Paying Attention

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Abstract

Humans are social animals. Is the desire for attention from other people a quantitatively important non-monetary incentive? I consider this question in the context of social media, where platforms like Reddit and TikTok successfully attract a large volume of user-generated content without offering financial incentives to most users. Using data on two billion Reddit posts and a new sample of TikTok posts, I estimate the elasticity of content production with respect to attention, as measured by the number of likes and comments that a post receives. I isolate plausibly exogenous variation in attention by studying posts that go viral. After going viral, producers more than double their rate of content production for a month. I complement these reduced form estimates with a large-scale field experiment on Reddit. I randomly allocate attention by adding comments to posts. I use generative AI to produce responsive comments in real time, and distribute these comments via a network of bots. Adding comments increases production, though treatment efficacy depends on comment quality. Taken together, the empirical evidence suggests that the attention labor supply curve is concave: producers value initial units of attention highly, but the marginal value of attention rapidly diminishes. Motivated by this fact, I propose a model of a social media platform which manages a two-sided market composed of content producers and consumers. The key trade-off is that consumers dislike low-quality content, but including low-quality content provides attention to producers, which boosts the supply of high-quality content in equilibrium. If the attention labor supply curve is sufficiently concave, then the platform includes some low-quality content, though a social planner would include even more.

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Attention plays an increasingly important role in the economy. Some of the most influential companies of the last two decades can be understood as *attention platforms*, firms which broker attention markets between consumers, content producers, and advertisers. Concretely, one commonality between Facebook, Google, Spotify, TikTok, and The New York Times is that each of these firms offers consumers access to content, and profits by auctioning off the attention of consumers to advertisers. Moreover, each of these firms use algorithms to influence which pieces of content consumers pay attention to, thereby shaping the allocation of consumer attention across posts, websites, songs, videos, and news articles.

Among attention platforms, social media firms have rapidly gained share in the market for attention. Twenty years ago, less than 5% of Americans were social media users. Now, that number is 72%, and the average user spends *15% of their waking hours* browsing content on these platforms.[2] Social media platforms capture attention by offering access to billions of pieces of new content each day, generated primarily by users who do not face direct financial incentives.[3]

How do the economies of social media platforms work? How should they be regulated? A literature in economics considers these questions, but tends to focus on the *financial* value of consumer attention to advertisers. In this paper, I provide new insights by revisiting an old idea: people value the attention of others *inherently*. This idea has important implications for how attention platforms work, because it means that the way that platforms allocate attention across content producers alters the incentives for producers to supply content.

The object of interest in this paper is what I call the *attention labor supply curve*. This curve captures the relationship between the amount of attention (views, likes, comments) that a content producer on social media receives and the supply of posts that they produce. In the empirical sections of the paper, I use reduced form and experimental methods to estimate the elasticity of content production with respect to attention at various points along the attention labor supply curve. In the theoretical section of the paper, I derive implications of the shape of the attention labor supply curve on the profit maximizing and welfare maximizing social media platform designs.

I primarily study Reddit, the seventh most visited website in the world.[4] Reddit is a large and rapidly growing social media platform based around interest-driven forums. Its traffic has quadrupled since 2018, and it hosts over 430 million monthly active users, making it comparable in size to LinkedIn, Twitter, Snapchat, and Pinterest.[5] Content producers on Reddit can post text,

[2]The social media usage comes from a Pew (2021) survey which shows that social media usage among American adults rose from 5% to 72% between 2005 and 2021. Slide 26 of the DataReportal (2023b) report indicates that the average user spends 2 hours and 31 minutes on social media each day, which is 15.1% of the average number of waking hours (16 hours and 42 minutes (Thomas, 2019)).

[3]Counting only posts on Instagram, Twitter, Facebook, and Snapchat, there are over 4 billion posts per day (Domo, 2022). Direct revenue sharing varies by platform, with some platforms not offering any direct compensation for regular users (e.g., Reddit, Facebook, Instagram), some platforms offering revenue shares only to very successful users (e.g., Snapchat, TikTok), and some offering revenue shares widely (e.g., Twitch, YouTube). Many content producers may face indirect financial incentives (e.g. brand deals for sucessful Instagram influencers).

[4]According to SEMRush (2023b), Reddit falls behind Google, YouTube, Facebook, Twitter, Wikipedia and Instagram. The exact ranking depends on the source: SimilarWeb claims that Reddit is the eighteenth most visited website (SimilarWeb, 2023c).

[5]According to SimilarWeb, Reddit was getting 282 million visits per month in 2018 compared to 1.9 billion in 2023

links, images, and videos. The primary advantage of Reddit as a setting is a prevailing norm of anonymity, which helps to isolate the attention incentive by reducing the presence of confounding social and financial incentives.

I estimate an attention labor supply curve on Reddit using data on the near-universe of Reddit posts from 2005-2022, which amounts to over two billion posts. I isolate plausibly exogenous variation in attention by focusing on content producers who "go viral." I define a post as viral if it reaches the 80^{th} percentile of the engagement distribution. I estimate a difference-in-differences design comparing content production around viral and non-viral posts. Producers who go viral produce 183% more posts per day for the subsequent month. The large volume of observational data allows me to estimate heterogeneous treatment effects for varying amounts of attention by estimating the difference-in-differences design on posts that go viral to varying degrees. This exercise traces out the attention labor supply curve for large amounts of attention. The key finding is that the attention labor supply curve is concave: producers value initial units of attention highly, but the marginal value of attention rapidly diminishes.

I replicate these reduced form results on TikTok, a video-based social media platform with over a billion monthly active users. I put together a new dataset that follows nine thousand TikTok content producers who produce 750,000 TikToks. After going viral, TikTok producers create 190% more posts per day over the subsequent month. Estimating heterogeneous treatment effects by the degree of virality shows that the attention labor supply curve on TikTok is also concave.

There are at least three plausible identification concerns with the difference-in-differences design. First, those who go viral may be selected. I show that pre-trends in the supply of posts around viral and randomly selected non-viral posts are similar in both level and trend on Reddit and TikTok, mitigating this concern.

Second, differences in content production after going viral could reflect changes in posting ability, which could be an underlying cause of virality and increased production. Here, I appeal to the sharp timing and overall shape of the treatment effects, which exhibit a spike-and-fade pattern that is inconsistent with a story of steadily increasing ability.

Third, going viral could confer non-attentional rewards. The institutional features of Reddit diminish this concern. Reddit offers no financial rewards to producers, and a strong norm of anonymity among producers restricts the ability to accrue external social or financial benefits. However, this concern is warranted on TikTok. While most TikTok users do not face direct financial incentives and garner engagement primarily from users they do not know, I cannot rule out that producers anticipate some social or financial returns from success on TikTok. Given this, results on TikTok can be interpreted as capturing the causal effects of engagement rather than mere attention.

I complement the reduced form analysis with a field experiment on Reddit. In contrast to the large attention shocks studied in the reduced form, the experiment measures the effect of allocating small amounts of attention to producers which sheds light on a distinct segment of the attention

(SimilarWeb, 2019, 2023b). Reddit claimed to have 430 million monthly active users in 2019, and has not released this statistic publicly since (Murphy, 2019). This was larger than the monthly active userbases of Twitter, LinkedIn, Snapchat, and Pinterest in 2019 (DataReportal, 2019).

labor supply curve.

I randomly allocate attention to content producers by using Reddit bots to add three or six comments to their posts. I then measure changes to their supply of posts over the next week. Comments are generated with a natural language processing pipeline built on top of the OpenAI Chat Completion API, the engine that powers ChatGPT. This novel experimental method allows me to respond with relevant, plausibly-human comments in real time as posts appear.

The experiment is large in scale. I pilot a thousand Reddit accounts which post six thousand comments on Reddit, and I track the production decisions of ninety thousand content producers. The primary, preregistered outcome is a quality-weighted measure of the number of posts produced by treated users.

Experimentally allocating attention increases production. Adding three comments causes Reddit producers to supply 15% more posts. The positive treatment effect of adding three comments is robust to alternative, preregistered measures of output including the probability of posting again and the count of posts, as well as to the inclusion of controls for prior posting frequency.

However, adding six comments has no effect across all measures of output on average. This null treatment effect is counterintuitive given the rest of the results in the paper. I show that it is explained in part by an unintended form of heterogeneity in treatment. The six comments treatment is more likely to be negatively received by the Reddit community. Comments in the six comments treatment have fewer upvotes, more downvotes, and are more likely to be accused of being bots. I decompose the treatment effect into the effect of high and low quality attention, splitting by the percentage of downvoted comments. High quality attention increases output, while low quality attention decreases output. After accounting for quality, the results of the experiment are largely consistent with the reduced form evidence.

Taken together, the empirical evidence confirms that attention is an effective non-monetary incentive. Across approaches, allocating attention to producers causes them to supply more posts. Moreover, the attention labor supply curve is concave: producers value initial units of attention highly, but the marginal value of attention rapidly diminishes.

In the theoretical section of this paper, I take the concavity of the attention labor supply curve as a starting point, and ask what it can teach us about the optimal design of social media platforms. I propose a model of a social media platform that manages a two-sided market composed of consumers and content producers. As is standard in two-sided markets, consumers value the size of the content producer side of the market, and content producers value the size of the consumer side of the market. However, in a departure from canonical models, markets clear in attention rather than prices.

Producers decide whether to create content depending on the amount of attention that they expect to receive. Attention depends endogenously on the number of consumers who choose to join the platform, and on a simple content recommendation algorithm that the platform selects. In particular, the platform directs attention to content as a function of quality. Quality is binary, and content realizes as good or bad exogenously. The platform decides how much good and bad content to offer to consumers, selecting from the content that was supplied by producers. Consumers decide whether or not to join the platform based on the quantity and quality of content that is available. Consumers like good content and dislike bad content. The central trade-off in the model is that showing additional bad content deters consumers from joining the platform, but showing bad content also provides additional attention to content producers, which boosts the aggregate supply of good content in equilibrium.

I study a platform whose profits scale with the number of consumers on the platform, reflecting the ad-revenue models typical of social media firms. The first result of the model is that the concavity of the attention labor supply curve determines the extent to which the platform should include bad content: if the supply curve is concave enough, then the platform should show a positive percentage of bad content. The intuition for this result is that if producers value the first few units of attention on their content highly enough, then guaranteeing producers some attention even when they produce bad content will cause many more producers to join the platform. If this generates a large enough increase in the aggregate supply of good content, then consumers' taste for additional good content can dominate their distaste for bad content.

The second result of the model is that a social planner who cares about producer utility would show a larger percentage of bad content than a profit maximizing platform. The intuition for this finding is that the platform only compensates producers to the extent that additional attention raises the value of the platform to consumers. In contrast, a social planner values the utility that content producers derive from attention directly. The attention incentive generates a wedge between the profit and welfare maximizing algorithms, which implies that "attention redistribution" can be welfare improving.

The empirical portion of this paper contributes to a large literature in economics which documents the effectiveness of various non-monetary incentives. Status concerns, social pressure, peer comparisons, awards, identity and purpose have all been shown to motivate people to exert effort.[6]

An interdisciplinary literature evaluates the efficacy of non-monetary incentives in the context of online spaces. An early causal contribution to this literature is Chen et al. (2010), who find that providing information on the median contribution rate encourages below-median users to supply additional reviews to an online movie review website. The efficacy of social comparisons and status as incentives online has since been demonstrated in a wide variety of contexts (Goes et al., 2016; Sun et al., 2017; Burtch et al., 2018; Kuang et al., 2019; Ke et al., 2020; Zhang et al., 2020; Ma et al., 2022).[7] I study the same setting and use a similar experimental method to Burtch et al. (2022), who document that awards on Reddit increase content production.

Within the empirical literature on non-monetary incentives, this paper is most closely related

[6]The literature on non-monetary incentives is extensive, and a complete review is beyond the scope of this paper. For status concerns, see Kuhn et al. (2011). For peer pressure, see DellaVigna et al. (2012, 2016); Perez-Truglia and Cruces (2017); DellaVigna and Pope (2018). For peer comparisons, see Kolstad (2013); Ager et al. (2022). For awards, see Delfgaauw et al. (2013); Ashraf et al. (2014); Neckermann et al. (2014). For identity, see Akerlof and Kranton (2000); Atkin et al. (2021). For purpose, see Ariely et al. (2008); Khan (2020).

[7]There is also earlier descriptive evidence of these ideas in the computer science literature (Lampe and Johnston, 2005; Arguello et al., 2006; Burke et al., 2009).

to work which evaluates the role of audience and engagement as incentives online. Zhang and Zhu (2011) find that when users in mainland China were blocked from Wikipedia, non-blocked users reduced their contributions. Wang et al. (2019) replicate this effect on Douban, a product review website. Other studies emphasize the role of follower networks. Toubia and Stephen (2013) experimentally add Twitter followers to accounts, and find heterogeneous treatment effects. Goes et al. (2014) find that product reviewers with more subscribers produce more and better reviews. Wei et al. (2021) find that followers increase content production on Twitter and Tencent Weibo. Content production responds to engagement as well. Lindström et al. (2021) show that posting behavior on Instagram and in a lab experiment are consistent with users valuing likes. The fact that people value social interaction online dovetails with work in the neuroscience literature which shows that likes on social media cause blood to flow to the area of the brain associated with pleasure (Eisenberger et al., 2003; Davey et al., 2010; Meshi et al., 2013).

I make two contributions to this large, interdisciplinary literature on non-monetary incentives. First, I provide evidence for the role of *mere* attention as an incentive in-and-of-itself. While prior work has established that social interactions can incentivize effort, this evidence comes from platforms where creators' identities and successes are public. In these contexts, higher engagement could bestow social, attentional, and (future) financial rewards. The norm of anonymity on Reddit allows me to better isolate the role of attention. Second, my large sample (two orders of magnitude larger than prior work in this literature) allows me to identify a treatment effect curve rather than a point estimate. This matters because I show that the shape of the attention labor supply curve affects optimal platform design.

The model relates to the theoretical literature on multi-sided platforms.[8] The model borrows structure from canonical models in this literature which study platforms that manage two-sided markets with network externalities (Rochet and Tirole, 2003; Caillaud and Jullien, 2003; Parker and Van Alstyne, 2005; Armstrong, 2006). Within this literature, the model is closest to a strand which focuses on platforms that can choose quality (Weyl, 2010; Veiga et al., 2017; Chan, 2023).

The model also relates to a theoretical literature which focuses on attention platforms specifically, using a wide variety of modeling techniques. Chen (2022) provides a general equilibrium model of a market for attention. Jain and Qian (2021) and Bhargava (2022) consider platforms with consumers and content producers, but focus on financial incentives.

My contribution to the theoretical literature is to introduce the notion that a platform can influence quality by algorithmically manipulating the way that the two sides of the market interact. This leads me to study a different object than the vast majority of the literature: rather than focusing on optimal pricing, I focus on optimal curation. While this kind of algorithmic matchmaking is not a feature of all canonical two-sided markets, it is a salient feature of the attention platforms that I study.[9]

The rest of the paper proceeds as follows. Section 1 covers some relevant institutional details of

[8] For a recent review of this literature, see Jullien et al. (2021) or Sanchez-Cartas and León (2021).

[9] For example, credit cards are a canonical two-sided market, but credit card companies do not meaningfully control whether consumers choose to shop at particular businesses within their network.

Reddit. Section 2 presents reduced form evidence on the shape of the attention labor supply curve using data from Reddit and TikTok. Section 3 presents the experimental strategy and results. Section 4 provides a theoretical analysis of how social media platforms should optimally allocate attention. Section 5 concludes.

1 Institutional Details of Reddit

Reddit is a large social media platform where users can post, vote on, and discuss a diverse array of content including text, links, images and video. In the United States, Reddit is the fourth largest social media platform by traffic and the ninth largest by userbase, with around 3 in 10 adults reporting that they use the platform.[10]

The majority of the empirical work in this paper is devoted to understanding content production on Reddit. Reddit differs from other social media platforms in many ways. In this section, I will focus on institutional details that are relevant for the interpretation of my results.

First, Reddit is structured around interest-based forums called subreddits. For example, r/gardening is a forum where 5.8 million users subscribe to view and participate in discussions of gardening. Similarly, there are subreddits devoted to most interests and topics: world news (r/worldnews), cute pictures (r/aww), media properties (r/GilmoreGirls), online humor (r/memes), and questions (r/AskReddit) each have dedicated forums. Overall, there more than 130,000 active subreddits.

Every post must be submitted to a specific subreddit. Submissions may require approval by the subreddit's volunteer moderation team, and typically must follow certain subreddit-specific stylistic rules. This interest-based division of the website is different from social networks like Facebook and Twitter which provide users with one go-to location to post top-level content.

Second, Reddit users are typically anonymous. This norm is acknowledged by the company which states that "the vast majority of redditors choose a name that represents them, without revealing who they are" (Reddit, 2023). Reddit encourages anonymity by providing new users with options for auto-generated usernames that are random combinations of words and numbers.

Anonymity is crucial to my research designs. At a conceptual level, anonymity helps rule out alternative stories where attention proxies for social or financial returns. At a practical level, the ability to credibly provide attention to users with bot accounts depends on the norm of anonymity which allows the bot accounts to blend in and provide plausibly human interactions.

Third, posts are distinct from comments on Reddit. Like Facebook, each post on Reddit has a dedicated comments section. This construction differs from Twitter, where replies to tweets are

[10] The 'fourth largest by traffic' statistic comes from SimilarWeb (2023a) which reports a Top Social Media Networks category. SEMRush (2023a) reports that Reddit is the third largest website by visits as of July 2023 across all websites, trailing only Google and YouTube but outpacing Facebook and Amazon. The 'ninth largest by userbase' statistic comes from slide 57 of the DataReportal (2023a)'s US Digital Report which cites a GWI survey of US adults. The eight larger social media platforms by userbase are Facebook, Instagram, Youtube, TikTok, Twitter, Snapchat, Pinterest, and LinkedIn, which have monthly active users that range from over 3 billion to around 450 million. Reddit's last publicly reported monthly active userbase is 430 million, as of 2020. I get to the claim 'ninth' by adding YouTube (which was not asked about, but is larger than Reddit) and by excluding iMessage and Facebook Messenger (which are typically understood as messaging clients, not social media platforms).

themselves tweets. This distinction is important for understanding the variation I study: typically, I look at how a change in the number of upvotes or comments on a post changes the number of subsequent posts that a Reddit user produces. I do not count subsequent comments made by a Reddit user as a measure of output. This means my results are not driven by users responding to comments on their popular posts, which may have been a concern on another platform like Twitter.

