The Impact of Social Nudges on User-Generated Content for Social Network Platforms

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Content-sharing social network platforms rely heavily on user-generated content to attract users and advertisers, but have limited authority over content provision. We develop an intervention that leverages social interactions between users to stimulate content production. We study *social nudges* whereby users connected with a content provider on a platform encourage her to supply more content. We conducted a randomized field experiment (N$= 993,676$) on a video-sharing social network platform, where treatment providers could receive messages from other users encouraging them to produce more videos but control providers could not. We find that social nudges not only immediately boosted video supply by 13.21% without changing video quality but also increased the number of nudges providers sent to others by 15.57%. Both the production-boosting and diffusion effects of social nudges were amplified when nudge senders and recipients had stronger ties. These effects, though declining over time, lasted beyond the day of receiving nudges. We replicate these results in a second experiment. To estimate the overall production boost over the entire network and conduct counterfactual analyses, we combine the experimental data with a social network model that captures the diffusion and over-time effects of social nudges. We showcase the importance of considering the network effects when estimating the impact of social nudges or optimizing social nudge seeding. This research highlights the value of leveraging co-user influence for platforms, and provides guidance for future research to incorporate the diffusion of an intervention into the estimation of its impacts within a social network.

Key words: Content Production, Platform Operations, Social Network, Field Experiment, Information-based Interventions

1. Introduction

Online content-sharing social network platforms such as Facebook and TikTok, where users create and consume content, are playing an increasingly important role in society. As of January 2021, an estimated 4.2 billion people, 53.6% of the world's population, use these platforms.[1] They have evolved into powerful marketing tools, reshaping the global economy. For example, advertising spending on these types of platforms is expected to reach US$110.6 billion in 2021.[2] User-generated

[1] https://datareportal.com/reports/digital-2021-global-overview-report.

[2] https://www.statista.com/outlook/dmo/digital-advertising/social-media-advertising/worldwide.

content (UGC) on these platforms can exert considerable influence on consumer decision-making, affecting sales of products and services (e.g., Chen et al. 2011).

These platforms, by nature, rely heavily on UGC to engage and retain both users and advertisers. However, since users who generate organic content (or "content providers") are not paid workers and UGC is essentially a public good, platforms have limited control over how often and how much users produce content and at what quality level (Yang et al. 2010, Gallus 2017). Hence, the underprovision of UGC has been a challenge that interests both practitioners (Pew Research Center 2010) and academics (Burtch et al. 2018, Huang et al. 2019, Kuang et al. 2019). Understanding drivers of content production and devising effective operational levers to motivate content production are vital for content-sharing social network platforms—this is the focus of our research.

A prominent feature of these platforms is that users have intensive social interactions with each other. The platforms can leverage the connections between users to stimulate UGC supply, as well as to help solve other operational problems. We study a novel kind of intervention that utilizes existing connections between users, capitalizes on psychological principles about when people are motivated to exert effort, and contains no financial incentives. Specifically, we study a type of *social nudge,* whereby a user's neighbors on a platform—platform users who are connected to this user—encourage her to supply more content on the platform.[3] We propose that by taking the time to nudge a user, neighbors convey that they value the user and her work. This subtle expression of recognition may make the user feel more competent and appreciated (Ryan and Deci 2000), which further motivates content provision (Grant and Gino 2010, Bradler et al. 2016).

Prior psychological and management research suggests that recognition from managers, companies, or platforms (Ashraf et al. 2014a,b, Bradler et al. 2016, Banya 2017, Gallus 2017) can boost recipients' production and retention. However, scant research has causally examined the motivating power of pure *peer recognition* that is not accompanied by financial incentives; moreover, this limited work has presented mixed evidence for the effectiveness of peer recognition in boosting production (Restivo and van de Rijt 2014, Gallus et al. 2020). Also, prior research has been silent about how interactions on a platform and its underlying social network could reinforce the effects of an intervention on production. Taking a more holistic perspective, we implemented large-scale field experiments to not only estimate the direct effect of our intervention (social nudges) on recipients' content production but also assess how being exposed to the intervention facilitates the spread of the intervention, which further stimulates additional recipients' content production. We

[3] The word *nudge* is a behavioral science concept for describing interventions that intend to change individuals' behaviors without altering financial incentives or imposing restrictions (Thaler and Sunstein 2009). Nudges are usually implemented by managers, marketers, and policy makers. We coin the term *social nudges* to refer to nonfinancial, nonrestrictive interventions that neighbors implement to influence others in the same network.

then incorporated empirical findings from these field experiments into a social network model to estimate the impact of our intervention on content production over the entire social network.

Specifically, we conducted two randomized field experiments on a large-scale video-sharing social network platform (hereafter "Platform O"). As on Facebook, each user on Platform O can have two roles: content provider and content viewer. Users can follow other users and be followed. In this setting, we refer to a user's followers and to the users whom the user herself follows as *neighbors*.

We study social nudges sent by one type of neighbor: a user's followers. For users involved in our experiments, their followers could send them a message to convey the interest in seeing their videos and nudge them to upload more videos. Users in our experiments were randomly assigned to either the treatment or the control condition. The only difference introduced by our experimental manipulation between conditions was whether users could actually receive social nudges: treatment users could receive social nudges sent by their neighbors but control users could not. Because the difference between the two groups of users lay in their roles as providers and our primary focus was content production, we hereafter refer to users involved in our experiments as *providers*. We conducted our main experiment—the focus of this paper—from September 12 to 14, 2018, and our second experiment—our replication study (see Online Appendix B)—from September 14 to 20, 2018.

Our main experiment, in which we analyzed $993,676$ providers, reveals several important findings. To begin with, we present five main findings about the effects of social nudges on recipients' content production (**direct effects of social nudges on production**). First, receiving social nudges boosted the number of videos that treatment providers uploaded on the day they received the first nudges by 13.21%, without causing providers to alter their video quality. This in turn increased consumption of treatment providers' content by 10.42%. Second, receiving a social nudge yielded a larger immediate boost in production when a provider and the follower who sent the nudge had a two-way tie (i.e., the provider was also following the follower) than when they had a one-way tie (i.e., the provider was not following the follower), suggesting that stronger ties between users strengthen the effect of social nudges on production. Third, the effect of receiving social nudges on production declined over time but remained significant until three days after social nudges were sent. Fourth, we showed that the difference in video supply between conditions was unlikely to be driven by control providers realizing that they were not allowed to receive social nudges and thus feeling resentful toward the platform. Fifth, leveraging data from another experiment on Platform O that studied nudges sent to providers *by the platform,* we found suggestive evidence that social nudges from peer users can more effectively boost production than platform-initiated nudges.

Next, we examined whether providers receiving social nudges became more likely to send nudges to users they follow, which, if holding true, could further boost production on the platform (**indirect effects of social nudges on production**). We present three key findings about nudge diffusion. First, treatment providers sent 15.57% more social nudges on the day of receiving social nudges, relative to control providers. Second, receiving a social nudge had a stronger effect on providers' willingness to send social nudges when they got a nudge from a two-way tie (vs. from a one-way tie). Third, the diffusion effect of social nudges declined over time and was significant within two days of receiving social nudges.

The diffusion of social nudges by nudge recipients as well as the over-time effects of social nudges impose challenges for estimating the impact of social nudges on production and in turn optimizing social nudge strategies in other counterfactual scenarios. We refer to the stationary effect of social nudges on content production on the entire social network where every user could receive and send social nudges as the *global effect* of social nudges. To precisely estimate the global effect of social nudges, we propose an infinite-horizon stochastic social network model. We model the social network embedded on Platform O as a directed graph in which each user is a node, and each following relationship is an edge. Based on our empirical evidence, the actual number of nudges sent on an edge in a period depends on both (1) the baseline number of nudges that would be sent without the influence of nudge diffusion and (2) the number of nudges its origin has received (i.e., the diffusion of nudge). Each user's production boost in a period is determined by all the social nudges she has received. We also incorporate the time-decaying effect of both direct and indirect effects of social nudges with estimated decaying factors. Leveraging such a social network model, we provide a framework to estimate the global effect of social nudges on production boost, and show that simply comparing the number of videos uploaded by treatment vs. control providers right after they were sent social nudges during the field experiment severely underestimates the global effect of social nudges. Moreover, via simulation, we showcase that platforms can use this model to optimize operational decisions regarding social nudges, highlighting this model's potential to improve platform performance.

In summary, we study a low-cost, behaviorally informed intervention that is initiated by platform neighbors and can be widely applied to users on a platform. Empirically, we document both its direct production-boosting effect and its diffusion by intervention recipients. Theoretically, we develop a model to incorporate the diffusion of an intervention into a social network model, thus allowing for a precise estimate of its global effect on production over the entire platform as well as optimization of its overall effectiveness. Methodologically, our work provides guidance to future researchers for more comprehensively estimating an intervention's causal effects on a social network. Practically, our proposed low-cost, psychology-based intervention is valuable to online content-sharing social network platforms for managing their UGC content, and our model can be a useful tool for platforms to optimize the strategy for increasing the global effect of an intervention.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 introduces our field setting, experimental design, and data. Sections 4 and 5 present the direct effect of social nudges on content production, and the diffusion of nudges, respectively. Section 6 describes the social network model, counterfactual analyses, and an optimization simulation. In Section 7, we discuss practical implications of our research and directions for future research.

2. Literature Review

Our research builds primarily on four streams of literature: production, peer effects and social networks, information-based interventions, and platform operations.

Production. Our work is most closely connected to research that seeks to motivate content generation on online content-sharing platforms. The interventions examined in prior work include financial incentives (e.g. rewarding content providers with money; Cabral and Li 2015, Burtch et al. 2018, Kuang et al. 2019), social norms (e.g., informing content providers about what most of their peers do; Chen et al. 2010, Burtch et al. 2018), performance feedback (e.g., informing content providers about their performances; Huang et al. 2019), hierarchies (e.g., ranking content providers based on their contributions to a website; Goes et al. 2016), symbolic awards (e.g., giving content providers badges based on their recent activities; Ashraf et al. 2014a, Restivo and van de Rijt 2014, Gallus 2017), and a combination of these tools (Burtch et al. 2018, 2019).

Our contribution to this literature is threefold. First, we study a novel intervention (social nudges) that leverages individual-to-individual peer recognition, contains no material incentives, and is applicable to all content providers on a platform. Apparently, social nudges differ fundamentally from financial incentives, social norms, performance feedback, and hierarchies. And, although social nudges are related to symbolic awards in the sense that both convey recognition without monetary incentives, awards must be given to a select body of users who deserve them (e.g., users who recently contributed UGC, top-performing users) in order to maintain their prestige and meaning, and thus they are more limited in their scope of application than social nudges.

Second, the nascent literature that examines recognition-based interventions (Frey and Gallus 2017) has mostly studied recognition communicated by authoritative figures such as managers and organizations (Ashraf et al. 2014a, Gallus 2017). The scant work examining the causal effect of peer recognition without financial incentives (Restivo and van de Rijt 2014, Gallus et al. 2020) presents mixed evidence for whether peer recognition can increase users' contributions. Specifically, Restivo and van de Rijt (2014) conducted a field experiment among the top 10% of providers to Wikipedia. They found that peer recognition increased production only among the most productive 1% providers but did not affect other providers who were relatively less productive (those at the 91st to 99th percentile). If anything, the treatment *reduced* retention of providers at the 91st to 95th percentile. In a field experiment among NASA's workforce, Gallus et al. (2020) found a null effect of peer recognition on individuals' contributions to a crowdsourcing platform in NASA. Thus, it remains an open question whether an intervention that conveys peer recognition boosts recipients' effort provision. We speak to this open question by implementing large-scale field experiments to test the effectiveness of an intervention that conveys peer recognition.

Third, prior studies have focused on testing the effects of an intervention on targets' content production, but they have rarely focused on whether and how the intervention diffuses (i.e., how a user, upon receiving the intervention, spreads and applies it to influence other users). We take a critical first step in this direction by not only empirically examining the diffusion of social nudges but also incorporating the diffusion process into our social network model to more accurately estimate the impact of our intervention on content production over the entire social network.

Within the production literature, our research is also related to prior studies on how to lift productivity in service and manufacturing settings. These studies have focused on four types of interventions for increasing productivity: those that (1) are based on workers' economic considerations (Lazear 2000, Celhay et al. 2019), (2) offer workers training (De Grip and Sauermann 2012, Konings and Vanormelingen 2015) or introduce information technology (Tan and Netessine 2020), (3) assign workers to various staffing or workload settings (Tan and Netessine 2014, Moon et al. 2018), and (4) capitalize on workers' psychological needs and tendencies (Kosfeld and Neckermann 2011, Roels and Su 2014, Song et al. 2018). These interventions are usually implemented by firms or managers. Extending this line of work, we develop and test a novel psychology-based intervention that does not originate from firms or managers but instead leverages peer recognition to motivate effort provision and production.

Peer effects and social networks. Research about peer effects (Zhang et al. 2017, Bramoullé et al. 2020) often investigates how schoolmates (Sacerdote 2001, Whitmore 2005), coworkers (Mas and Moretti 2009, Tan and Netessine 2019), family members (Nicoletti et al. 2018), residential neighbors, and friends (Kuhn et al. 2011, Bapna and Umyarov 2015) affect someone's own behaviors, ranging from mundane consumption and product adoption to consequential outcomes about education, health, and career.

We extend this literature about peer effects in two ways. First, whereas prior research cares about estimating how peers affect each other but does not usually distinguish whether peers exert influence passively (e.g., peers' choices are observed by others who then feel pressure to choose accordingly) or actively (e.g., peers persuade others to make certain choices), we clearly assess the active impact of peers by examining a novel kind of interaction initiated by peers because of their intention to influence others (i.e., peers send nudges to others in the hope of boosting others' production). Second, whereas prior research has normally focused on the effects of peers' outcomes (or behaviors) on another person's outcomes (or behaviors) in the same domain, our work simultaneously examines how peers actively influence another person's production via sending a social nudge as well as how the nudged person subsequently "learns," adopts the same tactic, and spreads this form of active influence via sending nudges to more peers.

Besides peer effects, we also speak to the literature that optimizes operational objectives based on social network models such as identifying key users (Ballester et al. 2006), seeding (Zhou and Chen 2016, Candogan and Drakopoulos 2020, Gelper et al. 2021), pricing (Candogan et al. 2012, Papanastasiou and Savva 2017, Cohen and Harsha 2020), and advertising (Bimpikis et al. 2016). Drawing insights from this literature, we propose an infinite-horizon stochastic social network model to characterize user interaction in a social network that allows for the precise calculation and optimization of an intervention's global effect. Our work takes this literature one step further by leveraging causal estimates from field experiments to calibrate model parameters, leading to an end-to-end implementation of such an optimization strategy.

Information-based interventions. Our work adds to the emergent OM literature that empirically tests the effectiveness of information-based interventions in solving operational problems. This literature has examined such interventions as offering customers more information about firms and the market (Buell and Norton 2011, Parker et al. 2016, Cui et al. 2019, Li et al. 2020, Mohan et al. 2020, Xu et al. 2021), and offering service providers more information about customers (Buell et al. 2017, Cui et al. 2020a). These interventions have been shown to increase customers' engagement with firms and perceived service value as well as to improve service speed and capacity. We contribute to this literature by designing a novel information-based intervention that originates from neighbors within a social network, then causally demonstrating its production-boosting effect and diffusion.

Platform operations. Finally, our research extends the growing literature that addresses operations problems on online platforms. This literature has examined how to build effective systems for pricing (Cachon et al. 2017, Bimpikis et al. 2019, Bai et al. 2019, Zhang et al. 2020), recommendations (Banerjee et al. 2016, Mookerjee et al. 2017), staffing rules (Gurvich et al. 2019, and optimization of content production (Caro and Martínez-de Albéniz 2020); it has also studied how to estimate and leverage the spillover effects across platform users (Zhang et al. 2019, 2020), and how to ensure service quality (Cui et al. 2020b, Kabra et al. 2020). We contribute to the platform operations literature by empirically demonstrating that allowing platform users to send social nudges—a low-cost, easy-to-implement strategy—could lift content production and, in turn, total capacity and consumption on content-sharing platforms.

3. Field Setting, Experiment Design, and Data

3.1. Field Setting and Experimental Design

To empirically examine the impact of social nudges, we collaborated with Platform O where each user can have two roles simultaneously—content provider and content viewer. Content providers (a) can upload videos for distribution on Platform O, (b) can decide when and what to post, and (c) do not get paid by Platform O for uploading videos. Content viewers can watch videos for free. Platform O, like most online content-sharing platforms, generates revenue primarily through online advertising (i.e., disseminating advertising videos to users).

Videos on Platform O are usually short, typically just a few seconds to a few minutes. Popular subjects include daily lives (e.g., views of a nearby park, work scenes, kids, pets), jokes or funny plots, performance (e.g., dancing, singing, making art), and know-how (e.g., cooking or makeup tips). Video content is usually displayed to users on one of three pages: (1) videos uploaded by providers they follow, (2) popular videos recommended by Platform O, and (3) videos of providers who are geographically close to a given user.

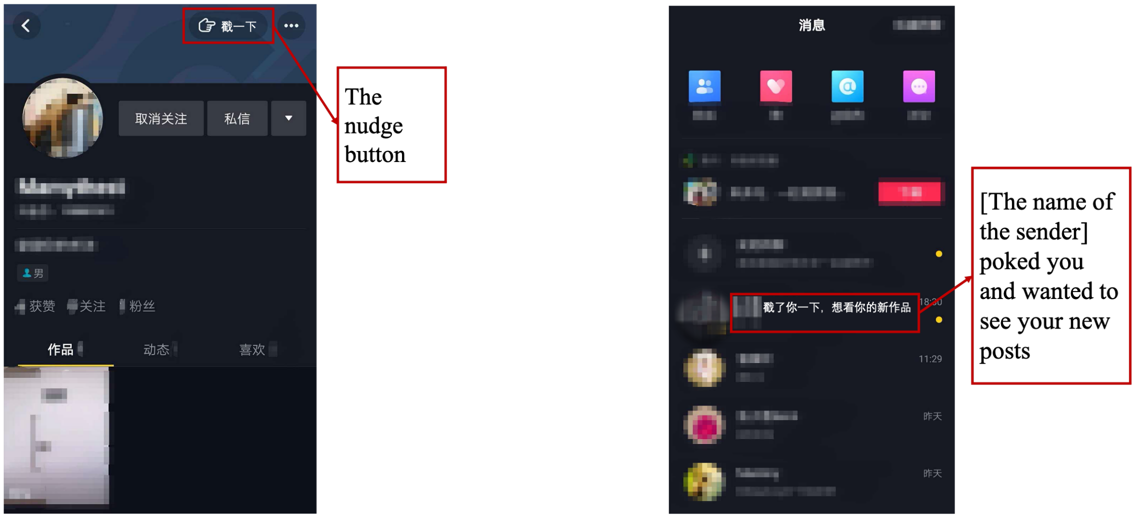
When watching a video, users can leave comments beneath the video and upvote it by clicking the *like* button. The only way for users to privately and directly communicate with each other on Platform O is through the private-message function. To establish closer relationships, users can click the "follow" button (available at the top of a video or on another user's profile page) to follow other users of interest.

