Regulatory warnings and endorsement disclosures on social media

Abhishek Rishabh*

Indian School of Business

Manish Gangwar

Indian School of Business

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*Corresponding Author: Abhishek Rishabh (abhishek_rishabh@isb.edu), Marketing Department, Indian School of Business, Gachibowli, Hyderabad 500032, India. We thank Ernst & Young - IEMS (No: EY_OEDI) grant for financial support and ISB Institute of Data Science (IIDS) for computational support. We also thank participants of the Chicago-ISB winter conference 2019 for providing useful feedback. Rest, usual disclosures hold. All mistakes are mine (Abhishek).

ABSTRACT

Social media platforms such as Instagram have become an essential channel for influencer marketing. Regulatory bodies such as FTC (in the US) and ASA (in the UK) require influencers on these platforms to declare an advertised social media post as an ad using hashtags such as #ad, #sponsored. However, often influencers fail to disclose the endorsements. To discourage these unprofessional practices, FTC sent warning notices to 90 influencers in March 2017. We use this event as a natural experiment to estimate the impact of FTC notices on a) influencers' disclosure levels and b) follower engagement. We curated a novel dataset that consists of nearly 150 thousand Instagram posts over 6 years period. As expected, we find that advertising disclosures increased significantly for the influencers who received the notice, and their follower engagement (likes and comments) was adversely affected.

Furthermore, we estimated the deterrence effect of FTC notices on other influencers. We find significant spillover effects on other influencers in the FTC jurisdiction. Specifically, the disclosure percent of the influencers who did not receive notice also increased compared to the control group, the influencers outside the FTC jurisdiction. Our findings provide valuable insights to regulators and social media managers on the direct and deterrence effects of regulator notices.

Keywords: Influencer Marketing, Endorsement Disclosures, Social Media Advertising

INTRODUCTION

The greater the power, the more dangerous the abuse.

-Edmund Burke

Social media platforms such as Instagram, Facebook, Twitter, etc., are becoming increasingly popular channels for advertising. Instagram brought in nearly USD 13.8 billion in revenue in 2020, whereas Facebook grossed USD 84 billion and Twitter grossed USD 3.2 billion in 2020 (Walton, 2020). Sponsored Ads, Banner Ads, and Influencer advertising are three major modes of advertising used by these platforms. Influencer advertising has recently seen exponential growth in terms of revenue. Specifically, the total estimated size of the influencer marketing industry is USD 9.7 billion in the year 2020. Moreover, it has grown 55% YoY since 2016 (Influencer Marketing Hub, 2020)

Influencer marketing refers to the practice of employing influencers on a particular social media platform to advertise a product. An influencer is someone who has the power to affect the purchasing decisions of others because of their authority, knowledge, position, or relationship with the audience. Influencers in social media make posts about a topic on their preferred platform(s) to engage their followers/audience. (Brown & Fiorella, 2013)

Firms engage with these influencers to advertise their product. Once a firm identifies an influencer or a set of influencers fit for their product/brand. Influencers are offered contracts to post a photo, video, story, etc. (formats of content on Instagram) to promote the product on their social media page (Lieber, 2018). Influencers are either paid a fixed amount proportional to their followers or are paid based on the performance of the post (number of likes, comments, CTA, etc.).

Regulation in the US and UK requires influencers to distinctly disclose their post as an ad if it is indeed an ad using hashtags such as #ad, #sponsored, #sponsorship, etc., (*Disclosures 101 for Social Media Influencers*, 2019). There have been growing concerns of non-disclosures on social platforms by the regulators, to the extent where regulators in the US and UK are cracking down on undeclared ads (Practice, 2018). According to some reports, most top celebrity social media endorsements violate FTC endorsement disclosure guidelines (Mediakix, 2017). Considering these practices, FTC sent notices to 90 influencers (Federal Trade Commission, 2017). Figure A1 in the Appendix is a copy of the notice sent out by the FTC.

Extant literature on endorsement disclosure in influencer marketing has argued for the presence of disclosure laws. Specifically, (Mitchell, 2017), (Fainmesser & Galeotti, 2019) and (Amy & Dina, 2019) in different settings in influencer marketing make a case for the presence of disclosure laws, albeit in a milder form. Given the industry's size, it is difficult for a regulator to assess each post of each influencer and make judgments on if the post is an ad. Therefore, it becomes important to evaluate the direct and indirect (deterrence) effects of one of the common corrective/ regulation enforcement tools available at the regulator's disposal, i.e., warning notices.

To fully understand the ramification of regulatory warnings, regulators must understand the impact of undeclared/covert advertising on consumers. Papers by (Darke & Ritchie, 2007) (Campbell et al., 2013) show that consumers respond negatively to future ads when a firm is involved in deceptive or covert advertising practices. However, to the best of our knowledge, not much is known in the social media context of influencer marketing. In this paper, we answer the following questions

1. What is the impact of warning notices on disclosure? Do influencers increase their disclosures after receiving notice from the regulator? If yes, by how much?
2. What is the impact of notices on follower engagement? Does follower engagement change after the influencer receives the regulatory notice and warnings?
3. Is there any deterrence effect of the notice on influencers who didn't receive (spillover) the FTC notice?

We contribute to both the influencer marketing and endorsement disclosure literature. With regards to the influencer marketing regulation literature, we estimate the efficacy of notices as an enforcement tool. In particular, the extant literature has established the upside and downside of the disclosure as a requirement. However, it is not clear how influencers react to the enforcement of such disclosure regulations. Moreover, the indirect/spillover effects of these notices on influencers who did not receive the notice are not apparent. Answer to these crucial questions can lead to a better understanding of the overall implications of notices as an enforcement tool.

Regarding the literature on undeclared advertising, we estimate the consumer response (engagement) on future posts of influencers who receive the notice. In particular, the extant literature on deceptive and covert advertising has established that the consumers respond negatively to future ads of firms/brands if they catch the firm is engaged in some deceptive advertising. However, it is not known both empirically and in the influencer marketing context how consumers(followers) respond to the future posts of influencers who receive notice from the regulator.

To answer the questions of interest in this paper, we collate data from three disparate sources, namely the FTC website[1], Instagram, and Hypeauditor[2]. We collected and analyzed nearly 150 thousand Instagram posts, across 60 prominent influencers (more than a million followers each), from 9 different countries and over six years. Our results have both managerial and policy implications. Our analysis suggests that the influencers and social media managers should be careful and pre-emptively disclose potential ads. If the regulator calls out the influencer, she might see reduced engagement on her future posts, thus decreasing revenue. On

1 https://www.ftc.gov/news-events/press-releases/2017/04/ftc-staff-reminds-influencers-brands-clearly-disclose

2 Hypeauditor is an Instagram analytics platform which freely provides information on top 1000 influencers according to it. https://hypeauditor.com/top-instagram/

the policy front, we show that notices turn out to be a crucial policing tool for regulators as it does not only have a direct impact but also has a substantial spillover effect leading to deterrence effect.

The rest of the paper is organized as follows; Institutional Background section provides details on the influencer marketing industry, regulation, and the FTC notice sent in 2017. The related Literature section covers the literature review and our contribution. Data Section describes how we collected the data from different sources and provides descriptive statistics. The empirical Strategy sections describe our empirical strategy to answer the questions of interest, followed by the results and discussion section. In the Discussion on Potential Mechanism Section, we provide probable and plausible explanations behind our results.

INSTITUTIONAL BACKGROUND

Influencer Marketing Industry

Influencers are people on social media who make regular posts about a topic on their preferred social media channels such as Instagram, Facebook, Twitter, LinkedIn, etc. They generate large followings of enthusiastic, engaged people who pay close attention to their views (Geyser, 2017). Moreover, influencers can create trends and encourage their followers to buy products they promote. (Influencer Marketing Hub, 2019).

Marketers/firms engage with these influencers to promote their products. Specifically, a firm through an agency chooses an influencer or a set of influencers to endorse a product on the influencer's social media channels. Once the influencer posts the ad on their social media channel, the post appears in the feed of the influencer's followers, and the followers can engage with these ads by liking, commenting, and sharing the post. The influencer can be compensated either based on the followers she has or the kind of engagement the ad receives, and there are many models of influencer compensation (Atkins, 2020).

As of 2020, the influencer marketing industry has been estimated to be nearly USD 9.7 Bn (Influencer Marketing Hub, 2020). From 2016 to 2020, the industry size has grown six times (see Figure 1). One of the reasons for this growth has been attributed to the return on investment it generates. For example, according to Influencer Marketing Hub, a dollar spent on influencer marketing earned a return of USD 5.78 (see Figure 2).

Given the size of this industry, it has made many influencers multi-millionaires to the extent where a few influencers charge upwards of USD 1 million for one post on their social media channel (Mejia, 2018). However, this industry is also prone to certain malpractices. Non-disclosure of advertising posts is one of them. Regulators are getting increasingly concerned about non-disclosures on social platforms, to the extent that regulators in the US and UK are cracking down on undeclared ads. (Practice, 2018) According to some reports, almost all top celebrity social media endorsements violate FTC endorsement disclosure guidelines (Mediakix, 2017). Apart from a few lawsuits (*Federal Trade Commission*, 2016), FTC in the US sent out notices to 90 influencers (Federal Trade Commission, 2017). The Commission found certain posts of these influencers to be non-compliant with the stipulated standards. UK advertising regulator Advertising Standard Authority (ASA) also did the same to 43 influencers and found similar non-compliance (The Fashion Law, 2017). Therefore, it will be useful to understand how these notices affect the disclosure behavior of influencers and how followers react to the influencers who are called out by the regulators. In this paper, we also assess the efficacy of these notices as a policing instrument.