Fourth, Reddit allows users to both 'upvote' and 'downvote' posts. This dual directional feedback is somewhat atypical, and is not found on Facebook, Instagram, TikTok or Twitter. Upvotes correspond roughly to likes and hearts on Facebook and Twitter, signifying that the user had a positive interaction with the content. Downvotes express the opposite. Upvotes and downvotes are inputs into Reddit's content sorting algorithms. The four content sorting algorithms are new (ordered by recency), best (ordered by the ratio of upvotes to downvotes), top (ordered by the absolute number of upvotes minus downvotes within a fixed window of time), and hot (ordered by the absolute number of upvotes minus downvotes puls a time deflator that penalizes older posts). Users can choose to view the whole website (the "frontpage") or any subreddit sorted by one of these four algorithms. Upvotes and downvotes get their names because upvotes move posts towards the top of Reddit and downvotes move posts towards the bottom of Reddit for users who view the website using the top, hot, and best sorting algorithms. The existance of downvotes matters for my paper due to a measurement issue: I observe the net of upvotes minus downvotes, but I do not observe the count of upvotes and downvotes separately. When I refer to upvotes in the results section, I am always referring to net upvotes.

Finally, the combination of Reddit's content sorting algorithms along with typical Reddit user content consumption patterns serves to de-emphasize the importance of profiles and user-following networks. For users who browse the frontpage or specific subreddits according to any of the sorting algorithms, the order in which they view posts does not depend on following networks at all.

That being said, profiles and follower networks do exist on Reddit. Users can navigate to a profile and view all of the content from that profile. Following a user causes their content to show up in the algorithmically curated Reddit feeds that are available to Reddit users with accounts (those without accounts can browse Reddit in all of the ways outlined above, but cannot vote or comment). However, even the algorithmically curated Reddit feed depends heavily on subreddit following decisions, and users are required to follow subreddits upon creation of an account.

The deemphasis of follower networks and profiles matters for the interpretation of the reduced form results, because it means that producers should not anticipate large changes to the popularity of future content driven by changes in their follower network after they go viral.

2 Reduced Form

In this section, I estimate the attention labor supply curve using observational data from Reddit and TikTok. In order to derive credible causal estimates, I study a large, plausibly exogenous shock to attention: going viral. Using difference-in-differences designs, I trace out the effect of going viral on the quantity and quality of content produced.

I find that going viral causes content producers to create more content without sacrificing quality. Moreover, I find that the attention labor supply curve is concave. Increases to content production scale with the size of the attention shock, but level off past a relatively low threshold of virality.

2.1 Reddit

2.1.1 Reddit Dataset and Limitations

I analyze Reddit using the Pushshift dataset (Baumgartner et al., 2020). This dataset is massive, containing information on the near-universe of Reddit posts from 2005-2022 (over 2 billion posts). The dataset catalogues the author, subreddit, post time, net score, and the number of comments on each Reddit post.

The Pushshift dataset is generated by repeatedly querying the official Reddit API. This method of data collection introduces some important limitations. Because each post is only queried once, the dataset is composed of snapshots of each post at the specific point in time that the API was queried.

If a post is created and deleted before it has been crawled, it will not be included in Pushshift. This is both a feature and a bug: it introduces a missing data problem, but the missing data is data that we may not want to count in the first place, as content that is quickly deleted might not meaningfully contribute to the supply of content from Reddit's perspective.

A second problem introduced by this method of data collection is that numerical assessments of engagement are not always an apples-to-apples comparison, since the time between when a post was posted and when the API was queried varies. This concern is somewhat mitigated by the lifecycle of Reddit posts, which see the vast majority of their engagement within the first day of posting.

For my analysis, I drop a variety of subreddits that plausibly involve monetary incentives which would undercut the attention incentive that I am to study. Specifically, I exclude posts on NSFW subreddits (approximately 20% of all posts), as content producers on these subreddits often use Reddit as a place to promote external businesses.

2.1.2 Correlational Evidence

The attention that a post receives is correlated with its producer's subsequent output. Figure 1 plots correlations between the number of comments on a Reddit post and four measures of content production in the week after the post. The outcome in Panel A is a quality-weighted measure of the number of posts produced. This measure is computed by taking the $\sum log(\max[score + 1, 1])$.[11] The outcome in Panel B is a binary variable that takes on one if the user makes at least one

[11] This measure has two main advantages. First, the max operator ensures that a post cannot contribute negatively to the quality-weighted quantity of posts, as $log(1) = 0$. Second, the choice to add one to the score reflects the fact that posts start with one upvote, so adding one ensures that a post which was not upvoted or downvoted will

additional post, which captures the extensive margin of posting. The outcome in Panel C is the total number of posts, a raw measure of quantity of content produced. Finally, the outcome in panel D is the score of posts conditional on posting, which I interpret as a measure of quality.

Across these four outcomes, a consistent pattern emerges: when posts receive more attention, the content creator tends to produce more and better posts over the next week. Moreover, the shape of each of these curves is concave, highlighting the potentially diminishing returns to giving creators attention from the platform's perspective.

However, these correlations also highlight the key threat to causal inference in this setting: perhaps people who produce posts which receive a lot of attention are systematically different. One plausible story is that attention on any given post reflects the author's skill at posting, a trait which could be correlated with post frequency and post quality. In this case, the correlations in Figure 1 could emerge via selection alone. To help disentangle the idea that attention drives content production from this reverse causality story, I now turn to a difference-in-differences causal inference design.

2.1.3 Identification Strategy

My identification strategy is a difference-in-differences design comparing the evolution of content production around viral posts and randomly selected posts. The idea behind this design is that going viral creates a sharp discontinuity in the amount of attention that a content producer receives. By studying discontinuities of different sizes (different degrees of virality), I use this design to trace out the attention labor supply curve.[12]

To construct a treatment group, I study the first time each author goes viral. Virality is an ambiguous concept, so I define degrees of virality based on upvote thresholds benchmarked to percentiles of the upvote distribution. The minimum virality threshold I consider is the 80^{th} percentile of the upvote distribution (21 upvotes). From there, I group producers into treatment groups depending on how viral their first viral post went. The cutoffs are defined by 2 percentile wide bins of the upvotes distribution. I define event time 0 as the date that the author posted the viral post.

To construct the placebo group, I randomly sample Redditors (Reddit user). Then, for each Redditor, I randomly sample a non-viral Reddit post and define event time 0 as the time of the random post's creation. For both treatment and placebo groups, I look at how content production evolves in a 30 day window around event time 0.

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contribute to posting supply. The choice of using log as a way to weight the score is arbitrary, but the function was chosen to reduce the influence of high scores. This is desirable in the context of Reddit because posts with 1000 upvotes are unlikely to be 1000 times better than posts with 1 upvote, due to the fact that upvoting is subject to a winning-begets-winning pattern. Specifically, upvotes push content to be seen by more people by moving content 'up' the website, which increases the chance that the content will get additional upvotes.

[12] Without further assumptions, this exercise teaches us about the relationship between additional engagement and future content supply. That relationship is important, and is the focus of Section 4. However, in order to interpret these results as tracing out the elasticity of labor supply with respect to attention (rather than engagement), we need to assume that going viral increases a content creator's beliefs about future attention returns in a way that scales linearly with the size of the viral event shock.

With this sample in hand, I estimate the following regression

$$Y_{idet} = \delta_i + \gamma_d + \sum_{x=-30}^{30} \mathbb{I}[e = x]\alpha_e + \sum_{x=-30}^{30} \mathbb{I}[t = 1]\mathbb{I}[e = x]\beta_e\epsilon$$

where i indexes individuals, d indexes days, e indexes time relative to the viral or placebo post (event time), and t indexes treatment status ($t = 1$ if the individual is treated, and 0 otherwise).

A recent and rapidly growing literature argues that estimating difference-in-differences designs with two-way fixed effects can cause certain estimation biases (Callaway and Sant'Anna, 2021). I overcome these biases using a two-stage estimation procedure following Gardner (2022).

This strategy rests on two identifying assumptions. First, I need to invoke a parallel trends assumption. In this context, the parallel trends assumption is that if a Redditor had not gone viral, their content production would have evolved in the same way that the control group's content production evolved. To provide evidence for this assumption, I compare trends for the control and treatment groups in the pre-period.

Second, in order for the difference-in-difference estimates to be interpreted as causal, I need to assume that the timing of virality is not correlated with other events that could explain the treatment effects. A particularly important version of this concern is that going viral could be an observable signal of an underlying change in a Redditor's relationship to Reddit and the production of content. For example, a Redditor might be more likely to go viral as they become more committed to posting on Reddit, or when they have discovered a successful content strategy. In this case, virality is just capturing changes in production ability, and it is not the attention itself that changes their rate of content production. To provide evidence for this assumption, I consider the shape and timing of treatment effects, and argue that it is inconsistent with most alternative stories. Additionally, intuitively, the reason I study viral events is precisely because I think that the exact timing of going viral is plausibly random.

2.1.4 Viral Difference-in-Differences Design

Going viral causes content producers to create more content. Figure 2 graphs the effect of virality on a quality-weighted measure of producer output. Panel A plots the event study coefficients for the treated group. Each point represents a 1 day bin, and event time 0 is the day that the viral post was created. The treatment effect is large. In comparison to the month before going viral, output increases by 0.21 units per day, which is a 373% increase over the pre-period mean of 0.06 units per day.

The event study coefficients in the pre-period appear flat, which supports the parallel trends assumption. The fact that the event study coefficients lie near zero implies that the viral producers are similar not only in trend but also in level, which is reassuring. However, it is worth noting that in the two days before going viral, there is a small jump in the rate of content production for viral producers relative to non-viral producers.

The event study coefficients also provide evidence regarding the second identifying assumption, which is that the timing of virality is not correlated with other changes or events that could affect production. In particular, one salient concern is that going viral could be correlated with changes in producer ability, and ability could be correlated with the rate of content production. The observed pattern of treatment effects is not consistent with this story. The sharp, discontinuous jump in production starting the day after virality suggests that the effect is due to something that changes discontinuously. The fading pattern of event study coefficients suggests that the treatment effect is consistent with an event or change which fades in influence over time. Both of these patterns are not consistent with a story of steadily increasing producer ability.

I use the difference-in-differences design to estimate the elasticity of content production with respect to attention at various points along the attention labor supply curve. Panel B of Figure 2 plots heterogeneity in the treatment effect by the degree of virality. Each point estimates the increase in quality-weighted output in the 30 days after going viral relative to the 30 days prior. Each point is estimated on a subset of viral posts that go viral within a two-percentile band of the upvotes distribution. Posts in the first viral point received between 21-26 upvotes (80th-82nd percentile), while posts in the tenth viral point received more than 531 upvotes (98th-100th percentile). The placebo point is the treatment effect of posting a non-viral post, estimated using a standard Callaway and Sant'Anna (2021) difference-in-differences design around random non-viral post. The key takeaway is that the treatment effects curve is relatively level for large amounts of attention: we cannot reject that the effect of 21 upvotes and the effect of 531 upvotes is the same. In contrast, the estimated effect of placebo posts on production is null.

I estimate the effect of virality on quantity and quality separately. Panels A and B of Figure 3 replicate the design of Figure 2 on the outcome posts per day, a simple and interpretable measure of production quantity. I find that going viral causes producers to create 0.068 more posts per day, which is 183% of the baseline of 0.037 posts per day in the per-period. Panel B shows that the treatment effect is stable across a wide variety of levels of virality, and null for placebo posts. Panels C and D replicate the difference-in-differences design on the average post score conditional on posting, which is a measure of post quality. I find null effects on this outcome variable. This implies that the additional posts that are being produced to virality are of equivalent quality on average to the posts that were being produced in the pre-period, so virality is not causing producers to substitute towards creating more low-quality posts.

Taking stock, these results show that a discontinuous change in the amount of attention that a content producer receives creates a sharp change in the quantity of content that they produce. Moreover, estimating heterogeneous treatment effects by degree of virality teaches us about the shape of the attention labor supply curve. Beyond a certain threshold of virality, the marginal effect of attention is small: getting 50 upvotes induces essentially the same effect on production as getting 500 upvotes.

2.2 TikTok

In this subsection, I estimate the attention labor supply curve on TikTok.

2.2.1 Institutional Details

TikTok is a social media platform emphasizing short-form video content of up to ten minutes. Users can create and share videos, typically accompanied by music or sound clips. Users can interact with videos by liking, commenting, bookmarking and sharing.

Relative to Reddit, TikTok presents a more complex environment for testing the thesis that attention drives content creation.

First, algorithms play an important role in the curation of content. TikTok's For You page is an algorithmically generated feed, and it is plausible that a content creator's past performance influences their future performance through the algorithm. This is in contrast to Reddit, where curation is largely done using the upvotes system which does not take into account an author's previous performance. In an attempt to circumvent this issue, I focus on outcomes that are driven by user and content creator decisions rather than the algorithm directly such as posts per day and likes per view.[13]

Second, TikTok provides greater opportunity for social returns or "clout" because it does not share a strong norm of anonymity like Reddit. Creators might value these social returns directly, or they may leverage them into monetary gain via personal businesses or marketing deals.

Third, TikTok provides direct monetary compensation for content in some circumstances, while no such compensation is available on Reddit. Specifically, if TikTok creators amass enough of a following, they are able to join the TikTok Creator Fund and earn money for the engagement they generate.[14]

One reason why we might still believe that the results of this section do speak to the importance of attention as an incentive is that the vast majority of interactions on TikTok are between strangers, thus restricting the potential for social incentives. Additionally, the vast majority of TikTok content producers are not successful enough to face direct monetary incentives for their content.

However, it is still the case that people could form beliefs about potential future monetary and social rewards due to success on TikTok. Nothing in the data allows me to explicitly test or rule out this hypothesis, and this is a distinct story from the attention-focused thesis of this paper. This concern is the reason why TikTok is not the primary site of analysis for this paper. However, concavity of production with respect to engagement (rather than mere attention) is sufficient for the purposes of applying the theoretical results of Section 4 to TikTok, as the results do not depend on the underlying rationale for why the attention labor supply curve is concave.

[13] Of course, the decision of the algorithm of who to show content does affect the likes per view that content receives. I think likes/view is an outcome that is less subject to this critique than likes or views alone which are both direct functions of how often the algorithm chooses to surface content, but I want to acknowledge that my likes/view outcome does not entirely fix this problem.

[14] Currently, the threshold for joining the TikTok Creator fund is 10,000 followers and 100,000 views accrued in the last 30 days. Additionally, creators must be from a set list of countries, and must produce content that accords with the terms of service.

2.2.2 TikTok Dataset Construction and Limitations

In order to study virality on TikTok, I put together a novel dataset combining information from two sources. Using TikTok's academic API, I collect the handles of 10,000 content producers who posted content after January 1, 2022.

I pass these handles to a scraper designed by Bright Data in order to extract metadata on all videos on a content creator's public profile page. The scraped data includes information on the post date, likes, views and shares of each TikTok. The visibility of view and share data is unique, and allows me to compute likes per view which functions as a measure of content quality. Likes per view is a particularly nice measure of quality because it is an estimate of the probability that a user will like a post.[15]

This data collection strategy has some important limitations. First, this is not a random sample of TikTok users. Instead, the sample is likely to be selected on the frequency of posting, as creators who post more frequently are likely to have shown up earlier in the TikTok Stream API.

Second, scraping of these profiles occurs in 2023, more than a year after the time that content producers enter my sample. Any posts that were created and deleted before the time of scraping will be missing from the dataset.

Third, Bright Data's scraping system has a limitation that prevents me from accessing posts before January 1, 2022. This changes the interpretation of the virality design, because I am studying the first viral event in my sample for each author which is not necessarily the first time that the author has gone viral. In my opinion, this limitation will lead to underestimating the true effect of virality, as the viral events I study are less likely to be novel to the producers. Due to the Jaunary 1, 2022 limitation, I exclude posts from before February 1, 2022 for the viral difference-in-differences design. This exclusion serves to guarantee that I observe a complete 30 day pre-period.

2.2.3 Correlational Evidence

I begin by documenting correlations between attention and content production. Plot A of Figure 4 is a binned scatterplot which correlates the likes on a post with the number of posts that an author creates in the subsequent 30 days. The graph looks relatively flat, though perhaps there is a positive and concave relationship between likes and subsequent posts between 50 and 300 likes.

Plot B of Figure 4 documents a clearer relationship. The outcome in this graph is the $\sum log(likes+1)$ over posts produced in the subsequent 30 days. This metric is intended as a quality-weighted measure of output, and it appears to have an increasing and concave relationship to the number of likes on a post.

However, the likes-based outcome of Plot B also highlights the central concern for interpreting correlations between engagement and content production: perhaps people whose posts get a large number of likes are systematically better at posting. In this case, it is possible that the concave

[15] One caveat is that likes per view is a good estimate of like probability for users who are similar to the users who have interacted with the post. Since users who interact with a post are chosen by TikTok's algorithm, they are likely to be selected. This means that the estimate of quality may not generalize to the larger TikTok population.

relationship in Plot B of Figure 4 is driven entirely by selection. In order to be able to better distinguish the correlational and causal stories, I turn to the viral post difference-in-differences design from Section 2.1.3.

2.2.4 TikTok Virality Results

In order to estimate the causal effect of attention on content production on TikTok, I implement a difference-in-differences design described in Section 2.1.3 comparing how content production evolves around the time of viral and randomly selected posts.