We conducted two randomized field experiments to causally test how social nudges from neighbors affect users' video production. The first experiment lasted from 2 p.m. on September 11, 2018, to 5 p.m. on September 14, 2018. This is our main study. Our second field experiment, which replicates the first experiment, lasted from 5 p.m. on September 14, 2018, to the end of September 20, 2018. This experiment (see Online Appendix B for the data and results) targeted a smaller, nonoverlapping group of providers but lasted longer.

For providers involved in our experiments, their followers could send them a standard message to nudge them to upload new videos if they had not published videos for one or more days.[4] To do so, followers simply clicked a button on the provider's profile page that read, "Poke this provider" (or *ChuoYiXia* in Chinese; see Figure 1 (a)). We refer to this behavior as "sending a social nudge."

Providers in our experiments were randomly assigned to either the treatment or the control condition. The only factor that we manipulated between the two conditions was whether providers were able to view social nudges sent to them. Specifically, treatment providers could see social nudges sent to them in their message center, along with other kinds of messages, whereas control

[4] Most providers could satisfy this requirement. For example, on the first day of the experiment, among all providers on Platform O who uploaded any videos in the past 30 days, 88% had not posted a video for one or more days.



(a) A Provider's Profile Page With the Nudge Button (b) A Social Nudge in the Message Center

Figure 1 How Social Nudges Are Sent by Neighbors and Displayed to Treatment Providers[6]

providers could *not* see the social nudges in their message center. The standard social-nudge message to all providers said, "[Name of the sender] poked you and wanted to see your new posts" (see Figure 1 (b)).[5] If treatment providers clicked on a social-nudge message, they would be directed to a list of all nudges that had ever been sent to them. On that page, newer nudges were displayed closer to the top. There, each social-nudge message read, "[Name of the sender] poked you [time when the nudge was sent] and wanted to see your new posts." We designed these social nudges to be bare-bones simple, and standardized, so as to examine as cleanly as possible the basic effect of being nudged by a neighbor.

3.2. Data and Randomization Check

For the main analyses, our sample of providers ($N = 993,676$) included all treatment providers and control providers who satisfied two criteria: (1) at least one of their followers sent them a social nudge during our experiment, and (2) they had never received any social nudges before the experiment.[7] Treatment and control providers in our sample preserved the benefits of random assignment, because our random assignment of providers into the treatment vs. control condition

[5] In the message center, the most recent message appears at the top. Messages about social nudges were not given a higher priority over other types of messages. In general, messages disappear only when providers delete them.

[6] To protect Platform O's identity, we digitally altered the app interface of a widely used video-sharing platform in China to obscure some nonessential details and reflect where the nudge button and social nudges are and what they look like on Platform O. Platform O has a similar app interface.

[7] In the few months before our first experiment, social nudges were being tested and developed; as a result, some providers in our experiment received social nudges before the experiment. We removed those providers, per our second selection criterion, in order to estimate how social nudges change behavior when a platform starts to implement the social-nudge function. Our results are qualitatively unchanged if we remove the second criterion and include all providers whose followers sent them at least one social nudge during our experiment (see Online Appendix A.1).

Table 1 Randomization Check

		Treatment Providers (1)	Control Providers (2)	P-Value of Two-Sample Proportion Test or t-test (3)
Statistics on the Day Prior to the Experiment	Proportion of Females	51.34%	51.38%	0.69
	Number of Followers	8.76×10^{-3}	-8.76×10^{-3}	0.76
	Number of Following	3.06×10^{-3}	-3.06×10^{-3}	0.38
Statistics During One Week Prior to the Experiment	Number of Uploaded Videos	-9.71×10^{-3}	9.71×10^{-3}	0.33
	Number of Days with Videos Uploaded	-1.04×10^{-2}	1.04×10^{-2}	0.30

Notes: All variables, other than the proportion of females, were standardized to have a zero mean and unit standard deviation. Regarding the proportion of females, we excluded the $8,895$ providers ($\sim$ 0.9%) who did not have gender information.

had no way of affecting whether and when their neighbors sent them the first social nudge during the experiment. To confirm the success of randomization among our sample of providers, we compared treatment providers (n = $496,976$) and control providers (n = $496,700$) in their gender, basic network characteristics, and preexperiment production statistics. As shown in Table 1, treatment and control providers in our sample had similar proportions of female providers, number of users who were following them ("number of followers") on the day prior to the experiment, and number of users they were following ("number of following") on the day prior to the experiment, as well as the number of videos they uploaded and the number of days when they uploaded any video during the week prior to the experiment. These results confirm that the treatment and control providers in our sample were comparable, suggesting that any difference between conditions after the experiment started should be attributed to our experimental manipulation—that is, whether providers could receive social nudges.

4. Direct Effects of Social Nudges on Content Production

We began our investigation by examining the effects of receiving social nudges on the recipient's content production (i.e., the direct effects of social nudges on content production). The time unit we focused on was one day, which matches the granularity of our data offered by Platform O. Platform O cares about aggregate daily metrics (e.g., daily active providers, daily new videos), which breaks down to daily metrics at the individual level (e.g., on a given day, whether a user uploaded any video, how many videos she uploaded). In addition, 79% of providers in our sample had median intervals of video postings[8] equal to or greater than one day, further confirming the appropriateness of using one day as the time unit.

[8] For each provider, we calculated the interval (in days) between any two videos she successively uploaded (which equaled zero if two videos were uploaded on the same day) from January 1, 2018, to the day before the main experiment, then we calculated her *median interval of video postings* across all pairs of successively uploaded videos.

4.1. Direct Effects of Social Nudges on Content Production on the First Reception Day

We first tested whether social nudges had a positive effect on content production on the first day when a provider could be affected—that is, the day a provider was sent the first social nudge during the experiment; we refer to it as the providers' *first reception day*. Most (97%) providers in our sample were sent only *one* social nudge on the first reception day, suggesting the effects of our intervention on the first reception day were mostly driven by receiving one social nudge. Our unit of analysis was a provider on her first reception day; we analyzed $993,676$ observations, with each provider contributing one observation.

We used the following ordinary least squares (OLS) regression specification with robust standard errors to causally estimate the effects of social nudges on the first reception day:

$$Outcome\ Variable_i = \beta_0 + \beta_1 Treatment_i + \epsilon_i \tag{1}$$

where $Outcome\ Variable_i$ is detailed later, and $Treatment_i$ is a binary variable indicating whether provider i was in the treatment (vs. control) condition.

To protect Platform O's data privacy, we standardized all continuous variables used in our regression analyses (including outcome variables and predictor variables) to have a zero mean and unit standard deviation. To make it easier to interpret the magnitude of each observed main effect, we also report its relative effect size, which we obtained by running the same regression on raw data without standardization and dividing the estimated average treatment effect (i.e., the coefficient on treatment) by the average of the corresponding outcome variable in the control condition.

For each provider i, we first examined the number of videos she uploaded on the first reception day ($Number\ of\ Videos\ Uploaded_i$). We used regression specification (1) to predict $Number\ of\ Videos\ Uploaded_i$; we report the regression results in column (1) of Table 2. The positive and significant coefficient on treatment indicates that receiving social nudges immediately had a positive effect on the nudge recipient's production. Specifically, receiving social nudges increased the number of videos uploaded on the first reception day by 0.0262 standard deviations ($p < 0.0001$), a 13.21% increase relative to the average in the control condition.

Two underlying forces may drive this production-boosting effect: (1) providers became more willing to upload at least one video on the first reception day, and (2) providers who decided to upload at least one video on the first reception day uploaded more videos on that same day. To test the presence of the first force, for each provider i, we examined whether or not she uploaded at least one video on the first reception day ($Upload\ Incidence_i$). To test the presence of the second force, we examined the number of videos uploaded on the first reception day among providers who uploaded at least one video that day ($Number\ of\ Videos\ Uploaded\ Conditional\ on\ Uploading\ Anything_i$).

Table 2 Direct Effects of Social Nudges on Content Production on the First Reception Day

	Main Treatment Effects			*Heterogeneous Treatment Effect*
Outcome Variable	Number of Videos Uploaded	Upload Incidence	Number of Videos Uploaded Conditional on Uploading Anything	Number of Videos Uploaded
	(1)	(2)	(3)	(4)
Treatment	0.0262****	0.0094****	-0.0168	0.0186****
	(0.0020)	(0.0005)	(0.0181)	(0.0025)
Two-Way Tie				0.0700****
				(0.0027)
Treatment * Two-Way Tie				0.0159***
				(0.0041)
Relative Effect Size	13.21%	13.86%		
Observations	993,676	993,676	71,883	993,676

Notes: Continuous variables (Number of Videos Uploaded and Number of Video Uploaded Conditional on Uploading Anything) were standardized to have a zero mean and unit standard deviation before entering the regressions. The unit of analysis for all columns was a provider on her first reception day. Columns (1), (2), and (4) include all providers in our sample. Column (3) includes the providers who uploaded at least one video on her first reception day. Robust standard errors are reported in parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

We used regression specification (1) to predict $\textit{Upload Incidence}_i$ and $\textit{Number of Videos Uploaded Conditional on Uploading Anything}_i$. Column (2) of Table 2 shows that receiving social nudges lifted the average probability of providers uploading any videos on the first reception day by 0.94 percentage points ($p < 0.0001$), a 13.86% increase relative to the average probability in the control condition. However, as shown in column (3) of Table 2, $\textit{Number of Videos Uploaded Conditional on Uploading Anything}_i$ did not statistically significantly differ between conditions ($p = 0.3533$). Altogether, these results suggest that the boost in video supply on the first reception day was mainly driven by the first force—that is, providers became more willing to upload something after receiving social nudges.

Inspired by the social network literature (e.g., Jackson 2005), we next examined whether social nudges from closer peers could be more motivating. To answer this question, we tested whether the direct effects of social nudges on content production became stronger if a provider was also following the follower who sent her a nudge (in which case we refer to the relationship between the provider and the nudge sender as a two-way tie) than if the provider was not following that follower (in which case we refer to their relationship as a one-way tie). For each provider i on her first reception day, we identified the follower who sent the first social nudge to provider i, i.e., *the first nudge sender*. We constructed a binary variable, $\textit{Two-Way Tie}_i$, which equals one if provider i was also following her first nudge sender and zero otherwise. We used the following regression specification with robust standard error to predict $\textit{Number of Videos Uploaded}_i$, where each observation was a provider on her first reception day:

$$\begin{aligned} \textit{Outcome Variable}_i =& \beta_0 + \beta_1 \textit{Treatment}_i + \beta_2 \textit{Two-Way Tie}_i \\ &+ \alpha_3 \textit{Treatment}_i * \textit{Two-Way Tie}_i + \epsilon_i \end{aligned} \tag{2}$$

Column (4) of Table 2 shows that the coefficient on the interaction between $Treatment_i$ and $Two\text{-}Way\ Tie_i$ is significant and positive (p < 0.001). This suggests that, consistent with the social network literature (Jackson 2005), receiving social nudges increased a provider's content production to a greater extent when the provider and the follower who sent the nudge had a two-way tie than when they had a one-way tie. Specifically, receiving a social nudge from a follower with a one-way tie boosted the number of videos uploaded on the first reception day by 0.0186 standard deviations (p < 0.0001), whereas receiving a social nudge from a follower with a two-way tie boosted the number of videos uploaded by 0.0345 (i.e., 0.0186 + 0.0159) standard deviations (p < 0.0001). The relative effect size, compared to the average number of videos uploaded in the control condition, is 9.35% (one-way tie) and 17.40% (two-way tie), respectively.

4.2. Direct Effects of Social Nudges on Content Consumption and Content Quality

Beyond video production, how do social nudges affect overall video consumption and video quality? To evaluate the direct effects of social nudges on video consumption, we focused on the total number of views each provider engendered that could be attributed to videos they uploaded on the first reception day. Specifically, for each provider i, $Total\ Views_i$ equals the total number of views across all videos that provider i uploaded on the first reception day. If provider i did not upload videos on the first reception day, $Total\ Views_i$ equals zero, which reflects the fact that no views were engendered by provider i as a result of her production effort on the first reception day. To address outliers, we winsorized $Total\ Views_i$ at the 95th percentile of nonzero values.[9] Note that following Platform O's common practice, for each video uploaded on the first reception day, we tracked the total number of views it received over the first week since its creation. Platform O normally uses the views each video accumulates during the first week after its creation to capture the short-term consumption it brings, because videos on Platform O are usually watched much more frequently during the first week and attract fewer views as time goes by.

We used regression specification (1) to predict $Total\ Views_i$. As shown in column (1) of Table 3, receiving social nudges increased the total views providers contributed to the platform as a result of their production effort on the first reception day by 0.0171 standard deviations, a 10.42% increase relative to the average in the control condition.[10]

To assess video quality, we collected four quality measures about every video uploaded on a provider's first reception day during the following week. Then we calculated the average of each

[9] Since the majority of providers produced no videos on the first reception day and consequently had a value of zero for $Total\ Views_i$, the 95th percentile of the raw values of $Total\ Views_i$ was small. Since we wanted to address extreme outliers caused by a small number of videos that went viral, we winsorized at the 95th percentile of nonzero values. That is, we replaced values of $Total\ Views_i$ that were greater than the 95th percentile of the nonzero values with the 95th percentile of the nonzero values. The result is robust if we winsorize at the 99th percentile of the nonzero values.

[10] The positive effect of social nudges on content consumption is robust if we use the total views a provider obtained on her first reception day as the outcome variable.

Table 3 Effects of Social Nudges on Video Consumption and Quality

Panel A: Main Treatment Effects					
Outcome Variable	Total Views	Complete View Rate	Like Rate	Comment Rate	Following Rate
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0171****	0.0007	-0.0176*	-0.0061	0.0041
	(0.0020)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
Observations	993,676	71,634	71,634	71,634	71,634
Relative Effect Size	10.42%		-1.51%		

Panel B: Investigating Why Treatment Providers Had Lower Like Rates Than Control Providers		
Outcome Variable	Historical Like Rate	Like Rate
	(1)	(2)
Treatment	-0.0521****	0.0078
	(0.0085)	(0.0062)
Historical Like Rate		0.5177****
		(0.0070)
Observations	69,594	69,594
Relative Effect Size	-3.48%	

Notes: All continuous variables were standardized to have a zero mean and unit standard deviation before entering the regressions. The unit of analysis for all columns was the provider level. Column (1) in Panel A includes all providers in our sample. Columns (2)–(5) in Panel A include providers whose videos uploaded on their first reception day were watched at least once in the following week. Columns (1)–(2) in Panel B include providers whose videos uploaded on their first reception day were watched at least once in the following week and whose earlier videos were watched at least once between January 1, 2018, and the day prior to the experiment (September 11, 2018). Robust standard errors are reported in parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

quality measurement across these videos: (1) the average percentage of times viewers watched a video until the end (*Complete View Rate*), (2) the average percentage of viewers who gave likes to a video (*Like Rate*), (3) the average percentage of viewers who commented on a video in the comments section beneath it (*Comment Rate*), and (4) the average percentage of viewers who chose to follow provider i while watching a video (*Following Rate*).

We used regression specification (1) to predict $Complete\ View\ Rate_i$, $Like\ Rate_i$, $Comment\ Rate_i$ and $Following\ Rate_i$. Columns (2), (4), and (5) of Table 3 Panel A indicate that social nudges did not significantly alter the complete view rate, comment rate, and following rate of videos uploaded on the first reception day (all p-values > 0.4). Column (3) suggests that videos uploaded by treatment providers on the first reception day were less likely to receive likes by 0.0176 standard deviations (1.51%) relative to videos uploaded by control providers ($p < 0.05$). To explore this difference in like rates, we further compared historical like rates between treatment and control providers who uploaded any videos on their first reception day. $Historical\ Like\ Rate_i$ equals the total number of likes provider i received from January 1, 2018, to the day prior to the experiment, divided by the total number of views provider i received during that same period. Column (1) of Table 3 Panel B shows that among these providers who uploaded videos on the first reception day, treatment providers' historical like rates were significantly lower than control providers', by

Table 4 Over-Time Direct Effects of Social Nudges on Content Production

Outcome Variable	Number of Videos Uploaded			
	On Day 1 (First Reception Day)	On Day 2	On Day 3	On Day 4
	(1)	(2)	(3)	(4)
Treatment	0.0262****	0.0129****	0.0065**	0.0006
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Relative Effect Size	13.21%	5.29%	2.54%	
Observations	993,676	993,676	993,676	993,676

Notes: Number of Videos Uploaded was standardized to have a zero mean and standard deviation before entering the regressions. The unit of analysis for all columns was a provider on Day t relative to the first reception day, where $t = 1$ means the first reception day. Columns (1)–(4) include all providers in our sample. Robust standard errors are reported in parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

0.0521 standard deviations (3.48%). This difference in historical like rates between treatment and control providers who uploaded videos on the first reception day could lead the like rates for videos uploaded on the first reception day to be lower in the treatment condition than in the control condition. In fact, when we predicted $Like\ Rate_i$ while controlling for $Historical\ Like\ Rate_i$, the coefficient on treatment was no longer significant (column (2) in Table 3 Panel B). Altogether, we found that social nudges did not *directly* cause providers to increase or decrease video quality.

4.3. Direct Effects of Social Nudges on Content Production Over Time

So far, we have shown that social nudges significantly lifted providers' willingness to upload videos on the first reception day, which in turn led them to contribute more views to the platform but did not change video quality. Next, we explore how the effect of receiving social nudges on content production changed over time. We compared the number of videos uploaded each day between treatment and control providers from the first reception day until the first day when the difference between conditions was not statistically significant. Specifically, for each day t starting from the first reception day (where t equals $1, 2, \cdots$ and $t = 1$ refers to the first reception day itself), we predicted $Number\ of\ Videos\ Uploaded_{it}$ using regression specification (1).