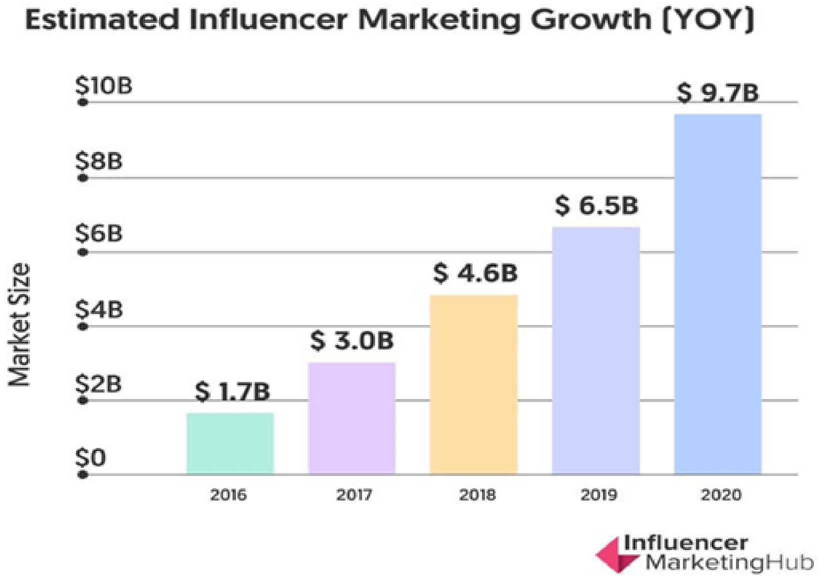

Figure 1: Influencer Marketing Industry market size and growth trend.

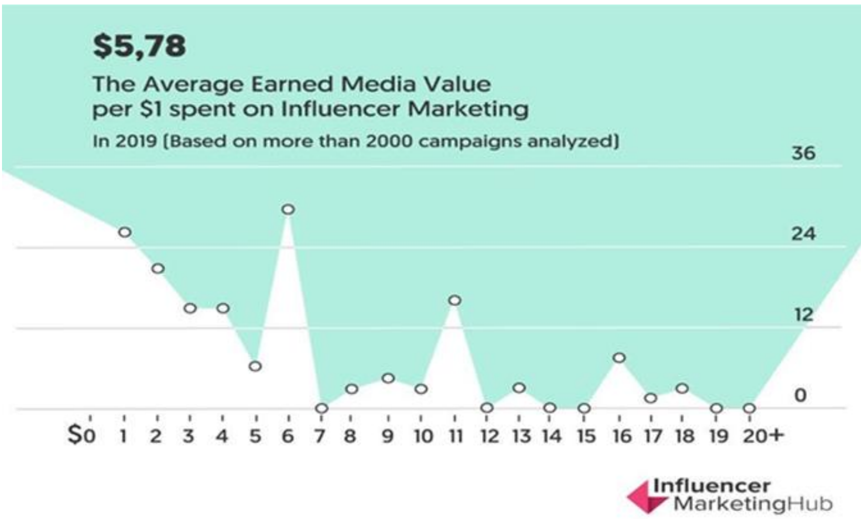

Figure 2: ROI on influencer marketing

FTC Notice

In March of 2017, FTC sent out notices to 90 influencers and the firms associated with them. The notice warned the firms and influencers to abide by the Endorsement Disclosure Regulation. Celebrities or influencers can influence public opinion leading them to make certain specific choices. Therefore, when influencers are paid to endorse a product, their opinion might be biased, and the consumers should know about it. The notice was sent based on recommendations by a few public watchdogs such as Public Citizen (*Online Influencers Called Out in Second Letter to FTC*, 2016). After the notice was sent, many media articles cited the notice and brought the influencer's endorsement disclosure malpractice to the public (Glenday, 2019; Lee, 2020; Mediakix, 2017).

RELATED LITERATURE

Our work lies at the intersection of two literature streams 1) Endorsement Disclosure Regulation 2) Consumer Response to Undeclared or Deceptive or Covert Advertising practices. Literature on Endorsement Disclosure has evolved primarily on celebrity endorsement disclosure. Celebrities are different from social media influencers on many fronts, such as similarity, trustworthiness, credibility (Schouten et al., 2020, Tips 2, 2018). Therefore, findings from celebrity endorsement disclosure literature may not be directly applicable to social media influencer marketers. Marketing literature has evolved substantially on the consumer response to undeclared advertising practices. However, most studies have considered the firm/brand and not the influencer as the entity that deceives the consumer. This difference might lead to different findings because the consumers interact differently with social media influencers than celebrities or brands (Schouten et al., 2020).

Endorsement Disclosure Regulation

Literature on endorsement disclosure regulation has tried to answer the effects of having endorsement disclosure on various stakeholders such as consumers, influencers, platforms, and regulators. Theoretical work by (Mitchell, 2017), (Amy & Dina, 2019) and (Fainmesser & Galeotti, 2019) and Empirical work by (Ershov & Mitchell, 2020) argue for milder endorsement disclosure regulations. Specifically, (Mitchell, 2017) argues that regulators should have an opt-in disclosure policy compared to a mandatory disclosure policy. Similarly, (Fainmesser & Galeotti, 2019) argue that a mandatory disclosure policy could backfire and not serve its primary purpose.

(Amy & Dina, 2019) show that a detailed disclosure policy may hurt the consumers. (Ershov & Mitchell, 2020) argue that countries that adopted the endorsement disclosure regulations ended up with increased disclosures and an increase in undeclared advertisements. These papers discuss the degree of endorsement disclosure that should be present and how much influencers disclose when the regulation is enforced. Therefore, there is some consensus that some or other form of disclosure regulation should be present. However, no work in our knowledge assesses the efficacy of a tool (notices/warning letters) that helps enforce an endorsement disclosure regulation.

Consumer Response to Undeclared Advertising

Marketers have tried to establish the effects of undeclared, deceptive, and covert advertising on consumer response. For example, (Darke & Ritchie, 2007) found that deceptive advertising engenders distrust among consumers through a series of lab experiments. Moreover, they establish that consumers might react negatively to future ads if they catch a firm engaging in deceptive advertising practices. It is important to note that the authors focused on the effects of deceptive advertising on brand-consumer relationships. (Campbell et al., 2013) shows through a series of lab experiments that covert marketing can increase brand recall and attitude. However, when caught by the consumer, these effects vanish. In the context of celebrity and firm scandals, papers by (Barth et al., 2019; Knittel & Stango, 2010; Rao & Wang, 2017) establish that a celebrity or a firm is caught in a scandal consumers respond negatively.

Contribution

In this paper, we contribute to the above two streams of literature by estimating the efficacy of a regulation enforcement tool, i.e., the notices; this is important because other regulators are also adopting notices as a regulation enforcement tool. To the best of our knowledge, we don't know of any papers that have empirically established the efficacy of notices to influencers as an enforcement tool. Our analysis of roughly 150 thousand Instagram posts finds that disclosure levels of influencers increased substantially after the notice was sent. Moreover, we find that disclosure levels of influencers who were indirectly impacted by the notice also increased substantially. We estimate both the direct and indirect impact of notices to enforce sponsorship disclosure regulation. We also contribute to the Undeclared Advertising literature by showing that when information of non-disclosures of influencers gets public, it can lead to punishments by followers/consumers in the future. We find that the consumer engagement dropped substantially for the influencers who got the notice, and we also found substantial spillover effects. Specifically, consumers respond negatively to influencers who didn't receive the notice, albeit to a lesser degree than influencers who got the notice. Moreover, we establish that these punishments aren't just concentrated on the influencers who are part of the regulator's crackdown, but these effects are country wide. We confirm the findings of Darke & Ritchie, 2007, Campbell et al., 2013 and extend the literature by establishing the deterrence effect through spillover.

DATA

Our dataset consists of nearly 147,600 Instagram posts, across 60 Influencers, from 9 different countries and eight different categories over a period spanning over six years from 2013 to 2019. Our data represents primarily big influencers with a substantive following ranging from 3 million to 146 million followers. We curated our dataset from three sources, namely, the FTC website, Hypeauditor, and Instagram. We collected the list of all the 90 influencers who got the FTC notice from the FTC website[3]. Hypeauditor is an Instagram influencer service that helps businesses find the right influencers for their social media campaigns. It provides a free list of 1,000 influencers on its website. We collected the list of these 1000 influencers and their corresponding characteristic variables such as Category, Followers, Audience Country, and Authentic Engagement. We find 33 influencers that are available in both lists, namely, FTC's and Hypeauditor's. These 33 influencers are the ones who have received notice from the FTC. Next, we identified similar influencers from the remaining 970 in the Hypeauditor's list who did not receive the FTC notice. The following section describes this process in detail.

Finding a comparable control group

Firms primarily use three criteria: Followers, Authentic Engagement, and Product Category to identify and engage with an influencer (Vodak et al., 2019). We use the same three variables for propensity score matching to identify similar influencers from the list of remaining 970 influencers in Hypeauditor dataset. From a Regulator's perspective, almost anyone could possibly be involved in the disclosure of non-compliance. Thus, every influencer is a probable suspect who could have got notice (intent to treat). Table A1 in the Appendix provides the summary of the balanced data after propensity score matching.

Figure 3 shows the comparison of the treated and the control group pre and post matching. Note that the matched treated and matched control groups are very similar.