Going viral on TikTok causes a quantitatively similar change in subsequent production in percentage terms. Figure 5 replicates the design of Figure 2 on a quality-weighted measure of output on TikTok. I define quality on TikTok using a likes-per-view ratio, and the outcome of interest is the sum of this value across all posts in each day. Panel A of Figure 5 shows that output increases by 0.049 units in the 30 days after going viral compared to the month prior. This effect represents a 289% increase in output relative to the pre-period baseline rate of 0.017 units per day. Panel B of Figure 5 estimates the shape of the attention labor supply curve on TikTok. Again, while placebo non-viral posts do not have a strong effect on output, the effect of attention beyond a threshold of virality is largely constant. This implies that the marginal effect of attention on content supply is low beyond this threshold.

The pre-period event study coefficients support the assumption that randomly selected posts are a valid control group. The flat slope of the coefficients supports the parallel trends assumption, and the fact that the coefficients are close to zero shows that the control and treatment groups are similar in level as well.

The pre-period event study coefficients also support the second assumption that the timing of virality is uncorrelated with other events or changes which could affect the production of TikToks. As with the estimates from Reddit, the event study coefficients on TikTok show a sharp jump at event time 1 followed by a fading effect, though the fade is less dramatic. These treatment effect coefficients are not consistent with any slow-moving traits that are correlated with going viral, such as changes in posting ability.

I decompose this main effect into the effect of virality on quantity and quality separately. Panels A and B of Figure 6 replicate the virality difference-in-differences design on the number of TikToks per day, an interpretable measure of quantity. Panel A shows that viral producers create 0.43 more TikToks per day, which is a 190% increase over the pre-period baseline of 0.24 TikToks per day. Panel B graphs heterogeneity in the treatment effect by the degree of virality, and confirms that the attention labor supply curve looks concave in terms of effects on quantity. Panels C and D of Figure 6 estimate the difference-in-differences design on the quality of TikToks produced, as measured by the likes-per-view ratio. Panel C shows that quality increases by 0.014 likes per view, which is 20% of the pre-period treatment effect. Panel D shows that the treatment effects on quality appear concave with respect to the degree of virality.

Taking stock, the results of the difference-in-differences design on TikTok are remarkably consistent with the results on Reddit. Going viral causes a large increase in the quantity of content produced: in both cases, the size of this increase is around 185% of the pre-period baseline rate of posting in terms of raw quantity. The TikTok results differ slightly with respect to quality: while I find null results on Reddit, I find small but significant results on TikTok. Regardless, in both contexts I find that the shape of the attention labor supply curve is concave, which is the crucial assumption that drives results in the theoretical analysis in Section 4.

3 Experiment

In the experiment, I study how randomly allocating attention to Reddit producers changes the quantity and quality of content that they create. I view the experiment as complementary to the reduced form analysis, as the two designs identify the elasticity of content production with respect to attention at different points along the attention labor supply curve. While the reduced form strategy identifies the effect of large attention shocks, the experiment identifies the effect of small shocks. Moreover, random assignment mechanically prevents selection on ability or other unobservables, which one of the primary identification concerns of the difference-in-differences design.

In order to generate experimental variation, I set up a system that monitors subreddits for posts, randomizes posts into treatment or control, generates responsive comments, and adds these comments to treated posts via a network of servers and Reddit bots. I then collect data on the posting behavior of treated and control users over the thirty days following randomization in order to document any changes to posting behavior.

I find that attention does cause producers to create more content. Adding three comments causes increases in the probability of posting again across all preregistered measures of output quantity. However, I find null treatment effects for adding six comments. I reconcile this result with the rest of the evidence in the paper by documenting that the six comments treatment induced an unintended form of heterogeneity in the quality of attention. Specifically, comments in the six comments treatment are less well received by the Reddit community: they are more likely to be downvoted, less likely to be upvoted, and replies are more likely to mention the word bot. Since these comments are generated in an identical way to the three comments treatment, this heterogeneity likely reflects community suspicion of the volume of comments. This post-hoc analysis of the experimental data suggests that the effect of attention on production is positive after accounting for quality.

3.1 Overview of the Experimental Design

First, I provide an overview of the experimental system. The experiment starts with an AWS server which monitors a set of subreddits for new posts. Each time a new Reddit submission is posted to one of these subreddits, the server is pinged.

When a post arrives, I check if the post's author has already entered the sample. If so, the author-post pair is skipped and nothing happens. Additionally, I attempt to exclude NSFW and bot accounts from the sample by leveraging posting history. If an author-post pair is not excluded for these reasons, it enters the sample.

With 98% probability, the post is randomized into the control group, and with 2% probability, the post is randomized into treatment. Among treated posts, 50% are randomized into the "three comments" treatment condition, and 50% are randomized into the "six comments" treatment condition.

If a post is randomized into treatment, I generate candidate comments using a natural language processing pipeline built on top of the OpenAI Chat Completion API, the large language model that powers ChatGPT. I provide the API with information on the subreddit and title of the post. If available, I provide the API with information on the first hundred words of the post and the post flair. I prompt the API to provide a short, positive comment. I query the API repeatedly to create candidate comments.

I then post three or six comments on treated posts, depending on the treatment group. I do this using a network of over a thousand Reddit accounts that I create for this experiment and that I pilot programatically. I refer to these accounts as 'Reddit bots.' I randomly select Reddit accounts from the network, and use these accounts to post the generated comments with a random lag between comments.

Finally, I set up a second server to track the posting behavior of treated and control Reddit users. I do this by repeatedly querying the Reddit API each day to see the history of posts by each user, and collect information on each new post produced. I keep track of the scores of each new post separately, collecting scores only after twenty-four hours have passed since the post was created in order to give each post a natural lifecycle with which to collect upvotes. I continue to collect information on posting behavior for thirty days after the moment of randomization.

3.2 Choice of Treatment Subreddits

I execute the experiment on small number of hand-selected subreddits. I exclude subreddits from the experiment for three independent reasons. First, there are many subreddits which would be ethically dubious to interact with given the fact that the comments I post are generated randomly using a large language model. I do not post on subreddits that involve advice seeking (relationship, legal, or otherwise), and I do not interact with posts that are tagged as 'serious.' I also avoid interacting with any subreddits that are concerned with mental or physical health as well as any subreddits that engage in the discussion of news or political discourse.

Second, there are many subreddits that are not included due to the fact that I do not believe that I am able to produce 'credible' responsive comments to the posts that are involved. The subreddits in this category tend to be highly specific fandom communities (sports, television, video games, and other media properties) as well as subreddits with content that cannot be easily understood and commented on with the information available from the title and subreddit.

Third, there are subreddits that I excluded because I believed that treatment would be functionally ineffective. These are subreddits where very few posts are made, and nearly all posts get a large degree of engagement. Given the already light-touch nature of treatment, my belief was that it would be infeasible to detect effects when additional comments were a drop in the ocean relative to baseline engagement.

For all three reasons, the subreddits included in the experiment are highly selected. The experiment can be thought of in part as an 'existence' argument, showing that, at least in some cases, attention does incentivize production. This selection issue highlights one way in which the reduced form evidence is complementary to the experiment, as the reduced form strategy can be estimated on all subreddits avoiding these selection concerns.

I hand check each a set of large subreddits for the conditions described above before the inclusion in the experiment. In the end, I include the following subreddits: r/Awww, r/AskReddit, r/Cats, r/Pics, r/MildlyInteresting, r/NoStupidQuestions, r/WhoWouldWin, r/SatisfyingAsFuck, r/RandomThoughts, r/WildlifePhotography, r/TwoSentenceHorror, r/OldSchoolCool.

3.3 Discussion of Treatment Conditions

There are two treatment conditions: adding three comments and adding six comments. The decision to include two treatment conditions was motivated by the theoretical model, which generates findings based on the shape of the attention labor supply curve. Because the control condition is equivalent to adding 0 comments, two treatment conditions identify the concavity of the labor supply curve.

The choice of including *only* two treatment conditions reflects power concerns as the experimental intervention is light-touch.

The choice of three and six comments as the two treatment conditions was arbitrary. I wanted to choose enough comments for the treatment to be noticeable to content creators, but I did not want to choose so many comments as to raise red flags that the attention might be spam.

3.4 Discussion of Credibility of Treatment

From the perspective of Reddit users, my bot accounts appear like regular Reddit accounts. They have profile pages and exhibit a relatively low commenting frequency so as to be consistent with human commenting patterns. I include a filter in the natural language processing pipeline that excludes all comments which make reference to large language models and related terms.

However, there are some aspects of these accounts that might have caused users to be suspicious. First, all accounts were created newly for the experiment, so each account is a few months old at the time that it commented (this knowledge is available to users on each account's profile page). Second, accounts have randomly generated names, no profile pictures, and make no posts. All of these traits are reasonably common for regular Reddit accounts, but Reddit users who were familiar with the distribution of profile characteristics on Reddit could plausibly have been suspicious that these accounts were more likely to be bots.

3.5 Outcome Data Collection Method

I collect data on the activity of treated and control Reddit users using the Reddit API. Each day, I queried the post history of each treated and control user. I use this information to update a dataset of posts by each user with any new posts that have been created during the intervening day. I continue to collect data on the posting behavior of Reddit users in my sample for thirty days after the time of randomization.

I only update the count of upvotes for posts in my dataset after twenty-four hours has past since the time of posting. The decision to wait twenty-four hours to collect upvote data reflects the fact that Reddit posts typically receive the majority of their overall engagement within the first twenty-four hours of their existence. I view the upvote count after twenty-four hours as a reasonably good measure for the overall success of the post.

One limitation of this data collection method is that I do not observe posts that are created and deleted within a twenty-four hour period. Additionally, I do not follow the success of posts after twenty-four hours, so I do not capture any success that posts garner after this moment.

3.6 Preregistred Outcome Variables

I pre-register one primary measure and three secondary measures of output.

I will refer to the primary outcome as 'quality-weighted output.' This measure is computed by taking the $\sum log(\max[\text{Upvotes} + 1, 1])$ for posts produced in the seven days after randomization. The max function ensures that a post cannot contribute less than zero to output.[16] The log function is a somewhat arbitrary functional form choice that is meant to offset the winning-begets winning nature of upvotes, an institutional feature that results in a long tailed distribution for upvotes. Specifically, a small number of posts on Reddit receive a very large number of upvotes. These posts are helped by the fact that upvotes move posts towards the top of the website, causing more people to view the post, which in turn can result in more upvotes. While I believe that a post which gets a thousand upvotes is certainly better than one that gets ten, due to this winning-begets-winning feature, I do not want to say that a one hundred upvote post represents one hundred times more output than a post that gets one upvote. Interpreting the measure as a whole now, the $\sum log(\max[\text{Upvotes}+1, 1])$ is a function which increases for each post with upvotes > 1 with larger increases for posts with more upvotes.

I also pre-register three secondary measures of output that are simpler.

The first secondary measure of output is the count of posts. This is a simple count of the number of posts made by the Reddit account in the seven days after randomization.

The next secondary measure is 'posting again': this is an indicator variable for whether the Reddit account posts in the seven days after randomization. This measure is intended to capture the extensive margin, and is deliberately coarse. It throws additional variation that could be

[16] This outcome is possible because my data includes some posts with 0 or -1 upvotes. The net upvotes distribution is censored at -1 in the Reddit API, so I do not observe posts that are heavily downvoted. They instead show up as having -1 upvotes.

gained from studying the count of posts, but ensures that no one person who posts very frequently influences the result too much.[17]

The final measure of output is the mean upvotes conditional on posting. This outcome is meant to be a measure of whether treatment changes the quality of posts. Mean upvotes is an imperfect measure of quality, precisely because of the winning-begets-winning dynamic described previously. However, I believe that average upvotes represents a reasonable measure that is at least positively correlated with true quality.

3.7 Deviations from Preregistration

Due to technical issues with the experiment, I made two significant changes to the way that the experiment was run relative to the preregistration document written on July 31, 2023.

The first change is that I abandon the treatment arms which involve adding upvotes to posts. These arms were dropped after I found that it was technically infeasible to implement this treatment at scale. Reddit has a relatively sophisticated system intended to prevent vote manipulation, and I was not able to have accounts engage in random upvoting without them being flagged and banned by this system.

The second deviation from preregistration is sample size. I initially preregistered a sample size of 100,000 treated units. In the preregistration, I also anticipated that technical issues may result in a smaller sample size, and committed to reporting the results on whatever sample I was able to collect.

The proposed 100,000 sample size became infeasible due to issues with scaling. As the comments arm of the experiment was scaled up, bots were quickly getting flagged and banned. Some subreddits that I had initially factored in when making back-of-the-envelope sample size calculations turned out to have strong moderation polices that resulted in account bans. For this reason, I had to run the experiment at a more moderate pace on a smaller number of subreddits, which resulted in a substantially smaller final sample size.

3.8 Results

Figure 7 plots the primary results for all four preregistered outcome variables measured during the week after treatment. The three comments treatment causes increases to quality-weighted output, the probability of posting again, and the count of posts. Each of these effect sizes represent around a 15% increase relative to the control group. Panel D plots the effects on mean score conditional on posting, a measure of quality. This effect is null, though it is imprecisely estimated. The three comment effect provides experimental evidence that allocating attention causes producers to exert more effort, which constitutes well identified evidence for the idea that attention can function as a non-monetary incentive. Figure 8 shows main results split by poster experience (above vs. below 50 prior posts). The qualitative pattern of results is the same for both treatment

[17] In principle, there is no upper limit to how many times that an account may post, and if bots or superstar Reddit posters end up unequally randomized, this could lead to spurious results.

groups, though estimates are more imprecise.

In contrast, I find null effects for the six comments treatment across all four measures of output in Figure 7. Moreover, the point estimates for the treatment effects on the probability of posting again and the count of posts appear negative, though these results are not statistically significant. Figure 8 shows null effects for the six comments treatment with high and low poster experience subgroups. This set of results is surprising, given the rest of the findings in the paper.

In order to investigate this null result, I document a particular kind of unintended treatment heterogeneity. I find that treatment comments were less well received in the six comments treatment compared to the three comments treatment. Figure 9 shows that comments in the six comments treatment have a higher rate of being downvoted, a lower rate of being upvoted, a lower chance of getting a reply from the treated Reddit poster, and a less positive average reply sentiment, as measured by the VADER sentiment model. I call replies as bot accusations if they include the word 'bot', 'bots', or 'ChatGPT.' I find that comments in the 6 comment treatment are 61% more likely to be accused of being bots, though the baseline rate is low in both cases (as the baseline rate of replying to comments at all is low). Overall, this analysis suggests that even though the two treatments use the same natural language processing pipeline to generate comments, the treatments are not received by the Reddit community in the same way. This heterogeneity in response to comments likely reflects community suspicion of the volume of comments in the 6 comment treatment condition.

Differences in the community response to treatment cause differences in the effect of treatment. Figure 10 plots the treatment effect split by high and low quality treatments, where I define quality by categorizing each treatment into having either above or below the average rate of net downvotes on comments. Net downvotes are a particularly good signal of comment quality, as they suggest that the comment was actively disliked. Within each treatment category, we see that good comments increase output relative to bad comments. This is true for quality-weighted output, the probability of posting again, and the count of posts produced. Overall, this analysis suggests that attention can increase output, but that the quality of attention matters.

4 A Theoretical Model of an Attention Platform

In Section 2 and Section 3, I document that attention causes content producers to increase their output. Moreover, I show that the labor supply of content producers is concave with respect to the attention incentive. Initial units of attention increase the amount of content supplied, but this increase levels off as more and more attention is received.

In this section, I take this empirical pattern as a starting point, and develop a model with the goal of understanding how the attention incentive informs the optimal design and regulation of social media platforms. In the model, a social media platform manages a two-sided market composed of content producers and consumers. The model builds on classic models of two-sided markets (Rochet and Tirole, 2003; Armstrong, 2006), but incorporates the idea that markets "clear in attention" rather than prices. That is, in equilibrium, the amount of attention that consumers supply must justify the quantity of producers who choose to produce content, and the amount of content produced must justify the amount of attention that consumers supply.

I study a platform whose profits scale with the number of consumers that choose to join. The platform acts as a curator, choosing which pieces of content to serve to consumers among those that have been created by producers. That is, the platform chooses the quantity and quality of content available to consumers subject to feasibility constraints. I interpret this choice as a simple content recommendation algorithm, the kind of algorithm that all major social media platforms use to generate personalized feeds. I use the model to derive results regarding the relationship between the shape of the attention labor supply curve and the optimal profit and welfare maximizing content recommendation algorithms.

The model delivers two key results. First, if the attention labor supply curve is sufficiently concave, then the platform maximizes consumer demand by showing some "bad" content. In the context of the model, bad content is content that provides consumers with negative utility. The intuition for this result is that showing bad content provides producers with additional attention, which boosts aggregate content supply in equilibrium. If consumers value a marginal unit of good content enough, then a large supply response justifies the inclusion of bad content on the platform.

Second, the percentage of bad content which maximizes consumer demand is a lower bound on the percentage of bad content which would maximize consumer welfare, producer welfare, social welfare, and the aggregate number of impressions. If the labor supply curve is sufficiently concave, then maximizing any of these objectives requires showing a strictly positive percentage of bad content.

An implication of the second result is that the algorithm which maximizes social welfare shows more bad content than the profit-maximizing algorithm. The intuition for this wedge is that the platform values producers only insofar as content supply allows them to attract consumers. In contrast, the social planner values consumer and producer utility. The planner trades-off some consumer utility for producer utility by showing more bad content to consumers in order to provide more attention to producers. This wedge implies that "redistributing attention" would be welfare improving.

All proofs are left to the theoretical appendix.

4.1 Model Setup

Overview. Before formalizing the model, I provide a brief overview. The model is static, but it may be helpful to think about the model as occurring in three stages.

1. First, the platform promises content producers a certain amount of attention. Observing this promise, potential content producers decide whether or not to produce content. The platform observes the quantity of good and bad content that producers have created.

2. Second, the platform curates the content. The platform chooses the quantity of good and

bad content that is available to consumers from among the content that has been produced.

3. Third, consumers observe the content that the platform offers, and decide whether to join the platform. Those who join the platform consume the content that is available, generating attention for content producers.

In equilibrium, the amount of attention that consumers produce must be equal to the promise made by the platform in the initial stage.

