Impact of Brand Sponsorship on Influencers-Audience Engagement: Evidence from Analyzing YouTube Videos

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Abstract

The growth of the influencer marketing industry warrants an empirical examination of the effect of posting sponsored videos on an influencer's reputation. We collect a novel dataset of user-generated YouTube videos created by prominent English-speaking influencers in the beauty and style category. We extract a rich set of theory-driven video features and use DiNardo-Fortin-Lemieux reweighting to construct comparable treatment and control groups that are matched at the influencer-video level. A difference-in-differences analysis on the matched sample finds a reputation-burning effect: posting a sponsored video, compared to posting an equivalent organic video, costs the influencer 0.17% of their reputation (operationalized as the number of subscribers). The reputation-burning effect is stronger among influencers with larger audiences; an analysis of audience engagement and comment text reveals a larger gap in the audience's response to sponsored vs. organic videos among influencers with larger (vs. smaller) audiences. Our study empirically tests an assumption of several theoretical works, contributes to the literature on influencer marketing and celebrity endorsements, and provides managerial implications for influencers, brands, and social media platforms.

Keywords: influencer marketing; social influencer; brand sponsorship; video analytics

1. Introduction

The influencer marketing industry was reportedly worth USD 6.0 billion in 2020 and is projected to grow to USD 84.89 billion by 2028 (a compound annual growth rate of 30.3%; Globe Newswire 2021). Market reports show that 75% of brands dedicated a specific budget to influencer marketing to engage consumers and promote brands (Geyser 2021). For example, The Ordinary paid TikTok influencers to post videos about the brand's Peeling Solution product and generated more than $1 million in sales in two weeks.

Influencers are effective marketers because they engage large audiences on social media platforms and appear as experts or trustworthy sources of information to their fans. They build authentic reputations by creating relevant and interesting organic content (Sokolova and Kefi 2019). Once an influencer is sufficiently popular, they can profit from their reputation by collaborating with brands—creating sponsored content (McQuarrie et al. 2013). Our study focuses on the influencer's reputation with their audience, operationalized as the influencer's number of subscribers. Avery and Israeli (2020) suggest that reputation is key in influencer marketing because reputation is the foundation of an influencer's ability to obtain profitable offers from brands. Hence, it is crucial to understand whether and how sponsored content impacts the influencer's reputation. It remains an open empirical question, though prior theoretical work on influencer marketing (Fainmesser and Galeotti 2021; Mitchell 2021) implicitly or explicitly assumes that an influencer who posts sponsored videos will damage their reputation.

Reputation is an important asset that can be accumulated, consumed, and restored—that is, reputation is cyclical (Liu 2011; Liu and Skrzypacz 2014). Liu (2011) characterizes reputation dynamics as interactions between a service provider (e.g., a firm or an influencer) and individual agents (e.g., consumers or audience), where the agents can form and/or update belief about the 'type' (good or bad reputation) of the service provider, by observing the provider's behavior; for example, through observing how a firm handled a customer complaint or launched a bad product, a consumer may stop purchasing from a firm if s/he believes that the firm has bad reputation.

In the context of social influencers, an influencer creates content on social media and audience (i.e.: social media users) consume the content; by observing the influencer's posting behavior (e.g.: post content, whether the post is brand-sponsored, etc.), audience form or update their perception about the influencer's reputation, which then impacts whether audience want to continue interacting with the influencer. For example, if the audience believe the influencer has good reputation, s/he may follow (or keep following)

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the influencer to continue “listening to” the influencer. In contrast, the audience may not follow (or stop following) the influencer if s/he does not believe the influencer has good reputation and hence “rejects” to listen to the influencer. Intuitively, a user’s decision to follow or unfollow an influencer reflects the user’s willingness to (continue to) interact with and hear from the influencer in the long run. Therefore, influencers’ gaining subscribers is a cumulative process similar to reputation building over time (Mitchell 2021), and the growth and declination in the number of subscribers an influencer possesses, to some extent, represents the dynamics in the influencer’s reputation and in their ability of influencing others. More subscribers suggest better reputation as it denotes that the influencer has the power to potentially influence and persuade more people who are willing to (continue to) listen to him or her—the foundation why brands want to collaborate with influencers especially the ones with many followers—to get in touch with and to influence the potential customers of brands (Avery and Israeli 2020).

There are various factors that could affect the influencer’s reputation (i.e.: the following and unfollowing behavior of their audience), with brand collaboration an important one. On the one hand, a social media influencer’s followers are often attracted by content that originates from another “ordinary” person who seems intrinsically motivated and noncommercial, and thus, more authentic and trustworthy than marketing communications (Haenlein et al. 2020). However, collaboration with brands may call this authenticity into question (Audrezet et al. 2020). In a market survey, 62% of consumers indicated that they were concerned that influencers capitalize on impressionable audiences and indicated that they might stop following an influencer who posted sponsored content (Forrester 2018). Past works on celebrity endorsement (Tripp et al. 1994) find that celebrities who endorse too many brands or products might lose credibility with their audiences. Thus, brand sponsorship may hurt the influencer’s reputation—a *reputation-burning* effect.

On the other hand, brand sponsorship might help an influencer’s reputation—a *reputation-strengthening* effect—by providing an opportunity to prove their worth and ability (Vamp 2020) and providing exclusive brand information that audience might not have easy access to (Casaló et al. 2018). Furthermore, since honesty is the best policy in word-of-mouth marketing (Abendroth and Heyman 2013), the disclosure of sponsorship may help safeguard the authentic experience that is central to an influencer’s relationship with their audience (Mediakix 2020).