3 https://www.ftc.gov/system/files/documents/foia_requests/1b-2017 00799_instagram_influencers_327_pgs.pdf

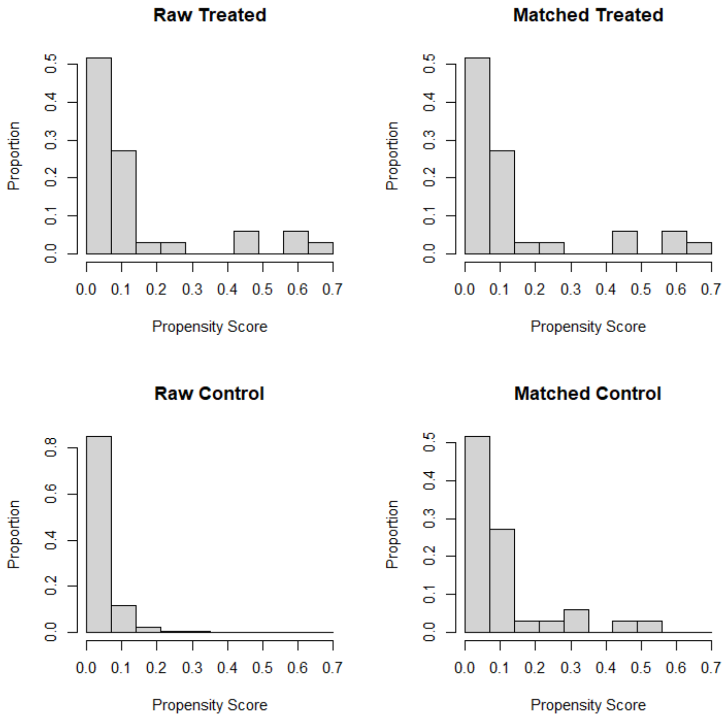

Figure 3: Raw vs. Matched Treatment and Control Groups

Once we have collected the list of 66 influencers (33 who got notice and 33 who didn't get a notice), we go to these influencer's Instagram pages and collect post-level data of each of these influencers. For each post, we collected information on the number of likes, number of comments, the hashtags, the tagged handles, type of post, date of a post, image description of each post. We were able to collect data on only 61 out of 66 influencers as some influencers have made their profile private. The complete list of influencers is present in Table A2 in the Appendix and the count of influencers by location is present in Table A3 in the Appendix.

Next, we label each post as an advertised post or non-advertising post based on the hashtags used by the influencer. FTC provides an exclusive list of hashtags that influencers need to declare a post as an ad. Out of 147,600 posts, we observed a total of 1050 posts were declared ad posts (this low percentage of a declared ad is common and is essentially a cause of concern for the regulators). Next, we aggregate data at the month level[4]. Table 1 compares the descriptive statistic of notified and not notified influencers before and after the notice was sent.

Table 1: Pre and Post Notice Means of Notified & Not Notified Influencers

	Notified Influencers		Not Notified Influencers	
	Pre Notice	Post Notice	Pre Notice	Post Notice
Disclosure Percent	1.06	2.86	0.394	1.24
Likes	437,286	913,453	292,626	667,725
Comments	11,794	11,906	4,067	5,314

We are interested in estimating the impact of the warning/notice by FTC on a) Disclosure Levels b) Follower Engagement. We will compare the effect of notices on the group of influencers who got the notice vs. the group which didn't use a) model-free evidence b) difference in difference approach.

Model Free Evidence

Figures 4, 5, and 6 represent trends of disclosure percent, log likes, and log comments.

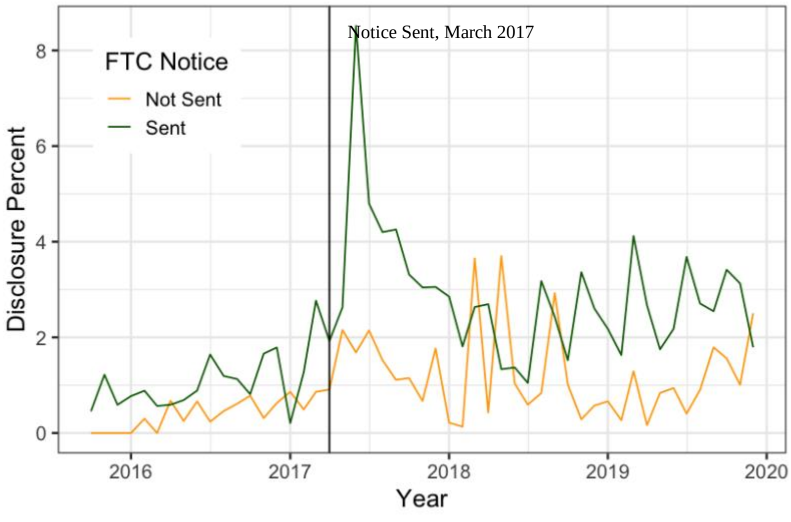

Figure 4: Disclosure Percent Trend – Notified vs. Not Notified Influencers

[4] $Disclosure\ Percent_{it} = \frac{Total\ Ad\ Posts_{it}}{Total\ Posts_{it}}$ for influencer 'i' for month 't'. Likes and comments are mean likes and comments in that month. For example, if an influencer makes 3 posts in month 't' likes/comments are mean likes/comments across 3 posts.

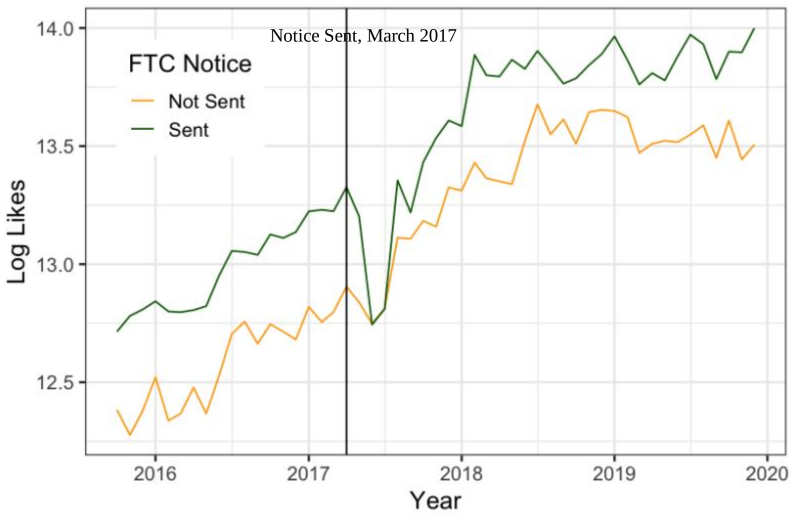

Figure 5: Log Likes Trend – Notified vs. Not Notified Influencers

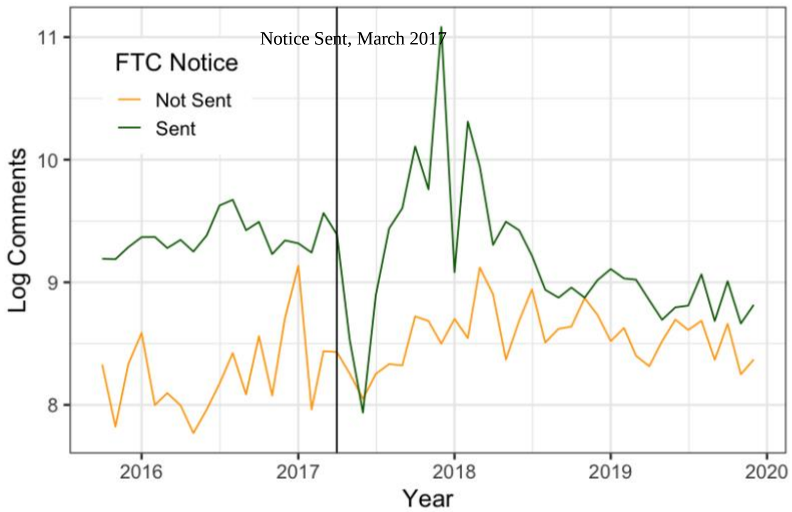

Figure 6: Log Comments Trend – Notified vs. Not Notified Influencers

Few things are worth noticing, first, note that the disclosure percentage had been relatively low before the notice was sent. However, after the notices were sent, there seems to be a substantial increase in disclosures among influencers. Second, note the spike in disclosure percentage in Figure 4, near the time when FTC notices were sent. Third, the follower engagement (likes and comments) seems to be increasing over time across both groups in Figures 5 and 6, respectively. However, the follower engagement appears to get a substantial reduction after the notice was sent for both the groups.

The Difference in Difference Approach

We use the difference in difference (DID) approach to formally test our conjectures to establish the effects observed in the model-free evidence section. We use the following diff-in-diff (DID) model setup (see Eq.1).

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \delta_\mathrm{t} + \beta_1\mathrm{InfluencerNotified_i} + \beta_2\mathrm{NoticeSent_t} + \beta_3\mathrm{InfluencerNotified_i} \times \mathrm{NoticeSent_t} + \epsilon_{\mathrm{it}} \quad (\mathrm{Eq.\,1})$$

In the Eq. 1 (Y_{it}) represent disclosure percent. The $InfluencerNotified_i$ is a dummy variable that represents influencers who were sent notices and the $NoticeSent_t$ is a time dummy variable that takes the value 0 before the notice was sent (March 2017) and value 1 after the notice was sent. The α_i represents the influencer fixed effect and the δ_t is the time-fixed effect. We are interested in β_3 (the coefficient on interaction effect), which represents how the disclosure behavior and follower response (likes and comments) change for influencers who got the notice vs. those who didn't. Table 2 compares the change in disclosure percentage of influencers after receiving the notice.