Table 4 shows that the effect of receiving social nudges on $Number\ of\ Videos\ Uploaded_{it}$ was largest on the first reception day (column (1)), decreased as time elapsed, but was positive and significant for a couple of days. Specifically, the number of videos uploaded was higher in the treatment condition than in the control condition by 13.21% on the first reception day (0.0262 standard deviations; $p < 0.0001$; column (1)), by 5.29% on the day after the first reception day (0.0129 standard deviations; $p < 0.0001$; column (2)), and by 2.54% on the second day after the first reception day (0.0065 standard deviations; $p < 0.0001$; column (3)). The effect of receiving social nudges on the nudge recipient's production was not significant on the third day after the first reception day ($p = 0.7644$; column (4)).

4.4. Additional Analyses About the Direct Effects of Social Nudges

This subsection is devoted to further discussion and analyses to supplement our main results.

Control Providers' Resentment. One potential alternative explanation for our observed difference in video production between treatment and control providers is that control providers somehow realized that their followers sent them social nudges they could not receive, which made them resent the platform and thus reduce their production. To examine this alternative explanation, we conducted two sets of additional analyses about the private-message function, the only way for connected users to directly and privately communicate with each other on Platform O (see Online Appendix C.1). First, we used the difference-in-differences (DiD) method to examine whether receiving private messages from followers who sent them social nudges during the experiment negatively affected control providers' content production. Second, we tested whether the treatment effect of social nudges on production differed between providers who received any private message from their first social-nudge sender during the experiment versus providers who did not. For both analyses, we found no evidence supporting the aforementioned alternative explanation.

Role of Likes and Comments. Since receiving social nudges could boost video production, nudge recipients might also receive more likes and comments due to the increased number of videos uploaded. One may conjecture that such positive feedback might in turn motivate nudge recipients to produce more. We tested how much the immediate increase in likes and comments due to the receipt of social nudges contributed to the effects of receiving social nudges on content production during the few days after the first reception day (see Online Appendix C.2). We found that increased likes and comments are neither the only reason nor the primary reason the effect of receiving social nudges on content production lasted a few days, since we observed only a slight to moderate decrease in the magnitude of the production-boosting effect of social nudges after the first reception day when we controlled for likes and comments providers obtained earlier. Hence, receiving social nudges per se is sufficient to boost video production beyond the first reception day, even without additional positive feedback from likes and comments.

Effects of Social Nudges Across Providers With Different Baseline Productivity. Restivo and van de Rijt (2014) show that a peer-recognition intervention motivates only the most productive 1% of content providers but not providers ranked at the 91st–99th percentile. We found that receiving social nudges boosted production among both the most productive 1% providers, providers ranked at the 91st–99th percentile, as well as providers ranked below the 91st percentile (see Online Appendix C.3). These results suggest that receiving social nudges is generally effective in motivating content provision across users with different levels of baseline productivity.

Comparison With Platform-Initiated Nudges. To motivate content provision, a platform may also directly nudge its users. To explore whether social nudges from peers are more effective than nudges sent by the platform, we leveraged another randomized field experiment where content

Table 5 Effect of Social Nudges on Nudge Diffusion on the First Reception Day

Outcome Variable	Number of Social Nudges Sent	
	(1)	(2)
Treatment	0.0325****	0.0060*
	(0.0020)	(0.0027)
Two-Way Tie		0.1304****
		(0.0028)
Treatment * Two-Way Tie		0.0565****
		(0.0040)
Relative Effect Size	15.57%	
Observations	993,676	993,676

Notes: Number of Social Nudges Sent was standardized to have a zero mean and unit standard deviation before entering the regressions. The unit of analysis for all columns was a provider on her first reception day. Columns (1)–(2) include all providers in our sample. Robust standard errors are reported in parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

providers were randomly assigned to either receive or not receive nudges from Platform O (see Online Appendix C.4). Adopting similar empirical analyses as described in this section, we found that social nudges boosted providers' production to a larger extent than platform-initiated nudges.

5. Indirect Effects of Social Nudges on Production via Nudge Diffusion

In Section 4, we examined how social nudges influenced nudge recipients' production quantity and quality as well as the content consumption they engendered. Next, inspired by the diffusion phenomenon in the social network literature (Zhou and Chen 2016), we examined the diffusion of social nudges. Specifically, we estimated how receiving social nudges affected the number of social nudges sent by the recipient to other providers they were following on the platform.

5.1. The Effects of Social Nudges on Nudge Diffusion on the First Reception Day

We began our investigation by testing how receiving social nudges facilitated nudge diffusion on the first reception day—the first day when a provider could be affected by social nudges during our experiment. Our unit of analysis was a provider on her first reception day, and we analyzed 993,676 observations, with each provider contributing one observation. We examined the number of social nudges sent by each provider i to other providers on the first reception day ($Number\ of\ Social\ Nudges\ Sent_i$). Similar to how we addressed outliers earlier, we winsorized $Number\ of\ Social\ Nudges\ Sent_i$ at the 95th percentile of nonzero values. We used regression specification (1) to predict $Number\ of\ Social\ Nudges\ Sent_i$. Column (1) of Table 5 shows that receiving social nudges on average increased the number of social nudges providers sent to others on the first reception day by 0.0325 standard deviations (15.57%; p < 0.0001).

Next we tested whether social nudges from closer peers could more effectively facilitate nudge diffusion. Similar to how we analyzed the heterogeneous treatment effect for the direct effects of social nudges on content production (Section 4.1), here we examined the heterogeneous treatment effects for nudge diffusion based on whether a provider and the follower sending her a nudge had a two-way tie or a one-way tie. Specifically, we used regression specification (2) to predict $\textit{Number of Social Nudges Sent}_i$.

Column (2) of Table 5 shows that the coefficient on the interaction between $\textit{Treatment}_i$ and $\textit{Two-Way Tie}_i$ is significant and positive ($p < 0.0001$), suggesting that receiving a social nudge motivated a provider to diffuse social nudges to a greater extent when the provider and the follower who sent the nudge had a two-way tie than when they had a one-way tie. Specifically, receiving a social nudge from a follower with a one-way tie boosted the number of social nudges a provider sent on the first reception day by 0.0060 standard deviations ($p < 0.05$), while receiving a social nudge from a follower with a two-way tie boosted the number of social nudges sent by 0.0625 (i.e., 0.0060+0.0565) standard deviations ($p < 0.0001$). The relative effect size, as compared to the average number of social nudges sent in the control condition, is 2.87% (one-way tie) and 30.02% (two-way tie), respectively. Combining these results with the findings in Section 4.1, we found that receiving social nudges both increased a provider's own content production to a greater extent and yielded a larger diffusion effect when the provider and the nudge sender were following each other than when only the nudge sender was following the provider, suggesting that social nudges from closer peers were more influential.

5.2. Effects of Social Nudges on Nudge Diffusion Over Time

Going beyond the first reception day, we next examined how receiving social nudges affected nudge diffusion over time. Similar to how we analyzed the direct effect of social nudges on content production over time, we compared the number of social nudges providers sent each day between treatment and control conditions from the first reception day on until the first day when the difference between conditions was not statistically significant. Specifically, for each day t starting from the first reception day (where t equals $1, 2, \cdots$ and $t = 1$ refers to the first reception day itself), we predicted $\textit{Number of Social Nudges Sent}_{it}$ using regression specification (1). We report the regression results in Table 6.

Table 6 shows that the effect of receiving social nudges on $\textit{Number of Social Nudges Sent}_{it}$ was largest on the first reception day (i.e., $t = 1$; column (1)) and decreased as time elapsed. Specifically, the number of social nudges sent to others was higher in the treatment condition than in the control condition by 15.57% on the first reception day (0.0325 standard deviations; $p < 0.0001$; column (1)), and by 7.87% on the day after the first reception day (0.0139 standard deviations; $p < 0.0001$; column (2)). This effect of receiving social nudges on nudge diffusion was not significant on the second day after the first reception day ($p = 0.1686$; column (3)).

Table 6 Effects of Social Nudges on Nudge Diffusion Over Time

Outcome Variable	Number of Social Nudges Sent		
	On Day 1 (First Reception Day)	On Day 2	On Day 3
	(1)	(2)	(3)
Treatment	0.0325****	0.0139****	0.0028
	(0.0020)	(0.0020)	(0.0020)
Relative Effect Size	15.57%	7.87%	
Observations	993,676	993,676	993,676

Notes: Number of Social Nudges Sent was standardized to have a zero mean and standard deviation before entering the regressions. The unit of analysis for all columns was a provider on Day t relative to the first reception day, where $t = 1$ means the first reception day. Columns (1)–(3) include all providers in our sample. Robust standard errors are reported in parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

6. A Social Network Model

Platforms may be interested in evaluating the global effect of social nudges—the impact of social nudges on production in the counterfactual scenario where *every* user on the platform can send and receive nudges—from experimental data *before* they decide to scale up the social-nudge function to all users. Platforms may also be interested in optimizing various operational decisions regarding social nudges, such as seeding. However, the diffusion of social nudges conducted by nudge recipients as well as the over-time effects of social nudges, which we document in Sections 4 and 5, impose challenges for these tasks.

A naïve approach is to simply use data from an experiment like ours to calculate the difference in the number of videos uploaded by treatment vs. control providers right after they were sent social nudges during the experiment, then to scale this difference to the entire user population of the platform. However, this approach is problematic for two reasons. First, it considers only the direct effect of social nudges on content production on the day a nudge is sent, not the accumulated direct effect over time. Second, it ignores the indirect effect of social nudges on content production via nudge diffusion, which can also accumulate over time. To tackle these challenges, we propose a novel social network model to capture both the over-time direct effect of social nudges on the nudge recipient's own production and the over-time diffusion of social nudges. Applying this model allows us to quantify both the direct and indirect effects of social nudges on content production over time, and thus more accurately estimate the global effect of social nudges.

6.1. The Model and the Global Effect

We model Platform O as a social network, denoted as $G = (V, E)$, in which $V := \{1, 2, 3, \ldots, |V|\}$ is the set of nodes (i.e., users on Platform O who can be viewers and providers) and $E := \{1, 2, 3, \ldots, |E|\}$ is the set of directed edges (i.e., the "following" relationship on Platform O). We use i, j and e, ℓ to denote nodes and edges, respectively. Let e_o and e_d be the origin and destination, respectively, of edge $e \in E$, so viewer i following provider j is represented as $e_o = i$ and $e_d = j$. We

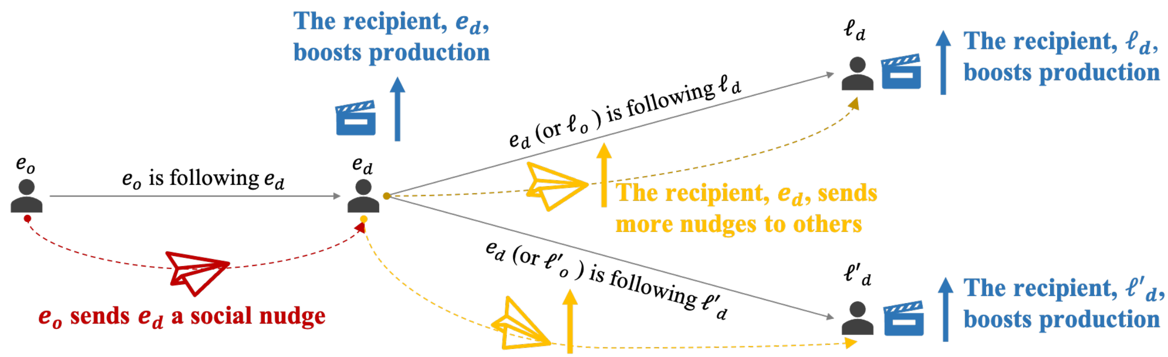


Figure 2 **How Social Nudges Influence Users on a Network**

model the dynamics of social nudges and their effects on providers' production using a discrete-time stochastic model with an infinite time horizon. We use t to index the discrete time period, i.e., $t=1,2,\ldots$. In particular, one may consider $t=1$ as the period when the social-nudge function starts to become available to all users on the platform. In our empirical context, we assume that each period corresponds to a day, consistent with the business practice of Platform O. In Figure 2, we depict the fundamental structure of the social network model. If e_o sends e_d a social nudge, the recipient, e_d, will not only (1) increase her production but also (2) send more social nudges to other providers whom she is following, which could further boost other providers' production. We summarize the notations involved in the social network model in Table 7.

We first model the over-time direct effect of social nudges on production. Let $x_i(t)$ denote the boost of provider i's production in period t due to the social nudges she has received before and during period t. We use $y_e(t)$ to indicate the number of nudges sent on edge e (from e_o to e_d) in period t. Let p_e denote the additional number of videos provider e_d would be expected to upload as a result of receiving one social nudge from viewer e_o on the day the nudge is received. Section 4 shows that, during our field experiment on Platform O, the direct effect of receiving social nudges on production gradually wears off over time. Thus, we capture the dynamic of production increment by the following dynamic equation:

$$x_i(t) = \sum_{1\le s\le t} \alpha_p^{t-s} \sum_{e\in E: e_d = i} p_e y_e(s) + \epsilon_i^x(t), \ \forall i \in V. \tag{3}$$

Here we let $\alpha_p \in (0,1)$ denote the time-discounting factor of social nudges' direct production-boosting effect. We denote the random noise of production boost for provider $i \in V$ in period t as $\epsilon_i^x(t)$, i.i.d. across different providers and periods with a zero mean and a bounded support.

We next turn to the diffusion of social nudges. Motivated by the empirical results in Section 5, we assume that the number of social nudges sent on an edge e in period t is driven by two additive factors. First, e_o sends μ_e nudges to e_d, which is not affected by the number of nudges e_o herself has

Table 7 Notations Involved in the Social Network Model

Notations	Interpretations
$G=(V,E)$	The network, in which V is the set of nodes and E is the set of directed edges.
$x_i(t)$	The boost of node i's production in period t due to nudges node i has received before (including) period t.
$y_e(t)$	The number of nudges sent from e_o to e_d in period t.
p_e	The additional number of videos provider e_d would be expected to upload in period t as a result of receiving one social nudge from viewer e_o in period t.
μ_e	The number of nudges that e_o sends to e_d without being affected by the nudges that e_o has received.
$d_{\ell e}$	The expected increase in the number of nudges sent on edge e in period t due to one additional nudge e_o receives in period t from edge ℓ (i.e. $\ell_d = e_o$).
$\epsilon_i^x(t), \epsilon_i^y(t)$	The i.i.d. random noises with a zero mean and a bounded support.
α_p, α_d	The time-discounting factors corresponding to p_e and $d_{\ell e}$, respectively.

received. Second, the diffusion effect described in Section 5 suggests that when a provider receives a nudge, she tends to send more nudges to other providers. This is equivalent to saying that the number of nudges she would send per provider she follows becomes higher. Combined, the dynamic of social nudges on the network G is captured by

$$y_e(t) = \mu_e + \sum_{1\le s\le t} \alpha_d^{t-s} \sum_{\ell\in E:\ell_d=e_o} d_{\ell e} y_\ell(s) + \epsilon_e^y(t), \ \forall e\in E. \tag{4}$$

Here the second term in Equation (4) embodies the diffusion effect. In particular, $d_{\ell e}$ captures the intensity of social-nudge diffusion. That is, $d_{\ell e}$ captures the expected increase in the number of nudges sent on edge e in a given period due to one additional nudge e_o receives in the same period on edge ℓ directing to e_o (i.e. $\ell_d = e_o$). Similar to α_p, $\alpha_d \in (0,1)$ denotes the time-discounting factor of nudge diffusion, which captures that the extent to which receiving a social nudge pushes nudge recipients to send out nudges decays over time, as discussed in Section 5. We denote the random noise of social nudges sent on edge e in period t as $\epsilon_e^y(t)$, i.i.d. across different edges and periods with a zero mean and a bounded support.

To quantify the global effect of social nudges, we characterize the long-run steady state of the system defined by Equations (3)–(4). Due to time-discounting factors, the dimension of this linear system is growing with t, so the long-run steady state characterization is not immediate. Nevertheless, Theorem 1, whose proof is in Online Appendix D.1, shows that the expected production and nudge quantities converge to a well-defined limit. For notation convenience, we define $d_{\ell e}=0$ if $\ell_d \neq e_o$, and the matrix $\mathbf{D} := (d_{\ell e} : (\ell, e)\in E^2)$. The matrix $\mathbf{D}$ with non-negative entries therefore captures the first-order diffusion on all edge pairs. We further let $\eta_e := p_e/(1-\alpha_p)$ and $\boldsymbol{\eta} := (\eta_e : e\in V)$. We use $\mathbf{I}$ to denote the identity matrix and $\boldsymbol{e}$ to denote the vector of ones. Let us write the total production increment in period t as $x(t) := \sum_{i\in V} x_i(t)$. We denote ℓ_q-norm of matrices by $||\cdot||_q$ for any $q\in[1,+\infty]$, which is the operator norm defined through $||\mathbf{A}||_q = \sup_{\boldsymbol{z}:||\boldsymbol{z}||_q\le 1} ||\mathbf{A}\boldsymbol{z}||_q$ for any squared matrix $\mathbf{A}$ and $\boldsymbol{z}$ with appropriate dimensions (Horn and Johnson 2012). Also, we say that the matrix $\mathbf{D}$ satisfies $\mathcal{C}_q(\delta)$ for some $\delta\in(0,1)$, provided that $||(1/(1-\alpha_d))\mathbf{D}||_q \le \delta$.

Theorem 1 *If matrix* $\mathbf{D}$ *satisfies* $\mathcal{C}_q(\delta)$ *for some* $q \in [1, +\infty]$ *and* $\delta \in (0,1)$, *it then follows that* $\lim_{t\to\infty} \mathbb{E}[x(t)] = x^*$ *and* $\lim_{t\to\infty} \mathbb{E}[\boldsymbol{y}(t)] = \boldsymbol{y}^*$, *where* x^* *and* $\boldsymbol{y}^*$ *satisfy* $x^* = \boldsymbol{\eta}^\top \boldsymbol{y}^*$ *and*

$$\boldsymbol{y}^* = \left(\mathbf{I} - \frac{1}{1-\alpha_d}\mathbf{D}\right)^{-1} \boldsymbol{\mu}. \tag{5}$$

We remark that the condition $\mathcal{C}_q(\delta)$ guarantees that $\mathbf{I} - (1/(1-\alpha_d))\mathbf{D}$ is invertible. Therefore, Equation (5) can be further expanded and admit a natural interpretation of (weighted) Bonacich centrality that is reminiscent of some past studies in network economics such as Ballester et al. (2006). In this literature, Bonacich centrality is defined for nodes on a network, whereas our centrality measure is for *edges*. The factors $1/(1-\alpha_d)$ in Equation (5) and $1/(1-\alpha_p)$ in the definition of $\boldsymbol{\eta}$ materialize the diffusion and production-boosting effects, respectively, accumulated over time. To summarize, Theorem 1 characterizes the global effect of social nudges in the steady state of the production and nudge diffusion process. Below, we delve into how to estimate the global effect x^* via an approximation scheme using data from our field experiment.