This paper asks the following research questions:

1) What is the impact (main effect) of posting a sponsored video, relative to posting an equivalent organic video, on the influencer’s reputation?
2) Does the impact of brand sponsorship vary with the influencer’s audience size? If so, what might be the possible reasons?
3) Does the impact of brand sponsorship vary with the popularity of the brand?

We explored a unique dataset of 85,669 user-generated YouTube videos created by 861 highly active English-speaking influencers in the beauty and lifestyle category. For each influencer, we collect the daily number of subscribers (as a proxy for the influencer’s dynamic reputation) and daily content-posting behavior from August 2019 to August 2020. For each video, we collect engagement information (likes and comments), whether it is sponsored or organic, and four categories of video features: basic video properties (Zhou et al. 2021), the influencer’s emotions and appearance (Zhang et al. 2021a), the influencer’s voice (Hwang et al. 2021), and visual aesthetics (Yeh et al. 2013). We include these categories of video features because they have been shown to affect the viewer’s attention, engagement, and perceived interpersonal relationship with the influencer (Ekman and Oster 1979).

The identification of the impact of posting a sponsored video on the influencer’s reputation is challenging for several reasons. First, for each influencer, brand sponsorship (i.e., the treatment) is sequential and irregular—an influencer may post multiple sponsored videos during the observation window, and the time interval between posts may vary within- and between-influencers. Hence, we cannot simply use one period or a uniform set of periods to split the data into pre-treatment and post-treatment periods. Second, we face a possible repeated treatment issue: a sponsored video might have an enduring effect, affecting both the influencer’s immediate reputation and the audience’s reaction to subsequent videos. Third, due to the observational nature of the data, our analysis is prone to selection bias such as influencer-brand selection (e.g., only certain types of influencers were selected by brands) and reverse causality (e.g., an influencer whose reputation is declining may be more inclined to take a sponsorship offer before they lose the opportunity to do so).

We address these challenges with a matching procedure and the difference-in-differences (DiD) method. The first and second challenges are addressed through the construction of a control group of influencer-video pairs, following prior research that faced similar challenges (Azoulay et al. 2010; Jäger 2016). To address the third challenge, we adopt DiNardo-Fortin-Lemieux reweighting (DFL; DiNardo et al. 1996) to match influencer-video pairs in the control group with those in the treatment group based on similar influencer and video features on a monthly basis. Then, we estimate DiD models on the matched sample (see Section 3 for details).

We report three main findings. First, we find a reputation-burning effect: posting a sponsored video, relative to posting an organic video with similar video features, costs the influencer 0.17% of their subscribers on average. The results are fairly robust to the model specification and hypothetical unobserved confounders (see Rosenbaum bounds test in section 4.1).

Second, we explore heterogeneity in the treatment effect based on the influencer's audience size and find that the negative effect is larger for influencers with larger audiences. We find a larger gap in engagement and trust between sponsored and organic videos among influencers with larger (vs. smaller) audiences. We reason that the influencers with smaller audiences often form stronger ties, so their audiences are more receptive to sponsored content (Avery and Israeli 2020).

Third, we explore heterogeneity based on the brand popularity. We find that the reputation-burning effect is mitigated when the promoted brand is less well-known (e.g., a niche or new brand). The result contradicts the predictions by the literature on traditional celebrity endorsements (McCracken 1989). We reason that followers may be more receptive to sponsored posts for new/niche brands because the influencer provides followers with brand information that otherwise is not easily accessible, consistent with the unique role that audiences expect influencers to play (Casaló et al. 2018).

Though our main research focus is brand sponsorship, audience's following/unfollowing decisions are not solely driven by brand sponsorship, but rather complicated. There may exist other factors that affect the audience's willingness to follow an influencer. For example, when an influencer has inappropriate behavior or rumor, audiences may feel angry and stop following him or her.[1] Arguably, such instance may not happen to influencers systematically and frequently.

Our research effort contributes to the three dimensions of the emerging literature on influencer marketing (Rajaram and Manchanda 2020; Fainmesser and Galeotti 2021; Mitchell 2021; Pei and Mayzlin 2021). First, to our knowledge we contribute one of the first empirical examinations to the nascent stream of theoretical work on how brand sponsorship impacts influencers. The existing theoretical research assumes, implicitly or explicitly, that an influencer's reputation will suffer if they post sponsored videos. For example, Mitchell (2021) models the dynamic relationship between an influencer and a follower. The relationship involves a "reap and sow" cycle in which the influencer oscillates between giving unbiased advice and monetizing the opportunity to advise. The studies assume that brand sponsorship is harmful for influencer reputation, but we are the first to empirically examine the effect.

Second, we contribute to the literature on influencer video advertising as the newest form of influencer marketing. Rajaram and Manchanda (2020) implement novel, interpretable deep learning architectures to analyze the relationship between the content of sponsored influencer videos and video views, interaction rates, and sentiment. Yang et al. (2021) develop an algorithm to predict the sales boost from a sponsored influencer video. They propose the concept of motion, a compact, intuitive, and interpretable summary statistic that predicts the sales boost from sponsored videos. While the existing works focus on the brand's perspective on the design and effectiveness of influencer ad content, our research investigates the reputation challenges facing influencers who produce sponsored videos.

Third, our exploration of heterogeneity in the reputation-burning effect provides interesting comparisons with the literature on celebrity endorsements, which argues that source credibility, product match-up, and value transfer are the possible reasons for effective celebrity endorsements (Sternthal et al. 1978; McCracken 1989; Choi and Rifon 2012). We find that sponsorship has more negative effects on influencers with larger audiences possibly because influencers with smaller audiences often form stronger ties and build up trust with their audiences, consistent with the source credibility model (Sternthal et al. 1978). Influencer-video fit mitigates the reputation-burning effect, consistent with the product match-up hypothesis (Choi and Rifon 2012). Finally, in contrast to the value transfer model (McCracken 1989), we find that influencers fare better when they promote less well-known brands.