Producers. Producers decide whether or not to produce content for the platform. Producers value the number of impressions i that their content receives. The number of impressions i is an equilibrium object which depends on the decisions of consumers and the platform, as well as on the quality of the content that the producer creates. Content is good with exogenous probability $q \in (0, 1)$ and bad otherwise. Good content receives i_g impressions while bad content receives i_b impressions. The utility that producers derive from attention is captured by $V(i)$. The attention utility function V is assumed to be positive, increasing, and concave.

Content producers face a heterogeneous cost of effort for producing content δ. Effort cost δ is distributed according to the probability density function $k(\delta)$ with cumulative density function $K(\delta)$. Producers decide to produce content if their expected attention returns outweigh their effort cost:

$$\mathbb{E}[V_P] = \begin{cases} qV(i_g) + (1-q)V(i_b) - \delta & \text{Create Content} \\ 0 & \text{Otherwise} \end{cases}.$$

Content producer supply S is given by

$$\begin{aligned} S := S(i_g, i_b) &= \int \mathbb{I}\{qV(i_g) + (1-q)V(i_b) > \delta\} k(\delta) d\delta \\ &= K(qV(i_g) + (1-q)V(i_b)). \end{aligned}$$

Since content is good with probability q, we can compute the supply of good and bad content, denoted S_g and S_b respectively:

$$\begin{aligned} S_g(i_g, i_b) &:= qS(i_g, i_b) \\ S_b(i_g, i_b) &:= (1-q)S(i_g, i_b). \end{aligned}$$

Producer welfare is given by

$$W_P = \int \max\{qV(i_g) + (1-q)V(i_b) - \delta, 0\} k(\delta) d\delta.$$

The Platform's Curation Choice. The platform chooses the number of pieces of good and bad content available to each consumer, subject to the constraint that it cannot show more content than has been supplied by producers. Denote the number of good and bad pieces of content available to each consumer on the platform by N_g and N_b. The platform must choose $N_g \le S_g, N_b \le S_b$. When $N_b < S_b$, the platform selects a random set of N_b pieces of bad content to show each consumer out of the pool of S_b pieces of content, so the aggregate consumer impressions of bad content are spread evenly across all pieces of bad content (and likewise for good content).

Consumers. Consumers choose whether or not to join the platform. To make this decision, they evaluate the platform as a whole, with their platform consumption utility $U(N_g, N_b)$ increasing in the number of good pieces of content on the platform N_g and decreasing in the number of bad pieces of content on the platform N_b. Each consumer faces an idiosyncratic fixed cost of joining the platform $\epsilon \sim l(\epsilon)$ with cumulative density function $L(\epsilon)$.

Define the consumer utility function $U_C(N_g, N_b)$

$$U_C(N_g, N_b) = \begin{cases} U(N_g, N_b) - \epsilon & \text{Join Platform} \\ 0 & \text{Otherwise} \end{cases}.$$

Consumer demand D for the platform is given by

$$\begin{aligned} D := D(N_g, N_b) &= \int \mathbb{I}\{U(N_g, N_b) > \epsilon\} l(\epsilon) d\epsilon \\ &= L(U(N_g, N_b)). \end{aligned}$$

Consumer welfare is given by

$$W_C = \int \max\{U(N_g, N_b) - \epsilon, 0\} l(\epsilon) d\epsilon.$$

Market Clearing Conditions. I make an assumption about the way that consumers behave in order to create a tight relationship between the amount of content offered to each consumer (N_g, N_b) and the number of impressions that producers receive (i_g, i_b).

Suppose the platform offers each consumer N_g pieces of good content and N_b pieces of bad content. Then, there are $D(N_g, N_b)$ consumers on the platform. The key assumption is that each consumer "consumes the platform." That is, each consumer views all N_g pieces of good content and N_b pieces of bad content.

Under this assumption, each of the D consumers views N_g pieces of good content to provide a total of DN_g impressions of good content. The platform distributes these impressions equally across the S_g pieces of good content, so each piece of good content gets $\frac{DN_g}{S_g}$ impressions.

For each $\theta \in \{g, b\}$, the market clearing conditions are

$$\underbrace{S_\theta(i_g, i_b)}_{\text{Supply of Content}} \times \underbrace{i_\theta}_{\text{Impressions per Content}} = \underbrace{D(N_g, N_b)}_{\text{Consumer Demand}} \times \underbrace{N_\theta}_{\text{Impressions per Consumer}}. \tag{1}$$

These conditions express the idea that the number of impressions supplied to producers must equal the number of impressions provided by consumers.

The Platform's Problem. The platform maximizes profit, which is assumed to be a function of the amount of good and bad content on the platform $\Pi(N_g, N_b)$. I start by assuming that $\Pi = D(N_g, N_b)$, meaning that profit scales with the number of consumers who choose to join the platform. This objective function reflects the advertising-based profit model of social media platforms. Later, I consider alternative objectives.

The platform chooses the amount of good and bad content available to consumers subject to the constraint that it cannot show more content than it has available. The supply of content depends endogenously on the platform's choices through the market clearing conditions. Formally, the platform's problem is

$$\begin{aligned} \max_{N_g, N_b} \quad & \Pi(N_g, N_b) \\ \text{subject to} \quad & N_g \leq S_g(i_g, i_b) \\ & N_b \leq S_b(i_g, i_b) \\ & S_g(i_g, i_b) i_g = D(N_g, N_b) N_g \\ & S_b(i_g, i_b) i_b = D(N_g, N_b) N_b. \end{aligned} \tag{2}$$

Observation. *The platform will show all available good content.* To see this, notice that showing good content both increases the objective function and loosens the constraints. This is because consumers like good content, so increasing the amount of good content on the platform increases the number of consumers on the platform, which increases the number of impressions, which increases supply. Formally, $N_g = S_g$. Applying market clearing, $i_g = D$.

Since the platform's decision about good content is trivial, the primary choice of interest is how the platform handles bad content. This decision can be summarized by a parameter β which is defined as the percentage of bad content that the platform chooses to show, out of the total amount of bad content that was supplied by producers.

$$\beta := \frac{N_b}{S_b}$$

This definition, along with market clearing, simplifies the expressions for supply and demand:

$$\begin{aligned} D(N_g, N_b) &= D(qS, \beta(1-q)S) \\ S(i_g, i_b) &= S(D, \beta D). \end{aligned}$$

The platform's problem can be rewritten as

$$\begin{aligned} \max_{\beta} \quad & \Pi = D(qS, \beta(1-q)S) \\ \text{subject to} \quad & 0 \leq \beta \leq 1. \end{aligned} \tag{3}$$

Observation. *If the supply of content is exogenously fixed, then the platform should show no* *bad content.* More formally, if the supply of content $S(D, \beta D)$ is fixed to some level $\overline{S} > 0$, then $\beta = 0$.[18]

The point is that if we shut down endogenous content supply concerns in this model, then there is no incentive for the platform to show any bad content. For a fixed supply of content, the platform maximizes profits by showing all of the good content ($N_g = S_g$) and none of the bad content ($N_b = 0$).

Assumption. For the rest of the model, assume that $\frac{\partial D}{\partial S} > 0$. Recall that $D(qS, \beta(1-q)S)$. This assumption means that, for any fixed ratio of good to bad content, having more content on the platform is desirable to consumers.[19]

4.2 The Platform's Profit Maximizing Strategy

Recall that $\beta \in [0, 1]$ is the percentage of bad content that the platform shows each consumer out of the supply of bad content S_b.

Definition. Let β_C^* denote the value of β that maximizes the number of consumers on the platform.

Definition. Let D_0 denote the equilibrium value of D when $\beta = 0$. Let D_1 denote the equilibrium value of D when $\beta = 1$.

Proposition 1. *If the producer attention utility function V is sufficiently concave and consumers value good content enough, then the platform shows consumers a positive percentage of bad content. More formally,*

- *Suppose that $\frac{\partial D}{\partial N_g} > -\frac{1}{2}\frac{\partial D}{\partial N_b}$ when evaluated at the equilibrium value of D when β is set to 0. For fixed values of $V(0)$ and $V(D_0)$, if $V'(0)$ is large enough and $V'(D_0)$ is small enough, then $\beta_C^* > 0$.*

If the producer attention utility function V is sufficiently concave, then the platform does not show consumers all bad content. More formally,

- *For fixed values of $V(0)$ and $V(D_1)$, if $V'(D_1)$ is small enough, then $\beta_C^* < 1$.*

Discussion. This proposition relates the way that producers value attention V to the optimal content recommendation algorithm β. All results center around β_C^*, which is the percentage of bad content that the platform should choose to show in order to maximize the number of consumers on the platform.

If the producer attention utility function is sufficiently concave, then the platform should show some, but not all, of the bad content that was supplied by producers. The intuition for this

[18] For a proof, see the appendix.

[19] This assumption could be justified by imagining some unmodeled consumer heterogeneity, so that larger pools of content allow for better targeting. In this case, consumers are not literally consuming the platform, but instead are consuming a fixed fraction of the platform, in order to allow room for search while still allowing for some importance for the overall supply of content offered by the platform.

proposition comes from the total derivative of consumer demand with respect to β.

$$\frac{dD}{d\beta} = \frac{\partial D}{\partial \beta} + \frac{\partial D}{\partial S}\frac{\partial S}{\partial \beta}$$

This expression showcases the two forces of the model. First, consumers dislike the inclusion of bad content on the platform, which corresponds to the partial derivative $\frac{\partial D}{\partial \beta} < 0$. Second, consumers like additional content supply ($\frac{\partial D}{\partial S} > 0$), and including additional bad content on the platform may increase content supply ($\frac{\partial S}{\partial \beta} > 0$). Whether the platform should choose to show bad content depends on which of these two forces dominates.

The reason that $\frac{\partial S}{\partial \beta}$ may be positive is because increasing β can increase the amount of attention content producers get when they produce bad content. When $\beta = 0$, producers get no attention in the bad state, and realize utility $V(0)$. If there are large utility returns to the first units of attention (i.e. $V'(0) >> 0$), then it can be worth it for the platform to show some bad content, because the large boost to expected producer utility will lead to a large boost to content supply in equilibrium.

By a similar logic, when $\beta = 1$, producers get attention utility $V(D_1)$ if they produce bad content. If the marginal utility of producers at this positive level of attention D_1 is small (i.e. $V'(D_1) \approx 0$), then the inclusion of the last units of bad content on the platform delivers a small boost to producer expected utility. In this case, the correspondingly small boost to equilibrium supply will not offset the direct costs to consumers.

We can think about the property of the function $\frac{\partial S}{\partial \beta}(\beta)$ that guarantees an intermediate solution as a kind of 'concavity' of the supply curve. If the derivative of S with respect to β is sharply increasing near zero and flattens out when β is large, then the optimal choice of β is somewhere in the middle. This is because increasing the amount of bad content on the platform β has a direct negative effect on consumers, so if the marginal gains to supply decline quickly as β grows large, then at some point these gains will not offset the direct costs to consumers.

This informal 'concavity' intuition extends down to the producer attention utility function V. Increasing the fraction of bad content β may increase the impressions of bad content i_b, which in turn increases producer utility in the bad state $V(i_b)$. If the marginal returns to the first unit of attention $V'(0)$ are large and the marginal returns to units of attention beyond some positive level of attention D_1 are small (i.e. $V'(D_1) \approx 0$), then the optimal amount of attention to offer to producers in the bad state is intermediate, since offering producers attention for bad content is costly to consumers.

4.2.1 Extension: Multiple Consumer Types

In the appendix, I extend the model to accommodate a second kind of consumer, which I call a *light* consumer. Rather than "consuming the platform" (i.e. contributing one impression to each piece of content on the platform $N_g + N_b$), light consumers provide a fixed amount of impressions M. Since M is assumed to be small relative to the overall supply of content, the platform has complete flexibility to choose the fraction of good and bad content that this type of consumer is offered.

If producers attention utility function V is linear, then the platform should only show light consumers good content. However, if V is sufficiently concave, then the platform should show light consumers some bad content.

This extension demonstrates that the intuition for Proposition 1 does not depend on the fact that the platform shows bad content *in addition* to good content. Even when showing bad content directly trades off with showing good content, the platform may still want to show some bad content.

4.3 The Social Planner's Welfare Maximizing Strategy

In this subsection, I consider a variety of alternative objectives that a platform or a social planner might want to pursue. For an agent choosing the percentage of bad content to show to consumers $\beta \in [0, 1]$, define the following objectives:

- Let β_C^* maximize the number of consumers on the platform $D(N_g, N_b)$.
- Let β_P^* maximize the number of producers on the platform $S(i_g, i_b)$.
- Let β_{CW}^* maximize consumer welfare W_C.
- Let β_{PW}^* maximize producer welfare W_P.
- Let β_{SW}^* maximize social welfare, which is a linear combination of producer and consumer welfare. Formally, for $\alpha \in (0, 1)$, social welfare is $W_S = \alpha W_C + (1 - \alpha) W_P$.
- Let β_I^* maximize the number of impressions, which is given by $D(N_g, N_b)(N_g + N_b)$.

Proposition 2. *The percentage of bad content which maximizes each of the welfare objectives is ordered*

$$\beta_P^* = \beta_{PW}^* \geq \beta_{SW}^* \geq \beta_{CW}^* = \beta_C^*.$$

Moreover, the percentage of bad content which maximizes impressions is larger than the percentage which maximizes the number of consumers on the platform:

$$\beta_I^* \geq \beta_C^*.$$

Discussion. This proposition makes two interrelated points. First, β_C^* is a lower bound on the percentage of bad content which maximizes a wide variety of objectives including consumer welfare, producer welfare, social welfare, and the aggregate number of impressions on the platform. Applying Proposition 1, if the attention labor supply curve is concave enough, then maximizing any of these objectives requires showing a strictly positive percentage of bad content on the platform.

Second, this proposition relates the optimal content recommendation algorithms that maximize consumer, producer, and social welfare. The planner should show less bad content to maximize consumer welfare, more bad content to maximize producer welfare, and an intermediate amount of bad content to maximize social welfare.

If we maintain the assumption that a profit-maximizing platform wants to maximize the number of consumers on the platform, then the platform chooses β_C^*. Since $\beta_C^* \leq \beta_{SW}^*$, there is a potential wedge between the profit and welfare maximizing algorithms.

This wedge implies that regulating content recommendation algorithms could be welfare improving. Specifically, a profit-maximizing platform may not be sending enough traffic to low-quality content. That the social planner would want to inconvenience users by showing them low-quality content might seem counterintuitive, but it may help to recognize that content producers on social media are people whose utility the social planner values. If these people value attention enough, then it can be worth it for the social planner to direct attention towards their content, even though users do not want to see it. In this case, the social planner engages in a kind of utility cross-subsidization: the planner includes bad content as a tool to trade-off some consumer utility for producer utility in order to maximize welfare.

5 Conclusion and Policy Implications

The last few decades have been marked by the rise of attention platforms. Search engines, streaming platforms, and social media companies each preside over markets where consumers, content producers, and advertisers interact.

In this paper, I analyze the optimal design and regulation of attention platforms through the lens of a classic idea: attention can function as a non-monetary incentive. This incentive matters because attention platforms use content recommendation algorithms to distribute consumer attention across content producers. Since producers value attention, these algorithms affect content supply.

I document that attention is an effective non-monetary incentive empirically. Using difference-in-differences designs, I find that going viral causes content producers on Reddit and TikTok to create more than twice as much content for a month without sacrificing quality. The rich nature of the observational data allows me to trace out an attention labor supply curve. I find that this curve is concave: the first units of attention sharply increase content supply, while marginal attention beyond a certain threshold is not influential.

I complement this reduced form evidence with a large scale field experiment. I user generative AI and a network of bots to randomly add comments to Reddit posts. Adding three comments to Reddit posts causes content producers to create 15% more posts, though I find a null effect for six comments. I show that differences in the efficacy of treatment are driven by differences in attention quality.

I develop a model of a social media platform that takes the attention incentive seriously. In the model, a social media platform manages a two-sided market between content creators and consumers. If the attention labor supply curve is sufficiently concave, than a platform should show a strictly positive percentage of bad content in order to maximize consumer demand. A welfare-maximizing social planner would show a larger percentage of bad content.

Looking forward, this paper gestures at two ways in which understanding the attention incentive could improve policy. First, accounting for attention can help us design healthier online communities. Given the meteoric rise of social media and its function as a forum that shapes our public discourse, getting the design of these online spaces right is important. Second, the value that people place on attention provides a novel justification for the regulation of social media algorithms. The model demonstrates that attention can create a wedge between profit-maximizing behavior and social welfare, which implies that regulating social media algorithms could have a positive impact.

More abstractly, this paper provides empirical evidence that attention is a psychological commodity which people value inherently. This fact has potentially wide-ranging implications across a variety of public policy areas, because the allocation of attention is a fundamental aspect of life as a social species. All of our relationships are mediated by the ways in which we choose to allocate our attention, and one of the core findings of this paper is that a little bit of attention goes a long way.