Table 2: Comparison of disclosure percent - notified vs. not notified influencers

	Dependent variable: DisclosurePercent			
	(1)	(2)	(3)	(4)
InfluencerNotified	0.596***	0.596***		
	(0.226)	(0.226)		
NoticeSent	0.923***		0.923***	
	(0.230)		(0.223)	
InfluencerNotified x NoticeSent	1.031***	1.031***	1.031***	1.031***
	(0.318)	(0.318)	(0.309)	(0.309)
Constant	0.170	-0.148	6.761***	6.443***
	(0.164)	(0.743)	(0.611)	(0.931)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.027	0.041	0.095	0.108
Adjusted R^2	0.027	0.024	0.084	0.083
Residual Std. Error	5.718 (df = 5181)	5.725 (df = 5098)	5.547 (df = 5122)	5.551 (df = 5039)
F Statistic	48.234*** (df = 3; 5181)	2.512*** (df = 86; 5098)	8.669*** (df = 62; 5122)	4.227*** (df = 145; 5039)
Note:				*p<0.1; **p<0.05; ***p<0.01

In all model specifications in table 2, we find that average disclosure percent of influencers has increased after receiving the notice. The DID coefficient (Influencer Notified x Notice Sent) turns out to be 1.031, implying that, compared to influencers who didn't get the notice, disclosure of notified set of influencers increased by 1.031%, representing nearly 100% increase in disclosures. (pre-notice means were almost 1%, whereas post notice means are almost 2%). Moreover, we find that the follower engagement in terms of likes and comments (see Table A4 and A5 in the Appendix) has decreased for the notified influencers[5].

[5] The DID effect presented for likes or comments (Y) represents
$$\left\{\log(Y_{Notified})^{PostNotice} - \log(Y_{Notified})^{PreNotice}\right\} - \left\{\log(Y_{NotNotified})^{PostNotice} - \log(Y_{NotNotified})^{PreNotice}\right\}$$

Potential issues with the above comparison and our approach to resolving it

The analysis presented above has a potential problem. The control group contains influencers from both within and outside the FTC jurisdiction. Therefore, the control group is potentially contaminated, and the SUTVA (Stable Unit Treatment Value Assumption) is violated. Thus, the effect of notices using the above approach could be biased. We address the control group contamination issue by dividing our influencers into three categories, namely, a) influencers who got the notice and were in the FTC jurisdiction (T1) b) influencers who didn't get the notice but were in the FTC jurisdiction (T2) c) influencer who were outside the FTC jurisdiction and didn't get the notice (C). Descriptive statistics across groups are presented in Table 3.

Table 3: Pre and Post Notice Means of T1, T2, and C groups.

	T1		T2		Control	
	Pre	Post	Pre	Post	Pre	Post
Disclosure Percent	1.06	2.86	0.905	2.62	0.086	0.396
Likes	437,286	913,453	434,510	730,841	205,918	629,154
Comments	11,794	11,906	4,141	5,708	4,021	5,073

Using this design, we are able to recover the true effect of notices on disclosures, likes, and comments. Specifically, now our control group C is not influenced by the regulation as these influencers are out of FTC jurisdiction. However, the influencers that belong to the FTC jurisdiction but did not receive the notice might take some corrective measure (deterrence effect) in terms of disclosure. Now, we estimate the spillover effects of regulatory notices on the T2 group in comparison to C group of influencers, thereby establishing the deterrence effect of notices.

Model Free Evidence

First, we present model-free evidence to get a preliminary idea of our results.

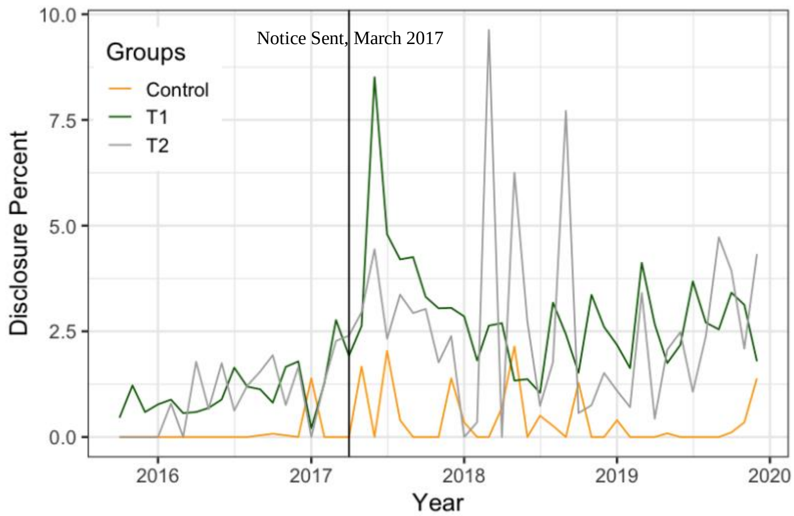

Figure 7: Disclosure Percent Trend – Across Treatment & Control Groups

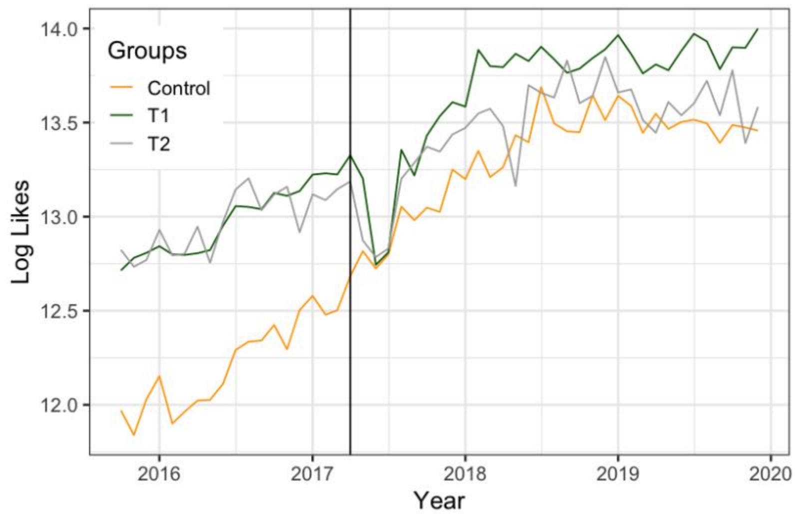

Figure 8: Log Likes Trend - Across Treatment & Control Groups.

Figure 7 shows the pre and post disclosure levels of the treatment and control groups. Here, we observe that the T1 group (that belongs to the US and got the notice) was disclosing far more to start with compared to the control group. Disclosure increased for both the groups (T1 and C) after the notices were sent in March 2017. However, the increase in the T1 group appears to be more than the increase in the control group. Comparing disclosure levels of influencers group T2 (that belongs to the US and did not get notice) and the control group, it appears that disclosure levels have increased for both the groups but more so for T2 than the control; alluding to the deterrence effect of FTC notices.

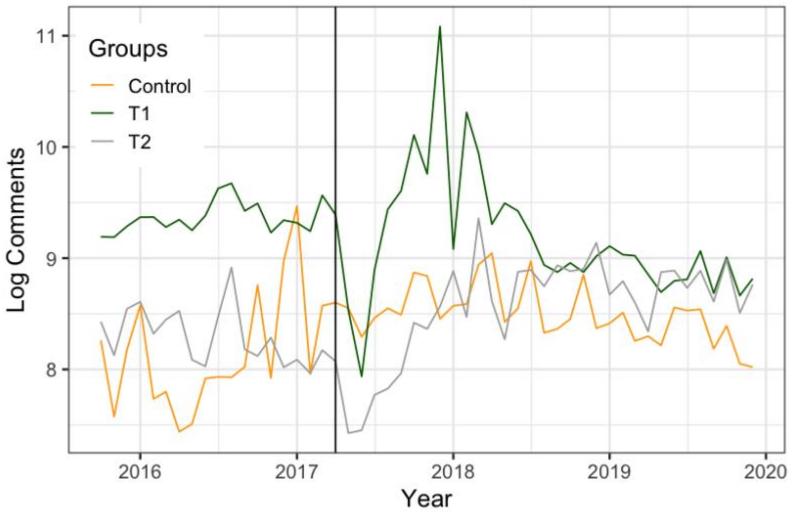

Figure 9: Log Comments Trend - Across Treatment & Control Groups.

Figure 8 represents the pre-post values for likes for T1 vs. C and T2 vs. C. In this case, too, it appears that both T1 and T2 groups were receiving far more likes compared to the control group. However, after the notices were sent, there seems to be a substantial decrease in likes for both T1 and T2 groups compared to the control group. However, it is difficult to discern which groups (T1 or T2) experienced a more significant decline in likes. Figure 9 represents the pre-post values for comments for T1 vs. C and T2 vs. C. The trends for comments also are not easy to discern. Thus, we assess and estimate the effect using DID approach in the following section.

