ON PEERS AND AGENT CHOICE

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ON PEERS AND AGENT CHOICE

Dedicated to my mother

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ABSTRACT

ON PEERS AND AGENT CHOICE

Abhishek Rishabh

In this dissertation I study the impact of decision by peers (others) on decision making of a focal agent. I study this effect in two broad marketing contexts a) influencer marketing b) charitable giving. In my first essay, I study how regulatory punishment on a set of social media influencers affects endorsement strategy of other influencers in the same regulatory environment. In my second essay, I study the effect of donation behavior of other donors on the focal donor. Specifically, I investigate the role of popularity of a charitable cause on donations of new donors and existing donors.

ESSAY 1 – Regulatory notices and endorsement disclosure 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 quasi-natural experiment setup 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 a 6 years period. We find that advertising disclosures increased 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. Our findings provide valuable insights to regulators and social media managers on the direct and deterrence effects of regulator notices.

ESSAY 2 – Popular or crowded: Subscription-Based Donations Subscription-based donations are becoming a popular fundraising tool as they are perceived to yield a high donor lifetime value. A common practice of online donation platforms is to display, for each cause (e.g., cancer treatment or education provision), the donor group size (number of people donating to that cause). We use data from a subscription-based donation platform to study the effect of displaying donor group size on new donors and current donors. We use a) repeat donations of individual donors and b) an exogenous shock to the platform that shifts the donor group size to identify its impact on the two donor groups. We find that displaying the number of donors can act as a double-edged sword — encouraging new donors (a "bandwagon" effect) while discouraging existing donors (a "bystander" effect) from subscribing. We suggest the managers be careful about displaying the number of donors as the net effect on subscriptions can vary with the "life cycle" of the charity and its donors. Specifically, managers can leverage this information when new donors signup but should not disclose this information to current and active donors.

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CHAPTER 1

Popular or Crowded: Subscription Based Donations

1.1. Introduction

Billions of dollars are raised for charitable donations every year (Mohan et al., 2019; Trust, 2021) . With increasing ease of donation through online channels, online donations have increased 21% YoY (Institute, 2021). This growth has led to the formation of many online donation platforms such as Donorbox, Double the Donation, GiveIndia, Ketto. Donation platforms provide a two-sided market for donors and nonprofits. The benefit for donors is a wide variety of causes to choose from, verified nonprofits and lower search costs. The benefits for nonprofits are access to a broad donor base, the ability to raise funds for multiple causes simultaneously, and lower cost to raise funds (Ozdemir et al., 2009). Donation platforms use one-time donation events and subscription-based donations as primary modes of raising donations. Although most donations are raised using one-time donation events, there is a shift towards a subscription-based donation model (MatchPro, 2020)). A subscription-based donation model is where a donor signs up for donating to a cause. A set amount is deducted every period (monthly or quarterly) from the donor's account to support the cause. It has been documented that when donors signup for subscription-based donations, they tend to donate more (amount and duration) than a one-time donation; a survey shows that donors on subscription-based donate 4.4 times more than one-time donation (Classy, 2018). One of the common strategies used by the donation platforms is to display the number of donors donating to a cause (donor group size). The extant literature seems to be divided on the effects of donor group size on donation. Specifically, on the one hand, papers argue that, 3 as in the product markets, there will be bandwagon[1] effects at play, and therefore, as the donor group size (popularity) increases, so will the donations (Cialdini and Goldstein, 2004; Reingen, 1982; Frey and Meier, 2004). However, on the other

[1]Bandwagon effects – people tend to adopt something primarily because others adopt it. In our context, it refers to an increase in the probability of donation based on more people donating to a particular cause.

hand, there is a strand of literature that argues for the bystander[2] effects at play, specifically, as the donor group size would increase, the probability of donation would go down (Darley and Latane, 1968; Panchanathan et al., 2013; Fischer et al., 2011). Furthermore, the decision process of donors in one- time donation is different from subscription-based donations. Specifically, in subscription- based donations, donors have to decide on a) which cause(s) to donate, b) the amount to donate, c) continue or cancel the donation in the subsequent periods d) donors receive an update on their donation (progress and impact) every month. However, in the case of one- time donations, donors mainly decide on the cause and donation amount. Therefore, given a) shift towards subscription-based donation in practice, b) unclear answers from the extant literature, and c) different underlying donor's decision process compared to one-time donations warrants an investigation into understanding the effects of donor group size on donations in the subscription-based donation context. This paper answers the following research questions in the subscription-based donation context.

