks the heterogeneity in how different content benefits from engagement graph visibility. Building on the AE's suggestion about leveraging engagement graphs to understand which content characteristics amplify engagement graph effects, we could extend our demand-side analysis to develop an empirical taxonomy of content based on engagement patterns. Using unsupervised clustering techniques on normalized engagement graph shapes, we could first classify different engagement graphs into distinct pattern types (e.g., front-loading engagement, multi-peak patterns) in a data-driven way. Then, we could estimate heterogeneous treatment effects by pattern type to systematically characterize which content structures benefit most from engagement graph visibility.

Feasibility Note: This analysis builds on our existing demand-side dataset and would require applying clustering algorithms to engagement graph data we can readily access. We expect this analysis to be feasible.

(C) Demand-Side Heterogeneity - Video Category

We could also explore category-level heterogeneity, examining whether engagement graph effects vary systematically across YouTube's content categories (educational, entertainment, etc.), providing more insights that go beyond what creators could intuitively derive from visual inspection of individual engagement graphs.

Feasibility Note: This analysis is feasible as it builds directly on our existing dataset.

(D*) Video Content Analysis and Suspense-Surprise Literature

We appreciate the review team's suggestion about using computer vision techniques to analyze video content and extending the suspense-surprise literature. However, this faces a challenge when applied to general video content.

The empirical studies in the suspense-surprise literature typically rely on structured environments, where viewers' beliefs of well-defined, one-dimensional outcomes can be credibly measured.[3] For YouTube videos generally, it is unclear how we could measure viewers' beliefs, or identify the specific outcomes viewers form expectations about. In most cases, such outcomes are unlikely to be easily characterized.

Feasibility Note: This analysis faces substantial feasibility challenges.

[3]This works well in sports and gaming contexts. For instance, Simonov et al. (2023) analyze video gaming contexts, where viewer expectations about match outcomes (which team wins) can be inferred from observable game scores and historical win probabilities, under rational expectation assumptions. Liu et al. (2020) analyze match outcomes in the baseball game context similarly.

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