Note that although we focus on the production increment x^* in the steady state rather than the total production quantity, one can model the expected production of user i in period t as $z_i(t) = \xi_i + x_i(t) + \epsilon_i^z(t)$ for all $i \in V$. Here we denote the provider i's expected production quantity in each period as ξ_i and use $\epsilon_i^z(t)$ to capture a zero mean random noise. By Theorem 1, if we define the total production quantity in period t as $z(t) := \sum_{i\in V} z_i(t)$, then $\lim_{t\to\infty} \mathbb{E}[z(t)] = \boldsymbol{e}^\top \boldsymbol{\xi} + x^*$.

6.2. Approximation for the Global Effect

To evaluate the global effect of social nudges on providers' production, by Theorem 1, we need to invert the $|E|^2$−dimensional matrix $\mathbf{I} - (1/(1-\alpha_d))\mathbf{D}$. For Platform O, the dimension of $\mathbf{D}$, i.e., $|E|^2$, is at the magnitude of 10^{32}. Inverting such a high-dimensional matrix is computationally infeasible. Therefore, we resort to an approximation scheme to quantify the steady-state (daily) number of social nudges between viewers and providers (i.e., $\boldsymbol{y}^*$), and the (daily) production boost from these nudges (i.e., x^*).

Toward this goal, we note that if $\mathbf{D}$ satisfies $\mathcal{C}_q(\delta)$ for some $\delta \in (0,1)$, the inverse of $\mathbf{I} - (1/(1-\alpha_d))\mathbf{D}$ is given by (see, e.g., Corollary 5.6.16 and Corollary 5.6.17 of Horn and Johnson 2012),

$$\left(\mathbf{I} - \frac{1}{1-\alpha_d}\mathbf{D}\right)^{-1} = \mathbf{I} + \sum_{k=1}^{+\infty} \frac{1}{(1-\alpha_d)^k}\mathbf{D}^k. \tag{6}$$

Motivated by this formula, we define a sequence of (approximate) steady-state social-nudge vectors, $\tilde{\boldsymbol{y}}(k)$, and total production boost from nudges, $\tilde{x}(k)$, indexed by $k \in \mathbb{Z}_+$, as follows:

$$\tilde{\boldsymbol{y}}(k) := \left(\mathbf{I} + \sum_{i=1}^{k} \frac{1}{(1-\alpha_d)^i}\mathbf{D}^i\right)\boldsymbol{\mu}, \text{ and } \tilde{x}(k) := \boldsymbol{\eta}^\top \tilde{\boldsymbol{y}}(k). \tag{7}$$

By Equation (6) and Theorem 1, under condition $\mathcal{C}_q(\delta)$, $\tilde{\boldsymbol{y}}(k)$ converges to $\boldsymbol{y}^*$ and $\tilde{x}(k)$ converges to x^* as k approaches infinity. In addition, since all the entries of $\mathbf{D}$ are non-negative, $\tilde{y}_j(k)$ is increasing in k for any $j \in E$, so is $\tilde{x}(k)$ increasing in k. Therefore, for each $k \in \mathbb{Z}_+$, $\tilde{\boldsymbol{y}}(k)$ is a (component-wise) lower bound of $\boldsymbol{y}^*$, and $\tilde{x}(k)$ is a lower bound of x^*.

We also emphasize that, due to the extremely high dimension of the matrix $\mathbf{D}$, evaluating $\tilde{\boldsymbol{y}}(k)$ and $\tilde{x}(k)$ for $k \geq 2$ is also computationally difficult. So we will evaluate the global effect through the approximation scheme (7) with $k = 1$. In fact, at the scale of Platform O, even evaluating $\tilde{\boldsymbol{y}}(1)$ and $\tilde{x}(1)$ involves matrix multiplications in extremely high dimensions, which is again computationally intractable. Therefore, we adopt another layer of approximation by downsampling a subset of providers from V (denoted as $\tilde{V}$). We estimate the total boost of these providers' own video supply brought by all the social nudges received by providers in $\tilde{V}$, denoted as $\hat{w}_0$, as well as the total production boost of the social nudges sent by providers in $\tilde{V}$ *as a result of the social nudges received by them* (i.e., the diffusion of nudges), denoted as $\hat{w}_1$. Hence, $\hat{w}_0$ captures the direct effect of social nudges and $\hat{w}_1$ captures the indirect effect in the steady state per period. Scaling these estimates by a factor of $\frac{|V|}{|\tilde{V}|}$ would therefore yield unbiased estimates of the true direct and indirect global effects. Therefore, we devise $\frac{|V|}{|\tilde{V}|}(\hat{w}_0 + \hat{w}_1)$ as an unbiased estimate for $\tilde{x}(1)$ (for a formal argument, please see Online Appendix D.2). We present a detailed estimation procedure in Algorithm 1. To obtain the estimate $\hat{w}$, we need to initialize Algorithm 1 with the parameters $\{\mu_e, p_e : e \in \tilde{E}\}$, $\{p_\ell : \ell \in \tilde{L}\}$, $\{d_{e\ell} : e \in \tilde{E}, \ell \in \tilde{L}, e_d = \ell_o\}$, α_p, and α_d. In Section 6.3, we introduce in detail how these key parameters are estimated, together with our evaluation of the global effect on production boost from social nudges.

6.3. Data-Driven Simulation of the Global Effect

In this subsection, we sketch the procedure to estimate the global effect of social nudges on Platform O. The estimation details are relegated to Online Appendix E. Based on Algorithm 1, quantifying such a global effect involves estimating the following four sets of parameters for Platform O: (1) the expected number of social nudges a user sends to each user whom she follows each day without being affected by nudge diffusion, i.e., μ_e for $e \in E$; (2) the effect of receiving one social nudge on boosting the nudge recipient's production, i.e., p_e for $e \in E$; (3) the intensity of social-nudge diffusion, i.e., $d_{e\ell}$ for $e, \ell \in E$ and $e_d = \ell_o$; and (4) the time discounting factors, i.e., α_p and α_d. Our estimation of μ_e is based on observational data, whereas that of p_e, $d_{e\ell}$, α_p, and α_d relies on experimental data. The estimation results are provided in the first column of Table 8. Next, we describe the process of estimating these parameters.

Algorithm 1 APPROXIMATE GLOBAL EFFECT OF SOCIAL NUDGES

Down Sampling: Uniformly randomly sample a subset of nodes $\tilde{V} \subset V$. Find the set of edges that point to a node in $\tilde{V}$, $\tilde{E} := \{e \in E : e_d \in \tilde{V}\}$), and the set of edges that originate from a node in $\tilde{V}$, $\tilde{L} := \{\ell \in E : \ell_o \in \tilde{V}\}$).

Parameter Initialization: For each $e \in \tilde{E}$, estimate μ_e and p_e. For each $\ell \in \tilde{L}$, estimate p_ℓ. For each $e \in \tilde{E}, \ell \in \tilde{L}, e_d = \ell_o$, estimate $d_{e\ell}$. Estimate α_d and α_p.

Direct Effect of Social Nudges on Content Production: Estimate

$$\hat{w}_0 := \sum_{i \in \tilde{V}} \sum_{e \in \tilde{E}, e_d = i} \frac{\mu_e p_e}{1 - \alpha_p}.$$

Indirect Effect of Social Nudges on Content Production: Estimate:

$$\hat{w}_1 := \sum_{i \in \tilde{V}} \sum_{e \in \tilde{E}, \ell \in \tilde{L}, e_d = \ell_o = i} \frac{\mu_e d_{e\ell} p_\ell}{(1 - \alpha_p)(1 - \alpha_d)}$$

Total Production Boost on the Entire Population: Scaling the estimates back to V:

$$\hat{w} := \frac{|V|}{|\tilde{V}|}(\hat{w}_0 + \hat{w}_1)$$

Table 8 Estimation of Parameters in the Social Network Model

Parameter	Estimation Results Using Data from the Main Experiment (1)	Replication Experiment (2)
p_e	0.05492	0.05156
α_p	0.6345	0.6945
$d_{e\ell}$	0.0008436	0.0009200
α_d	0.3750	0.3378

Notes: To protect Platform O's data security, we are not permitted to disclose the raw estimates of p_e and $d_{e\ell}$. The values of p_e and $d_{e\ell}$ reported here equal the raw estimates of p_e and $d_{e\ell}$ multiplied by a fixed constant. We report α_p and α_d using the raw estimates.

Estimation of μ_e. Due to Platform O's rule that a user can send no more than one social nudge to another user each day, estimated μ_e (and $d_{e\ell}$) falls between 0 and 1. In this case, the parameter μ_e measures the expected probability of e_o sending a social nudge to e_d per day when e_o has not received nudges from her followers recently. We estimate μ_e by taking advantage of the fact that providers in the control group of our social-nudge experiment cannot receive nudges (and thus cannot be motivated to send more nudges out because of receiving nudges themselves) during the experiment. We sampled 5 million edges uniformly at random from all edges whose origin was in the control condition of our social-nudge experiment. Here, we do not require the origins of these edges to satisfy the selection criteria of our analysis sample mentioned in Section

3 since we use this random edge sample to represent the overall edges on Platform O. We fit the logistic regression model Equation (17) in Online Appendix E to predict μ_e, using features based on the commonly recognized characteristics in the network economics literature (see, e.g., Jackson 2010) such as the degrees of a node in V (measured by the number of followers and the number of followings the node has) and the strength of an edge in E (measured by whether e_o and e_d has a bi-directional relationship, i.e., whether there exists $e' \in E$ such that $e'_o = e_d$ and $e'_d = e_o$). Table 19 in Online Appendix E.1 reports the estimated coefficients. We implement a fivefold cross-validation to evaluate the performance of this logistic regression model, which has a 99.99% average accuracy and an AUC (area under the curve) value of 0.78, suggesting qualified prediction performance. Then, for all the edges in $\tilde{E}$, we can estimate the probability that e_o will nudge e_d in a given period by Equation (18) in Online Appendix E.

Estimation of p_e and α_p. Recall that the parameter p_e ($e \in E$) measures the immediate positive effect of receiving *one* social nudge from e_o on provider e_d's production, i.e., the production-boosting effect in the same time period when the nudge is sent. The time discounting factor α_p indicates that receiving one social nudge from e_o boosts provider e_d's production by $p_e \alpha_p^t$ in the t^{th} period after e_d receives the nudge. To cleanly estimate p_e and α_p, from the analysis sample of our social-nudge experiment (as defined in Section 3), we identify $962,120$ providers who were sent only *one* social nudge on their first reception day (accounting for 97% of the analysis sample).

We estimate the production-boosting effect of receiving a social nudge by comparing providers' production between the treatment and control conditions on and after their first reception day, adopting regression specification (1) for each day since the first reception day. The regression results are reported in Table 20 in Appendix E.2. Then we solve the nonconvex program (19) in Online Appendix E.2 to jointly estimate p_e and α_p. We show the estimation results in Table 8 column (1).

Estimation of $d_{e\ell}$ and α_d. The estimation of $d_{e\ell}$ and α_d follows a similar approach to that of (p_e, α_p). The parameter $d_{e\ell}$ measures the increase in e_d's probability of sending a social nudge to ℓ_d on the day of receiving *one* social nudge from e_o ($e_d = \ell_o$). By definition, $d_{e\ell} = 0$ if $e_d \neq \ell_o$. The parameter α_d quantifies the time-discounting factor of such effect, such that receiving one social nudge from e_o boosts the number of nudges provider e_d would send to ℓ_d by $d_{e\ell}\alpha_d^t$ in the t^{th} period after e_d receives the nudge. We focus on the subset of providers from the analysis sample of our social-nudge experiment who (1) were sent only *one* social nudge on their first reception day and (2) were following at least one user the day before the main experiment. We estimate the diffusion effect of a social nudge by comparing the number of nudges providers sent per following relationship between the treatment and control conditions on and after their first reception day, adopting regression specification (1) for each day since the first reception day. The regression results are reported in Table 21 in Appendix E.3. We solve the nonconvex program (20) in Online Appendix E.3 to obtain $d_{e\ell}$ and α_d. The estimation results are shown in Table 8 column (1).

Estimation of the Global Effect. Before presenting the estimate of the global effect of social nudges on production using Algorithm 1, we first demonstrate the naïve benchmark mentioned earlier. Specifically, we simply use data from our experiment to calculate the difference in the number of videos uploaded by treatment vs. control providers on the first day when they are sent a social nudge, then we scale this difference to the entire population on the platform by the average number of providers who are sent social nudges on the platform per day.

For example, during our main social-nudge experiment, treatment providers uploaded 13.21% more videos on the first reception day than control providers (see column (1) of Table 2 in Section 4.1). Let $\hat{u}$ denote the absolute production difference per user between treatment and control providers on the first day they were sent social nudges during the experiment. Note that the true value of $\hat{u}$ cannot be disclosed due to data security concerns. The naïve estimation would calculate the total effect of social nudges on content production on the platform as $\hat{u} \cdot N$, where N is the average number of providers on the platform who are sent social nudges by their followers per day. The latter quantity N can be estimated by (1) the number of providers in the analysis sample of our social-nudge experiment who received social nudges on a day, divided by (2) the ratio of the number of providers targeted by the experiment to the total number of providers on the platform. To fairly compare this naïve approach to calculate the effect of social nudges on production with our estimation based on the social network model, we first calculate the global effect of social nudges among 1 million providers (i.e., to multiply $\hat{u}$ by the average number of providers among 1 million providers who are sent social nudges per day). The naïve approach estimates that the total boost of video uploads caused by social nudges among 1 million providers is 48.65 videos per day.

Following Algorithm 1, we approximate the total production boost of social nudges on the entire network on a given day in the steady state by downsampling a subset of providers $\tilde{V}$ where $|\tilde{V}| = 1,000,000$. To protect sensitive data, we can only report the boost on $\tilde{V}$ without re-scaling back to the entire platform (i.e., $\hat{w}_0 + \hat{w}_1$). The estimation results are presented in Table 9 column (1). For those 1 million randomly sampled providers in $\tilde{V}$, the accumulated direct production boost is $\hat{w}_0 = 130.08$ videos per day, and the accumulated indirect production boost from social-nudge diffusion is $\hat{w}_1 = 10.59$ videos per day, yielding a total production boost of $\hat{w}_0 + \hat{w}_1 = 140.67$ videos per day. Therefore, our results suggest that the indirect production boost from nudge diffusion accounts for at least 8.14% of the direct effect (i.e., 10.59/130.08). In addition, we remark that the above estimation results also suggest using $\tilde{x}(1)$ is a reasonable approximation of x^* with a tiny loss. Specifically, the (first-order) indirect effect from nudge diffusion is about 8.14% of the direct effect. Therefore, the production boost from second- and higher-order diffusion accounts for about 0.72% (i.e., $\frac{0.0814^2}{1-0.0814}$) of the direct effect.

Table 9 Estimation of the Global Effect of Social Nudges

	The Naïve Approach Using Data from the Main Experiment	The Network-Modeling Approach Using Data from the Main Experiment		The Network-Modeling Approach Using Data from the Replication Experiment	
	(1)	(2)		(3)	
Direct Effect	48.65	130.08	*One Day:* 47.55 *Beyond One Day:* 82.53	146.06	*One Day:* 44.63 *Beyond One Day:* 101.44
Indirect Effect		10.59		12.24	
Global Effect		140.67		166.30	
The Ratio of Indirect Effect to Direct Effect		8.14%		8.38%	

Notes: When reporting the direct effect estimated by the network-modeling approach, we not only present the estimated overall direct effect over time (e.g., 130.08 for the first experiment), we also separately show the estimated direct effect on the day of receiving nudges (e.g., 47.55) and the estimated direct effect beyond that day (e.g., 82.53).

It is clear that our social network model could help address the substantial underestimate of social nudges' total production boost that the naïve estimation approach would generate. The more precise estimation of social nudges' global effect over the entire user population using the social network model (140.67 per day for 1 million providers) is 2.89 times as large as the naïve estimation (48.65 per day for 1 million providers). The gap between these two estimations comes from two factors: (1) the social network model includes the over-time accumulation of the direct boosting effect of social nudges on recipients' production, which yields a 167% (i.e., $(130.08-48.65)/48.65$) increase compared to the naïve estimation; and (2) the model also incorporates nudge diffusion, which accounts for another 22% (i.e., 10.59/48.65) increase. Above all, our social network model provides a framework to causally quantify the global effect of our intervention (including its direct and indirect effects), which will be underestimated by the naïve estimation method. This framework could be used to estimate the global effect of other interventions on a social network.

Robustness Check for Global Effect Estimates. As the first robustness check, we resample $\tilde{V}$ and reestimate the global effect of social nudges using parameters estimated from our main social-nudge experiment. The results based on this new sample are reported in Online Appendix E.4—they confirm that the global-effect estimates reported in Table 9 are robust.

As the second robustness check, we reestimate (p_e, α_p) and $(d_{e\ell}, \alpha_d)$ based on the same method described above but using data from the second social-nudge experiment. The estimation details are reported in Online Appendix E.5. The estimation results of (p_e, α_p) and $(d_{e\ell}, \alpha_d)$ are fairly consistent between our two experiments (see Table 8).

In addition, we apply Algorithm 1 and the data from the second social-nudge experiment to estimate the global effect of social nudges. We report the estimation results in Table 9 column (2). Compared to the naïve estimation, including the over-time accumulation of the direct boosting effect of social nudges on recipients' production leads to a 200% (i.e., $(146.06-48.65)/48.65$)

increase, and considering nudge diffusion leads to an additional 25% (i.e., 12.24/48.65) increase. The indirect production boost from social-nudge diffusion accounts for at least 8.38% (i.e., 12.24/146.06) of the direct production effect. All of these results are fairly consistent with our estimation results based on data from the first social-nudge experiment (see Table 9). Such consistency confirms the robustness of our estimation and validates the accuracy of our social network model in quantifying the global effect of social nudges on production boost on Platform O.

6.4. Optimizing the Global Effect

In the previous section, we estimate the global effect of social nudges under the circumstance where users naturally decide whether to send social nudges to whom, which reflects the situation at Platform O at the time of our experiments. In this section, we propose a way to demonstrate how we can leverage our social network model in optimizing the platform's operational decisions regarding social nudges.