Comparing disclosure and follower engagement across T1, T2 with C

Next, to formally establish the causal impact of notices on a) disclosure levels b) follower engagement, we use a difference in difference approach. We estimate Eq.2 and the coefficient of interest are β_4 *and* β_5.

$$\text{Disclosure Percent}_{it} = \beta_0 + \beta_1 \text{NoticeSent}_t + \beta_2 \text{NoticeUS}_i + \beta_3 \text{NoNoticeUS}_i + \beta_4 \text{ NoticeUS}_i \times \text{NoticeSent}_t + \beta_5 \text{ NoNoticeUS}_i \times \text{NoticeSent}_t + \epsilon_{it} \quad (\text{Eq. } 2)$$

where, $\text{Disclosure Percent}_{it} = 100 * \frac{\text{Total Ad Posts}_{it}}{\text{Total Posts}_{it}}$ for influencer i at time t .

Change in disclosure levels after the notice is captured by β_4 for the T1 group (influencers who got the notice and were in the US), and by β_5 for the T2 group (influencers who didn't get the notice and were in the US). The definition of all the variables used in DID estimation is present in Table 4.

Table 4: Variables and their definitions used in DID estimation.

Variable	Definition
$Disclosure\ Percent_{it}$	Disclosure percent of influencer 'i' over a period 't'.
$NoticeSent_t$	Dummy for a time of notice
$NoticeUS_i\ (T1)$	Dummy for influencers in the US who got the notice
$NoNoticeUS_i$ (T2)	Dummy for influencers in the US who didn't get the notice
$Comments_{it}$	Comments of influencer 'i' over a period 't'
$Likes_{it}$	Likes of influencer 'i' over a period 't'

DID RESULTS AND DISCUSSION

Do influencers increase their disclosures after receiving notice from the regulator?

The results of our estimated DID model (Eq. 2) are present in Table 5. Firstly, observe that coefficient on both Notice Sent and Notice Not Sent in the US ($\beta_2\ and\ \beta_3$ in Eq. 2 are positive and significant, implying that, on average, the disclosure percent of the T1 and T2 groups belonging to US jurisdiction is higher than the control group. We find the DID parameter, i.e., $NoticeUS_i\ \times NoticeSent_t$ (β_4) to be positive and significant.

Table 5: Direct and Spillover effects of notice on disclosure percent.

	Dependent variable: DisclosurePercent			
	(1)	(2)	(3)	(4)
NoticeUS	0.729***	0.729***		
	(0.259)	(0.260)		
NoNoticeUS	0.351	0.351		
	(0.337)	(0.337)		
NoticeSent	0.358		0.358	
	(0.292)		(0.283)	
NoticeUS × NoticeSent	1.595***	1.595***	1.595***	1.595***
	(0.364)	(0.365)	(0.354)	(0.354)
NoNoticeUS × NoticeSent	1.488***	1.488***	1.488***	1.488***
	(0.473)	(0.474)	(0.460)	(0.460)
Constant	0.037	-0.281	6.761***	6.443***
	(0.207)	(0.751)	(0.611)	(0.930)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.033	0.047	0.097	0.110
Adjusted R^2	0.032	0.030	0.086	0.085
Residual Std. Error	5.702 (df = 5179)	5.708 (df = 5096)	5.542 (df = 5121)	5.546 (df = 5038)
F Statistic	35.431*** (df = 5; 5179)	2.828*** (df = 88; 5096)	8.714*** (df = 63; 5121)	4.278*** (df = 146; 5038)
Note:				*p<0.1; **p<0.05; ***p<0.01

Compared to the control group, the average disclosure percentage levels for influencers who got the notice increased by 1.6%; this represents an increase of nearly 160% (as the pre-notice disclosure means were almost 1% and post-disclosure means were almost 2.6%). It is clear from the results that notices sent by FTC did have its intended effect, in that influencers started disclosing more after they received the notice. The direct effect part of the results above is in line with endorsement disclosure regulation literature. Specifically, there is some consensus in the literature that the influencers tend to disclose more when disclosure regulations are present. Therefore, it is not surprising that the influencers tend to disclose more when regulation is enforced (through notices/warnings).

Does follower engagement change after the influencer receives the notice?

Next, we estimate the diff-in-diff (DID) model for engagement, particularly for likes and comments. Eq. 3 below represents the DID model for likes; we are interested in β_4 *and* β_5. Note that we control for both disclosure percent and comments. We control for disclosure levels because the notices by FTC may change the level of disclosure by influencers that in turn affects the engagement of a post. We use comments as a control variable as some posts might be more engaging than others, leading to higher likes and comments.

$$\begin{aligned}\log(\mathrm{Likes}_{it}) = {} & \beta_0 + \beta_1 \mathrm{NoticeSent}_t + \beta_2 \mathrm{NoticeUS}_i + \beta_3 \mathrm{NoNoticeUS}_i \\ & + \beta_4\ \mathrm{NoticeUS}_i \times \mathrm{NoticeSent}_t + \beta_5\ \mathrm{NoNoticeUS}_i \times \mathrm{NoticeSent}_t \\ & + \beta_6 \log(\mathrm{DisclosurePercent}_{it}) + \beta_7 \mathrm{Comments}_{it} + \epsilon_{it}\ (\mathrm{Eq.}\,3)\end{aligned}$$

The Eq. 4 represents the DID model for comments; the setup and variables of interest are similar to Eq. 3 for likes.

$$\begin{aligned}\log(\mathrm{Comnts}_{it}) = {} & \beta_0 + \beta_1 \mathrm{NoticeSent}_t + \beta_2 \mathrm{NoticeUS}_i + \beta_3 \mathrm{NoNoticeUS}_i \\ & + \beta_4\ \mathrm{NoticeUS}_i \times \mathrm{NoticeSent}_t + \beta_5\ \mathrm{NoNoticeUS}_i \times \mathrm{NoticeSent}_t \\ & + \beta_6 \log(\mathrm{DisclosurePercent}_{it}) + \beta_7 \mathrm{Likes}_{it} + \epsilon_{it}\ (\mathrm{Eq.}\,4)\end{aligned}$$

We report the results for two measures of follower engagement, i.e., the likes and comments in Table 6 and Table A6 (in the Appendix), respectively.

Table 6:Direct and Spillover effects of notice on likes

	Dependent variable: log(Likes)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.304^{***}	0.233^{***}	0.108^{*}	0.019
	(0.067)	(0.065)	(0.060)	(0.057)
NoticeUS	2.510^{***}	2.524^{***}		
	(0.154)	(0.148)		
NoNoticeUS	2.084^{***}	2.089^{***}		
	(0.199)	(0.191)		
NoticeSent	3.954^{***}		3.966^{***}	
	(0.172)		(0.142)	
NoticeUS × NoticeSent	-2.593^{***}	-2.578^{***}	-2.552^{***}	-2.534^{***}
	(0.215)	(0.208)	(0.177)	(0.167)
NoNoticeUS × NoticeSent	-2.349^{***}	-2.334^{***}	-2.306^{***}	-2.287^{***}
	(0.280)	(0.270)	(0.230)	(0.216)
Constant	8.844^{***}	6.436^{***}	11.038^{***}	8.687^{***}
	(0.122)	(0.427)	(0.309)	(0.438)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.146	0.219	0.428	0.503
Adjusted R^2	0.145	0.206	0.421	0.488
Residual Std. Error	3.363 (df = 5178)	3.242 (df = 5095)	2.767 (df = 5120)	2.601 (df = 5037)
F Statistic	147.410^{***} (df = 6; 5178)	16.074^{***} (df = 89; 5095)	59.982^{***} (df = 64; 5120)	34.669^{***} (df = 147; 5037)
Note:				*p<0.1; **p<0.05; ***p<0.01

Results of DID estimates on likes are reported in Table 6. First, note that the influencers who got the notice experienced more average likes compared to the control group. We control for the disclosure percent, as it might be a confounder because after the notices were sent, the influencers might change their disclosure behavior which in turn might lead to different likes. DID estimates (NoticeUS × NoticeSent) for the influencers who got the notice (T1 group of influencers) are negative and significant. This implies that after the notices were sent, the T1 group of influencers experienced a reduction in engagement in terms of likes, although they started disclosing more. One of the interpretations of reduced likes could be that followers punish these influencers because they have been misled. Our results conform with the literature on deceptive advertising and covert marketing. We discuss more on this conjuncture in our 'Discussion of Potential Mechanism' section.

Comments are another measure of follower engagement. It is important to note that writing comments could be more effortful than likes. The results for comments are reported in Table A6 (in the Appendix). We notice similar patterns in the results of comments as in likes, which signals the robustness of our results. First, the influencer who got the notice experienced more comments per post compared to the control group. DID parameter (NoticeUS × NoticeSent) turns out to be negative and significant, which implies after the notices were sent, followers commented less on the posts of influencers who got the notice.

Is there any deterrence effect of notices on influencers who didn't receive the FTC notice?

We find a substantial deterrence effect on the influencers who did not get the notice but are in the FTC jurisdiction. We capture the deterrence effect through spillover effects. These are present in the disclosure levels measure and the follower engagement measures (Likes and Comments). In Table 5, the interaction coefficient (No NoticeUS × NoticeSent) represents the spillover effect on disclosure levels. The disclosure of influencers who didn't get the notice but were in the FTC jurisdiction increases, 1.4% compared to the control group (nearly 140% increase in disclosure level compared to pre-notice levels), indicating the deterrence effect of notices.