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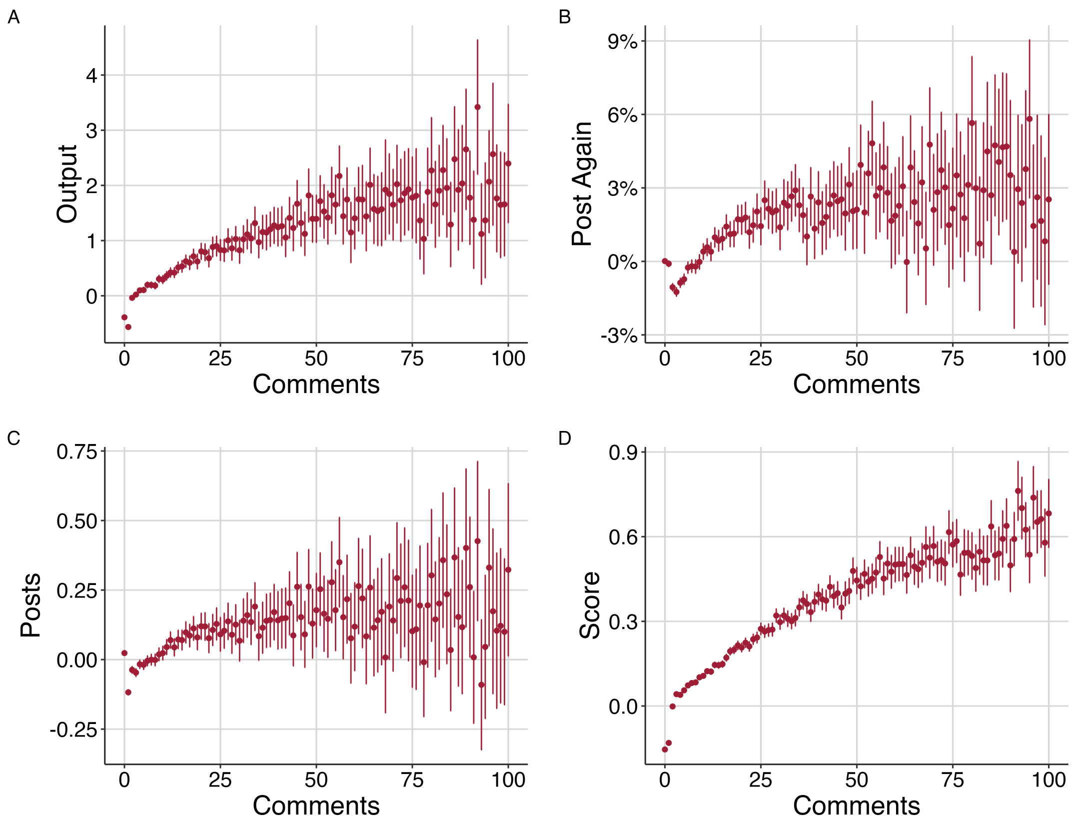
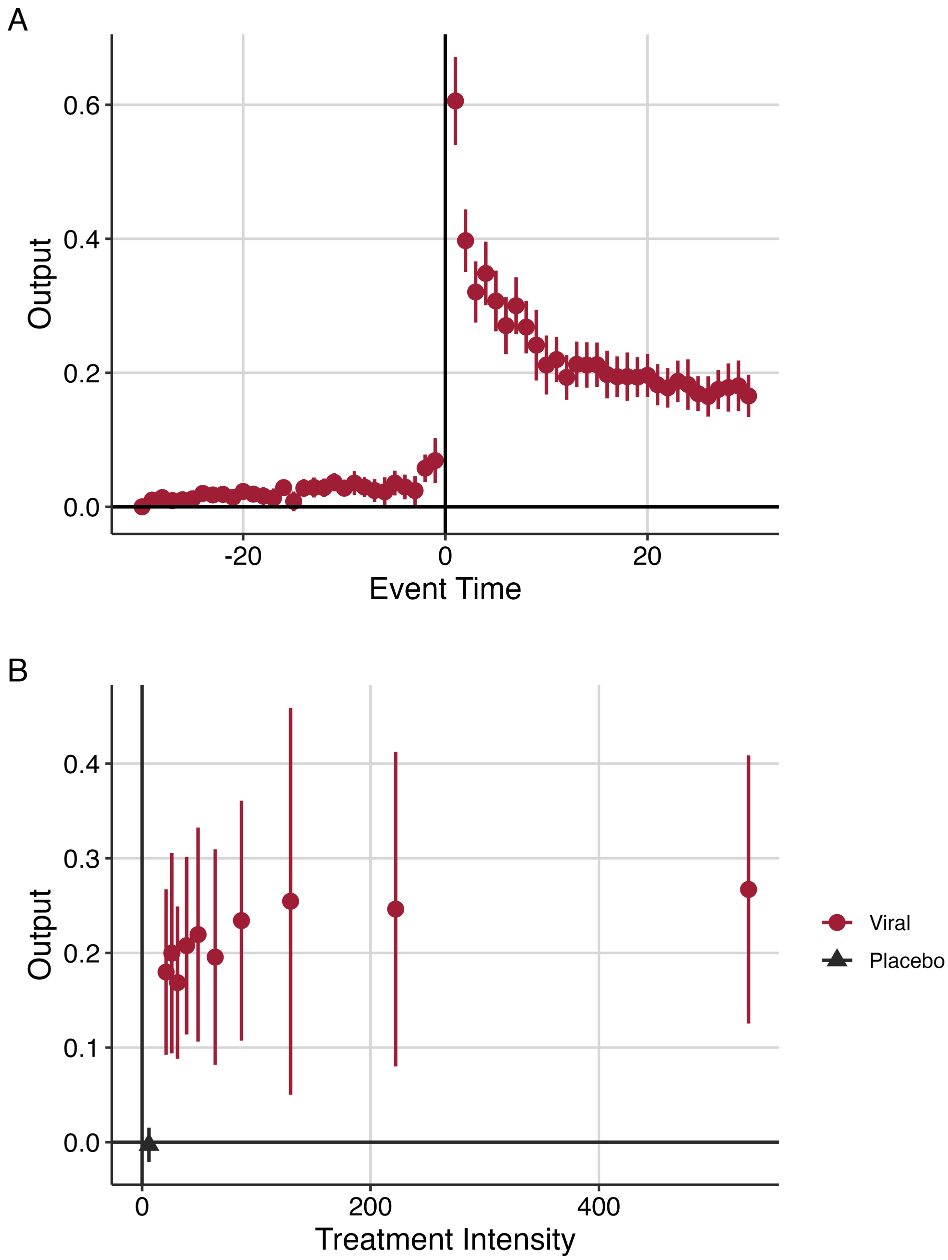
6 Figures

Figure 1: Correlation between Attention and Production



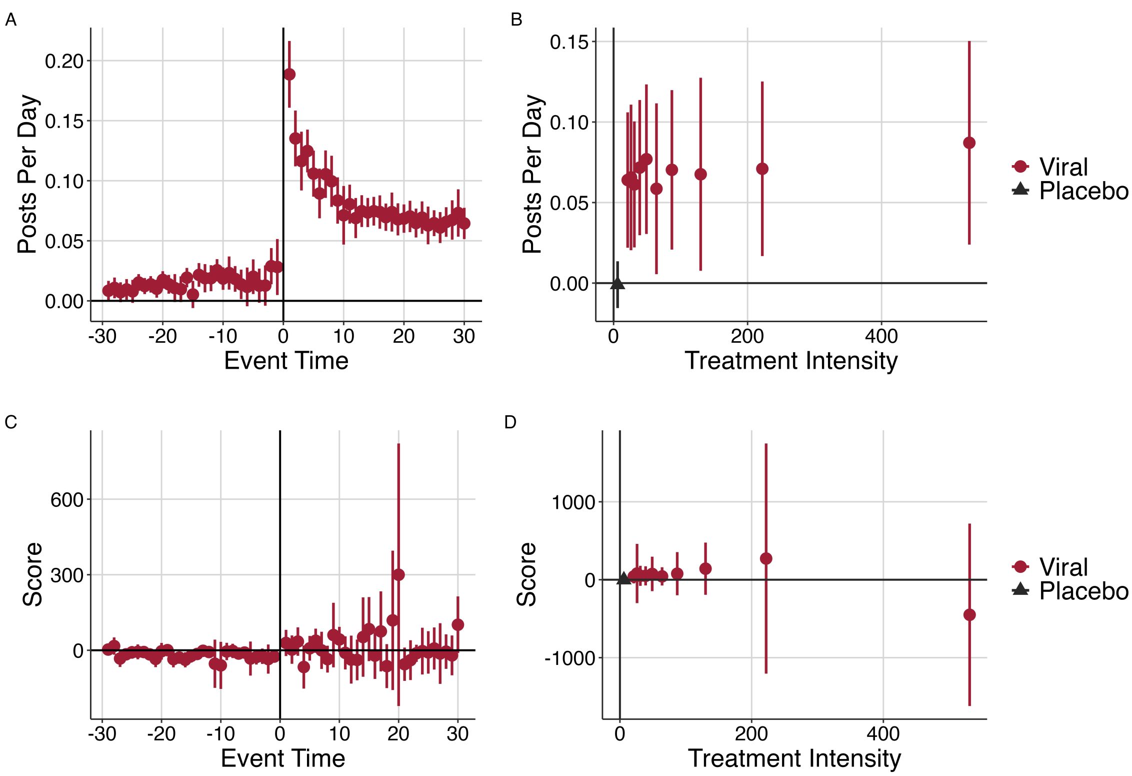
Notes: This figure presents correlations between the attention that a Reddit post receives, as measured by the number of comments, and various measures of content production by the post's author over the next week. Each point represents a one-comment bin, and bars represent 95% confidence intervals. The outcome in Plot A is $\sum log(\text{score}+1)$, which is a quality-weighted measure of output. The outcome in Plot B is an indicator for if any posts are produced in the next week, capturing the extensive margin. The outcome in Plot C is quantity, measured by the count of posts. The outcome in Plot D is quality, measured by the average score of posts. All outcomes are demeaned by subreddit.

Figure 2: The Effect of Virality on Production



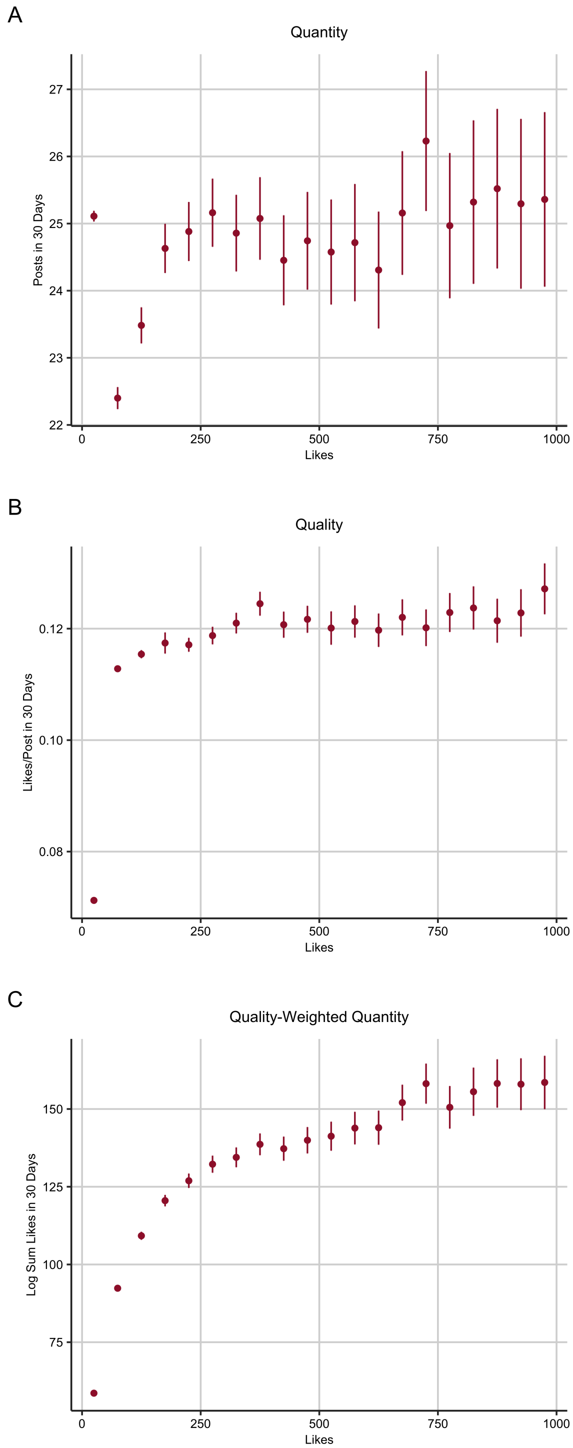
Notes: This difference-in-differences design compares how the production of Reddit posts evolves around viral and randomly selected posts. Posts are viral if they surpass the 80^{th} percentile of the upvotes distribution. The outcome variable is a quality-weighted measure of output: $\sum log(\max(\text{upvotes} + 1, 1))$. In Plot A, each point represents a 1 day bin. Event time 0 is the day that the viral or random post was created, and is excluded from the graph. Output increases by 0.21 units per day in the 30 days following going viral relative to the random baseline, which is 373% increase over the pre-period mean of 0.06 units per day. Plot B estimates the attention labor supply curve by graphing heterogeneity in the treatment effect by the degree of virality. Each point is the output of the difference-in-differences design estimated on the subset of posts that go viral within a two-percentile band of the upvotes distribution. Posts in the first viral point received between 21-26 upvotes (80^{th}-82^{nd} percentile), while posts in the tenth viral point received more than 531 upvotes (98^{th}-100^{th} percentile). The placebo point is the treatment effect of posting a non-viral post, estimated using a difference-in-differences design around random non-viral post. Bars represent 95% confidence intervals.

Figure 3: The Effect of Virality: Quantity vs. Quality



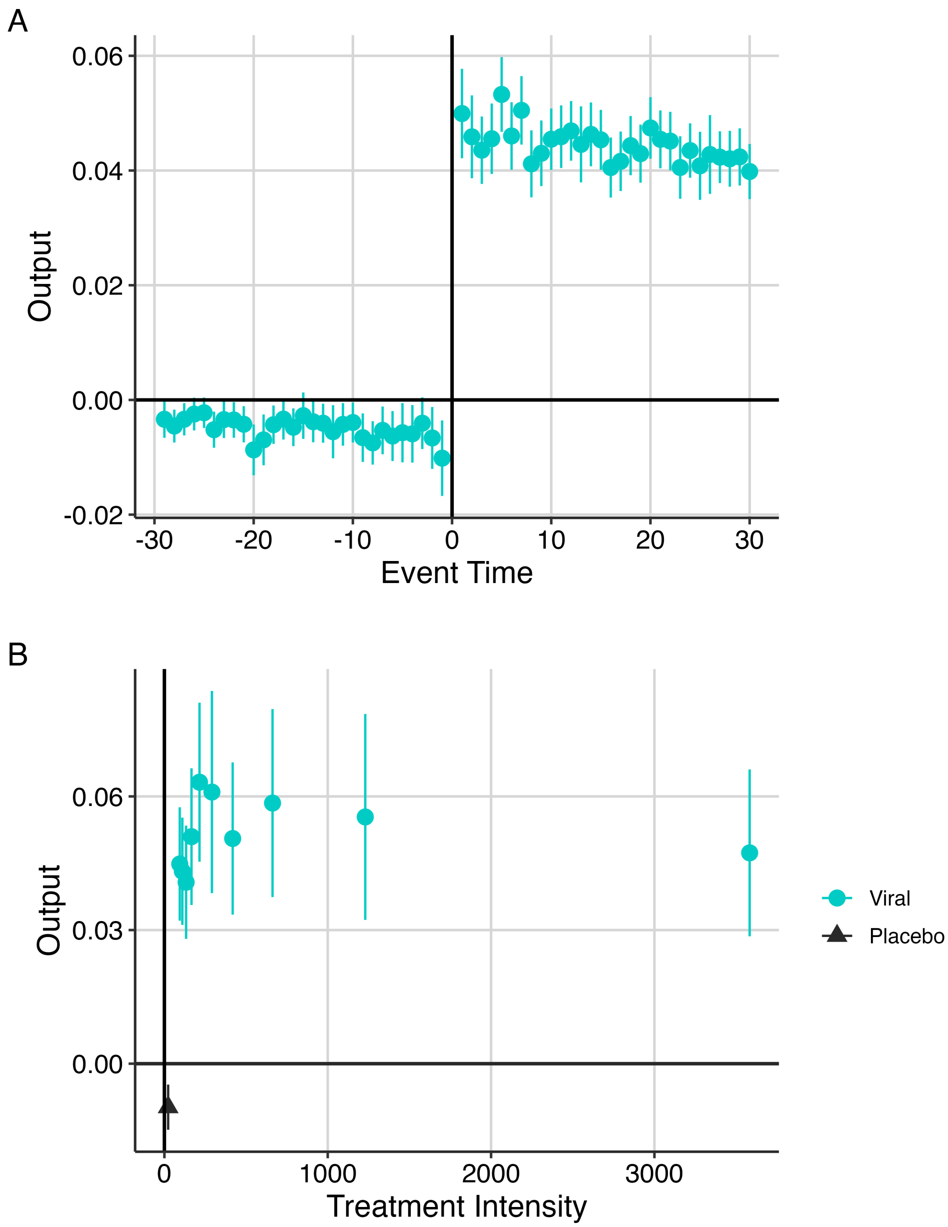
Notes: This figure repeats the difference-in-differences design of Figure 2 for two alternative outcomes. Plots A and B consider the number of posts per day, an interpretable measure of the quantity of output. Viral producers post 0.068 more posts per day, which is 183% of the baseline of 0.037 posts per day. Plots C and D analyze effects on the mean score conditional on posting, which is a measure of post quality. Going viral does not significantly change post quality.