Specifically, assuming that Platform O can use a lever to motivate users to send social nudges to target providers (e.g., sending users pushes that recommend them to send social nudges to specific providers), we seek to explore how the platform optimizes the global effect of social nudges, as well as to estimate the extent to which the optimization can increase the global effect compared to a random dissemination strategy. Without loss of generality, we consider the circumstance where Platform O can select a set of n edges $K \subset E$ (i.e., $|K| = n$) and send pushes to the origins of these edges, encouraging them to send out social nudges to the corresponding destination nodes. Assuming that user e_o will, on average, send more nudges to e_d if the platform encourages her to do so, we denote that for each $e \in K$, the average number of social nudges sent per day will increase by a relative effect of δ_μ after e_o receives one push from Platform O (i.e., from μ_e to $\mu_e(1+\delta_\mu)$).[11] This means, users who originally are more likely to send social nudges will be motivated by pushes to a larger extent.

Recall that the global effect of social nudges is $\boldsymbol{\eta}^T \left(\mathbf{I} - (1/(1-\alpha_d))\mathbf{D}\right)^{-1} \boldsymbol{\mu}$ as shown in Theorem 1, and can be approximated by $\boldsymbol{\eta}^T \left(\mathbf{I} + (1/(1-\alpha_d))\mathbf{D}\right) \boldsymbol{\mu}$ as shown in Section 6.2. We use $\boldsymbol{\mu}_K \in \mathbb{R}^{|E|}$ to represent an $|E|-$dimensional vector with an entry representing an edge $e \in K$ (resp. $e \notin K$) equal to μ_e (resp. 0). Therefore, if Platform O selects an edge set K to which pushes are sent, the additional production boost due to pushes is given by $\boldsymbol{\eta}^T \left(\mathbf{I} - (1/(1-\alpha_d))\mathbf{D}\right)^{-1} \boldsymbol{\mu}_K \delta_\mu$, and a reasonable approximation is

$$\Delta(K) := \boldsymbol{\eta}^T \left(\mathbf{I} + \frac{1}{1-\alpha_d}\mathbf{D}\right) \boldsymbol{\mu}_K \delta_\mu. \tag{8}$$

[11] Our method of deriving the optimization strategy can be easily carried over to a setting where the average number of social nudges sent per day will increase by an absolute effect of δ_μ after e_o receives one push from Platform O (i.e., from μ_e to $\mu_e + \delta_\mu$) for each $e \in K$.

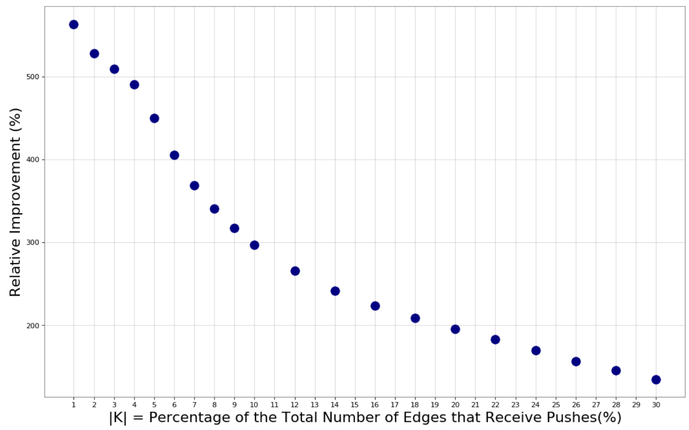


Figure 3 **Relative Improvements of the Optimal Strategy Over the Random Strategy as $|K|$ Changes**

Next, we examine two potential strategies Platform O could use to select the set of edges K: (a) the *random strategy*, which randomly selects $|K| = n$ edges from E; and (b) the *optimal strategy*, which selects $K^* = \arg\max_{K \subset E, |K|=n} \Delta(K)$. For each edge $e \in E$, define an associated nudge index

$$\nu_e := \frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell:\ell_o = e_d} \frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)} \tag{9}$$

We note that the optimal strategy K^* is uniquely characterized by selecting n edges in E with the highest nudge indices.

Table 10 **Global Effect of Social Nudges for Different Strategies**

	Setting	Δ_o	Δ_r	Ξ
		(1)	(2)	(3)
(1)	$\lvert K\rvert = 0.1\lvert E\rvert$, $\delta_\mu = 100\%$	54.77	13.78	297%
(2)	$\lvert K\rvert = 0.1\lvert E\rvert$, $\delta_\mu = 10\%$	5.48	1.38	297%

Comparison Between Random and Optimal Strategies. Naturally, a platform may adopt the random strategy, because it is the most straightforward, simple way to stimulate social nudges sent on a platform. However, the optimal strategy based on our network modeling may be more effective as it considers (1) which following relationships will be motivated to send a social nudge by one push to a larger extent, and (2) which user will create a larger diffusion of nudges after receiving a nudge. To compare the performances of these two strategies, we define Δ_r (resp. Δ_o) as the additional production boost under the random (resp. optimal) strategy, and $\Xi := (\Delta_o - \Delta_r)/\Delta_r \times 100\%$ as the relative improvement of the optimal strategy over the random strategy. We evaluate these two strategies based on the same sample of $\tilde{V}$ as the one used to generate the global effect estimates in Table 9 column (1). We examine how Ξ changes according to δ_μ and the number of pushes the platform sends, and we have two primary observations.

First, we notice that the nudge index ν_e is independent of δ_μ (the effectiveness of the pushes), and that Δ_o and Δ_r proportionally change with δ_μ. Hence, the relative improvement of the optimal strategy over the random baseline Ξ should be independent of δ_μ. For example, as shown in rows (1)–(2) of Table 10, when the platform sends pushes to 10% of the total edges in the network, regardless of whether δ_μ are 100% or 10%, the relative improvements of the optimal strategy over the random strategy are both 297%. Second, we notice that for a given δ_μ, the relative improvement of the optimal strategy over the random strategy decreases in a convex fashion as $|K|$ becomes larger. For example, in Figure 3, setting δ_μ as 100%, we calculate the relative improvement of the optimal strategy over the random strategy as $|K|$ grows from 1% to 30% of the total number of edges. The relative improvement of the optimal strategy over the random strategy decreases from 563% to 135%, when $|K|$ changes from 1% to 30% of the total number of edges.

In sum, we show that our social network model could help the platform optimize, among other things, its strategy to encourage users to send nudges. The platform's optimal strategy as suggested by our model is much more effective in boosting production than the natural random strategy.

7. Conclusions and Discussion

In two field experiments on a large online content-sharing social network platform, we consistently found that social nudges not only directly boosted nudge recipients' production but also stimulated more content provision by motivating nudge recipients to send more nudges to others. These effects were amplified when nudge recipients and nudge senders had stronger ties and persisted beyond the day nudges were sent. Inspired by these results, we developed a novel social network model that incorporates the diffusion and over-time effects of social nudges into the estimation of social nudges' global effect. We found that the naïve approach simply based on experiments underestimates social nudges' total production boost—our model helps address this issue. Moreover, via a simulation example, we demonstrated the advantage of adopting our social network model to find strategies to optimize the global effect of social nudges.

Our research offers important practical implications for content-sharing social network platforms. First, social nudges can be a cost-effective intervention for these platforms to lift production on the supply side and consequently increase consumption on the demand side. Platforms are naturally eager to control costs. Compared to financial incentives, social nudges require minimal costs on the platform's end. In fact, due to the success of social nudges observed in our experiments, after the second experiment, Platform O scaled up this function, enabling all users to receive (and send) social nudges as long as they (or the target they want to nudge) have not uploaded any video for a day or more. Second, this work highlights the value of leveraging co-users' influence. Content-sharing social network platforms have little authority over their users' actions (such as when and how much they supply), rendering it challenging for these platforms to implement heavy-handed interventions to achieve desired outcomes. However, one of their advantages lies in connecting users and facilitating transactions or relationships between users. Thus, platforms can guide co-users to influence each other as a way to improve overall user engagement on platforms. Third, by showcasing that the diffusion of social nudges is crucial for measuring and optimizing the effects of social nudges on production, our work reveals the importance of platforms considering the diffusion of an intervention when they decide whether to scale up the intervention and how to maximize its effectiveness. Furthermore, by exploring an optimal seeding strategy for maximizing the global effect of social nudges, our method may inspire platform managers to leverage a model like ours to find strategies to enhance the power of an intervention.

Several limitations of our research open up interesting avenues for future research. For one, the type of social nudge we examined is simple, private, and subtle. It was standardized across users, contained simple content, and leveraged no additional psychological principles. It was visible only to recipients in the message center. As more messages arrived in the message center, previously received social-nudge messages were pushed down and might become not visible on the front page of the message center. Using such a light-touch, bare-bones social nudge allows us to provide a clean test of the effect of being nudged. Future research could examine how to design social nudges to produce stronger, longer-lasting effects—for example, by incorporating persuasion techniques and additional psychological insights into nudge messages, allowing senders to write personalized messages, or publicly displaying social nudges in a dedicated area. Another limitation of this research is that we could not causally study the effects of repeatedly receiving social nudges, since the number of social nudges sent to each provider was not exogenous. Future research could randomly assign people to receive varying numbers of nudges and causally estimate how the effects of social nudges change with the number of nudges received.

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Online Appendices

A. Robustness Checks of the Main Results From the First Social-Nudge Experiment

A.1. Analyzing All Providers Who Were Sent at Least One Social Nudge in the Experiment

For analyses reported in the main text, we focused on providers who had never received any social nudges before the first social-nudge experiment (as explained in Section 3), in order to estimate how social nudges change behavior when a platform starts to implement the social-nudge function. In this section, we report the production-boosting and diffusion effects of social nudges among all providers whose followers sent them at least one social nudge during our experiment ($N = 1,946,118$), as a robustness check.

Using regression specification (1), we predicted the number of videos a provider uploaded (*Number of Videos Uploaded*) and the number of social nudges sent by a provider to other providers (*Number of Social Nudges Sent*) on the first reception day. As shown in Table 11, receiving social nudges boosted the number of videos upload on the first reception day by 9.53% (0.0222 standard deviations; $p < 0.0001$), and increased the number of social nudges sent to other providers by 13.92% (0.0323 standard deviations; $p < 0.0001$). Therefore, the immediate effects of receiving social nudges are qualitatively unchanged if we examine all providers whose followers sent them at least one social nudge during our experiment.

A.2. Predicting Production Within 24 Hours Following the First Nudge

In the main text, we examined videos providers uploaded on the first reception day, defined as the calendar date the first social nudge was sent to them during the experiment. As a robustness check, we tracked the number of videos each provider uploaded during 24 hours since the first social nudge. We constructed two outcome variables: *Number of Videos Uploaded Within 24 Hours Following the First Nudge* and *Upload Incidence Within 24 Hours Following the First Nudge*. We predicted these outcome variables using regression specification (1).

As shown in Table 12, treatment providers boosted the number of videos uploaded within 24 hours following the first social nudge by 12.45% (0.0297 standard deviations; $p<0.0001$; column (1)) and increased

Table 11 Effects of Social Nudges Among All Providers Who Were Sent at Least One Social Nudge in the First Social-Nudge Experiment

Outcome Variable	Number of Videos Uploaded on the First Reception Day	Number of Social Nudges Sent on the First Reception Day
	(1)	(2)
Treatment	0.0222^{****}	0.0323^{****}
	(0.0014)	(0.0014)
Relative Effect Size	9.53%	13.92%
Observations	1,946,118	1,946,118

Note: Robust standard errors are reported in the parentheses. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$; $^{****}p<0.0001$. Columns (1)–(2) include all providers whose followers sent them at least one social nudge during our first social-nudge experiment. Number of Videos Uploaded and Number of Social Nudges Sent were standardized to have zero mean and unit standard deviation before entering the regressions.

Table 12 Effects of Social Nudges on Content Production Within 24 Hours Following the First Nudge

Outcome Variable	Number of Videos Uploaded Within 24 Hours Following the First Nudge	Upload Incidence Within 24 Hours Following the First Nudge
	(1)	(2)
Treatment	0.0297^{****}	0.0131^{****}
	(0.0020)	(0.0006)
Relative Effect Size	12.45%	13.22%
Observations	$993,676$	$993,676$

Notes: Columns (1)–(2) include all providers in the sample. Number of Videos Uploaded Within 24 Hours Following the First Nudge was standardized to have a zero mean and unit standard deviation before entering the regression. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

their likelihood of uploading any video within 24 hours following the first social nudge by 13.22% (1.31 percentage points; p<0.0001; column (2)). These results suggest that the positive effect of social nudges on content production is robust to this alternative time frame.

B. The Second Social-Nudge Experiment as a Replication

We conducted another experiment to replicate the effects of social nudges on production and diffusion that we observed in the first field experiment (Sections 4 and 5). The replication experiment lasted from 5pm on September 14, 2018 to the end of September 20, 2018. It lasted longer than the main experiment and targeted a nonoverlapping but smaller sample of providers than the main experiment.[12] Providers targeted by the replication experiment were randomly assigned into either the treatment condition or the control condition. Similar to our main experiment (Section 3), our analysis of the replication experiment focused on providers who satisfied two criteria: (1) at least one of their followers sent them a social nudge during the experimental period, and (2) they had never received any social nudges before the experiment. Our final analysis sample consisted of $678,090$ qualified providers, among whom $338,415$ were in the treatment condition and $339,675$ were in the control condition.

B.1. Direct Effects of Social Nudges on Content Production (Replicated)

We first examined the production-boosting effect of receiving social nudges over time in the second experiment. Specifically, using regression specification (1), we predicted $\textit{Number of Videos Uploaded}_{it}$ each day from the first reception day on until the first day when the difference between conditions was not statistically significant. We report the estimation results in Table 13, which shows that the effect sizes observed in the second experiment are comparable to the effect sizes observed in the main experiment (Table 4). Therefore, our results on the direct production-boosting effects of social nudges are robust.

B.2. Effects of Social Nudges on Nudge Diffusion (Replicated)

Next we tested the diffusion effect of receiving social nudges over time in the second experiment. Specifically, for each day t starting from the first reception day, we predicted $\textit{Number of Social Nudges Sent}_{it}$ using

[12] We first randomly sampled a portion of providers to be included in the main experiment. Then among the remaining providers, we randomly sampled a smaller portion of providers to be involved in the replication experiment.

Table 13 Over-Time Direct Effects of Social Nudges on Content Production (Replicated)

Outcome Variable	Number of Videos Uploaded			
	On Day 1 (First Reception Day)	On Day 2	On Day 3	On Day 4
	(1)	(2)	(3)	(4)
Treatment	0.0228****	0.0107****	0.0083***	0.0033
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Relative Effect Size	11.83%	7.79%	3.96%	
Observations	678,090	678,090	678,090	678,090

Notes: Number of Videos Uploaded was standardized to have a zero mean and unit standard deviation before entering the regressions. The unit of analysis for all columns was a provider on Day t relative to the first reception day, where $t=1$ means the first reception day. Columns (1)–(4) include all providers in our sample. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

Table 14 Over-Time Effects of Social Nudges on Nudge Diffusion (Replicated)

Outcome Variable	Number of Social Nudges Sent				
	On Day 1 (First Reception Day)	On Day 2	On Day 3	On Day 4	On Day 5
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0325****	0.0215****	0.0084***	0.0057*	0.0039
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Relative Effect Size	16.25%	14.16%	5.78%	4.02%	
Observations	678,090	678,090	678,090	678,090	678,090

Notes: Number of Social Nudges Sent was standardized to have a zero mean and unit standard deviation before entering the regressions. The unit of analysis for all columns was a provider on Day t relative to the first reception day, where $t=1$ refers to the first reception day. Columns (1)–(5) include all providers in our sample. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

regression specification (1) until the first day when the difference between conditions was not statistically significant. We report the estimation results in Table 14, which shows that the effect sizes observed in the second experiment are comparable to the effect sizes observed in the main experiment (Table 6). Therefore, our results on the diffusion of social nudges are robust.

C. Additional Analyses about the Direct Effects of Social Nudges

C.1. Addressing an Alternative Explanation about Control Providers' Resentment

As explicated in Section 1, we expected social nudges to boost content production because providers receiving social nudges might feel more valued by others and thus more motivated to supply effort. However, one potential alternative explanation for our observed difference in video production between treatment and control providers is that through other ways beyond the message center, control providers realized that their followers sent them social nudges but they could not receive these social nudges, which might make control providers feel resentful toward the platform and thus reduce their production. As mentioned in Section 3, the only way for users to directly communicate with each other on the platform is through the private-message function. It is plausible that during our experiment followers privately messaged providers after sending them social nudges, which led control providers to realize that they were blocked from viewing nudges. To address this alternative explanation, we conducted two sets of additional analyses.

First, we examined how private messages influenced control providers. If control providers knew via private messages that their followers sent them a social nudge but they were not allowed to see the nudge and if this created resentment, we should expect that receiving private messages from followers who sent them social nudges during the experiment negatively impacted control providers' content production. To test this possibility, we used the DiD method. This analysis included two observations per control provider, with one observation corresponding to the first reception day and one observation corresponding to the day before the experiment. For each observation of provider i, her content production equaled the number of videos uploaded on the corresponding day (either the first reception day or the day before the experiment). The DiD regression specification is formulated as below

$$\begin{aligned} Outcome\ Variable_{it} = \beta_0 + \beta_1 Private\ Messages\ Incidence_i + \beta_2 First\ Reception\ Day_{it} \\ + \beta_3 Private\ Messages\ Incidence_i * First\ Reception\ Day_{it} + \epsilon_{it} \end{aligned} \tag{10}$$

whereby *Private Messages Incidence*$_i$ was a binary variable that equaled one if the follower who sent provider i the first social nudge in the experiment (i.e., provider i's first social-nudge sender) also sent any private messages to i between the start date of the experiment and provider i's first reception day (including both ends) and zero otherwise[13]; and *First Reception Day*$_{it}$ was a binary variable that equaled one if an observation corresponded to the first reception day and zero if the observation corresponded to the day before the experiment. We clustered standard errors by provider.

As shown in Table 15 Panel A, since the coefficient on the interaction between *Private Messages Incidence*$_i$ and *First Reception Day*$_{it}$ is positive ($p < 0.0001$), we have no evidence to suggest that receiving private messages from followers who sent them social nudges during the experiment would reduce control providers' content production.

Second, we split the whole provider sample in our experiment into two subsamples based on whether each provider's first social-nudge sender sent any private messages to the provider between the start date of the experiment and provider i's first reception day (including both ends). Within each subsample, we compared the *Number of Videos Uploaded* on the first reception day between treatment and control conditions using regression specification (1).