This work provides managerial implications for influencers, brands, and social media platforms. For influencers who wish to benefit from sponsorships, our estimation of the economic impact of brand sponsorship provides a baseline with which influencers can evaluate the hidden economic tradeoff involved in sponsorship offers. For brands, we offer

[1] An example would be Elle Darby, who was previously a top YouTube influencer but has lost thousands of followers after her vile racist tweets resurfaced.

insight that may inform a more nuanced strategy for choosing influencers; most brands currently rely on the influencer's reputation alone (Hwang et al. 2021). Our results, however, suggest that influencers with more subscribers are not necessarily better brand partners because larger audiences tend to respond more negatively to sponsored content. Lastly, platforms may benefit from cautioning influencers with larger audiences about the harms of brand sponsorship or could increase incentives for them to post organic content. This could help reduce the exodus of active users who lose trust in and decrease engagement with influencers.

2. Research Context and Data

Our research context is YouTube, one of the major influencer marketing platforms globally. As of 2020, YouTube had an estimated 2.1 billion users, and each day, YouTube viewers watched over one billion hours of videos and generated many billions of views. We choose to focus on the beauty and lifestyle category because it attracts the highest volume of brand sponsorships (Schwemmer and Ziewiecki 2018).

2.1. Influencer and Sponsorship Data

We use the number of subscribers as a proxy for the influencer's reputation with their fans because gaining subscribers is a cumulative process, similar to building a reputation over time (Mitchell 2021). Intuitively, a user's decision to follow or unfollow an influencer reflects the user's perception of their relationship with the influencer. Besides, the number of subscribers captures the influencer's reach, ability, and influence on social media (Avery and Israeli 2020). From a data tracking website, noxinfluencer.com, we obtain influencer's number of subscribers and video views each day during the observation window. The influencer's cumulative number of views is used as an alternative measure of reputation in a robustness test.
Following Hwang et al. (2021), we extract sponsorship disclosure information from the video description box; the Federal Trade Commission's celebrity endorsement policies require influencers to disclose sponsorships. We find that 5,993 of the 85,669 videos (7.0%) were sponsored, and 333 of the 861 influencers (38.7%) posted at least one sponsored video during our observation window. We refer to the 333 as "sponsored influencers" and the remaining 528 as "non-sponsored influencers."

2.2 Video Data

For each YouTube video in the sample, we collect audience engagement information (the number of views, likes, dislikes, and comments) and video release information (date, video length, title, and description) from the video's YouTube page (see an example in Figure 1).

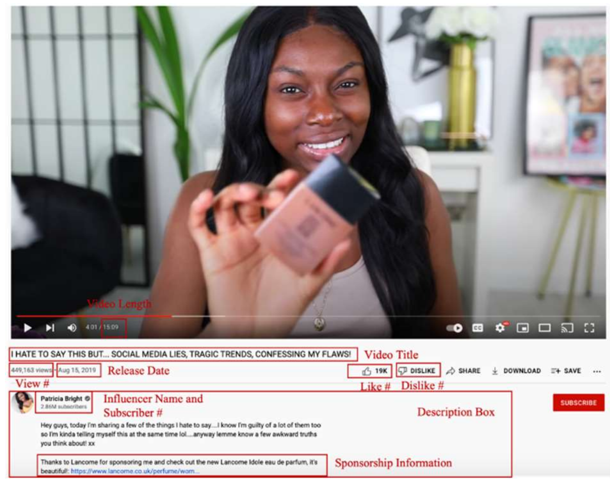

Figure 1 Information Collected From Each YouTube Video

We use machine learning models to extract the images, audio, and speech from each video. Then, to capture what the audience can see, hear, and feel about the influencers, we theorize and extract 33 variables in four categories that may affect the viewer's attention and engagement: basic video properties, the influencer's emotions and appearance, the influencer's voice, and visual aesthetics.

We consider five basic video properties (*video length, scene number, average scene length, speaking rate,* and *sentiment*) that may affect attention and engagement (Zhou et al. 2021).

Next, we measure the influencer's emotions and appearance, by first identifying any human faces in each video, as human face is a primary channel for the nonverbal communication (Ekman and Oster 1979). We apply Face++[2] to quantify seven emotions in each video image (frame) with a face; we average the values across images for each emotion. We extract five appearance features (*gender, age, smile, attractiveness,* and *number of faces*) that may affect perceptions of the influencer's personality, which could affect their reputation (Zhang et al. 2021a).

We consider characteristics of the influencer's voice because an influencer may adjust their voice in

[2] https://www.faceplusplus.com/emotion-recognition

sponsored videos (Hwang et al. 2021). We use techniques from affective computing (Scherer et al. 1973) and automated speech recognition (Eyben et al. 2010) to extract four vocal features (*loudness, pitch, loudness variability,* and *talking duration*) that may affect the viewer's perception of traits like dominance (Scherer et al. 1973), attractiveness (Fraccaro et al. 2011), and capability (Peterson et al. 1995).

Finally, we measure two types of aesthetic features because aesthetics can affect viewer preferences and satisfaction (e.g., Yeh et al. 2013). Following Zhou et al. (2021), we extract three motion features (*foreground motion area*, *motion magnitude*, and *motion direction*) and five color features (*warm hue proportion, saturation, brightness, contrast of brightness,* and *clarity*).