Figure 4: The Effect of Virality: Quantity vs. Quality



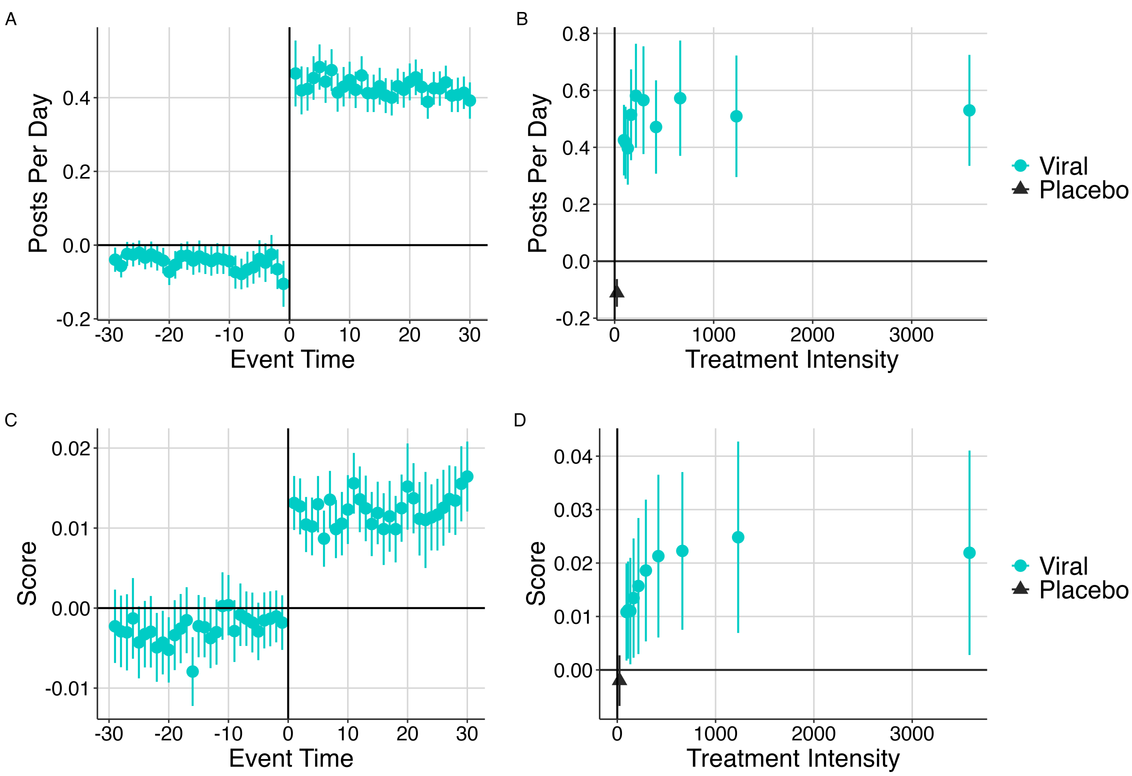
Notes: This figure graphs correlations between the likes that a TikTok post receives and the quality and quantity of content that the post's author produces over the next 30 days. Plot A depicts the number of posts made in the subsequent 30 days. Plot B depicts the quality of posts, measured in terms of likes/view. The outcome in Plot C is $\sum log(likes + 1)$ of posts produced in the next 30 days, which is a quality-weighted measure of output. Posts are grouped into 50-like bins. Bars represent 95% confidence intervals.

Figure 5: The Effect of Virality on Production on TikTok



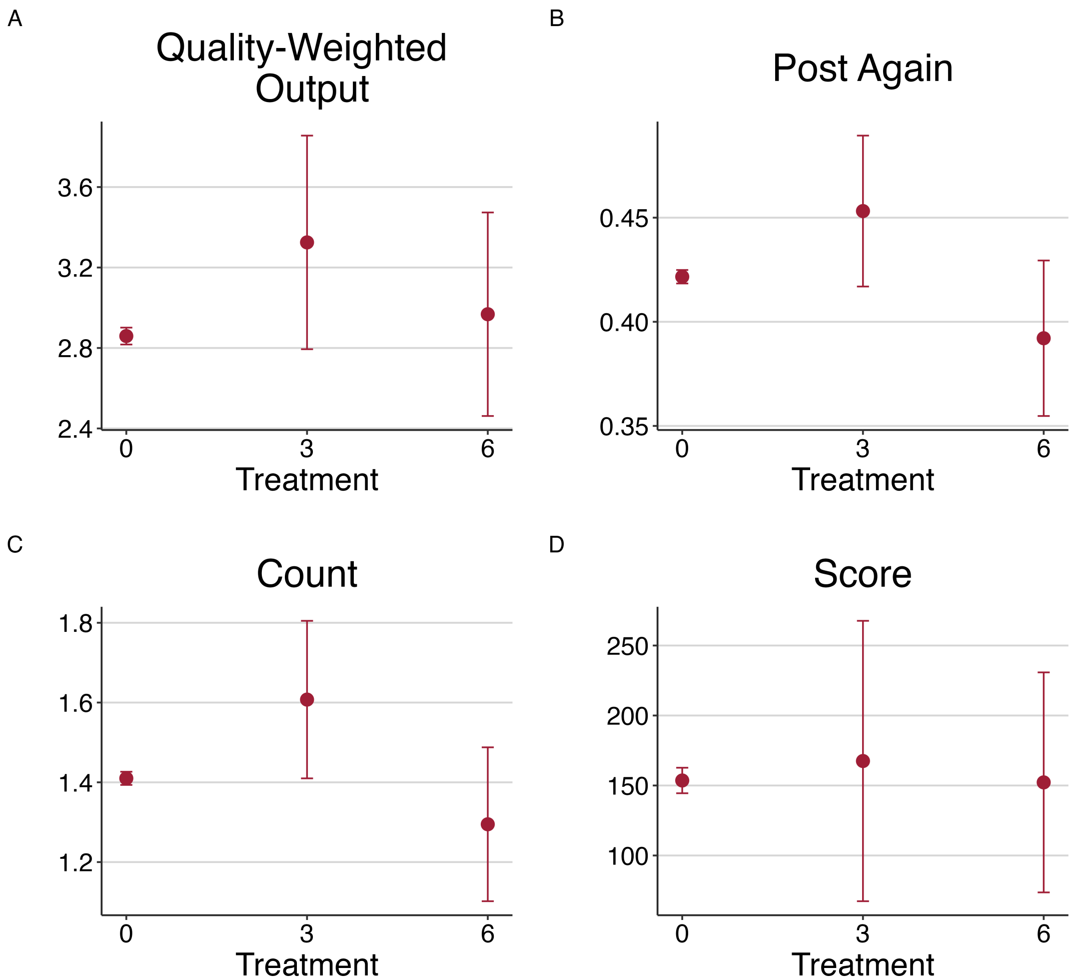
Notes: This figure replicates the difference-in-differences design of Figure 2 on TikTok. The outcome is a quality-weighted of output, where quality is measured by likes per view. Posts are viral if they surpass the 80^{th} percentile of the likes distribution. In Plot A, each point represents a 1 day bin. Event time 0 is the day that the viral or random TikTok is created, and is excluded from the graph. Output increases by 0.049 units per day in the 30 days following going viral TikTik relative to the random baseline, which is 279% increase over the pre-period rate of 0.017 units per day. Plot B graphs heterogeneity in the treatment effect by the degree of virality. Each point is the output of the difference-in-differences design estimated on the subset of posts that go viral within a two-percentile band of the upvotes distribution. Posts in the first viral point received between 94-110 likes (80^{th}-82^{nd} percentile), while posts in the tenth viral point received more than 3,583 upvotes (98^{th}-100^{th} percentile). The placebo point is the treatment effect of posting a non-viral post, estimated using a difference-in-differences design around random non-viral post. Bars represent 95% confidence intervals.

Figure 6: The Effect of Virality on TikTok: Quantity vs. Quality



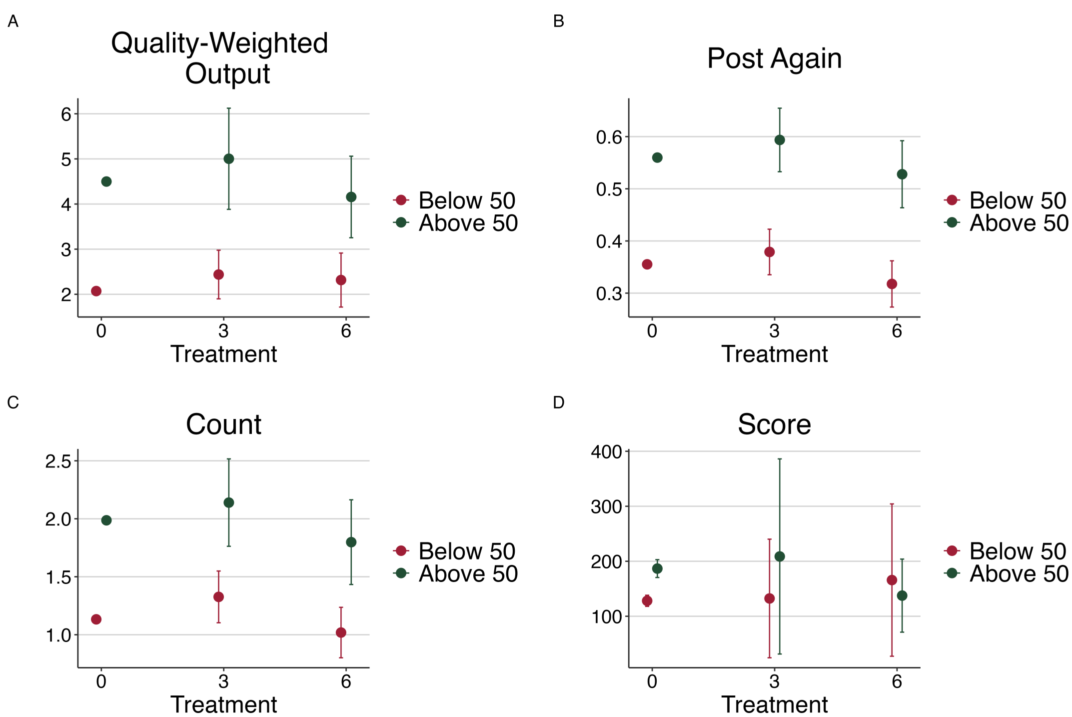
Notes: This figure repeats the difference-in-differences design of Figure 5 for two alternative outcomes. Plots A and B consider the number of TikToks per day, an interpretable measure of the quantity of output. Viral producers post 0.43 more TikToks per day, which is 190% of the baseline of 0.24 TikToks per day. Plots C and D analyze effects on the mean score conditional on posting, which is a measure of post quality. Going viral increases average post quality by 0.014 units which is 20% of the pre-period mean quality of 0.07 units.

Figure 7: The Effect of Attention on Production: Experimental Evidence



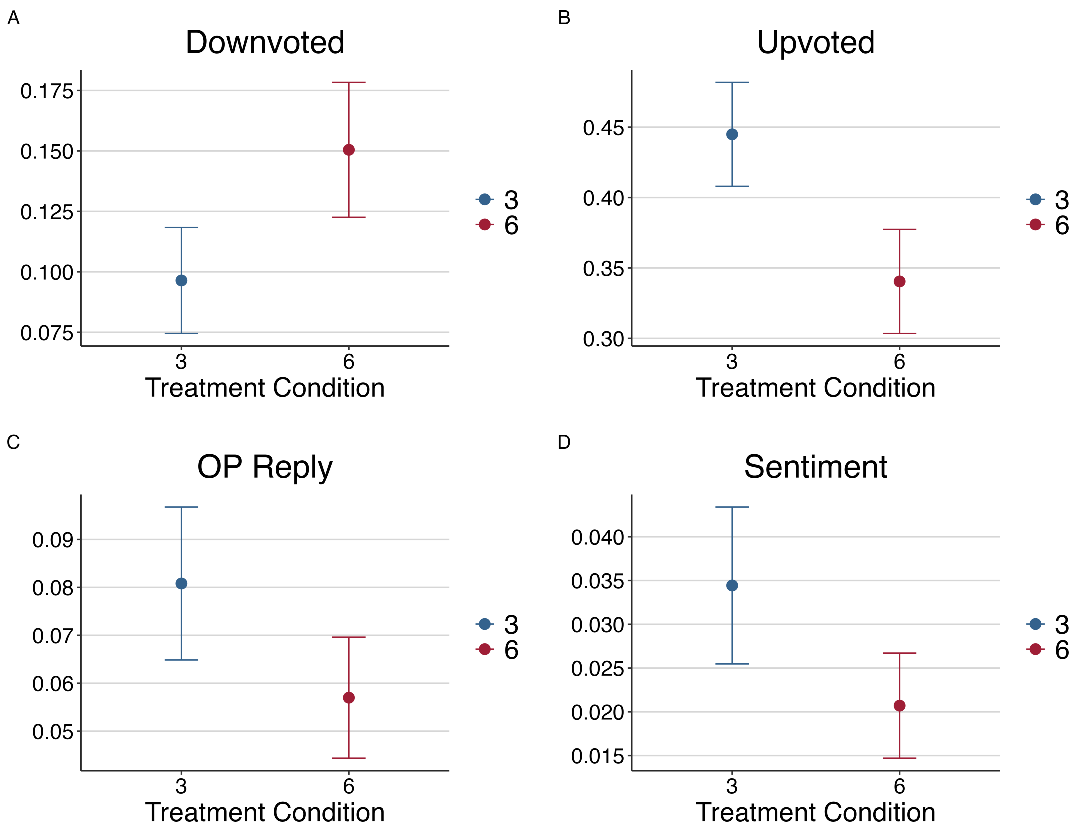
Notes: This figure plots all main outcomes in the experiment. There are four preregistered outcome variables. Panel A plots a quality-weighted measure of output, computed by taking the sum of the log of the score of posts produced. Panel B plots the the probability of posting again, a measure of the extensive margin. Panel C plots a count of posts, an interpretable measure of quantity. Finally, Panel D plots the mean score conditional on posting, a measure of quality. All outcomes are measured in the 7 days after treatment. The 3 comments treatment increases the the quality-weighted measure of output, the probability of posting again, and the count of posts over the next week, but has no effect on average score.. I find null effects for the 6 comment treatment across all outcomes.

Figure 8: Heterogeneity by Poster Experience



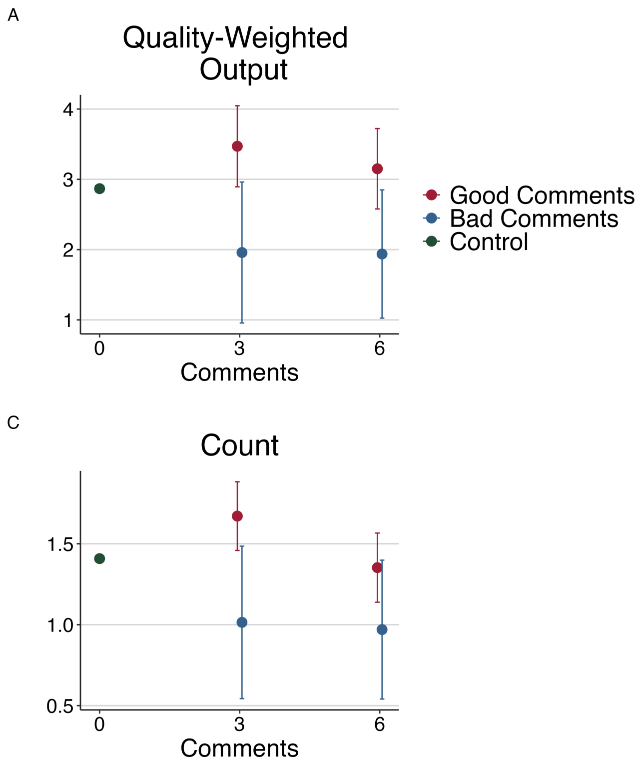
Notes: This figure plots a pre-registered split in the main treatment by user experience. Users are grouped by whether or not they have below 50 prior posts at the time of randomization. The point estimates of this heterogeneity split mirror the pooled results of the experiment for both groups, though the estimates are noisy and null effects cannot be rejected.

Figure 9: Heterogeneity in Comment Quality by Treatment Condition



Notes: This figure plots four measures of comment quality by treatment condition. Panel A shows that comments in the six comment treatment have an above average probability of being downvoted. This result of this split is analyzed in Figure 10. Panel B shows that comments in the three comment treatment have an above average probability of being upvoted. Panel C shows that the original poster is more likely to reply to comments in the three comments treatment. Panel D shows that the average sentiment of replies to the three comments treatment is higher. Sentiment is measured using the VADER sentiment model, and larger numbers reflect a more positive sentiment. Bars represent 95% confidence intervals.

Figure 10: Heterogeneity by Comment Quality



Notes: This figure plots heterogeneity in the four experimental outcomes, splitting the sample by a measure of average comment quality. Specifically, the sample is split on the average rate that a comment was downvoted, which is a sign that a comment was actively disliked. There is a large degree of heterogeneity by comment quality. Quality-weighted output, the count of posts, and the probability of posting again are all significantly larger for high quality comments when compared to low quality comments within the same treatment condition. This heterogeneity provides an explanation for the average null effect for the six comments treatment condition: comments in the six comments treatment are more likely to be downvoted, and downvoted comments have negative treatment effects.

7 Theoretical Appendix

7.1 Recasting the Model in terms of a Single Policy Parameter

Equation 2 represents the platform's problem in terms of four choice variables N_g, N_b, i_g, i_b. In this subsection, I will show that the problem can be represented in terms of a single choice variable β, where β will represent the percentage of available bad content that the platform chooses to show.

Expressing N_g^* and i_g^* in terms of S and D. The first thing to notice is that the platform always wants to show consumers all of the good content it has available. This means each piece of good content on the platform will be seen by all consumers on the platform. Formally,

Lemma 3. *$N_g^* = S_g$. $i_g^* = D$.*

Proof. In the platform's problem, the objective function $D(N_g, N_b)$ is strictly increasing in N_g. Since N_g increases the objective directly, the only reason not to choose the maximum feasible N_g is if increasing N_g tightens the constraints of the maximization problem. The two inequality constraints are $0 \leq N_g \leq S_g$ and $0 \leq N_b \leq S_b$. S_b and S_g are both strictly increasing functions of $S(i_g, i_b)$, which itself is strictly increasing in both of its arguments. Recall the expressions for i_g and i_b.

$$i_g = \frac{N_g}{S_g} D(N_g, N_b)$$
$$i_b = \frac{N_b}{S_b} D(N_g, N_b)$$

Since both of these expressions are increasing in N_g, we can see that both constraints are strictly loosening in N_g. Then, the optimal choice of N_g must be the maximum feasible choice of N_g since increasing N_g increases the objective function and loosens the constraints. So, we have that $N_g^* = S_g$. This result immediately simplifies the expression for i_g^*:

$$i_g^* = \frac{DN_g^*}{S_g} = D$$

Expressing N_b and i_b in terms of S, D and β. Because the platform's choice of N_g^*, i_g^* is trivial, the primary decision of interest in this model is how the platform handles bad content. It will be notationally convent to think about the amount of bad content shown N_b as fraction of the total amount of bad content available, S_b. Define

$$\beta := \frac{N_b}{S_b}$$

This definition allows us to express i_b in terms of β and D.

$$i_b = \frac{DN_b}{S_b} = \beta D$$

The parameter β is defined in and out of equilibrium, so the expression for N_b in terms of S_b and β holds in and out of equilibrium. The expression for i_b in terms of β, S, and D depends on implementing the equality constraint. Applying these new definitions to the equilibrium quantities i_b^* and N_b^* gives

$$\begin{aligned} N_b^* &= \beta S_b \\ i_b^* &= \beta D \end{aligned}$$

Expressing the Platform's Problem in terms of β. Taking stock of the above definitions and results, we can now to express the equilibrium parameters $N_g^*, N_b^*, i_g^*, i_b^*$ in terms of β as well as the supply and demand functions S and D.