As shown in Table 15 Panel B, no matter whether a provider got any private messages from their first social-nudge sender, receiving social nudges increased treatment providers' content production, relative to control providers' (both p-values < 0.001). The relative effect size is very similar among providers who got private messages from their first social-nudge sender (14.15% as shown in column (1)) and among providers who did not get private messages from their first social-nudge sender (12.36% as shown in column (2)).

Altogether, these results do not support the alternative explanation: it is unlikely that communication from followers via private messages led control providers to find out they could not view social nudges, elicited resentment, and thus reduced their motivation to produce videos. In addition, note that all broadcasters selected into our analysis sample had not received any social nudges before the experiment. Thus, it is unlikely for providers in our analysis to naturally realize that they did not receive social nudges during the experiment without any hints from followers.

[13] To protect user privacy, Platform O could not share the content of private messages with us. Thus, we could not use content analysis to identify whether each provider's first social-nudge sender told the provider about the nudge in their private communications, but instead we used whether a provider received private messages from their first social-nudge sender as a proxy, since receiving such private messages was the only plausible channel for control providers to find out the blocking of social nudges.

Table 15 The Role of Private Messages in Content Production Among Control Providers

Panel A: DiD Analysis about Private Messages Among Control Providers	
Outcome Variable	Number of Videos Uploaded
	(1)
Private Messages Incidence	0.1603****
	(0.0116)
First Reception Day	0.1258****
	(0.0020)
Private Messages Incidence	0.2248****
* First Reception Day	(0.0203)
Observations	993,400

Panel B: Comparison of Two Subsamples Based on Private Message Incidence		
Outcome Variable	Number of Videos Uploaded	
Subsample	*Providers Who Received Any Private Messages From the First Social-Nudge Sender*	*Providers Who Received No Private Messages From the First Social-Nudge Sender*
	(1)	(2)
Treatment	0.0710***	0.0235****
	(0.0192)	(0.0020)
Relative Effect Size	14.15%	12.36%
Observations	28,142	965,534

Notes: Number of Videos Uploaded was standardized to have a zero mean and standard deviation before entering the regressions. Panel A includes all control providers in our sample, with each control provider contributing two observations. Standard errors in Panel A are clustered at the provider level. Column (1) in Panel B includes treatment and control providers who received any private messages from their first social-nudge sender between the start date of the experiment and the first reception day, and column (2) in Panel B includes treatment and control providers who did not receive any private messages from their first social-nudge sender in this period. Robust standard errors reported in the parentheses in Panel B. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

C.2. Role of Likes and Comments

As mentioned in Section 3, when viewers watch a video, they can mark that they like the video and leave comments below the video. Since receiving social nudges could immediately boost video production (see Section 4.1), nudge recipients may also immediately receive more likes and comments due to the increased number of videos uploaded. Such positive feedback from viewers may in turn motivate nudge recipients to produce more videos going forward. This raises the question of whether and to what extent the immediate increase in likes and comments due to receiving social nudges drives the observed over-time effect of social nudges on nudge recipients' content production (as shown in Section 4.3).

To answer this question, we first tested whether receiving social nudges led the recipient to obtain more likes and comments. For each provider on her first reception day, we calculated the number of likes and comments she obtained that day (*Number of Likes on the First Reception Day* and *Number of Comments on the First Reception Day*, respectively)[14]. Using regression specification (1), we predicted these two outcome variables. As shown in Table 16 Panel A, treatment providers obtained more likes than control providers on the first reception day by 0.0112 standard deviations, or 4.52% ($p < 0.0001$; column (1)); treatment providers

[14] We winsorzied these two variables because they were highly skewed (due to a small number of providers being too popular). We winsorized each variable by replacing values greater than the 95th percentile of this variable's nonzero values with the 95th percentile of this variable's nonzero values.

Table 16 Effects of Social Nudges on Content Production With or Without Controlling for the Role of Likes and Comments

Panel A		
Outcome Variable	Number of Likes on the First Reception Day	Number of Comments on the First Reception Day
	(1)	(2)
Treatment	0.0112****	0.0108****
	(0.0020)	(0.0020)
Relative Effect Size	4.52%	5.40%
Observations	993,676	993,676

Panel B				
Outcome Variable	Number of Videos Uploaded Following the First Reception Day			
	(1)	(2)	(3)	(4)
Treatment	0.0129****	0.0091****	0.0094****	0.0090****
	(0.0020)	(0.0019)	(0.0019)	(0.0019)
Number of Likes on the First Reception Day		0.3374****		0.2299****
		(0.0009)		(0.0018)
Number of Comments on the First Reception Day			0.3225****	0.1253****
			(0.0009)	(0.0018)
Relative Effect Size	5.29%	3.74%	3.87%	3.68%
Observations	993,676	993,676	993,676	993,676

Panel C				
Outcome Variable	Number of Videos Uploaded on the Second Day Following the First Reception Day			
	(1)	(2)	(3)	(4)
Treatment	0.0065**	0.0061**	0.0063**	0.0061**
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Number of Likes the Day Following the First Reception Day		0.1209****		0.0853****
		(0.0010)		(0.0020)
Number of Comments the Day Following the First Reception Day			0.1152****	0.0408****
			(0.0010)	(0.0020)
Relative Effect Size	2.54%	2.40%	2.46%	2.42%
Observations	993,676	993,676	993,676	993,676

Notes: All continuous variables were standardized to have a zero mean and unit standard deviation before entering the regressions. All columns in Panels A, B, and C include all providers in the sample. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

obtained more comments than control providers on the first reception day by 0.0108 standard deviations, or 5.40% ($p < 0.0001$; column (2)). Hence, treatment providers obtained more likes and comments after they received social nudges, relative to control providers.

We next tested how much the immediate increase in likes and comments due to the receipt of social nudges contributed to the effects of receiving social nudges on content production during the few days after the first reception day. In one series of regressions, we predicted the *Number of Videos Uploaded* the day following the first reception day using regression specification (1), and we compared the regression results with or without controlling for the number of likes or comments a provider obtained the day before (i.e., *Number of Likes on the First Reception Day* and *Number of Comments on the First Reception Day*). According to Table 16 Panel B, without controlling for likes or comments on the first reception day, we found that receiving social nudges boosted the number of videos uploaded by 0.0129 standard deviations (5.29%, $p < 0.0001$; column (1) of Panel A) on the day following the first reception day. This effect reduced but remained statistically significantly when we controlled for the number of likes a provider got on her first reception day (column (2)), the number of comments she got on her first reception day (column (3)), or both (column (4)).

Further, we predicted the *Number of Videos Uploaded* on the *second day* following the first reception day using regression specification (1), and we compared the regression results with or without controlling for the number of likes or comments a provider obtained the day before (i.e., on the day following the first reception day). As shown in Table 16 Panel C, the positive effect of receiving social nudges on content production two days later reduced only slightly when we added these control variables.

Altogether, these findings indicate that getting more likes and comments after treatment providers uploaded more videos in response to social nudges contributed to some extent to the over-time effect of social nudges on content production. However, increased likes and comments are not the only reason, neither are they the primary reason the effect of receiving social nudges on content production lasted a few days, since we observed only a slight to moderate decrease in the magnitude of the production-boosting effect of social nudges after the first reception day when we controlled for likes and comments providers obtained earlier. This suggests that receiving social nudges per se is sufficient to motivate video production a few days, even without additional positive feedback providers receive due to their increased production along the way[15].

C.3. Effects of Social Nudges Across Providers With Different Baseline Productivity

The scant prior literature that has examined the causal effects of peer recognition without financial incentives has not provided a clear answer to the question of whether peer recognition can boost recipients' production (Restivo and van de Rijt 2014, Gallus et al. 2020). In a field experiment involving top 10% of providers to Wikipedia, Restivo and van de Rijt (2014) found that peer recognition increased only the most productive 1% of content providers but not providers ranked at the 91st–99th percentile. To test whether the production-boosting effect of social nudges can generalize to providers with different levels of baseline productivity, we divided the providers in our sample into three subsamples: providers whose historical production—the number of videos uploaded during the week prior to the experiment—was (1) below or at the 90th percentile of the distribution of historical production across all providers in the sample ("*low-productivity providers*"; ignored by Restivo and van de Rijt (2014)), (2) in the 91st–99th percentile range ("*medium-productivity providers*"; comparable to the definition of less-productive providers in Restivo and van de Rijt (2014)), and (3) at the 100th percentile ("*high-productivity providers*"; comparable to the most productive 1% providers in Restivo and van de Rijt (2014)). For each subsample, we separately estimated the effect of receiving social nudges on the day of nudges being sent. That is, we predicted $\textit{Number of Videos Uploaded}_i$ on the first reception day using regression specification (1).

[15] We conducted these analyses because it is *theoretically* interesting to tease apart whether the lingering effect of receiving social nudges on content production is driven by providers obtaining an increased amount of positive feedback on their videos or by providers feeling motivated by social nudges per se. But *practically speaking*, we believe the feedback mechanism is meaningful because increased likes and comments are *consequences* of the initial boost in content production in response to social nudges. Thus, we do not distinguish these mechanisms when we calculate the global impact of social nudges in Section 6.

As shown in Table 17, the number of videos uploaded on the first reception day was boosted by 19.37% (0.0220 standard deviations; $p < 0.0001$; column (1)) among low-productivity providers, by 6.91% (0.0577 standard deviations; $p < 0.0001$; column (2)) among medium-productivity providers, and by 7.67% (0.2145 standard deviations; $p < 0.05$; column (3)) among high-productivity providers. Overall, these results suggest that not only the most productive 1% of providers but also providers whose historical production was in the 0th-99th percentile range were also motivated by receiving social nudges.

Table 17 Direct Effects of Social Nudge Across Providers With Different Historical Production Levels

Outcome Variable	Number of Videos Uploaded on the First Reception Day		
Subsample	*Low-Productivity Providers*	*Medium-Productivity Providers*	*High-Productivity Providers*
	(1)	(2)	(3)
Treatment	0.0220^{****}	0.0577^{****}	0.2145^{*}
	(0.0015)	(0.0124)	(0.0926)
Relative Effect Size	19.37%	6.91%	7.67%
Observations	901,286	83,838	8,552

Notes: Number of videos uploaded was standardized to have a zero mean and unit standard deviation before entering the regressions. Each column includes the providers in the corresponding subsample. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

C.4. Comparison Between Social Nudges and Platform-Initiated Nudges

Receiving a social nudge and its implied recognition may make providers feel more valued, thus motivating them to produce new videos. However, such information communicated via social nudges from neighbors may not be passed on by nudges from the platform to encourage production. To explore whether social nudges have effects beyond regular nudges sent from companies, we leveraged another randomized field experiment that tested the effects of receiving nudges from Platform O. We refer to this experiment as the *platform-initiated nudge experiment*. The platform-initiated nudge experiment randomly targeted a subset of users on Platform O, no matter whether they were targeted by the social-nudge experiments. We note that comparing the results of our main social-nudge experiment versus the platform-initiated nudge experiment does not causally estimate the difference between social nudges and platform-initiated nudges. Specifically, since the two experiments were conducted in different time periods and providers were not randomly assigned to receive one of these two types of nudges, the providers included in the two experiments were not exactly comparable. As described below, we sought to construct samples from the two experiments that were as comparable to each other as possible.

Experiment Design and Data. The platform-initiated nudge experiment was conducted between 9AM on July 22, 2019 and 5AM on August 30, 2019. Half of the providers were randomly assigned to the treatment condition, and the other half to the control condition. During the experiment, the platform identified providers who published a video one or more years ago exactly on the same date. For these providers, Platform O created a message that read, “On this day X years ago, you posted a video. Post another one to capture the moments today!” where “X” was filled in with the actual number of years that

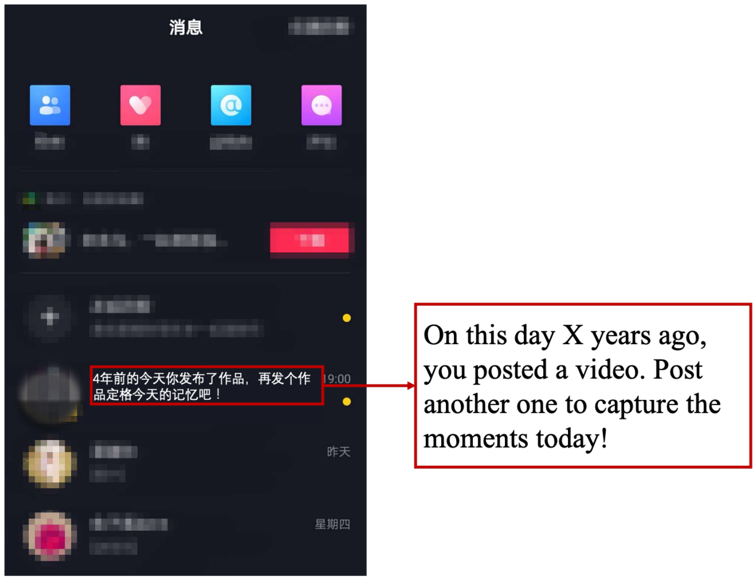

Figure 4 **A Platform-Initiated Nudge**

had elapsed.[16] The only factor that we manipulated between treatment and control providers was that Platform O actually sent out the aforementioned message to treatment providers on that date, but not to control providers. Therefore, control providers could not receive any platform-initiated nudges. Messages about platform-initiated nudges were displayed in the Message Center, the same as social nudges (see Figure 1 (b)).

We first selected treatment and control providers who were qualified to be sent at least one message from Platform O during our experiment. For these providers, we defined "the first reception day" as the day when they first became qualified to be sent Platform O's nudge message. The sample selection criteria and the definition of the first reception day here match our approach in the social-nudge experiment.

The Effect of Receiving Platform-Initiated Nudges on Production. We first examined the effect of receiving platform-initiated nudges on content production, both on the first reception day and in the next few days. Consistent with our analytical strategy for the social-nudge experiment (Section 4.3), we examined how receiving nudges from Platform O affected providers' production each day between treatment and control providers among the full sample of providers from the first reception day on until the first day when the difference between conditions was not statistically significant. Specifically, for each day t starting from the first reception day (where t equals $1, 2, \cdots$ and $\mathrm{t} = 1$ refers to the first reception day itself), we predicted $\textit{Number of Videos Uploaded}_{it}$ using regression specification (1).

[16] To avoid disturbing providers, Platform O sent out a maximum of two messages to each provider in one week. Specifically, on the first day of each week during the experiment, for provider i, Platform O identified the dates during that week on which provider i uploaded any video exactly one or more years ago. If more than two dates satisfied the criterion, Platform O picked the dates on which the video uploaded exactly one or more years ago had the highest or second highest views (among all videos uploaded in the same week one or more years ago).

[16] Similar to Figure 1, we created Figure 4 by modifying the app interface of a widely-used video-sharing platform whose interface is similar to Platform O, in order to protect Platform O's identity.

We report the regression results in Table 18 Panel A. On the first reception day, the platform-initiated nudge treatment lifted the number of videos uploaded by 0.0105 standard deviations ($p < 0.0001$), which amounts to a 5.55% increase relative to the average in the control condition, as shown in column (1). On Day 2 (the day following the first reception day), the number of video uploaded was higher in the treatment condition than in the control condition by 0.0026 standard deviations, or 1.37% ($p < 0.0001$; column (2)); on Day 3 (the second day from the first reception day), the increase was 0.0019 standard deviations, or 0.99% ($p < 0.01$; column (3)). The effect of receiving platform-initiated nudges on the nudge recipient's production was not significant on Day 4 (the third day after the first reception day; column (4)).

Table 18 Comparison of Social Nudge and Platform-Initiated Nudge

Panel A: Direct Effects of Platform-Initiated Nudges on Content Production				
Outcome Variable	Number of Videos Uploaded			
	On Day 1 (First Reception Day)	On Day 2	On Day 3	On Day 4
	(1)	(2)	(3)	(4)
Treatment	0.0105****	0.0026****	0.0019**	0.0011
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Relative Effect Size	5.55%	1.37%	0.99%	
Observations	11,043,476	11,043,476	11,043,476	11,043,476

Panel B: Comparison of Social Nudges and Platform-Initiated Nudges Using an Overlapping Sample of Providers		
Outcome Variable	Number of Videos Uploaded On Day 1 (First Reception Day)	
	Platform-Initiated Nudges	*Social Nudges*
Treatment	0.0152	0.0216***
	(0.0093)	(0.0063)
Relative Effect Size		12.35%
Observations	63,467	63,467

Notes: Number of videos uploaded was standardized to have a zero mean and unit standard deviation before entering the regressions. Panel A includes all providers who satisfied sample selection criteria for the platform-initiated nudge experiment. The unit of analysis in Panel A was a provider on Day t relative to the first reception day, where $t = 1$ means the first reception day. Panel B includes providers who were selected for both the social-nudge experiment and the platform-initiated nudge experiment. The unit of analysis in Panel B was a provider on her first reception day. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

Next we compared the production-boosting effects of social nudges and platform-initiated nudges. Figure 5 displays the relative effect sizes of these two kinds of nudges, as well as the corresponding 95% confidence intervals.[17] The effect of receiving platform-initiated nudges on *Number of Videos Uploaded*$_{it}$ was generally below that of receiving social nudges. In particular, on the reception day (i.e., $t = 1$), receiving social nudges increased the number of uploaded videos by 13.21% ($p < 0.0001$), more than twice as large as the increase of 5.55% ($p < 0.0001$) engendered by receiving platform-initiated nudges; on the day following the first reception day (i.e., $t = 2$), receiving social nudges increased the number of uploaded videos by 5.29% ($p < 0.0001$),

[17] We obtained the relative effect size each day by applying regression specification (1) to raw data without standardization and dividing the coefficient on treatment on a day by the average of the outcome variable in the control condition that day. The upper (lower) bound of each 95% confidence interval in Figure 5 equaled the upper (lower) bound of the 95% confidence interval of the corresponding regression coefficient on treatment (based on raw data) divided by the average of the outcome variable in the control condition.