3. Empirical Framework

3.1. Treatment and Control Groups

We operationalize reputation as the number of subscribers, and we use the reputation three days[3] after video posting to examine the impact of brand sponsorship on the post-treatment outcome variable.[4] The treatment, *brand sponsorship*, occurs whenever an influencer posts a sponsored video. Our identification of the treatment effect has three main challenges. First, brand sponsorship (i.e., the treatment) is irregular and sequential for each influencer; influencers do not follow any particular timeline or pattern of video posting. Hence, we cannot simply use one period or a uniform set of periods to split the data into pre-treatment and post-treatment periods. Second, the treatment effect might carry over to later periods such that a sponsored video may affect not only the influencer's immediate reputation but also the audience's reaction to subsequent organic videos (i.e., a repeated treatment issue). Third, the observational nature of the data comes with two main sources of possible endogeneity: reverse causality (e.g., if influencers know their reputation is declining, they may be more inclined to post sponsored videos before they lose the opportunity to do so) and selection bias. In addition, there may exists differences between sponsored and organic videos, and such differences in the video features might lead to a difference in the influencer's reputation afterwards.

Past works (Azoulay et al. 2010; Jäger 2016) face similar research settings and identification challenges, so we follow their matched sampling approach. For example, Azoulay et al. (2010) estimated the magnitude of spillovers generated by 112 academic "superstars" who died prematurely; the authors constructed a matched control for each scientist who experienced the death of a superstar collaborator (i.e., superstar-collaborator pairs). The three key steps in Azoulay et al. (2010) are the identification of a control group, the matching procedure to construct a balanced sample, and the estimation of a DiD model.

It's worth noting that, despite sharing lots of common aspects, our study differs from Azoulay et al. (2010) in two ways. First, the nature of 'treatment': as explained in Section 3.2, brand sponsorship is an endogenous decision, which is jointly decided by influencer and brand, while the premature death of collaborator is arguably exogenous. To reduce the risk of endogeneity, we perform a matching procedure to construct sample where organic influencer-video pairs and sponsored influencer-video pairs are similar in terms of a set influencer and video characteristics that influence the brand sponsorship decision. We next perform a sensitively analysis—Rosenbaum bounds test—and verifies that our results are robust to hypothetical unobservables that may affect the brand sponsorship process and influencer's reputation simultaneously. Second, the person-to-person dyad fixed effect: the dyad effects between a superstar and the collaborators are controlled for in Azoulay et al. (2010) as they are important to collaborator's productivity. However, any dyad fixed effect between an influencer and an audience is much weaker; even the micro influencers have at least 1000 followers, while each superstar probably has only a few or dozens of collaborators. Therefore, the dyad effect would be more pronounced in the research collaboration than in our audiences following influencer setting. Besides, Azoulay et al. (2010) use the dyad fixed effects to control for individual characteristics while we explicitly control for many influencer characteristics such as the influencers' career age, gender, video posting frequency that may affect their reputation.

Our unit of analysis is the influencer-video pair. A pair belongs to the treatment group if the video is

[3] We focus on the reputation three days after video posting because 1) most video views occur shortly after posting (a plot of the cumulative video views against the number of days since posting reveals a concave growth curve) and 2) three days is a short enough post-treatment window to minimize the risk of overlap between consecutive video postings (median number of videos posted per week in our dataset: 1.39). As a robustness check, we use the reputation two or four days after video posting, and we obtain similar results.

[4] As robustness checks, we use the absolute change in the number of subscribers and the relative change in the number of subscribers as the dependent variable (Appendix B.1), and we use the number of views as a proxy for reputation (Appendix B.2).

sponsored, and it belongs to the control group if the influencer did not post any sponsored videos during the observation window (i.e., non-sponsored influencers, as defined in Section 2.1). We exclude organic videos that were posted by sponsored influencers. Hence, the treatment group consists of sponsored videos by sponsored influencers, and the control group consists of organic videos by non-sponsored influencers. Our approach to the identification of a control group helps address the first empirical challenge (i.e., irregular, sequential video posting); within-influencer variation in posting patterns no longer matters when we analyze each influencer-video pair as a separate event. Also, because we include only the non-sponsored influencers in the control group, we mitigate concerns about possible carryover effects from a sponsored video to an organic video posted by the same influencer. The final sample contains 63,880 videos, with 57,991 videos in the control group and 5,889 sponsored videos in the treatment group.[5]

3.2. Constructing a Balanced Sample

The DFL reweighting strategy (DiNardo et al. 1996) is a semiparametric matching approach that balances a sample on observed characteristics. DFL reweighting preserves differences in sample sizes by incorporating the fraction of the sample that is in the treatment group when computing the inverse of the predicted treatment probability as the sample weight; this is beneficial because it fixes the distribution of observable traits across groups. For example, if the control influencer-video pairs have a higher proportion of high-quality videos than the treatment influencer-video pairs, the DFL procedure will down-weight high-quality videos and up-weight low-quality videos in the control group.

We conduct DFL reweighting at the influencer-video level to ensure that the weighted treatment and control groups are comparable on both influencer and video features.[6] For influencer characteristics, we include the average weekly video postings, length of the channel name, career age (days since the first video posting date), and the influencer's reputation three days prior to video posting.

By matching both sets of characteristics, we reduce the risk of endogeneity from the influencer-brand joint decision. Most brand-sponsored posts reflect a two-step process: 1) the brand reaches out to the influencer they hope to partner with, and 2) the influencer decides to collaborate with the brand.