Specifically, write demand in terms of β and supply as follows

$$\begin{aligned} D &:= D(N_g^*, N_b^*) \\ &= D(S_g, \beta S_b) \\ &= D(qS, \beta(1-q)S) \end{aligned}$$

Similarly, write supply in terms of demand and β as follows

$$\begin{aligned} S &:= S(i_g^*, i_b^*) \\ &= S(D, \beta D) \end{aligned}$$

Then, the platform's problem is

$$\begin{aligned} \max_{\beta} \quad & \Pi = D(qS, \beta(1-q)S) \\ \text{subject to} \quad & 0 \leq \beta \leq 1 \end{aligned} \tag{4}$$

Lemma 4. *If the supply of content is exogenously fixed, then platform should show no bad content. Let β_Π^* denote the platform's profit maximizing choice of β. Fix the supply of content $S(D, \beta D)$ to some level $\overline{S} > 0$. Then, $\beta_\Pi^* = 0$.*

Proof. Consider the firm's profit maximization problem for a fixed supply of content $\overline{S}$:

$$\begin{aligned} \max_{\beta} \quad & \Pi = D(q\overline{S}, \beta(1-q)\overline{S}) \\ \text{subject to} \quad & 0 \leq b \leq 1 \end{aligned}$$

We know that $D(N_g, N_b)$ is decreasing in its second argument. Once supply is fixed, β only appears in the expression for N_b. Then, to maximize Π, we should choose β to minimize $N_b = \beta(1-q)\overline{S}$. Since $(1-q)\overline{S}$ is a positive constant, this expression is minimized when $\beta = 0$.

7.2 The Platform's Profit Maximizing Strategy

Proposition 5. *If the producer attention utility function V is sufficiently concave and consumers value good content enough, then the platform shows consumers a positive percentage of bad content.*

- *More formally, suppose that $\frac{\partial D}{\partial N_g} > -\frac{1}{2}\frac{\partial D}{\partial N_b}$ when evaluated at D_0. For fixed values of $V(0)$ and $V(D_0)$, if $V'(0)$ is large enough and $V'(D_0)$ is small enough, then $\beta_C^* > 0$.*

If the producer attention utility function V is sufficiently concave, then the platform does not show consumers all bad content.

- *For fixed values of $V(0)$ and $V(D_1)$, if $V'(D_1)$ is small enough, then $\beta_C^* < 1$.*

Proof.

We are interested in whether $\beta_C^* > 0$. Consider the equilibrium where we exogenously fix $b = 0$. Call the equilibrium level of demand $D_0 := D(S_0, 0)$ where $S_0 := (D_0, 0)$.

Consider the profit equation

$$\Pi = D(qS, \beta(1-q)S)$$

Take the total derivative of this equation with respect to β.

$$\begin{aligned}\frac{d}{d\beta}&[\Pi = D(qS, \beta(1-q)S)] \\ \frac{dD}{d\beta} &= \frac{\partial D}{\partial \beta} + \frac{\partial D}{\partial S}\frac{\partial S}{\partial \beta}\end{aligned}$$

The platform should choose $\beta_C^* > 0$ if the total derivative is positive at 0. This condition is

$$0 < \frac{\partial D}{\partial \beta}(0) + \frac{\partial D}{\partial S}(0)\frac{\partial S}{\partial \beta}(0)$$

Note that

$$\begin{aligned}\frac{\partial D}{\partial \beta}(0) &= \frac{\partial D(S, \beta S)}{\partial \beta}(0) \\ &= D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S + \frac{\partial S}{\partial \beta}]\end{aligned}$$

where $D^1(S_0)$ denotes the derivative of D with respect to it's first argument, N_g, evaluated at the level S_0. Additionally, note that

$$\begin{aligned}\frac{\partial D}{\partial S}(0) &= \frac{\partial D(S, \beta S)}{\partial S}(0) \\ &= D^1(S_0) + \beta D^2(0) \\ &= D^1(S_0)\end{aligned}$$

So, the inequality condition is

$$
\begin{aligned}
0 &< D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S_0 + \frac{\partial S}{\partial \beta}] + D^1(S_0)\frac{\partial S}{\partial \beta}(0) \\
0 &< 2D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S_0 + \frac{\partial S}{\partial \beta}] \\
-D^2(0)S_0 &< 2D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)\frac{\partial S}{\partial \beta} \\
-D^2(0)S_0 &< [2D^1(S_0) + D^2(0)]\frac{\partial S}{\partial \beta}
\end{aligned}
$$

By assumption $2D^1(S_0) + D^2(0) > 0$, so we can move this term to the other side without flipping the inequality.

$$
\frac{-D^2(0)S_0}{2D^1(S_0) + D^2(0)} < \frac{\partial S}{\partial \beta}
$$

where the left hand side of this inequality is a positive term that is constant with respect to V' holding fixed $V(0)$ and $V(D_0)$, which are terms that determine S_0 and D_0 in equilibrium when $b = 0$ exogenously.

Consider the derivative at $\frac{\partial S}{\partial \beta}(0)$. Recall that supply is given by

$$
\begin{aligned}
S := S(i_g, i_b) &= \int \mathbb{I}\{qV(i_g) + (1-q)V(i_b) > \delta_j\}k(\delta_j)d\delta_j \\
&= \int \mathbb{I}\{qV(D) + (1-q)V(\beta D) > \delta_j\}k(\delta_j)d\delta_j \\
&= K(qV(D) + (1-q)V(\beta D))
\end{aligned}
$$

Taking the first derivative, we have

$$
\frac{\partial K(\mathbb{E}[V])}{\partial \beta} = k(\mathbb{E}[V])\frac{\partial \mathbb{E}[V]}{\partial \beta}
$$

where

$$
\begin{aligned}
\frac{\partial \mathbb{E}[V]}{\partial \beta} &= \frac{\partial}{\partial \beta}[qV(D(\beta)) + (1-q)V(\beta D(\beta))] \\
&= qV'(D(\beta))D'(\beta) + (1-q)V'(\beta D(\beta))[D(\beta) + \beta D'(\beta)]
\end{aligned}
$$

Evaluating this derivative at $b = 0$, we have

$$
\frac{\partial \mathbb{E}[V]}{\partial \beta}(0) = qV'(D(0))D'(0) + (1-q)V'(0)D(0)
$$

Then, the derivative of supply with respect to β evaluated at $b = 0$ is

$$\frac{\partial K(\mathbb{E}[V])}{\partial \beta}(0) = k(qV(D) + (1-q)V(0))[qV'(D(0))D'(0) + (1-q)V'(0)D(0)]$$

Rewriting our expression in D_0 notation,

$$\begin{aligned}
\frac{\partial S}{\partial \beta}(0) &= k(qV(D_0) + (1-q)V(0))[qV'(D_0)D_0' + (1-q)V'(0)D_0] \\
&= k(qV(D_0) + (1-q)V(0))[qV'(D_0)D^1(S_0)[D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S + \frac{\partial S}{\partial \beta}]] + (1-q)V'(0)D_0]
\end{aligned}$$

since

$$\begin{aligned}
\frac{\partial D}{\partial \beta}(0) &= \frac{\partial D(S, \beta S)}{\partial \beta}(0) \\
&= D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S + \frac{\partial S}{\partial \beta}]
\end{aligned}$$

Isolating $\frac{\partial S}{\partial \beta}(0)$,

$$\begin{aligned}
\frac{\partial S}{\partial \beta}(0) &= k(\cdot)[qV'(D_0)[D^1(S_0)\frac{\partial S}{\partial \beta} + D^2(0)[S + \frac{\partial S}{\partial \beta}]] + (1-q)V'(0)D_0] \\
\frac{\partial S}{\partial \beta}(0) &= \frac{\partial S}{\partial \beta}(0)[k(\cdot)qV'(D_0)D^1(S_0) + k(\cdot)D^2(0)] + k(\cdot)D^2(0)S + k(\cdot)(1-q)V'(0)D_0 \\
\frac{\partial S}{\partial \beta}(0) &= \frac{k(\cdot)D^2(0)S + k(\cdot)(1-q)V'(0)D_0}{1 - [k(\cdot)qV'(D_0)D^1(S_0) + k(\cdot)D^2(0)]}
\end{aligned}$$

If $k(\cdot)qV'(D_0)D^1(S_0) < 1$, then the denominator is positive. So, if $V'(D_0)$ small enough, this denominator is positive.

The numerator $k(\cdot)D^2(0)S + k(\cdot)(1-q)V'(0)D_0$ can be made arbitrarily large for $V'(0)$ large enough.

So, for $V'(D_0)$ small enough and $V'(0)$ large enough, the derivative $\frac{\partial S}{\partial \beta}(0)$ can be made arbitrarily large. Under the conditions described above, for $\frac{\partial S}{\partial \beta}(0)$ large enough, the total derivative $\frac{dD}{d\beta}(0) > 0$.

Claim 2

Now, consider the total derivative expression at $\beta = 1$

$$\frac{dD}{d\beta}(1) = \frac{\partial D}{\partial \beta}(1) + \frac{\partial D}{\partial S}\frac{\partial S}{\partial \beta}(1)$$

The platform should choose $\beta < 1$ if the total derivative is negative at $\beta = 1$. This condition is

$$0 > \frac{\partial D}{\partial \beta}(1) + \frac{\partial D}{\partial S}(1)\frac{\partial S}{\partial \beta}(1)$$

Note that

$$\begin{aligned}\frac{\partial D}{\partial \beta}(1) &= \frac{\partial D(S,\beta S)}{\partial \beta}(1)\\ &= D^1(S_1)\frac{\partial S}{\partial \beta} + D^2(S_1)[S_1 + \frac{\partial S}{\partial \beta}]\end{aligned}$$

where $D^1(S_1)$ denotes the derivative of D with respect to it's first argument and $D^2(S_1)$ denotes the derivative of D with respect to it's second argument. Additionally, note that

$$\begin{aligned}\frac{\partial D}{\partial S}(1) &= \frac{\partial D(S,\beta S)}{\partial S}(1)\\ &= D^1(S_1) + \beta D^2(S_1)\\ &= D^1(S_1) + D^2(S_1)\end{aligned}$$

Substituting in these expressions, the inequality condition is

$$\begin{aligned}0 &> D^1(S_1)\frac{\partial S}{\partial \beta}(1) + D^2(S_1)[S_1 + \frac{\partial S}{\partial \beta}(1)] + [D^1(S_1) + D^2(S_1)]\frac{\partial S}{\partial \beta}(1)\\ 0 &> \frac{\partial S}{\partial \beta}(1)[D^1(S_1) + D^2(S_1) + D^1(S_1) + D^2(S_1)] + D^2(S_1)S_1\\ -D^2(S_1)S_1 &> 2\frac{\partial S}{\partial \beta}(1)[D^1(S_1) + D^2(S_1)]\end{aligned}$$

By assumption, $D^1(S_1) + D^2(S_1) > 0$ (from assuming $\frac{\partial D}{\partial S} > 0$), so we can rearrange terms.

$$\frac{-D^2(S_1)S_1}{2[D^1(S_1) + D^2(S_1)]} > \frac{\partial S}{\partial \beta}(1)$$

Now, recall the expression for $\frac{\partial S}{\partial \beta}$. Taking the first derivative, we have

$$\frac{\partial K(\mathbb{E}[V])}{\partial \beta} = k(\mathbb{E}[V])\frac{\partial \mathbb{E}[V]}{\partial \beta}$$

where

$$\begin{aligned}\frac{\partial \mathbb{E}[V]}{\partial \beta} &= \frac{\partial}{\partial \beta}[qV(D(\beta)) + (1-q)V(\beta D(\beta))]\\ &= qV'(D(\beta))D'(\beta) + (1-q)V'(\beta D(\beta))[D(\beta) + \beta D'(\beta)]\end{aligned}$$

Evaluating this derivative at $\beta = 1$, we have

$$\frac{\partial \mathbb{E}[V]}{\partial \beta}(1) = qV'(D(1))D'(1) + (1-q)V'(D(1))[D(1) + D'(1)]$$

Then, the derivative of supply with respect to β evaluated at $\beta = 1$ is

$$\begin{aligned}\frac{\partial S}{\partial \beta}(1) &= k(V(D_1))[qV'(D_1)D_1' + (1-q)V'(D_1)[D_1 + D_1']] \\ &= k(V(D_1))[V'(D_1)D_1' + (1-q)V'(D_1)D_1]\end{aligned}$$

Recall that $D_1' = D^1(S_1)\frac{\partial S}{\partial \beta} + D^2(S_1)[S_1 + \frac{\partial S}{\partial \beta}]$. Then,

$$\begin{aligned}\frac{\partial S}{\partial \beta}(1) &= k(V(D_1))[qV'(D_1)D_1' + (1-q)V'(D_1)[D_1 + D_1']] \\ &= k(\cdot)[V'(D_1)D^1(S_1)\frac{\partial S}{\partial \beta}(1) + D^2(S_1)[S_1 + \frac{\partial S}{\partial \beta}(1)] + (1-q)V'(D_1)D_1] \\ &= \frac{\partial S}{\partial \beta}(1)[k(\cdot)V'(D_1)D^1(S_1) + k(\cdot)D^2(S_1)] + k(\cdot)D^2(S_1)S_1 + k(\cdot)(1-q)V'(D_1)D_1 \\ &= \frac{k(\cdot)D^2(S_1)S_1 + k(\cdot)(1-q)V'(D_1)D_1}{1 - [k(\cdot)V'(D_1)D^1(S_1) + k(\cdot)D^2(S_1)]}\end{aligned}$$

In the denominator, the only negative term is $k(\cdot)V'(D_1)D^1(S_1)$, so if $V'(D_1)$, the denominator will be positive.

In the numberator, $k(\cdot)D^2(S_1)S_1$ is negative and $k(\cdot)(1-q)V'(D_1)D_1$ can be made arbitrarily small as $V'(D_1)$ grows small.

Then, $\frac{\partial S}{\partial \beta}(1)$ can be made arbitrarily close to zero (or negative) as $V'(D_1)$ grows small. In particular, chose $V'(D_1)$ such that the inequality condition derived above holds (which is possible since the left hand side is a positive constant with respect to $V'(D_1)$).

"Sufficiently Concave" To justify the phrasing of the proposition that these results hold if the function V is "sufficiently concave", consider the following Taylor Expansion.

$$V'(D_0) \approx V'(0) + D_0 V''(0)$$

If $V''(0)$ is negative enough (i.e. V is very concave), then $V'(D_0)$ can be made arbitrarily small (by assumption, it cannot be negative, as V is assumed to be increasing). Reversing this expression, write

$$V'(0) \approx V'(D) - D_0 V''(D)$$

Again, for $V''(D)$ negative enough, $V'(0)$ can be made arbitrarily large.

In practice, for these expressions to hold V must be in a class where the Taylor Expansions are 'close enough', but the point of these expressions is just to capture the idea that having a very sharp positive derivative at 0 and a very flat derivative at some positive point D_0 or D_1 can be understood through the lens of concavity.

7.3 The Social Planner's Welfare Maximizing Strategy

Proposition 6. *The percentage of bad content which maximizes each of the welfare objectives is weakly ordered*

$$\beta_P^* = \beta_{PW}^* \geq \beta_{SW}^* \geq \beta_{CW}^* = \beta_C^*$$

Moreover, the percentage of bad content which maximizes impressions is weakly larger than the percentage which maximizes the number of consumers on the platform:

$$\beta_I^* \geq \beta_C^*.$$

Proof. First I will show that maximizing consumer welfare is equivalent to maximizing the number of consumers on the platform, and maximizing producer welfare is equivalenet to maximizing the number of producers on the platform.

Recall that

$$W_C = \int \max\{U(N_g, N_b) - \epsilon, 0\} l(\epsilon) d\epsilon$$

The social planner wants to choose β to maximize W_C. The integrand is weakly increasing in $U(N_g, N_b)$, and β does not enter the problem elsewhere, so the social planner's problem is equivalent to choosing β to maximize $U(N_g, N_b)$.

Now consider the platform's profit maximizing problem. The platform wants to choose β to maximize

$$\Pi = D(\beta) = \int \mathbb{I}\{U(N_g, N_b) > \epsilon\} l(\epsilon) d\epsilon$$

This integrand is also weakly increasing in $U(N_g, N_b)$, so the platform's problem is also equivalent to choosing β to maximize $U(N_g, N_b)$. Then, $\beta_{CW}^* = \beta_C^*$.

Next, consider the content producer welfare function.

$$W_P = \int \max\{qV(D(\beta)) + (1-q)V(\beta D(\beta)) - \delta, 0\} k(\delta) d\delta$$

The social planner wants to choose β to maximize W_P. The integrand is weakly increasing in $qV(D(\beta)) + (1-q)V(\beta D(\beta))$, and β does not enter the problem elsewhere, so the social planner's problem is equivalent to choosing β to maximize $qV(D(\beta)) + (1-q)V(\beta D(\beta))$.

Compare this to the supply function.

$$S := S(i_g, i_b) = \int \mathbb{I}\{qV(D(\beta)) + (1-q)V(\beta D(\beta)) > \delta\} k(\delta) d\delta$$

Again, this function is weakly increasing in $qV(D(\beta)) + (1-q)V(\beta D(\beta))$, and β does not enter the problem elsewhere, so the problem is equivalent to choosing β to maximize $qV(D(\beta)) + (1 - q)V(\beta D(\beta))$. Then, $\beta^*_{PW} = \beta^*_P$.

Next, I will show that the optimal policy to maximize the three welfare objects are weakly ordered. The goal is to show that $\beta^*_{PW} \geq \beta^*_{SW} \geq \beta^*_{CW}$. I will start by showing that $\beta^*_{PW} \geq \beta^*_{CW}$.