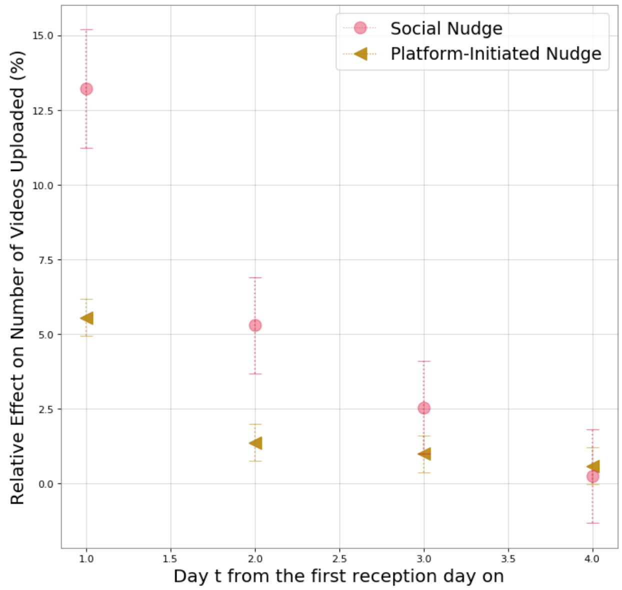

Figure 5 **Comparing the Relative Effect Size of Receiving a Platform-Initiated Nudge Versus Social Nudge Over Time**

Note: The error bars represent 95% confidence intervals.

almost three times as large as the increase of 1.37% (p $<$ 0.0001) brought by receiving platform-initiated nudges; on the second day following the first reception day (i.e., $t = 3$), receiving social nudges increased the number of uploaded videos by 2.54% (p $<$ 0.01), almost twice as large as the increase of 0.99% (p $<$ 0.01) from by receiving platform-initiated nudges.[18]

In addition, as a robustness check, we analyzed only providers who were included in both the platform-nudge experiment and our main social-nudge experiment (N=$63,467$) to as cleanly estimate the difference between these two kinds of nudges as possible. Among these overlapping providers, we re-analyzed the direct effects of receiving social nudges or platform-initiated nudges. Since the effects of social nudges and platform-initiated nudges on the recipients' production among these overlapping providers were no longer statistically significant after the first reception day, we focused on comparing these effects on the first reception day. As shown in Table 18 Panel B, the effect of receiving platform-initiated nudges on the number of videos uploaded on the first reception day was not significant (p $= 0.10$; column (1))[19], while receiving social nudges significantly boosted the number of videos uploaded on the first reception day by 0.0216 standard deviations,

[18] Notably, during the four days since the first reception day (including the first reception day itself) for which we reported the day-by-day effects of both nudges, most (88%) providers were sent only one social nudge in the social-nudge experiment, and most (89%) providers were sent only one platform-initiated nudge in the platform-initiated nudge experiment. Hence, the production-boosting effects of both social nudges and platform-initiated nudges were mostly driven by one nudge, making the comparison fair.

[19] Even if we put aside whether the estimated effect was statistically significant, receiving platform-initiated nudges was estimated to increase the number of videos uploaded on the first reception day by 0.0152 standard deviations (or 4.54%) among the overlapping sample of providers, which was still lower than the effect of receiving social nudges on the number of videos uploaded on the first reception day (i.e., 0.0216 standard deviations or 12.35%).

or 12.35% (p < 0.001; column (2)). These results further provide suggestive evidence that social nudges boosted providers' production to a larger extent than platform-initiated nudges.

D. Proofs for the Social Network Model

D.1. Proof of Theorem 1

Let us assume throughout the proof that $\mathbf{D}$ satisfies $C_q(\delta)$ for $q \in [1, \infty)$. The proof follows for any $q \in [1, \infty)$ because we rely only on the sublinearity and submultiplicativity of operator norms. Recall that the system of the social network model is defined by Equations (3) and (4).

Let us denote by $\boldsymbol{y}^*(t) := \mathbb{E}[\boldsymbol{y}(t)]$. Since $\epsilon_e^y(t)$ is the random error with a zero mean and a finite support, it then follows that $\boldsymbol{y}^*(t) = \boldsymbol{\mu} + \sum_{1 \le s \le t-1} \alpha_d^{t-s} \mathbf{D} \boldsymbol{y}^*(s) + \mathbf{D}\boldsymbol{y}^*(t)$, or equivalently

$$\boldsymbol{y}^*(t) = (\mathbf{I} - \mathbf{D})^{-1} \left(\boldsymbol{\mu} + \sum_{1 \le s \le t-1} \alpha_d^{t-s} \mathbf{D} \boldsymbol{y}^*(s) \right). \tag{11}$$

Before we directly focus on $\{\boldsymbol{y}^*(t)\}_{t=1}^{+\infty}$, we truncate the number of lags for the ease of argument. That is, we consider the following system with a fixed positive integer M:

$$y_e^M(t) = \mu_e(t) + \sum_{\max\{t-M,1\} \le s \le t} \alpha_d^{t-s} \sum_{\ell \in E : \ell_d = e_o} d_{\ell e} y_\ell(s) + \epsilon_e^y(t),$$

for all $e \in E$, and for all $i \in V$

$$x_i^M(t) = \sum_{\max\{t-M,1\} \le s \le t} \alpha_p^{t-s} \sum_{e \in E : e_d = i} p_e y_e(s) + \epsilon_i^x(t).$$

Let us also define $\boldsymbol{y}^{*,M}(t) := \mathbb{E}\boldsymbol{y}^M(t)$. Then, it follows that

$$\boldsymbol{y}^{*,M}(t) = (\mathbf{I} - \mathbf{D})^{-1} \left(\boldsymbol{\mu} + \sum_{\max\{t-M,1\} \le s \le t-1} \alpha_1^{t-s} \mathbf{D} \boldsymbol{y}^*(s) \right), \tag{12}$$

provided that $\mathbf{I} - \mathbf{D}$ is invertible. Let the spectral radius of a matrix be $\rho(\cdot)$. Then $\rho(\mathbf{D}) \le ||\mathbf{D}||_q < 1 - \alpha_d < 1$, in which the first inequality is due to the fact that the spectral radius of any square matrix is bounded by any operator norm of the matrix. As a result, $\mathbf{I} - \mathbf{D}$ is invertible and $(\mathbf{I} - \mathbf{D})^{-1} = \sum_{i=0}^{\infty} \mathbf{D}^i$ (see, e.g., Horn and Johnson 2012). Next, we present a series of technical lemmas toward the proof of Theorem 1.

Lemma 2 *The following results regarding $\{\boldsymbol{y}^{*,M}(t)\}_{t=1}^{+\infty}$ holds.*

(*a*) *It follows that $\{\boldsymbol{y}^{*,M}(t)\}_{t=1}^{+\infty}$ is a Cauchy sequence for any M such that $1 \le M < \infty$.*

(*b*) *There exists a positive constant θ such that $||\boldsymbol{y}^{*,M}(t)||_q \le \theta$ and $||\boldsymbol{y}^*(t)||_q \le \theta$ for any $t \in \mathbb{Z}_+$ and $M \in \mathbb{Z}_+$.*

Note that a Cauchy sequence is always bounded, but the second term of Lemma 2 implies these sequences are uniformly bounded over any M, including when $M = \infty$. This fact is useful in the proof of Lemma 3, but slightly strong than necessary. Now let us turn to the sequence $\{\boldsymbol{y}^*(t)\}_{t=1}^{+\infty}$. We state the following lemma.

Lemma 3 *For any $\epsilon > 0$, there exists $\bar{M}$ such that if $M \ge \bar{M}$, $||\boldsymbol{y}^*(t) - \boldsymbol{y}^{*,M}(t)||_q \le \epsilon$ uniformly for t.*

Lemmas 2 and 3 together imply that $\{\boldsymbol{y}^*(t)\}_{t=1}^{+\infty}$ is also a Cauchy sequence, and therefore the limit of the sequence $\{\boldsymbol{y}^*(t)\}_{t=1}^{+\infty}$ exists. In particular, given any ϵ, there exists M and T such that $||\boldsymbol{y}^*(t)-\boldsymbol{y}^{*,M}(t)||_q \leq \epsilon/3$ for any t, and $||\boldsymbol{y}^{*,M}(t_1)-\boldsymbol{y}^{*,M}(t_2)||_q \leq \epsilon/3$ for any $t_1, t_2 \geq T$. Consequently, it holds that

$$||\boldsymbol{y}^*(t_1)-\boldsymbol{y}^*(t_2)||_q \leq ||\boldsymbol{y}^*(t_1)-\boldsymbol{y}^{*,M}(t_1)||_q + ||\boldsymbol{y}^{*,M}(t_1)-\boldsymbol{y}^{*,M}(t_2)||_q + ||\boldsymbol{y}^{*,M}(t_2)-\boldsymbol{y}^*(t_2)||_q \leq \epsilon,$$

and $\{\boldsymbol{y}^*(t)\}_{t=1}^{+\infty}$ is Cauchy, whose limit we write as $\boldsymbol{y}^*$. Let us note that by Equation (11)

$$\boldsymbol{y}^*(t+1) = (\mathbf{I}-\mathbf{D})^{-1}\left(\boldsymbol{\mu} + \sum_{1\leq s\leq t} \alpha_d^{t+1-s}\mathbf{D}\boldsymbol{y}^*(s)\right) \tag{13}$$

and

$$\alpha_1\boldsymbol{y}^*(t) = (\mathbf{I}-\mathbf{D})^{-1}\left(\alpha_d\boldsymbol{\mu} + \sum_{1\leq s\leq t-1} \alpha_d^{t-s+1}\mathbf{D}\boldsymbol{y}^*(s)\right). \tag{14}$$

Taking the difference between Equation (13) from Equation (14) leads to $\boldsymbol{y}^*(t+1) - \alpha_d\boldsymbol{y}^*(t) = (\mathbf{I}-\mathbf{D})^{-1}\left((1-\alpha_d)\boldsymbol{\mu} + \alpha_d\mathbf{D}\boldsymbol{y}^*(t)\right)$. Letting $t\to+\infty$ on both sides leads to $\boldsymbol{y}^* - \alpha_d\boldsymbol{y}^* = (\mathbf{I}-\mathbf{D})^{-1}\left((1-\alpha_d)\boldsymbol{\mu} + \alpha_d\mathbf{D}\boldsymbol{y}^*\right)$. Reorganizing the terms, we have $\boldsymbol{y}^* = \boldsymbol{\mu} + 1/(1-\alpha_d)\mathbf{D}\boldsymbol{y}^*$. Therefore, $\boldsymbol{y}^* = (\mathbf{I} - 1/(1-\alpha_d)\mathbf{D})^{-1}\boldsymbol{\mu}$, because the spectral radius of $1/(1-\alpha_d)\mathbf{D}$, i.e., $\rho(1/(1-\alpha_d)\mathbf{D})$, satisfies

$$\rho\left(\frac{1}{1-\alpha_d}\mathbf{D}\right) \leq \left|\left|\frac{1}{1-\alpha_d}\mathbf{D}\right|\right|_q < 1$$

because of our assumption. The proofs of $\lim_{t\to\infty}\mathbb{E}\boldsymbol{x}(t) = \boldsymbol{x}^*$ and $x_i^* = \frac{1}{1-\alpha_p}\sum_{e\in E: e_d=i} p_e y_e^*$, for all $i\in V$ are similar to our arguments so far. Therefore, we omit this part and conclude the proof. □

Next, we prove Lemmas 2 - 3. The following fact is useful and we relegate its proof to the last.

Lemma 4 *It holds that* $\frac{\alpha_d}{1-\alpha_d}||(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}||_q < 1$.

Proof of Lemma 2. Toward the proof of item (a) in Lemma 2, let us fix M. Consider two real number sequences $\{\boldsymbol{y}^1(t)\}_{t=1}^M$ and $\{\boldsymbol{y}^2(t)\}_{t=1}^M$, and let $\bar{\boldsymbol{z}}^i = (\mathbf{I}-\mathbf{D})^{-1}\left[\boldsymbol{\mu} + \sum_{1\leq s\leq M}\alpha_d^{M-s+1}\mathbf{D}\boldsymbol{y}^i(s)\right]$, for $i=1,2$. It then follows that

$$\begin{aligned}
||\bar{\boldsymbol{z}}^1 - \bar{\boldsymbol{z}}^2||_q &= \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\sum_{1\leq s\leq M}\alpha_d^{M-s+1}\mathbf{D}\left(\boldsymbol{y}^1(s)-\boldsymbol{y}^2(s)\right)\right|\right|_q \\
&\leq \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q \left|\left|\sum_{1\leq s\leq M}\alpha_d^{M-s+1}\left(\boldsymbol{y}^1(s)-\boldsymbol{y}^2(s)\right)\right|\right|_q = \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q \cdot \sum_{1\leq s\leq M}\alpha_d^{M-s+1}\cdot\left|\left|\left(\hat{\boldsymbol{y}}^1-\hat{\boldsymbol{y}}^2\right)\right|\right|_q \\
&\leq \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q \left|\left|\cdot\sum_{1\leq s\leq M}\alpha_d^{M-s+1}\cdot\mathbf{D}\right|\right|_q \max_{1\leq s\leq M}\left|\left|\left(\boldsymbol{y}^1(s)-\boldsymbol{y}^2(s)\right)\right|\right|_q
\end{aligned} \tag{15}$$

in which the first inequality follows due to the sub-multiplicity of ℓ_2-norm and the second equality follows from definition

$$\hat{\boldsymbol{y}}^i := \left(\sum_{1\leq s\leq M}\alpha_d^{M-s+1}\boldsymbol{y}^i(s)\right)\Big/\left(\sum_{1\leq s\leq M}\alpha_d^{M-s+1}\right),$$

and the sub-mulplicity of ℓ_2-norm, and the last inequality follows from the convexity of ℓ_2-norm. By Lemma 4, $(\alpha_d/(1-\alpha_d))||(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}||_q = c$ for some constant $c<1$. Therefore, since $\sum_{1\leq s\leq M}\alpha_d^{M-s+1} \leq \alpha_d/(1-\alpha_d)$, we observe

$$||\bar{\boldsymbol{z}}^1 - \bar{\boldsymbol{z}}^2||_q \leq c\cdot\max_{1\leq s\leq M}\left|\left|\left(\boldsymbol{y}^1(s)-\boldsymbol{y}^2(s)\right)\right|\right|_q. \tag{16}$$

As a result of (16), if we define $w(t) = ||\boldsymbol{y}^{*,M}(t+1) - \boldsymbol{y}^{*,M}(t)||_q$, for $k \geq 1$ it holds $w(kM+1) \leq c \cdot \max_{1\leq s\leq M}\{w((k-1)M+s)\}$. Similarly, $w(kM+2) \leq c \cdot \max\left\{ \max_{2\leq s\leq M}\{w((k-1)M+s)\}, w(kM+1)\right\} \leq c \cdot \max_{1\leq s\leq M}\{w((k-1)M+s)\}$, in which the second inequality follows from $w(kM+1) \leq c \cdot \max_{1\leq s\leq M}\{w((k-1)M+s)\}$. Induction shows that $w(kM+s) \leq c \cdot \max_{1\leq t\leq M}\{w((k-1)M+t)\}$ for all s satisfy $1 \leq s \leq M$. Let us define $\tau = \max_{1\leq s\leq M}\{w(s)\}$. By induction one can verify that $w(kM+s) \leq c^k\tau$, for all $k \geq 0$ and $1 \leq s \leq M$. This implies that for some k, k', s and s' such that $Mk'+s' \geq Mk+s$, we have

$$||\boldsymbol{y}^{*,M}(Mk'+s') - \boldsymbol{y}^{*,M}(Mk+s)||_q \leq \sum_{i=Mk+s}^{Mk'+s'-1} ||\boldsymbol{y}^{*,M}(i+1) - \boldsymbol{y}^{*,M}(i)||_q \leq \sum_{i=2Mk+s}^{+\infty} ||\boldsymbol{y}^{*,M}(i+1) - \boldsymbol{y}^{*,M}(i)||_q$$

$$= \sum_{i=Mk+s}^{+\infty} w(i) \leq \sum_{j=0}^{\infty} Mc^{k+j}\tau = Mc^k \cdot \frac{\tau}{1-c},$$

where the first inequality follows from triangular inequality. This implies that $\{\boldsymbol{y}^{*,M}(t)\}_{t=1}^{+\infty}$ is a Cauchy sequence. This finishes the proof of item (a) in Lemma 2.

Let us recall from Lemma 4 that $\alpha_d/(1-\alpha_d) \cdot ||(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}||_q = c$ for some constant $c < 1$. Let us choose a positive constant θ satisfying $||(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\mu}||_q + c\theta \leq \theta$ and $||\boldsymbol{y}^{*,M}(1)||_q \leq \theta$ for all $M \leq +\infty$ (note that we understand $\boldsymbol{y}^{*,\infty}(t)$ as $\boldsymbol{y}^{*,\infty}(t) = \boldsymbol{y}^*(t)$). This choice of θ is possible since $||\boldsymbol{y}^{*,M}(1)||_q = ||\boldsymbol{y}^{*,M'}(1)||_q$ for any M, M'. Furthermore, for any t and M such that $1 \leq t, M \leq +\infty$, we argue that $||\boldsymbol{y}^{*,M}(t)||_q \leq \theta$ by induction. Fix M and let us assume that this holds that any $s < t$. It then holds by Equation (12) that,

$$\begin{aligned}
||\boldsymbol{y}^{*,M}(t)||_q \leq & ||(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\mu}||_q + \sum_{\max\{t-M,1\}\leq s\leq t-1} \alpha_d^{t-s} \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\boldsymbol{y}^*(s)\right|\right|_q \\
\leq & ||(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\mu}||_q + \sum_{\max\{t-M,1\}\leq s\leq t-1} \alpha_d^{t-s} \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q ||\boldsymbol{y}^*(s)||_q \\
\leq & ||(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\mu}||_q + \frac{\alpha_d}{1-\alpha_d} \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q \theta \leq ||(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\mu}||_q + c\theta \leq \theta,
\end{aligned}$$

in which the first inequality follows form the sublinearity of ℓ_2-norm, the second inequality follows from the submulplicity of ℓ_2-norm, the third inequality follows from the geometric sum, the fourth inequality follows from the definition of c, and the last inequality follows from the definition of θ. This concludes the proof of the second item. $\square$

Proof of Lemma 3. Clearly, $||\boldsymbol{y}^*(t) - \boldsymbol{y}^{*,M}(t)||_q = 0$ for $t \leq M+1$ by Equation (12). Assume that $t > M+1$ and $||\boldsymbol{y}^*(s) - \boldsymbol{y}^{*,M}(s)||_q \leq \epsilon$ holds for all $s < t$. By the subadditivity of ℓ_2-norm, we have

$$||\boldsymbol{y}^*(t) - \boldsymbol{y}^{*,M}(t)||_q \leq \sum_{1\leq s<t-M} \alpha_d^{t-s} \left|\left|(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\boldsymbol{y}^*(s)\right|\right|_q + \left|\left|(\mathbf{I}-\mathbf{D})^{-1} \cdot \sum_{\max\{t-M,1\}\leq s\leq t-1} \alpha_d^{t-s}\mathbf{D}\left(\boldsymbol{y}^{*,M}(s) - \boldsymbol{y}^*(s)\right)\right|\right|_q$$

The first term goes to zero as $M \to \infty$, because $||\boldsymbol{y}^*(t)||_q$ is bounded by Lemma 2. More specifically, it holds that $\sum_{1\leq s<t-M} \alpha_d^{t-s} \leq \sum_{s=M}^{\infty} \alpha_d^s = \alpha_d^M/(1-\alpha_d) \to 0$. Therefore, the first term vanishes as M is large.