Brands choose influencers based on several selection criteria such as reach/reputation (typically measured as the number of subscribers), engagement rate, relevance, content quality, and frequency of posts (Griesel 2021; Hwang et al. 2021). For instance, the beauty tool and skincare product brand Vanity Planet considers both the follower count and average view count of an influencer.[7] Influencers do not always accept sponsorship offers; the influencer may decline because they want to take a break from making videos or are dissatisfied with the brand's financial offer (Hwang et al. 2021). Thus, we include characteristics to account for the likelihood that an influencer will receive a sponsorship offer (e.g., career age, the frequency of video postings, and pre-posting reputation) and the likelihood that an influencer will accept a sponsorship offer (e.g., whether the video is posted on weekend, which might affect the influencer's availability). Due to data limitation, we cannot control for factors such as a brand's marketing budget and the payment that an influencer receives from the brand. Note that the audience also do not observe these unobserved factors. Hence such factors cannot directly influence how the audience reacts to a sponsored video; they may, however, affect the audience *indirectly* through the content quality (e.g., an influencer may have more incentive to produce a high-quality video or appears to be happier in the sponsored video, if the sponsorship offer is generous), which we control for by including the video features.

Lastly, although the matching process is conducted on an extensive set of observed factors, we cannot exclude unobservables that may influence the brand sponsorship process and influencer reputation simultaneously. As discussed in Section 4.1, a Rosenbaum bounds analysis confirms that our results based on the DFL method are fairly robust to hypothetical unobservables.

[5] The final video sample number (63,880) is different from the raw video sample number (85,669). This is because we follow Azoulay et al. (2010) and Jäger (2016) to construct the control group and exclude all the organic videos from the influencers who have ever posted sponsored videos. In addition, the matching procedure left 104 sponsored influencer-video pairs unmatched and thus were excluded from subsequent analyses.

[6] We can't control for audience characteristics as YouTube doesn't share who the audiences or followers are. However, influencers that share similar characteristics tend to have large overlap in their audiences (Cheng et al. 2022). Through matching influencer and video features, we indirectly controlled for audience characteristics.

[7] Vanity Planet influencer application website: https://www.vanityplanet.com/pages/influencer-application.

4. Results

4.1 Main Effect of Posting a Sponsored *(*vs. Organic*)* Video on the Influencer's Reputation

Table 1 reports the results from estimating our main DiD model in Equation (1). In column (1), we estimate the model on the DFL-reweighted sample (our main model); in column (2), we estimate the model on a sample that was matched with an alternative method, propensity score matching, as a robustness test. The results are similar between the two columns, suggesting that the findings are robust to the matching method and controls. We focus on the results in column (1) for the rest of this section.

The estimated coefficient of the treatment status indicator, $After\_Sponsorship_{j,t+1}$, is negative and significant (b = -0.00177, $p < 0.001$), suggesting a reputation-burning effect: posting a sponsored video, compared to posting an equivalent (i.e., with similar video features) organic video, costs the influencer 0.17% of their subscribers. A back-of-the-envelope calculation suggests that the treatment effect translates into a loss of viewership that is worth approximately $1,530 in annual income (= 0.17% * 150 videos per year * 0.004 USD per video view * 1,500,000 subscribers).[8]

Is the economic harm of the reputation loss balanced out by the commission fee for the sponsored content? The commission varies widely across platforms and by the number of followers. For a YouTube influencer with around 1.5 million subscribers, brands pay an average of about $30,000 per sponsored video. *Prima facie*, this suggests that the revenue earned from the sponsorship outweighs the cost of the reputation harm. However, note that brands pay commissions as lump-sum payments, while the reputation harm caused by one sponsored post may have lasting effects. The average influencer in our sample had been active for six years (as of August 2020), so the lifetime effect of one sponsored post is up to $10,000.[9]

	(1)		(2)	
	Main Model			
VARIABLES	**(DFL reweighting)**		**Robustness (PSM)**	
	ESTIMATES	**S.E.**	**ESTIMATES**	**S.E.**
After_Sponsorship	**-0.00177*** **	**(0.000281)**	**-0.00160*** **	**(0.000313)**
	Influencer Characteristics			
Log_ Channel_ Preceding_Subscriber	0.997***	(0.000380)	0.996***	(0.000480)
Days_Since_First_Posting	-0.00000109***	(0.000000164)	-0.00000143***	(0.000000164)
Channel_Title_Length	0.000175***	(0.0000479)	0.0000366	(0.0000599)
Weekly_Video_Number	0.000591***	(0.000100)	0.000306**	(0.0000989)
Female	-0.000609	(0.000376)	-0.000413	(0.000489)
Observations	63880		10714	
AIC	-852891.4		-62526.7	
BIC	-852438.2		-62155.5	

Note: Column (1) is estimated on the DFL-reweighted sample, and column (2) is estimated on the PSM sample. Our dependent variable is log-transformed. There are fewer observations in the PSM sample because we use one-to-four matching and drop all the unmatched observations. Control variables are not presented due to page limit. Standard errors are in parentheses and are clustered at the influencer-month level. * p < 0.05; ** p < 0.01; *** p < 0.001

Table 1 Main Effect of Posting a Sponsored (vs. Organic) Video on the Influencer's Reputation

Robustness. The treatment and control groups are matched on observed characteristics. But it is possible that unobserved confounding factors that were not included in the matching procedure affected both the likelihood of treatment and the treatment outcome, thereby introducing bias into the estimated treatment effect. Though we cannot empirically test whether such unobservables exist, we can assess the robustness of our main results to hypothetical unobservables through a Rosenbaum bounds analysis (Rosenbaum 2002). The results suggest that the estimated negative treatment effect would be invalid only if unobserved confounds alter the *OR* of treatment by at least 60%, suggesting a robustness that is at the upper end of the range reported in the literature (20% to 60%).

Our results are also robust to alternative model specifications, alternative reputation measure, alternative explanation of YouTube's recommendation algorithm, possible cumulative process of brand sponsorship, and characteristics of brands and topics that are featured in videos.