The interaction coefficient (No NoticeUS × NoticeSent) in Table 6 and Table A6 in the Appendix represent the spillover effect of notices on follower engagement (likes and comments) on the influencers in the FTC jurisdiction but didn't get the notice. Specifically, after the notices were sent, these influencers also experienced a reduction in follower engagement. It is important to note the order of effects (NoticeUS × NoticeSent vs. NoNoticeUS × NoticeSent) for all the measures (disclosure percent, likes, and comments). We find that the influencers who got the notice were affected more on all fronts compared to the influencers who didn't get the notice but were in the FTC jurisdiction. This serves as a sanity check, as this is something one would expect. It is useful for the regulators as well as for managers to account for these effects. The reason being, many firms pay influencers based on the performance of an ad, measured by likes and comments. Therefore, reduced engagement from the followers can reduce the influencer revenue and, thereby, platform revenue, making regulatory notices effective policing mechanism.

DISCUSSION ON POTENTIAL MECHANISM

Our results can be summarized in two broad categories 1- Efficacy of notices 2-Consumer response to undeclared advertisements. To summarize our findings, we find both direct and spillover effects in the two categories. In this section, we will try to explain the possible mechanism behind these results.

Efficacy of notices - Direct Effect

It is easy to understand that influencers tend to disclose more truthfully after receiving the warning notice from the regulator. An opposing side of this argument can be that influencers would ignore the warning from the regulator. However, given the possible flak from the regulator, which could lead to a permanent suspension of the social media account along with a fine, this seems like an unlikely scenario. Moreover, there is enough documented evidence on a firm response to regulator notices and warnings, making the direct effect more convincing (Darke et al., 2008). Specifically, the possible fear of either getting involved in a lawsuit or being imposed with other regulatory fines leads to influencers disclosing better after the notice.

Efficacy of notices - Spillover Effect

We find substantive spillover effect of notices on influencers who didn't get the notice but were in the FTC jurisdiction. On the one hand, it can be argued that influencers who don't get the notice don't correct their disclosure behavior because a) FTC didn't target them b) influencers were unaware of these crackdowns. Although these reasons seem plausible, they are improbable primarily because influencers' social media channels are multimillion-dollar businesses. Therefore, it is safe to assume that a) influencers are aware of events in their industry, such as regulatory enforcement. Moreover, there were many media articles about this b) influencers would be strategic in that they would know/infer the downside of getting a notice from the regulator.

Conversely, it can be argued that there will be spillover effects of these notices for the following reasons; a) influencers would correct their behavior in time because the FTC might take stricter action in its next round of crackdowns, and influencers might receive a harsher penalty for their disclosure malpractice, and b) these influencers might observe that when FTC sends notices to influencers, there are certain adverse effects on these influencers in terms of consumer response and brand association.

We find evidence of this in our analysis. Therefore, it can be concluded that notices have far-reaching effects; specifically, the theory of deterrence in penology can explain why these influencers start disclosing better (Holmes, 1981).

Consumer Response to undeclared advertising - Direct Effect

Consumer response to undeclared advertising by influencers who were sent the notice was found to be negative. To this end, one might argue that influencers enjoy demi-god status, and their followers rarely, if ever, punish them. However, extant literature in marketing related to deceptive advertising, undeclared advertising points towards the fact that consumers tend to punish firms/brands if they catch them involved in deceptive advertising. The underlying cause of this punishment is the loss of trust in the influencers. (Pollay, 1986) .

Consumer Response to undeclared advertising - Spillover Effect

Although it seems unlikely that consumers would punish influencers who were not caught in any malpractice, the extant literature on deceptive, covert advertising largely doesn't find any industrywide spillover effects of consumers' response. Therefore, one would expect to find no spillover effect in the current case too. However, we find that consumers respond negatively to the influencers in the FTC jurisdiction but weren't sent the notice. Interestingly, we found papers related to scandals to show industrywide adverse effects. Specifically, (Knittel & Stango, 2010) shows that a celebrity scandal leads to a loss of value for brands that employ those celebrities. However, for competing brands, the decrease or increase in value depends on whether they employed the fallen celebrity or not. Similarly, (Barth et al., 2019) finds adverse spillover effects for suppliers and competitors in the Volkswagen emission scandal. Therefore, spillover effects are driven by consumer's belief that other influencers may also be involved in similar non-disclosure malpractice.

LIMITATIONS AND ROBUSTNESS CHECKS

In the results presented above, we have aggregated data at the monthly level and use the entire data span (2013-2019) to evaluate the effects. In order to check the robustness of our results, we run multiple models with multiple variations. We are interested in two phenomena, a) Direction – disclosure percent increases after the notices were sent and follower engagement reduced after the notice was sent. B) Order- effect on influencers of notices is greater than the influencers who didn't receive the notice but were in the FTC jurisdiction.

First, as presented in all DID regression results, we run our models with and without time and influencer fixed effects.This generated four combinations, and our results are consistent across most of the combinations. Second, our main results were estimated using complete data (2013 to 2019). For robustness, we consider two more cuts on data, namely, Oct 2016 to Aug 2017 (highly local effects) and June 2016 to December 2017 (local effects). We find that our findings (order and direction) are consistent across all the levels except in one case (see Table 7 for summary and Table A7 to A12 in the Appendix) [6].

Table 7: Model variations for robustness check

	Data Span (Local Effects)						Clustering	
	Full		Local		Highly Local			
	Direction	Order	Direction	Order	Direction	Order	Direction	Order
Disclosure	✓	✓	✓	✓	✓	×	✓	✓
Likes	✓	✓	✓	✓	✓	✓	✓	✓
Comments	✓	✓	✓	✓	✓	✓	✓	✓

To account for correlated error terms across influencers, we cluster the errors and report the robust standard error. We find all our results consistent with our base models (represented in Eq.(2), (3), and (4)). The summary of the results is reported in the clustering column in Table 7, and complete results are available in Tables A13 to A15 in the Appendix.

We tried to answer the questions in this paper to the best of available data and our data collection capabilities; however, we would like to point to the following limitations of our paper. First, as always researchers wish that more data is available that could help with richer analysis. For example, to create comparable influencer treatment and control groups, it will be helpful to get a more comprehensive dataset than what is available with Hypeauditor, i.e., the list and variables of the top 1000 influencers. Specifically, researchers can find a match with all the 90

[6] For local and highly local effects disclosure Percent as dependent variable although gives correct order and direction but the results don't cross the 90% significance level. We transformed the disclosure percent to log(Disclosure Percent), here we find the significant results which yield the correct order and direction.

influencers and a more extensive dataset than the Hypeauditor 1000 list. Ideally, it can lead to a sample of nearly 180 influencers compared to 60 present in the current study.

Second, in our current analysis, we have analyzed the effect of notice sent by the US regulator. However, recently (in 2020) UK regulator has also sent out notices to nearly 43 UK-based influencers. It would be helpful to study the efficacy of notices and warning letters across different regulators and at least confirm or reject the effects found in our study. However, when policy evaluations are done, it is common to analyze the effect of policy in one context or setting and take learning before deploying similar policy changes.

Third, we could not collect post-level comments data for each influencer due to API restrictions. To further enhance this study, it would be useful to do a textual analysis of the comments obtained from the ad posts and compare them with non-ad posts. Specifically, researchers could do sentiment analysis of all the comments for a particular post and compare an overall sentiment to ad posts with the non-ad post before and after the notices were sent. Moreover, researchers can analyze the comments which contain the product mention and evaluate the sentiment of these posts.

CONCLUSION

In this paper, we study the direct and spillover effects of enforcing endorsement disclosure requirements in the context of influencer marketing. In 2017, FTC sent out notices to 90 influencers questioning their disclosure malpractice. We study this event using a causal inference approach to find that the disclosure percentage of influencers who received the notice increased. Moreover, the disclosure percent of influencers in the FTC jurisdiction who did not receive the notice also increased. Furthermore, follower engagement of the influencers who receive the notice decreases substantially.

Interestingly, the follower engagement of the influencers who did not receive the notice but were in FTC jurisdiction also goes down, thereby establishing a spillover effect of notices. In summary, we establish disclosure enforcement through notices as an effective policing instrument in the influencer marketing industry. However, we want to highlight the deterrence effects of this enforcement tool and suggest regulators account for the spillover effects.

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APPENDIX

Table- A1:Summary of balance matched data using propensity score matching

	Means Treated	Means Control	Std. Mean Diff.	eCDF Mean	eCDF Max
Distance	0.1432	0.1319	0.0638	**0.0018**	0.0606
Followers	40M	39.4M	0.0259	**0.1008**	0.2424
Authentic Engagement	544K	535K	0.0149	**0.0672**	0.2121
Actors	0.1818	0.2424	-0.1571	**0.0606**	0.0606
Beauty	0	0	0	**0**	0
Blogger	0	0	0	**0**	0
Lifestyle	0.0606	0.0606	0	**0**	0
Modeling	0.3636	0.3333	0.063	**0.0303**	0.0303
Music	0.1818	0.1515	0.0786	**0.0303**	0.0303
Politics	0	0	0	**0**	0
Sports	0.2121	0.2121	0	**0**	0

Table A2: List of Influencers - Treatment and Control Group

Notified	**Not Notified**	
Notice Sent - U.S. (Treatment 1)	**Notice Not Sent - U.S. (Treatment 2)**	**Notice Not Sent (Control)**
Vanessa Hudgens	Cara Delevingne	Bruna Marquezine
Chelsea DeBoer	Colton Haynes	Chris Hemsworth
Gigi Hadid	Justin Timberlake	F.C. Bayern
Ian Somerhalder	Nicki Minaj	BTS
Wardell Curry	Nike	Deepika Padukone
Kendall	QuavoHuncho	Gareth Bale
Amber Rose	Ryan Reynolds	Gisele
Asap Rocky	Vin Diesel	Team India Cricket
Victoria Justice	Zac Efron	Veveta
Serena Williams	Zach King	James Rodriquez
Marcelo Vieira Jr.	Zane Hijazi	Kylian Mbappe
Kylie Jenner		Katy Perry
Bella Thorne		Lee Dong Hae
Emily Ratajkowski		Manuel Neuer
Irina Shayk		Nike Football (Soccer)
Drake		Paulo Gustavo
Lucy Hale		Raisa
Khloe Kardashian		Taylor Swift
Dan Bilzerian		
Rita Ora		