For a contradiction, assume that $\beta^*_{PW} < \beta^*_{CW}$.

In order to choose β to maximize producer welfare, we want to choose β that maximizes $qV(D(\beta)) + (1 - q)V(\beta D(\beta))$. We know that β^*_{CW} maximizes $D(\beta)$, by definition.

Then, it must be the case that $V(D(\beta^*_{CW})) > V(D(\beta^*_{PW}))$ because V is an increasing function.

Moreover, it must be the case that $V(\beta^*_{CW} D(\beta^*_{CW})) > V(\beta^*_{PW} D(\beta^*_{PW}))$ because we have assumed that $\beta^*_{PW} < \beta^*_{CW}$ and we know that $D(\beta)$ is maximized at β^*_C.

But, this means that $qV(D(\beta^*_{CW}))+(1-q)V(\beta^*_{CW} D(\beta^*_{CW})) > qV(D(\beta^*_{PW}))+(1-q)V(\beta^*_{PW} D(\beta^*_{PW}))$, so β^*_{CW} provides higher producer welfare than β^*_{PW}. This contradicts the definition of β^*_{PW}, because we have identified a value of $\beta \neq \beta^*_{PW}$ that generates more producer welfare, so β^*_{PW} is not optimal. Then, $\beta^*_{PW} \geq \beta^*_{CW}$.

Next, consider the relationship between β^*_{CW} and β^*_{SW}. Recall that social welfare is assumed to be a linear combination of producer and consumer surplus. Consider a social planner trying to maximize W_S with $\alpha \in (0, 1)$.

$$
\begin{aligned}
W_S &= \alpha W_C + (1 - \alpha) W_P \\
&= \alpha \left(\int \max\{U(N_g, N_b), 0\} l(\epsilon) d\epsilon \right) \\
&+ (1 - \alpha) \left(\int \max\{qV(i_g) + (1 - q)V(i_b) - \delta, 0\} k(\delta) d\delta \right)
\end{aligned}
$$

For a contradiction, suppose that $\beta^*_{SW} < \beta^*_{CW}$. Note that, by definition, β^*_{CW} maximizes consumer welfare. Additionally, we have already shown that choosing $\beta < \beta^*_{CW}$ provides strictly less welfare to producers. Then, consider selecting $\beta = \beta^*_{CW}$. This increases both consumer and producer welfare relative to β^*_{SW}. But, this is a contradiction with the definition of β^*_{SW}, because it means that there exists a $\beta \neq \beta_{SW}$ that provides strictly larger social welfare. Then, we have that $\beta^*_{SW} \geq \beta^*_{CW}$.

Finally, consider the relationship between β^*_{PW} and β^*_{SW}. For a contradiction, suppose that $\beta^*_{SW} > \beta^*_{PW}$. By definition, β^*_{PW} maximizes producer welfare.

Now, consider consumer welfare, which depends on maximizing $U(N_g, N_b) = U(S, \beta S)$. By assumption, this function is increasing in its first argument, and decreasing in its second argument, because consumers like good content and dislike bad content. We're interested in the comparison of consumer welfare at two points β^*_{PW} and β^*_{SW}. Since maximizing producer welfare maximizes the number of producers on the platform, it must be the case that $S_{PW} > S_{SW}$.

Now, by assumption, $\frac{\partial D}{\partial S} > 0$, so we know that $D(S_{PW}, \beta S_{PW}) > D(S_{SW}, \beta S_{SW})$ for a fixed

β. In particular, consider β^*_{PW}, so we have

$$D(S_{PW}, \beta^*_{PW} S_{PW}) > D(S_{SW}, \beta^*_{PW} S_{SW})$$

Moreover, since demand is decreasing in its second argument, it must the case that

$$D(S_{SW}, \beta^*_{PW} S_{SW}) > D(S_{SW}, \beta^*_{SW} S_{SW})$$

since we have assumed that $\beta^*_{SW} > \beta^*_{PW}$. Then,

$$D(S_{PW}, \beta^*_{PW} S_{PW}) > D(S_{SW}, \beta^*_{SW} S_{SW})$$

This means that choosing β^*_{PW} provides higher consumer welfare than choosing β^*_{SW}. But, if β^*_{PW} provides higher consumer welfare and higher producer welfare, then we have found $\beta \neq \beta^*_{SW}$ that provides higher social welfare, which contradicts the definition of β^*_{SW}. So, we have that $\beta^*_{SW} \leq \beta^*_{PW}$.

Finally, consider maximizing the number of impressions on the platform. This is given by

$$\begin{aligned}\Pi &= D(N_g, N_b)(N_g + N_b)\\ &= D(S, \beta S)(S + \beta S)\end{aligned}$$

For a contradiciton, assume that $\beta^*_I < \beta^*_C$. By definition, β^*_C maximizes demand. Moreover, we have already shown that $\forall b < \beta^*_C$, $S(b) < S(\beta^*_C)$. But, this means that every term in the views profit function (D, S, β) is larger for β^*_C than for $\beta^*_I < \beta^*_C$, so we have identified a $\beta \neq \beta^*_I$ that generates a larger number of impressions. This contradicticts the definition of β^*_I, so it must be that $\beta^*_I \geq \beta^*_C$.

7.4 Multiple Consumer Types

Up until this point, I have considered one type of consumer who decides whether or not to join the platform. If this consumer joins the platform, then they "consume the platform" in the sense that they contribute one impression i for every piece of content on the platform $(N_g + N_b)$. While this assumption can be relaxed so that consumers views a fixed percentage of the platform, one reasonable objection is that many people consume a negligible fraction of content relative to the size of the platform. In this section, I will extend the model to account for an alternative type of consumer who consumes a fixed number of impressions M. I will refer to the initial type of consumer as a "heavy consumer" and call this new type of consumer a "light consumer."

Because M is assumed to be small in proportion to the supply of content, the platform has complete control over the allocation of M towards good and bad content. Define f as the fraction of a light consumer's impressions that go to good content.

Demand for light consumers $D_L(f, S)$ can depend on f as well as the total amount of content on the platform S. Intuitively, the reason that supply will still enter the demand function for light consumers who do not consume the whole platform is if there is an unmodeled horizontal differentiation in content, so that having more content implies having more types of content which attract different kinds of casual users.

Equilibrium (Heavy + Light). The market clearing equations must be rewritten to account for the inclusion of light consumers. An equilibrium in this model is a tuple $N_g^*, N_b^*, f^*, i_g^*, i_b^*$ such that:

1. The market for impressions of good content clears.

$$\underbrace{qS(i_g^*, i_b^*)}_{\substack{\text{Supply of}\\ \text{Good Content}}} \times \underbrace{i_g^*}_{\substack{\text{Impressions per}\\ \text{Good Content}}} = \underbrace{D_L(f, S)}_{\text{Light Consumer Demand}} \times \underbrace{fM}_{\substack{\text{Good Impressions per}\\ \text{Light Consumer}}} + \underbrace{D_H(N_g^*, N_b^*)}_{\text{Heavy Consumer Demand}} \times \underbrace{N_g^*}_{\substack{\text{Good Impressions per}\\ \text{Heavy Consumer}}}$$

2. The market for impressions of bad content clears.

$$\underbrace{(1-q)S(i_g^*, i_b^*)}_{\substack{\text{Supply of}\\ \text{Bad Content}}} \times \underbrace{i_b^*}_{\substack{\text{Impressions per}\\ \text{Bad Content}}} = \underbrace{D_L(f, S)}_{\text{Light Consumer Demand}} \times \underbrace{(1-f)M}_{\substack{\text{Bad Impressions per}\\ \text{Light Consumer}}} + \underbrace{D_H(N_g^*, N_b^*)}_{\text{Heavy Consumer Demand}} \times \underbrace{N_b^*}_{\substack{\text{Bad Impressions per}\\ \text{Heavy Consumer}}}$$

3. The composition of content shown on the platform is feasible.

$$N_g^* \leq S_g^* = qS^*(i_g^*, i_b^*)$$
$$N_b^* \leq S_b^* = (1-q)S^*(i_g^*, i_b^*)$$

Platform's Problem (Light Consumers). The platform's problem is

$$\begin{aligned} \max_{N_g, N_b, f, i_b, i_g} \quad & \Pi = D_H(N_g, N_b) + D_L(f, S) \\ \text{subject to} \quad & N_g \leq S_g(i_g, i_b) \\ & N_b \leq S_b(i_g, i_b) \\ qS(i_g, i_b) \times i_g &= fD_L(f, S)M + D_H(N_g, N_b) \times N_g \\ (1-q)S(i_g, i_b) \times i_b &= (1-f)D_L(f, S)M + D_H(N_g, N_b) \times N_\beta \end{aligned} \tag{5}$$

Now I will consider one case where the demand from light consumers increases when they are shown more good content. In particular, suppose that $D_L(S, f) = fS$.

Expressions for i_g and i_b Use the equality constraints to get an expression for i_g.

$$\begin{aligned} qS(i_g, i_b) \times i_g &= f^2 MS + D_H(N_g, N_b) \times N_g \\ i_g &= \frac{f^2 MS + D_H(N_g, N_b) \times N_g}{qS(i_g, i_b)} \\ i_g &= \frac{f^2 M + D_H(N_g, N_b)}{q} \end{aligned}$$

Similarly, use the other equality constraint to get an expression for i_b.

$$\begin{aligned} (1-q)S(i_g, i_b) \times i_b &= (1-f)fMS + D_H(N_g, N_b) \times N_b \\ i_b &= \frac{(1-f)fMS + D_H(N_g, N_b) \times N_b}{(1-q)S(i_g^*, i_b^*)} \\ i_b &= \frac{(1-f)fM + \beta D_H(N_g, N_b)}{(1-q)} \end{aligned}$$

Recasting this problem in β notation, the platform's problem is:

$$\begin{aligned} \max_{\beta, f} \quad & \Pi = D_H(S, \beta S) + fS \\ \text{such that} \quad & 0 \leq b \leq 1 \\ & 0 \leq f \leq 1 \\ & i_g = \frac{f^2 M + D_H(N_g, N_b)}{q} \\ & i_b = \frac{(1-f)fM + \beta D_H(N_g, N_b)}{(1-q)} \end{aligned}$$

Lemma 7. *If the producer attention utility function V is linear, then the platform should only show light consumers good content. Formally, if $V(i) = \beta i + \zeta$ with $\beta > 0$, then $f^* = 1$.*

Proof. Take the derivative $\frac{\partial \Pi}{\partial f}$.

$$\begin{aligned} \frac{\partial \Pi}{\partial f} &= \frac{\partial D_H}{\partial S}\frac{\partial S}{\partial f} + S + f\frac{\partial S}{\partial f} \\ &= \frac{\partial S}{\partial f}(\frac{\partial D_H}{\partial S} + f) + S \end{aligned}$$

By assumption, $\frac{\partial D_H}{\partial S} > 0$, $S > 0$ and $f \geq 0$. Then, if $\frac{\partial S}{\partial f} > 0$, $\frac{\partial \Pi}{\partial f}$ is always positive, so profit will be maximized at $f = 1$.

We want to know the sign of $\frac{\partial S}{\partial f}$. Since $V(i) = \beta i + \zeta$,

$$\begin{aligned}
S &= K(qV(\frac{f^2 M + D_H(N_g, N_b)}{q}) + (1-q)V(\frac{(1-f)fM + \beta D_H(N_g, N_b)}{(1-q)})) \\
&= K(\beta f^2 M + \beta D_H(N_g, N_b) + \zeta + \beta(1-f)fM + \beta\beta D_H(N_g, N_b) + \zeta) \\
&= K(\beta f M + D_H(N_g, N_b) + \beta D_H(N_g, N_b) + 2\zeta)
\end{aligned}$$

The derivative of the inner term with respect to f is βM which is positive since $\beta, M > 0$. Then, supply is increasing in f, so profit is increasing in f, so the platform should choose the maximum feasible f, $f^* = 1$.

Lemma 8. *If the producers attention utility function V is concave and $q < 0.5$, then $f^* < 1$.*

Proof. Recall that

$$\begin{aligned}
\Pi &= D_H + fS \\
\frac{\partial \Pi}{\partial f} &= \frac{\partial D_H}{\partial S}\frac{\partial S}{\partial f} + S + f\frac{\partial S}{\partial f} \\
&= \frac{\partial S}{\partial f}(\frac{\partial D_H}{\partial S} + f) + S
\end{aligned}$$

We are interested in finding a condition for when this derivative will be negative when $f = 1$.

$$\begin{aligned}
0 &> (\frac{\partial D_H}{\partial S} + f)\frac{\partial S}{\partial f} + S(i_g, i_b) \\
-(\frac{\partial D_H}{\partial S} + f)\frac{\partial S}{\partial f} &> S(i_g, i_b) \\
-\frac{\partial S}{\partial f} &> \frac{S(i_g, i_b)}{\frac{\partial D_H}{\partial S} + f} \\
-\frac{\partial S}{\partial f} &> \frac{S(i_g, i_b)}{\frac{\partial D_H}{\partial S} + 1}
\end{aligned}$$

In order for this condition to hold, it must be that $\frac{\partial S}{\partial f}$ is negative, since the right hand side of the inequality is the ratio of two positive terms. Recall the expression for supply in this model:

$$S = K(qV(\frac{fM}{q} + \frac{D_H(N_g, N_b)}{q}) + (1-q)V(\frac{(1-f)M}{(1-q)} + \frac{\beta D_H(N_g, N_b)}{(1-q)})$$

First, consider how the inner term changes with respect to f.

$$
\begin{aligned}
y &= qV(\frac{f^2M}{q} + \frac{D_H(N_g,N_b)}{q}) + (1-q)V(\frac{(1-f)fM}{(1-q)} + \frac{\beta D_H(N_g,N_b)}{(1-q)} \\
\frac{\partial y}{\partial f} &= qV'\left(\frac{f^2M}{q} + \frac{D_H(N_g,N_b)}{q}\right) \times \frac{2fM}{q} + (1-q)V'\left(\frac{(1-f)fM}{(1-q)} + \frac{\beta D_H(N_g,N_b)}{(1-q)}\right) \times [\frac{M}{(1-q)} - 2f\frac{M}{(1-q)}] \\
&= 2fMV'\left(\frac{f^2M}{q} + \frac{D_H(N_g,N_b)}{q}\right) + [M-2fM]V'\left(\frac{(1-f)fM}{(1-q)} + \frac{\beta D_H(N_g,N_b)}{(1-q)}\right) \\
&= MV'\left(\frac{(1-f)fM}{(1-q)} + \frac{\beta D_H(N_g,N_b)}{(1-q)}\right) \\
&+ 2fM[V'\left(\frac{f^2M}{q} + \frac{D_H(N_g,N_b)}{q}\right) - V'\left(\frac{(1-f)fM}{(1-q)} + \frac{\beta D_H(N_g,N_b)}{(1-q)}\right)]
\end{aligned}
$$

Evaluating the derivative of the inner term at $f = 1$, we have

$$
\frac{\partial y}{\partial f}(1) = MV'\left(\frac{\beta D_H(N_g,N_b)}{(1-q)}\right) + 2M[V'\left(\frac{M}{q} + \frac{D_H(N_g,N_b)}{q}\right) - V'\left(\frac{\beta D_H(N_g,N_b)}{(1-q)}\right)]
$$

If we call $\frac{\beta D_H(N_g,N_b)}{(1-q)} = x$, we know that this expression is equivalent to

$$
\begin{aligned}
\frac{\partial y}{\partial f}(1) &= MV'(x) + 2M[V'(x+\delta) - V'(x)] \\
&= M[V'(x+\delta) - V'(x)]
\end{aligned}
$$

Since M is positive, the size of this derivative depends on the relative size of $V'(x+\delta)$ and $V'(x)$. For $q > 0.5$, we know that δ is positive. To see this, consider the inequality

$$
\frac{M}{q} + \frac{D_H(N_g,N_b)}{q} > \frac{\beta D_H(N_g,N_b)}{(1-q)}
$$

Since $\frac{M}{q} > 0$, this inequality will hold if

$$
\begin{aligned}
\frac{D_H(N_g,N_b)}{q} &> \frac{\beta D_H(N_g,N_b)}{(1-q)} \\
1-q &> qb \\
1 &> q + qb \\
0.5 &> q
\end{aligned}
$$

where we use the fact that $b \leq 1$.

Then, V concave and $q < 0.5$ guarantees that $\frac{\partial y}{\partial f}(1) < 0$. Moreover, if $v'(x) >> v'(x+\delta)$, then $\frac{\partial y}{\partial f}$ can be made arbitrarily negative.

Now, thinking about the larger derivative $\frac{S}{f}$, note that

$$\frac{S}{f} = k(\cdot)\frac{\partial y}{\partial f}$$

where we know that $k(\cdot)$ is positive and is constant for fixed values of q, b, D_H, M, as well as fixed values of $V(\frac{M}{q} + \frac{D_H(N_g,N_b)}{q})$ and $V(\frac{\beta D_H(N_g,N_b)}{(1-q)})$. Then, fixing all of these values, but letting $v'(x)$ be large, guarantees an arbitrarily negative $\frac{\partial S}{\partial f}$.

Choose $V'(x)$ large enough to satisfy $-\frac{\partial S}{\partial f} > \frac{S(i_g,i_b)}{\frac{\partial D_H}{\partial S}+1}$, which is possible because the terms on the right hand side of the inequality do not depend on $V'()$.

Then, $f^* < 1$.

Discussion. These two lemmas relate the producer valuation function V to the optimal fraction of good content to show light consumers f. The key takeaway is that for V concave enough, the platform should show light consumers some bad content. This is true even though showing light consumers bad content directly trades off with showing light consumers good content. The intuition for this result is that choosing $f = 1$ means all of the attention from light consumers is going to content producers in the good state. For concave V, producers would prefer it if some attention was redistributed from the good state to the bad state since they are receiving less attention in the bad state, so choosing $f < 1$ will increase supply. If V is concave enough, then choosing slightly lower f will result in a large increase in supply, and it will be optimal to choose $f^* < 1$. The idea is that a large increase in content supply will increase demand of heavy consumers in a way that more than offsets the loss in demand of light consumers from choosing $f < 1$, so total profits will increase.