4.2 Heterogeneous Effect by the Influencer's Audience Size

Experticity (2016) and Barker (2019) show that sponsored content is perceived as more authentic and trustworthy when posted by influencers with smaller audiences (i.e., fewer subscribers). We reason that the influencer's audience size might moderate the effect of sponsorship on reputation. We find that the reputation burning effect is stronger for influencers with larger audiences.

[8] According to https://influencermarketinghub.com/how-much-do-youtubers-make/, the average YouTube channel receives $3–5 per 1,000 video views. In our data, on average an influencer posts 150 videos in a year, with an income of 0.004 USD per video view. For a back-of-the-envelope calculation, we assume that an influencer has 1,500,000 subscribers and every subscriber watches each posted video once.

[9] We recognize that many influencers in our dataset continued to post after August 2020, so the average duration of a top-tier influencer's career probably is longer than six years. We use this as a conservative estimate for the back-of-the-envelope approximation.

We explore the cause of heterogeneity by analyzing measures of audience engagement and trust. We reason that the influencers with smaller audiences may have a tighter community (i.e., the network ties are stronger; Segura 2018). We test this possibility by analyzing the audience's response to the post (reflected in the number of likes and comments on the video; Rajaram and Manchanda 2020) and trust in the post and/or influencer (reflected in the comment text; Tabor 2020). We examine whether and how the audience response differs between sponsored and organic videos and whether the *difference in responses* varies with the influencer's audience size.

Following Rajaram and Manchanda (2020), we analyze the top 300 comments as identified by YouTube's proprietary algorithm.[10] We find valid comments for 59,959 of the 63,880 matched videos in our sample,[11] yielding 7,506,942 records total. We use the Emotion Lexicon (NRC; see Mohammad and Turney 2013) to analyze the emotions reflected in the comment text.

We operationalize all audience response variables as rates (i.e., we divide the raw count by the number of subscribers) to control for the possibility that an influencer's audience size directly affects the volume of engagement and comments, which is a common practice when measuring content performance (Keyhole 2020). We rank the influencers by their subscriber counts and create three categories: small-audience (the bottom quartile), large-audience (the top quartile), and medium-audience (the middle two quartiles). Figure 2 visualizes the estimated effects of sponsorship on the three audience response variables for medium-audience and large-audience influencers relative to small-audience influencers—the baseline.

We find that the difference in engagement ("likes" and comments) between sponsored videos and organic videos is greater for medium- and large-audience influencers than for small-audience influencers. [12]Also, sponsored videos generally are perceived as less trustworthy than organic videos, but the difference in trust is most pronounced for large-audience influencers, followed by medium-audience and then small-audience influencers. Taken together, Figure 2 supports our argument that the reputation-burning effect is stronger for influencers with larger (vs. smaller) audiences because their audiences are generally less trusting and less engaged with a sponsored video, than with a similar organic video.

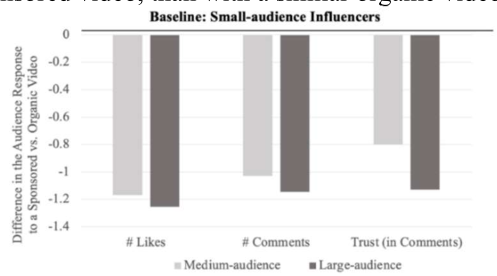

Figure 2. The Influencer's Audience Size Moderates the Response to Sponsored vs. Organic Videos

4.3. Heterogeneous Effect by Brand Popularity

Finally, we examine brand popularity as a potential moderator of the reputation-burning effect because the value transfer model in the celebrity endorsement research suggests that perceptions of the celebrity and brand may be transferable (McCracken 1989; Batra and Homer 2004; Miller and Allen 2012). In addition, from a two-sided market perspective (Rochet and Tirole 2006), sponsored content featuring brand with different popularity level may bring different content utilities to viewers, which will also influence viewers' perception of brand sponsorship. In the influencer marketing context, we conjecture that an influencer might suffer less reputation harm from partnering with a highly popular brand (e.g., Lancôme) than with a less popular brand (e.g., Vanity Planet, a direct-to-consumer brand) because popular brands may have more positive spillover on the influencer's reputation.

We collect the price, rating, review volume, and "love" count of each product on Sephora.com (see Figure 3), a leading multinational retailer of personal care and beauty products. For each brand in our sample, we average the information across all products offered by the brand. Then, we rank the brands by their average "love" count (which reflects the desire of consumers to "save" the brand to their favorites list) and categorize the brands as *less popular* (the bottom 50%; less well-known brands) and *more popular* (the top 50%; more well-known brands). Some brands in our sample are new enough or niche enough that they do not appear on Sephora's website; we classify them

[10] Some comments have replies from other audience members or from the influencers themselves; each reply counts as a separate record. The average video in our sample has 434.37 comments. For videos with 300 comments or fewer, we retrieve all the comments.

[11] Of the original 63,880 videos, 3,921 could not be found, received no comments, disabled the comment function, or received only comments with emojis and scrambled characters.

[12] This is opposite from what we say in the introduction, where we compared the raw engagement numbers from sponsored and organic videos. Here, we regress engagement on sponsorship and the interactions between sponsorship and categorized audience size, influencer characteristics, and video features. Then, we visualize the regression results in Figure 5.

as *non-Sephora*.[13] We control for the price, rating, and review volume to address the concern that the "love" count captures brand quality as well as popularity.