Troian Bellisario Kourtney Kardashian David Beckham Zlatan Ibrahimovic Jav Alvarrez LeBron James Maisie Williams Marina Ruy Barbosa Neymar Jr. Niall Horan Pharrell Williams Zendaya	

Table A3: Influencers by location and group

	Count of Influencers		
	Notified	**Not Notified**	
Country	**Notice Sent (Treatment 1)**	**No Notice Inside U.S. (Treatment 2)**	**No Notice Outside U.S. (Control)**
Brazil	4	0	8
Colombia	0	0	1
France	0	0	1
Germany	0	0	1
India	0	0	3
Indonesia	0	0	3
Russia	1	0	0
Spain	0	0	1
United States	27	11	0
Grand Total	32	11	18

Table A4:Comparison of likes (engagement) - notified vs. not notified influencers

	Dependent variable:			
	log(Likes)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.314***	0.244***	0.074	-0.015
	(0.067)	(0.066)	(0.060)	(0.057)
InfluencerNotified	1.718***	1.730***		
	(0.135)	(0.130)		
NoticeSent	3.061***		3.097***	
	(0.137)		(0.113)	
InfluencerNotified x NoticeSent	-1.703***	-1.694***	-1.673***	-1.662***
	(0.189)	(0.183)	(0.156)	(0.146)
Constant	9.634***	7.229***	11.066***	8.713***
	(0.097)	(0.425)	(0.312)	(0.443)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.127	0.201	0.417	0.492
Adjusted R^2	0.127	0.187	0.410	0.477
Residual Std. Error	3.399 (df = 5180)	3.279 (df = 5097)	2.793 (df = 5121)	2.630 (df = 5038)
F Statistic	189.134*** (df = 4; 5180)	14.713*** (df = 87; 5097)	58.208*** (df = 63; 5121)	33.407*** (df = 146; 5038)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A5:Comparison of comments (engagement) - notified vs. not notified influencers

	Dependent variable:			
	log(Comments)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.212***	0.174***	0.037	-0.013
	(0.050)	(0.049)	(0.040)	(0.039)
InfluencerNotified	1.226***	1.233***		
	(0.099)	(0.097)		
NoticeSent	1.602***		1.628***	
	(0.101)		(0.076)	
InfluencerNotified x NoticeSent	-1.232***	-1.227***	-1.210***	-1.204***
	(0.139)	(0.136)	(0.104)	(0.099)
Constant	6.028***	4.286***	7.514***	5.798***
	(0.072)	(0.317)	(0.209)	(0.298)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.070	0.130	0.487	0.549
Adjusted R^2	0.069	0.116	0.480	0.535
Residual Std. Error	2.505 (df = 5180)	2.442 (df = 5097)	1.871 (df = 5121)	1.770 (df = 5038)
F Statistic	97.025*** (df = 4; 5180)	8.788*** (df = 87; 5097)	77.095*** (df = 63; 5121)	41.930*** (df = 146; 5038)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A6:Direct and Spillover effects of notice on comments

	Dependent variable:			
	log(Comments)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.192***	0.154***	0.051	0.001
	(0.049)	(0.049)	(0.040)	(0.038)
NoticeUS	1.710***	1.718***		
	(0.114)	(0.111)		
No NoticeUS	1.267***	1.270***		
	(0.147)	(0.143)		
NoticeSent	1.993***		2.003***	
	(0.127)		(0.095)	
NoticeUS × NoticeSent	-1.618***	-1.610***	-1.589***	-1.578***
	(0.159)	(0.155)	(0.119)	(0.113)
NoNoticeUS × NoticeSent	-1.024***	-1.016***	-0.993***	-0.983***
	(0.207)	(0.201)	(0.155)	(0.147)
constant	5.548***	3.804***	7.502***	5.787***
	(0.090)	(0.319)	(0.208)	(0.297)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	5,185	5,185	5,185	5,185
R^2	0.083	0.144	0.491	0.553
Adjusted R^2	0.082	0.129	0.484	0.539
Residual Std. Error	2.487 (df = 5178)	2.423 (df = 5095)	1.864 (df = 5120)	1.762 (df = 5037)
F Statistic	78.457*** (df = 6; 5178)	9.645*** (df = 89; 5095)	77.126*** (df = 64; 5120)	42.314*** (df = 147; 5037)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A7: Direct and Spillover Effects – Disclosure Percent -Local Effect

	Dependent variable:			
	log(DisclosurePercent)			
	(1)	(2)	(3)	(4)
NoticeUS	0.320***	0.320***		
	(0.077)	(0.077)		
NoNoticeUS	0.254**	0.254**		
	(0.100)	(0.100)		
NoticeSent	0.062		0.062	
	(0.089)		(0.076)	
NoticeUS × NoticeSent	0.271**	0.271**	0.271***	0.271***
	(0.112)	(0.112)	(0.095)	(0.095)
NoNoticeUS × NoticeSent	0.221	0.221	0.221*	0.221*
	(0.145)	(0.145)	(0.124)	(0.124)
Constant	0.029	0.019	0.545***	0.535***
	(0.061)	(0.118)	(0.164)	(0.185)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	1,159	1,159	1,159	1,159
R^2	0.078	0.089	0.359	0.371
Adjusted R^2	0.074	0.072	0.322	0.324
Residual Std. Error	0.825 (df = 1153)	0.826 (df = 1136)	0.705 (df = 1095)	0.705 (df = 1078)
F Statistic	19.452*** (df = 5; 1153)	5.058*** (df = 22; 1136)	9.739*** (df = 63; 1095)	7.932*** (df = 80; 1078)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A8: Direct and Spillover Effects – Likes -Local Effects

	Dependent variable:			
	log(Likes)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.258***	0.275***	0.040	0.061
	(0.100)	(0.101)	(0.074)	(0.074)
NoticeUS	1.683***	1.678***		
	(0.263)	(0.263)		
NoNoticeUS	1.566***	1.561***		
	(0.340)	(0.340)		
NoticeSent	1.618***		1.631***	
	(0.303)		(0.187)	
NoticeUS × NoticeSent	-1.502***	-1.506***	-1.443***	-1.448***
	(0.380)	(0.380)	(0.234)	(0.232)
NoNoticeUS × NoticeSent	-1.350***	-1.354***	-1.302***	-1.306***
	(0.493)	(0.493)	(0.304)	(0.301)
Constant	10.618***	10.343***	11.827***	11.539***
	(0.209)	(0.399)	(0.403)	(0.450)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	1,159	1,159	1,159	1,159
R^2	0.059	0.071	0.661	0.672
Adjusted R^2	0.054	0.052	0.642	0.648
Residual Std. Error	2.800 (df = 1152)	2.803 (df = 1135)	1.724 (df = 1094)	1.709 (df = 1077)
F Statistic	12.096*** (df = 6; 1152)	3.764*** (df = 23; 1135)	33.392*** (df = 64; 1094)	27.300*** (df = 81; 1077)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A9: Direct and Spillover Effects – Comments -Local Effects

	Dependent variable:			
	log(Comments)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.148*	0.171**	-0.001	0.030
	(0.076)	(0.076)	(0.048)	(0.047)
NoticeUS	1.244***	1.237***		
	(0.200)	(0.199)		
NoNoticeUS	1.077***	1.071***		
	(0.258)	(0.258)		
NoticeSent	0.900***		0.909***	
	(0.231)		(0.121)	
NoticeUS × NoticeSent	-1.033***	-1.039***	-0.992***	-1.001***
	(0.289)	(0.288)	(0.152)	(0.147)
NoNoticeUS × NoticeSent	-0.955**	-0.960**	-0.922***	-0.928***
	(0.375)	(0.374)	(0.197)	(0.191)
Constant	6.462***	6.325***	7.448***	7.294***
	(0.159)	(0.302)	(0.262)	(0.286)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	1,159	1,159	1,159	1,159
R^2	0.044	0.065	0.748	0.769
Adjusted R^2	0.039	0.046	0.734	0.751
Residual Std. Error	2.130 (df = 1152)	2.122 (df = 1135)	1.121 (df = 1094)	1.084 (df = 1077)
F Statistic	8.830*** (df = 6; 1152)	3.431*** (df = 23; 1135)	50.854*** (df = 64; 1094)	44.151*** (df = 81; 1077)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A10: Direct and Spillover Effects – Disclosure Percent -Highly Local Effects

	Dependent variable:			
	log(DisclosurePercent)			
	(1)	(2)	(3)	(4)
NoticeUS	0.316***	0.316***		
	(0.102)	(0.102)		
NoNoticeUS	0.185	0.185		
	(0.133)	(0.133)		
NoticeSent	0.063		0.063	
	(0.115)		(0.099)	
NoticeUS × NoticeSent	0.314**	0.314**	0.314**	0.314**
	(0.144)	(0.144)	(0.124)	(0.124)
NoNoticeUS × NoticeSent	0.374**	0.374**	0.374**	0.374**
	(0.188)	(0.188)	(0.161)	(0.161)
Constant	0.043	0.007	0.492**	0.455**
	(0.082)	(0.129)	(0.214)	(0.230)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	732	732	732	732
R^2	0.090	0.101	0.381	0.393
Adjusted R^2	0.084	0.083	0.323	0.325
Residual Std. Error	0.849 (df = 726)	0.849 (df = 716)	0.730 (df = 668)	0.728 (df = 658)
F Statistic	14.327*** (df = 5; 726)	5.388*** (df = 15; 716)	6.533*** (df = 63; 668)	5.832*** (df = 73; 658)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A11: Direct and Spillover Effects – Likes -Highly Local Effects