With an argument similar to Lemma 2, the second term can be bounded by

$$\left|\left|\sum_{\max\{t-M,1\}\leq s\leq t-1} \alpha_d^{t-s}(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}\right|\right|_q \max_{t-M\leq s\leq t-1}\{||\boldsymbol{y}^{*,M}(s) - \boldsymbol{y}^*(s)||_q\} \leq c \max_{t-M\leq s\leq t-1}\{||\boldsymbol{y}^{*,M}(s) - \boldsymbol{y}^*(s)||_q\},$$

which by the induction hypothesis is bounded by $c\epsilon$. Therefore, as long we pick M large enough so that the first term is bounded by $(1-c)\epsilon$, we have $||\boldsymbol{y}^*(t)-\boldsymbol{y}^{*,M}(t)||_q \le \epsilon$. □

Proof of Lemma 4. As argued in the proof of Theorem 1, $||\mathbf{D}|| < 1-\alpha_d$ implies that $\mathbf{I}-\mathbf{D}$ is invertible and $(\mathbf{I}-\mathbf{D})^{-1} = \sum_{i=0}^{\infty} \mathbf{D}^i$ where the convergence is understood element-wise. Therefore,

$$||(\mathbf{I}-\mathbf{D})^{-1}\mathbf{D}||_q = ||\sum_{i=0}^{\infty}\mathbf{D}^i \cdot \mathbf{D}||_q = ||\sum_{i=1}^{\infty}\mathbf{D}^i||_q \le \sum_{i=1}^{\infty}||\mathbf{D}^i||_q \le \sum_{i=1}^{\infty}||\mathbf{D}||_q^i < \sum_{i=1}^{\infty}\alpha_d^i = \frac{\alpha_d}{1-\alpha_d}.$$

Therefore, the conclusion follows. □

D.2. Proof of Unbiasedness for Algorithm 1

Proposition 1 *Algorithm 1 yields an unbiased estimate for $\tilde{x}(1)$.*

Proof of Proposition 1. As shown in Section 6.2, the total production boost can be theoretically approximated as $\tilde{x}(1)$ by including all providers on the entire social network (the node set V), and is practically approximated as $\hat{w}$ according to our Algorithm 1 by sampling a subset of providers from V (i.e., $\tilde{V}$). Now we prove that $\hat{w}$ is an unbiased estimate for $\tilde{x}(1)$.

First, reorganizing the sum by nodes rather than edges, we have

$$\begin{aligned}\tilde{x}(1) &= \boldsymbol{\eta}^\top \left(\mathbf{I} + \frac{1}{(1-\alpha_d)}\mathbf{D}\right)\boldsymbol{\mu} = \sum_{e\in E}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ \ell_d=e_o}\frac{\mu_e d_{\ell e} p_e}{(1-\alpha_p)(1-\alpha_d)}\right)\\ &= \sum_{e\in E}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right) = \sum_{i\in V}\left(\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right).\end{aligned}$$

Note that $\hat{w}$ is defined as

$$\hat{w} = \frac{|V|}{|\tilde{V}|}\sum_{i\in\tilde{V}}\left(\sum_{e\in\tilde{E}:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in\tilde{L}:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right).$$

where $\tilde{E} := \{e \in E : e_d \in \tilde{V}\}$ and $\tilde{L} := \{\ell \in E : \ell_o \in \tilde{V}\}$. Clearly, we can replace $\tilde{E}$ and $\tilde{L}$ with E respectively in the definition of w. Moreover, for each node i in V, we use a binary random variable $s_i \in \{0,1\}$ to denote whether node i is selected in the sample $\tilde{V}$. Then, we can write w as

$$\begin{aligned}\hat{w} &= \frac{|V|}{|\tilde{V}|}\sum_{i\in\tilde{V}}\left(\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right)\\ &= \frac{|V|}{|\tilde{V}|}\sum_{i\in V}\left(s_i\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right).\end{aligned}$$

Since we uniformly and randomly sample the node set $\tilde{V}$, we have, for each $i \in V$, $\mathbb{E}[s_i] = \frac{|\tilde{V}|}{|V|}$. Hence,

$$\begin{aligned}\mathbb{E}[\hat{w}] &= \frac{|V|}{|\tilde{V}|}\sum_{i\in V}\left(\mathbb{E}[s_i]\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right)\\ &= \frac{|V|}{|\tilde{V}|}\sum_{i\in V}\left(\frac{|\tilde{V}|}{|V|}\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right)\\ &= \sum_{i\in V}\left(\sum_{e\in E:\ e_d=i}\left(\frac{\mu_e p_e}{1-\alpha_p} + \sum_{\ell\in E:\ e_d=\ell_o}\frac{\mu_e d_{e\ell} p_\ell}{(1-\alpha_p)(1-\alpha_d)}\right)\right) = \tilde{x}(1).\end{aligned}$$

This concludes the proof. □

E. Social Network Model Estimation Details

In this section, we present the estimation details for the global effect of social nudges, including the parameters needed in Algorithm 1: μ_e $(e \in E)$, p_e $(e \in E)$, $d_{e\ell}$ $(e, \ell \in E$ and $e_d = \ell_o)$, α_p, and α_d. We also present two robustness checks.

E.1. Estimation of μ_e

Recall that the parameter μ_e measures the probability that e_o will send a nudge to e_d in a given period when e_o has not received nudges from her followers recently. We estimate μ_e by taking advantage of the fact that providers in the control group of our social-nudge experiment cannot receive nudges (and thus cannot be motivated to send more nudges out because of receiving nudges themselves) during the experiment. We uniformly and randomly sampled $5,000,000$ edges from all edges whose origins were in the control group of our social-nudge experiment. Here, we do not require the origins of these edges to satisfy the selection criteria of our analysis sample mentioned in Section 3 since we use this random edge sample to represent the overall edges on Platform O. Our goal is to train a prediction model to estimate μ_e for each $e \in E$.

We fit the logistic regression model (17) to predict μ_e, i.e., the probability that $\textit{Social-Nudge Incidence}_e = 1$. We select features based on the commonly recognized characteristics in the network economics literature (see, e.g., Jackson 2010) such as the degrees of a node in V (measured by the number of followers and the number of followings the node has) and the strength of an edge in E (measured by whether e_o and e_d has a bi-directional relationship, i.e., whether there exists $e' \in E$ such that $e'_o = e_d$ and $e'_d = e_o$). Among a large set of network-based features that we explore, our final logistic regression model includes features that satisfy two criteria: (1) the coefficient on the feature is statistically significant, and (2) the combination of selected features maximizes the performance of the logistic regression model. Specifically, the final retained features include (i) whether e_o's number of followers was greater than the median value across all origin nodes in the sample (*Large Number of Followers for* e_o), (ii) whether e_o's number of followings was greater than the median value across all origin nodes in the sample (*Large Number of Following for* e_o), (iii) whether e_d was also following e_o ($\textit{Two-Way Tie}_e$), and (iv) the baseline productivity (which equals the average number of videos uploaded per day across the 30 days before the experiment) of e_d (*Baseline Productivity of* e_d)[20].

$$
\begin{aligned}
&\log\left(\frac{\mathbb{P}(\textit{Social-Nudge Incidence}_e = 1)}{1 - \mathbb{P}(\textit{Social-Nudge Incidence}_e = 1)}\right) \\
=&\beta_0 + \beta_1 \textit{Large Number of Followers for } e_o + \beta_2 \textit{Large Number of Following for } e_o \\
&+ \beta_3 \textit{Two-Way Tie}_e + \beta_4 \textit{Baseline Productivity of } e_d + \epsilon_e
\end{aligned} \tag{17}
$$

Table 19 reports the estimated coefficients (β_i) and the standard errors of the estimates. We implement a five-fold cross validation to evaluate the performance of this logistic regression model, which has a 99.99% average accuracy and a 0.78 Area Under Curve (AUC), suggesting qualified prediction performance. For all the edges in $\tilde{E}$, we can estimate the probability that e_o will nudge e_d in a given period by Equation (18).

$$
\begin{aligned}
\frac{1}{\mu_e} = 1 + \exp(-(&\beta_0 + \beta_1 \textit{Large Number of Followers for } e_o + \beta_2 \textit{Large Number of Following for } e_o \\
&+ \beta_3 \textit{Two-Way Tie}_e + \beta_4 \textit{Baseline Productivity of } e_d))
\end{aligned} \tag{18}
$$

[20] The correlation between the baseline productivity and social-nudge incidence is -0.0021.

Table 19 The Results of a Logistic Regression Model Predicting Social-Nudge Incidence

	Coefficient	Standard Error
	(1)	(2)
Intercept	-9.9943****	0.1204
Large Number of Followers for e_o	1.4398****	0.1309
Large Number of Following for e_o	-0.8518****	0.1013
Two-Way Tie$_e$	1.0309****	0.1048
Baseline Productivity of e_d	-0.3977****	0.0951

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

E.2. Estimation of p_e and α_p

Recall that the parameter p_e ($e \in E$) measures the immediate positive effect of receiving *one* social nudge from e_o on provider e_d's production. By "immediate positive effect", we mean the production-boosting effect in the same time period when the nudge is sent. The time discounting factor α_p indicates that receiving one social nudge from e_o boosts provider e_d's production by $p_e\alpha_p^t$ in the t^{th} period after e_d receives the nudge. To cleanly estimate p_e and α_p, from the analysis sample of our first social-nudge experiment (as defined in Section 3), we identify $962,120$ providers who were sent only *one* social nudge on their first reception day. Since those providers were not sent any nudges prior to the experiment (per the selection criteria of our analysis sample), they were sent one social nudge for the first time on their first reception day.

Table 20 Over-Time Direct Effects of Receiving One Social Nudge on Content Production

Panel A: Main Experiment					
Outcome Variable	Number of Videos Uploaded				
	on Day 1 (First Reception Day)	on Day 2	on Day 3	on Day 4	
	(1)	(2)	(3)	(4)	
Treatment	0.0263 ****	0.0125****	0.0077****	0.0003	
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	
Relative Effect Size	13.71%	5.28%	3.12%		
Observations	$962,120$	$962,120$	$962,120$	$962,120$	
Panel B: Replication Experiment					
Outcome Variable	Number of Videos Uploaded				
	on Day 1 (First Reception Day)	on Day 2	on Day 3	on Day 4	on Day 5
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0237****	0.0183****	0.0102****	0.0060*	0.0028
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Relative Effect Size	12.68%	8.56%	5.01%	2.98%	
Observations	$655,001$	$655,001$	$655,001$	$655,001$	$655,001$

Note: Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001. Number of Videos Uploaded was standardized to have a zero mean and unit deviation before entering the regressions. Panel A includes providers who were sent only one social nudge on their first reception day in the main experiment. Panel B includes providers who were sent only one social nudge on their first reception day in the replication experiment. The unit of analysis for all columns was a provider on Day t, where t=1 refers to the first reception day.

Since we jointly estimate parameters p_e and α_p, we focus on estimating p_e as the average treatment effect. That is, p_e is independent of the edge $e \in E$. Specifically, we first estimate the coefficient on treatment (i.e, β_1) in (1) for each day t since the first reception day (where $t=1$ refers to the first reception day itself) until β_1 becomes statistically insignificant on a given day t. The dependent variable examined here is *Number of Videos Uploaded*$_{it}$. On Day 4 (i.e., three days after the first reception day), β_1 is no longer statistically significant, so we use the estimates of β_1 from Day 1 to Day 3. The regression results are reported in Table 20.

We denote $p(t)$ as the regression coefficient on treatment estimated using raw data without standardization for Day t $(t=1,2,3)$. In Table 20, we report the corresponding regression coefficient on treatment using standardized data to protect Platform O's data security. We jointly estimate (p_e,α_p) by minimizing the sum of squared errors in the following nonconvex program:

$$\min_{(p_e,\alpha_p)}\left\{\sum_{t=1}^{3}\epsilon_t^2 \;\middle|\; p(t)=p_e\alpha_p^{t-1}+\epsilon_t, t=1,2,3\right\} \tag{19}$$

Solving (19) yields p_e and α_p, which we report in Table 8 column (1).

E.3. Estimation of $d_{e\ell}$ and α_d

The parameter $d_{e\ell}$ measures the increase in e_d's probability of sending a social nudge to ℓ_d on the day of receiving *one* social nudge from e_o $(e_d=\ell_o)$. By definition, $d_{e\ell}=0$ if $e_d\neq\ell_o$. The parameter α_d quantifies the time discounting factor of such effect such that receiving one social nudge from e_o boosts the number of nudges provider e_d would send to ℓ_d by $d_{e\ell}\alpha_d^t$ in the t^{th} period after e_d receives the nudge. We focus on the subset of providers from the analysis sample of our social-nudge experiment who (1) were sent only *one* social nudge on their first reception day and (2) were following at least one user the day before the main experiment.

Consistent with the estimation of p_e and α_p, we jointly estimate parameters $d_{e\ell}$ and α_d. Due to the joint estimation, we focus on estimating $d_{e\ell}$ as the average treatment effect. That is, $d_{e\ell}$ is independent of the edge $e,\ell\in E$. Specifically, we first estimate the coefficient on treatment (i.e., β_1) in (1) for each day t since the first reception day (where $t=1$ refers to the first reception day) until β_1 becomes statistically insignificant on a given day t. The dependent variable examined here is *Number of Social Nudges Sent per Edge*$_{it}$. It equals the number of social nudges sent by provider $i\in V$ on day t since the first reception day divided by her number of following. Starting from Day 3, β_1 is no longer statistically significant, so we use the estimates of β_1 from Day 1 to Day 2. The regression results are reported in Table 21.

We denote $d(t)$ as the regression coefficient estimated using raw data without standardization for Day t $(t=1,2)$. In Table 21, we report the corresponding regression coefficient on treatment using standardized data to protect Platform O's data security. We jointly estimate $(d_{e\ell},\alpha_d)$ by minimizing the sum of squared errors in the following nonconvex program:

$$\min_{(d_e,\alpha_d)}\left\{\sum_{t=1}^{2}\epsilon_t^2 \;\middle|\; d(t)=d_{e\ell}\alpha_d^{t-1}+\epsilon_t, t=1,2\right\} \tag{20}$$

Solving (20) yields $d_{e\ell}$ and α_d, which we report in Table 8 column (1).

E.4. Robustness Check by Resampling $\tilde{V}$

We resample $\tilde{V}$ and reestimate the global effect of social nudges using parameters estimated from our main social-nudge experiment. As shown in Table 22, the estimation results based on the new sample of $\tilde{V}$ are very similar to the results based on the sample reported in Section 6.3.

Table 21 Over-Time Diffusion Effects of Receiving One Social Nudge

Panel A: Main Experiment			
Outcome Variable	Number of Social Nudges Sent per Edge		
	on Day 1 (First Reception Day)	on Day 2	on Day 3
	(1)	(2)	(3)
Treatment	0.0080^{***}	0.0049^{*}	0.0025
	(0.0021)	(0.0021)	(0.0021)
Relative Effect Size	10.55%	8.06%	
Observations	947,730	947,730	947,730

Panel B: Replication Experiment			
Outcome Variable	Number of Social Nudges Sent per Edge		
	on Day 1 (First Reception Day)	on Day 2	on Day 3
	(1)	(2)	(3)
Treatment	0.0082^{***}	0.0050^{*}	0.0010
	(0.0025)	(0.0025)	(0.0025)
Relative Effect Size	10.89%	9.06%	
Observations	640,920	640,920	640,920

Notes: Number of Social Nudges Sent per Edge was standardized to have a zero mean and unit standard deviation before entering the regressions. Panel A includes providers who were sent only one social nudge on their first reception day in the main experiment and were following at least one user the day before the main experiment. Panel B includes providers who were sent only one social nudge on their first reception day in the replication experiment and were following at least one user the day before the replication experiment. The unit of analysis for all columns was a provider on Day t, where t=1 refers to the first reception day. Robust standard errors are reported in the parentheses. *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001.

Table 22 Estimation of the Global Effect of Social Nudges

	The Estimation Result			
	Reported in Section 6.3		Based on Another Sample of $\tilde{V}$	
	(1)		(2)	
Direct Effect	130.08	*One Day:* 47.55 *Beyond One Day:* 82.53	132.85	*One Day:* 48.56 *Beyond One Day:* 84.29
Indirect Effect	10.59		10.87	
Global Effect	140.67		143.72	
The Ratio of Indirect Effect to Direct Effect	8.14%		8.19%	

E.5. Robustness Check With the Replication Experiment

We check the robustness of our estimation results for the social network model using the replication experiment. Regarding the parameters p_e and α_p, we estimate the coefficient on treatment (i.e., β_1) in (1) for each day t where outcome variable is *Number of Videos Uploaded*$_{it}$ since the first reception day (where $t=1$ refers to the first reception day itself) until β_1 becomes statistically insignificant on a given day t. For the replication experiment, on day 5, β_1 is no longer statistically significant. So we use the estimates of β_1 from Day 1 to Day 4 to jointly estimate p_e and α_p. The regression results using standardized data are presented in Panel B of Table 20. The corresponding solution to the nonconvex program (19) yields p_e and α_p, which we report in Table 8 column (2) and are consistent with the estimates derived from the first experiment.

Regarding the parameters $d_{e\ell}$ and α_d, we estimate the coefficient on treatment (i.e, β_1) in (1) for each day t where outcome variable is *Number of Social Nudges Sent per Edge*$_{it}$ since the first reception day (where $t=1$

refers to the first reception day itself) until β_1 becomes statistically insignificant on a given day t. Starting from Day 3, β_1 is no longer statistically significant, so we use the estimates of β_1 from Day 1 to Day 2 to jointly estimate $d_{e\ell}$ and α_d. The regression results are presented in Panel B of Table 21. The corresponding solution to the nonconvex program (20) yields $d_{e\ell}$ and α_d, which we report in Table 8 column (2) and are consistent with the estimates derived from the first experiment.

With these parameter estimates, we apply Algorithm 1 to reestimate the global effect and the results are reported in column (3) of Table 9. The consistent estimations using data from the main and the replication experiments suggest that our estimation for the global effect of social nudges is robust and reliable.