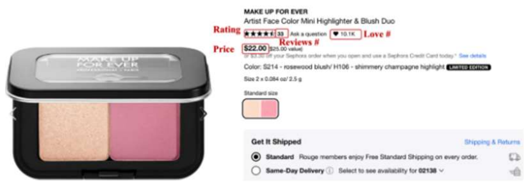

Figure 3 Product Information, Used to Calculate Brand Popularity, on the Sephora Website

As shown in Table 2, both coefficients of the interaction terms are positive and significant (b = 0.00230, $p < 0.001$ for $After\_Sponsorship_{j,t+1} \cdot Less\_Popular_j$; b = 0.00159, $p < 0.01$) for $After\_Sponsorship_{j,t+1} \cdot Non\_Sephora_j$). In other words, it helps mitigate the reputation-burning effect if the sponsored video is for a less-well-known brand or for a niche/new brand than if it is for a more-well-known brand—opposite from the predictions of the value transfer model in the celebrity endorsement research (McCracken 1989). The divergence may be attributable to the unique brand seeding process of influencer marketing, which often heavily influences the brand discovery process of subscribers (Carmicheal 2021). Casaló et al. (2018) find that audiences appreciate sponsored content from small and niche brands because audiences otherwise might not have easy access to the information, whereas information about popular brands is easy to find. It seems that influencers, more than celebrities, are expected to embody the informative role of advertising (Ozga 1960), so audiences have more appreciation for the unique role and value of influencers when they promote less-well-known and niche brands. From viewer comments, we find anecdotal evidence that audience appreciate influencers when influencers help with their brand discovery, even in sponsored videos.

VARIABLES	ESTIMATES	S.E.
After_Sponsorship (Reference: More_Popular)	-0.00332***	(0.000515)
Less_Popular	-0.00226***	(0.000545)
Non_Sephora	-0.00228**	(0.000797)
After_Sponsorship X Less_Popular	**0.00230*** **	**(0.000564)**
After_Sponsorship X Non_Sephora	**0.00159** **	**(0.000495)**
Influencer Characteristics		
Log_Channel_Preceding_Subscriber	0.997***	(0.000386)
Days_Since_First_Posting	-0.00000116***	(0.000000166)
Channel_Title_Length	0.000189***	(0.0000493)
Weekly_Video_Number	0.000535***	(0.0000985)
Female	-0.000266	(0.000375)
Constant	0.0600***	(0.00642)
Observations	63880	
AIC	-852849.4	
BIC	-852323.6	

Note: The model is estimated on the DFL-reweighted sample. We also control for video engagement and video features in table 2, but don't report their coefficients due to limited space. Our dependent variable is log-transformed. Standard errors are in parentheses and are clustered at the influencer-month level.
* p < 0.05; ** p < 0.01; *** p < 0.001

Table 2 Heterogeneity by Brand Popularity

5. Conclusion and Discussions

We analyze how an influencer's reputation is affected by posting a We analyze how an influencer's reputation is affected by posting a sponsored video relative to posting an equivalent organic video. We employ state-of-art video analytics on user-generated videos and use DFL reweighting to create matched treatment and control groups of influencer-video pairs. A DiD analysis on the matched sample reveals a *reputation-burning effect*: posting a sponsored (vs. organic) video leads to a loss of 0.17% of the influencer's reputation. The results are robust to hypothetical unobservables and extensive robustness tests.

Our study empirically validates a fundamental assumption of several theoretical works (Fainmesser and Galeotti 2021; Mitchell 2021) on social influencers: that brand sponsorship harms the influencer's reputation. We also contribute to emerging yet nascent research on influencer video advertising, the newest form of influencer marketing. Finally, we offer valuable comparisons with the celebrity endorsement literature (Sternthal et al. 1978; Choi and Rifon 2012). In particular, while more-popular brands benefit from celebrity endorsements, we find that the reputation-burning effect is mitigated when the sponsored post features less-well-known brands, highlighting the unique, informative role that audiences expect from social influencers.

This study provides managerial implications for influencers, brands, and social media platforms. *For influencers*, our estimation of effect of posting a sponsored video represents a baseline with which influencers can assess the tradeoff between building their reputation via organic content or monetizing their existing reputation for profit via brand-sponsored content—at the expense of future reputation (and associated profit). In addition, we show that

[13] We manually checked the sponsored brand list. A few large brands such as M.A.C, Ulta Beauty, and L'Oréal Paris are not listed on Sephora's website, so we assign them the average value of all products on Sephora's website. The results are robust when excluding these few brands from the data.

influencers can mitigate the harm of posting sponsored videos by creating content that is aligned with their usual organic content and by working with less-well-known brands (in addition, influencers may consider adjusting the video features; see Appendix C.1). *For brands*, our results may inform influencer selection. Brands usually use the audience size of influencers as a primary criterion and go after influencers with larger audiences. Yet we find that larger (vs. smaller) audiences respond more negatively to sponsored content, so even though the brand's reach is wider, the sponsored video may not have the desired effects. *For platforms*, we caution that the increasing prevalence of influencer-brand collaboration may threaten long-term audience engagement. For example, Facebook recently announced the demise of Lasso, its short-video sharing platform (similar to TikTok), due to a lack of active users. [14] In particular, platforms should be advised that influencers with larger audiences tend to be hurt the most by brand sponsorship. By cautioning these influencers about the risks of sponsorship, or by increasing their incentives to post organic content, platforms may be able to reduce the exodus of active users who have lost trust in influencers and become less engaged on the platform.

6. References

Abendroth L, Heyman J (2013) Honesty is the best policy: The effects of disclosure in word-of-mouth marketing. *J. Marketing Comm*. 19(4):245–257.

Audrezet A, de Kerviler G, Moulard JG (2020) Authenticity under threat: When social media influencers need to go beyond self-presentation. *J. Bus. Res.* 117: 557–569.