	Dependent variable:			
	log(Likes)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.301**	0.308**	0.050	0.056
	(0.121)	(0.122)	(0.088)	(0.088)
NoticeUS	1.273***	1.270***		
	(0.335)	(0.336)		
NoNoticeUS	1.109**	1.108**		
	(0.433)	(0.434)		
NoticeSent	0.958**		0.974***	
	(0.377)		(0.225)	
NoticeUS × NoticeSent	-1.042**	-1.044**	-0.963***	-0.965***
	(0.473)	(0.473)	(0.282)	(0.280)
NoNoticeUS × NoticeSent	-0.844	-0.846	-0.750**	-0.752**
	(0.614)	(0.615)	(0.366)	(0.363)
Constant	11.053***	11.075***	11.899***	11.910***
	(0.267)	(0.420)	(0.486)	(0.518)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	732	732	732	732
R^2	0.038	0.048	0.685	0.695
Adjusted R^2	0.030	0.026	0.655	0.661
Residual Std. Error	2.769 (df = 725)	2.774 (df = 715)	1.650 (df = 667)	1.637 (df = 657)
F Statistic	4.718*** (df = 6; 725)	2.237*** (df = 16; 715)	22.716*** (df = 64; 667)	20.263*** (df = 74; 657)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A12: Direct and Spillover Effects – Disclosure Percent -Highly Local Effects

	Dependent variable:			
	log(Comments)			
	(1)	(2)	(3)	(4)
log(DisclosurePercent)	0.153*	0.168*	-0.026	-0.008
	(0.091)	(0.092)	(0.056)	(0.055)
NoticeUS	0.925***	0.920***		
	(0.253)	(0.252)		
NoNoticeUS	0.712**	0.709**		
	(0.327)	(0.326)		
NoticeSent	0.475*		0.486***	
	(0.285)		(0.145)	
NoticeUS × NoticeSent	-0.780**	-0.784**	-0.723***	-0.729***
	(0.357)	(0.356)	(0.182)	(0.175)
NoNoticeUS × NoticeSent	-0.678	-0.683	-0.611***	-0.617***
	(0.463)	(0.462)	(0.236)	(0.227)
Constant	6.746***	6.823***	7.495***	7.558***
	(0.201)	(0.316)	(0.313)	(0.324)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Observations	732	732	732	732
R^2	0.025	0.046	0.769	0.788
Adjusted R^2	0.017	0.024	0.747	0.764
Residual Std. Error	2.092 (df = 725)	2.084 (df = 715)	1.062 (df = 667)	1.024 (df = 657)
F Statistic	3.145*** (df = 6; 725)	2.141*** (df = 16; 715)	34.645*** (df = 64; 667)	33.064*** (df = 74; 657)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A13: Clustered - Robust SE - Disclosure Percent

	Dependent Variable			
	DisclosurePercent			
	1	2	3	4
(Intercept)	0.037	-0.281+	-0.181**	0.47
	(0.033)	(0.146)	(0.06)	(0.436)
NoticeUS	0.729***	0.729***	6.942***	5.974***
	(0.086)	(0.087)	(1.518)	(1.578)
NoNoticeUS	0.351**	0.351**	-0.189	2.048**
	(0.112)	(0.111)	(0.357)	(0.784)
NoticeSent	0.358**	1.492+	0.358**	0.18
	(0.113)	(0.901)	(0.112)	(0.579)
NoticeUS x NoticeSent	1.595***	1.595***	1.595***	1.595***
	(0.284)	(0.286)	(0.277)	(0.279)
NoNoticeUS x Notice ent	1.488***	1.488***	1.488***	1.488***
	(0.398)	(0.398)	(0.389)	(0.389)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Num.Obs.	5185	5185	5185	5185
R2	0.061	0.084	0.199	0.222
R2 Adj.	0.06	0.069	0.189	0.2
se_type	HC2	HC2	HC2	HC2
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Table A14: Clustered - Robust SE - Likes

	Dependent Variable:			
	Log(Likes)			
	1	2	3	4
(Intercept)	8.844***	6.436***	10.647***	8.238***
	(0.188)	(0.634)	(0.234)	(0.544)
log(DisclosurePercent)	0.304***	0.233***	0.108***	0.019
	(0.031)	(0.032)	(0.027)	(0.028)
NoticeUS	2.510***	2.524***	0.391	0.449
	(0.209)	(0.204)	(0.283)	(0.282)
NoNoticeUS	2.084***	2.089***	0.974*	0.945*
	(0.253)	(0.245)	(0.381)	(0.383)
NoticeSent	3.954***	6.264***	3.966***	6.365***
	(0.200)	(0.678)	(0.168)	(0.558)
NoticeUS × NoticeSent	-2.593***	-2.578***	-2.552***	-2.534***
	(0.232)	(0.226)	(0.189)	(0.181)
NoNoticeUS × NoticeSent	-2.349***	-2.334***	-2.306***	-2.287***
	(0.297)	(0.283)	(0.268)	(0.253)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Num.Obs.	5185	5185	5185	5185
R2	0.146	0.219	0.428	0.503
R2 Adj.	0.145	0.206	0.421	0.488
se_type	HC2	HC2	HC2	HC2

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A15: Clustered - Robust SE - Comments

	Dependent Variable: Log(Comments)			
	1	2	3	4
(Intercept)	5.548***	3.804***	8.182***	6.435***
	(0.124)	(0.409)	(0.201)	(0.351)
log(DisclosurePercent)	0.192***	0.154***	0.051+	0.001
	(0.033)	(0.032)	(0.027)	(0.026)
NoticeUS	1.710***	1.718***	-0.680**	-0.648**
	(0.142)	(0.140)	(0.243)	(0.224)
NoNoticeUS	1.267***	1.270***	-0.500+	-0.516+
	(0.169)	(0.164)	(0.289)	(0.274)
NoticeSent	1.993***	3.705***	2.003***	3.777***
	(0.145)	(0.466)	(0.101)	(0.350)
NoticeUS × NoticeSent	-1.618***	-1.610***	-1.589***	-1.578***
	(0.171)	(0.169)	(0.121)	(0.116)
NoNoticeUS × NoticeSent	-1.024***	-1.016***	-0.993***	-0.983***
	(0.208)	(0.200)	(0.171)	(0.161)
Time Fixed Effects	N	Y	N	Y
Influencer Fixed Effects	N	N	Y	Y
Num.Obs.	5185	5185	5185	5185
R2	0.083	0.144	0.491	0.553
R2 Adj.	0.082	0.129	0.484	0.539
se_type	HC2	HC2	HC2	HC2

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

United States of America
FEDERAL TRADE COMMISSION
Washington, D.C. 20580

Mary K. Engle
Associate Director

{*Date*}

{*Address*}

Dear {*Influencer*}:

The Federal Trade Commission is the nation's consumer protection agency. As part of our consumer protection mission, we work to educate marketers about their responsibilities under truth-in-advertising laws and standards, including the FTC's Endorsement Guides.[1]

I am writing regarding your attached Instagram post endorsing {*product or service*}.[2] You posted a picture of {*description of picture*}. You wrote, "{*quotation from Instagram post*}."

The FTC's Endorsement Guides state that if there is a "material connection" between an endorser and the marketer of a product – in other words, a connection that might affect the weight or credibility that consumers give the endorsement – that connection should be clearly and conspicuously disclosed, unless the connection is already clear from the context of the communication containing the endorsement. Material connections could consist of a business or family relationship, monetary payment, or the provision of free products to the endorser.

The Endorsement Guides apply to marketers and endorsers. [If there is a material connection between you and {*Marketer*}, that connection should be clearly and conspicuously disclosed in your endorsements.] *or* [It appears that you have a business relationship with {*Marketer*}. Your material connection to that company should be clearly and conspicuously disclosed in your endorsements.] To make a disclosure both "clear" and "conspicuous," you should use unambiguous language and make the disclosure stand out. Consumers should be able to notice the disclosure easily, and not have to look for it. For example, consumers viewing posts in their Instagram streams on mobile devices typically see only the first three lines of a longer post unless they click "more," and many consumers may not click "more." Therefore, you should disclose any material connection above the "more" button. In addition, where there are multiple tags, hashtags, or links, readers may just skip over them, especially where they appear at the end of a long post.

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[1] The Endorsement Guides are published in 16 C.F.R. Part 255.

[2] The post is available at {*URL*}.

{*Influencer*}
{*Date*}
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If you are endorsing the products or services of any marketers with whom you have a material connection, you may want to review the enclosed FTC staff publication, *The FTC Endorsement Guides: What People are Asking*. I'm also enclosing a copy of the *Endorsement Guides* themselves. (Both documents are available online at business.ftc.gov.)

If you have any questions, please contact Mamie Kresses at (202) 326-2070 or mkresses@ftc.gov. Thank you.

Very truly yours,

Mary K. Engle
Associate Director
Division of Advertising Practices

Figure A1: Letter from FTC to influencers