Avery J, Israeli A (2020) Influencer marketing. Technical Note N9-520-075, Harvard Business School, Cambridge, MA.

Azoulay P, Zivin JG, Wang J (2010) Superstar extinction. *Quart. J. Econom*. 125(2):549–589.

Barker S (2019) Micro vs. macro influencer marketing: Know the difference. Accessed November 2021

Batra R, Homer P (2004) The situational impact of brand image beliefs. *J. Consumer Psych*. 14(3):318–330.

Carmicheal K (2021) What is content seeding & how does it work? Accessed January 2022,

Casaló Ariño L, Flavian C, Ibáñez Sánchez S (2018) Influencers on Instagram: Antecedents and consequences of opinion leadership. *J. Bus. Res* 117(July).

Choi S, Rifon N (2012) It is a match: The impact of congruence between celebrity image and consumer ideal self on endorsement effectiveness. *Psych. Marketing* 29(9):639–650.

DiNardo J, Fortin N, Lemieux T (1996) Labor market institutions and the distribution of wages, 1973–1992: A semiparametric approach. *Econometrica* 64(5):1001–1044.

Ekman P, Oster H (1979) Facial expressions of emotion. *Annual Rev. Psych.* 30(1):527–554.

Experticity (2016) New research shows micro-influencers have more impact than average consumers Accessed November 2021

Eyben F, Wöllmer M, Schuller B (2010) openSMILE -- The Munich Versatile and Fast Open-Source Audio Feature Extractor. *Proc. of the 18th ACM Internat. Conf. on Multimedia* (ACM, NY), 1459–1462.

Fainmesser IP, Galeotti A (2021) The market for online influence. *Amer. Econom. J. Microeconomics* 13(4):332–372.

Forrester, J (2018) 47% of consumers are fatigued by repetitive influencers. Accessed February, 2022,

Geyser W (2021) The state of influencer marketing 2021: Benchmark report. Accessed January 2022

Globe Newswire (2021) Global influencer marketing platform market report 2021. Accessed January 22,

Griesel D (2021) Influencer campaigns: Considerations when choosing creatives. Accessed July 10, 2021,

Hwang S, Liu X, Srinivasan K (2021) Voice analytics of online influencers—soft selling in branded videos.

Jäger S (2016) How substitutable are workers? Evidence from worker deaths.

Keyhole (2020) How do I calculate engagement rate? Accessed August 2021

Liu Q (2011) Information acquisition and reputation dynamics. *Rev. Econom. Stud*. 78(4):1400–1425.

Liu Q, Skrzypacz A (2014) Limited records and reputation bubbles. *J. Econom. Theory* 151:2–29.

McCracken G (1989) Who is the celebrity endorser? Cultural foundations of the endorsement process. *J. Consumer Res.* 16(3):310–21.

McQuarrie E, Miller J, Phillips B (2013) The megaphone effect: Taste and audience in fashion blogging. *J. Consumer Res*. 40:136–158.

Mediakix (2020) Sponsored influencer content: What you need to know. Accessed August 8, 2021,

Mitchell M (2021) Free ad(vice): Internet influencers and disclosure regulation. *RAND J. Econom*. 52(1):3–21.

Mohammad SM, Turney PD (2013) Crowdsourcing a word-emotion association lexicon. *Comput. Intelligence* 29(3):436–465.

Ozga SA (1960) Imperfect markets through lack of knowledge. *Quart. J. Econom*. 74:29–52.

Pei A, Mayzlin D (2021) Influencing Social Media Influencers Through Affiliation. *Marketing Sci*.

Peterson RA, Cannito MP, Brown SP (1995) An exploratory investigation of voice characteristics and selling effectiveness. *J. Personal Selling Sales Management* 15(1):1–15.

[14] https://techcrunch.com/2020/07/01/lasso-facebook-tiktok-shut-down/.

Quoc L, Mikolov T (2014) Distributed representations of sentences and documents. *Proc. Machine Learn. Res.* 32(2):1188–1196.

Rajaram P, Manchanda P (2020) Video influencers: Unboxing the mystique.

Rosenbaum PR (2002) *Observational Studies*, 2nd ed. (Springer, New York).

Scherer K, London H, Wolf JJ (1973) The voice of confidence: Paralinguistic cues and audience evaluation. *J. Res. Personality* 7(1):31–44.

Schwemmer C, Ziewiecki S (2018) Social media sellout: The increasing role of product promotion on YouTube. *Social Media Soc.* 4(3).

Segura P (2018) Your new target audience: Segments of micro-influencers. Accessed September 2021

Sonnenberg A (2021) How to partner with YouTube micro-influencers. Accessed January 2022

Sternthal B, Dholakia R, Leavitt C (1978) The persuasive effect of source credibility: Tests of cognitive response. *J. Consumer Res.* 4(4):252–60.

Tripp C, Jensen T, Carlson L (1994) The effects of multiple product endorsements by celebrities on consumers' attitudes and intentions. *J. Consumer Res.* 20:535–547.

Vamp (2020) How can creators benefit from branded content ads? Accessed August 9, 2021

Yang J, Zhang J, Zhang Y (2021) First law of motion: Influencer video advertising on TikTok.

Zhang S, Friedman E, Zhang X, Srinivasan K, Dhar R (2021a) Serving with a smile on Airbnb: Analyzing the economic returns and behavioral underpinnings of the host's smile.

Zhou M, Chen GH, Ferreira P, Smith MD (2021) Consumer behavior in the online classroom: Using video analytics and machine learning to understand the consumption of video courseware. *J. Marketing Res.* 58(6):1079–1100.