1. Does a higher donor group size leads to more new donors?

2. Does higher donor group size leads to more current donors cancelling their donation subscription?

3. Should a donation platform provide information (display) donor group size information?

4. Do the above findings persist for different cause categories and different types of donors?

We work with one of India's largest subscription-based donation platforms to answer the above questions. The platform (website) started its operations in 2017, provides a gamut of nearly 300 causes[3] across four categories (nutrition, livelihood, education, and healthcare) for donors to choose from. Each cause has its webpage where donors can get more information about the cause, including how many donors are donating to the cause then (donor group size). The minimum donation amount can vary from Rs 100 (USD 1.35[4]) per month to Rs

[2]Bystander effects – the propensity to help someone decreases in presence of others. In our context, it refers to decrease in probability of donation (help) if others are already donating to a particular cause.

[3]Examples of causes include, a) help underprivileged children with their education, b) support cancer patients with chemotherapy sessions.

[4]Exchange rates as of Nov 2021

11,500 (USD 155) per month. The platform donor base of nearly 10,000 (as of Dec 2020) monthly active donors, primarily based out of India, North America, and Western Europe. We have transaction-level data from the platform's inception to Dec 2020. Furthermore, we have information on major strategic decisions by the platform from its inception. Our data is unique compared to the extant literature in that a) we have transaction- level data for subscription-based donations, b) a wide variety of causes c) a wide variety of donors. Therefore, with this data, we can not only comment on the impact of donor group size on donations in the subscription-based donation context, but our results are also more generalisable due to a variety of causes and donors. We are interested in a) effect of donor group size on new donors b) the effect of donor group size on current donors. Both these relationships can be biased due to multiple types of endogeneities. Next, we explain why these relationships can be biased. Consider the first relationship, the effect of donor group size (X1) on new donors (Y1). As discussed earlier, higher the donor group size, more new donors would join ($Y_1 \leftarrow X_1$) . However, as more new donors join, it would lead to higher donor group size as these new donors will become the part of donor group ($X_1 \leftarrow Y_1$), leading to a typical endogeneity concern arising from reverse causality. Now, consider the second relationship, the effect of donor group size (X_2) on current donors (Y_2). As discussed earlier, one strand of literature argues that higher donor group size would lead to lower donation probabilities or higher cancellations.However, if a donor cancels, it would lead to a lower donor group size ($X_2 \leftarrow Y_2$) . Again, this leads to the trap of reverse causality. Furthermore, some unobserved factors could affect both X and Y together for example, certain types of causes (saving a child's life vs providing books for the underprivileged) would be more appealing than others. To address the endogeneity issues in both the relationships (joiners vs DGS and cancellations vs DGS), we use an exogenous shock (the event) as the source of variation for identification. The event was a collaboration between the focal donation platform and many eCommerce retailers in India. In this collaboration[5], consumers and

[5] Donation platform was advertised on the retailers' websites in the form of landing page banners. However, the donation wasn't tied to any offer on the retailer's website. Furthermore, employees and volunteers of the donation platform organised information sessions for the employees of the collaborating retailers.

employees of the retailers were informed about the focal donation platform. Post the event; there was an 'unexpected' increase in the number of donors (donor group size) for some causes on the donation platform. Therefore, this shock serves as a random intervention. Furthermore, the causes which experienced an unexpected increase[6] in donor group size are labelled as treated causes and others as untreated causes or the control group. Next, we explain how our setup helps us to causally establish the effect of donor group size on joiners and cancellations. First, consider the relationship between joiners and donor group size. The donors, who joined the platform (the treated causes) just after the event, experienced an unusually larger donor group than the control group. Therefore, the event serves as a random intervention. For further illustration, consider a toy example, consider two exactly similar causes. The number of joiners & donor group size are observed for each cause every month. Suppose for one of the causes, there is a sudden increase (shock) in donor group size and post the shock; there is a sudden change in joiners; this increase can be attributed only to the sudden rise in donor group size. The counterfactual is present in the control group. Post the event, the control group didn't experience a sudden increase in joiners because it didn't experience an increase in donor group size. Second, consider the relationship between cancellations and donor group size. In this case, the donors who were donating to a cause just before the shock, for them, the shock was an unexpected event, i.e., the sudden increase in the donor group size for the treated causes. Therefore, if the cancellations for the treated causes increases compared to the control, that increase can be attributed to the event (sudden increase in donor group size). Therefore, using the event as the source of exogenous variation, we can causally estimate the impact of donor group size on the number of joiners (new donors) and the number of cancellations of the existing donors. We use a difference in difference type model on the monthly aggregated data. In the DID set-up, the event serves as the intervention; the causes which experience an increase in the donor group size are labelled as the treatment group and the others as the control group. We complement the DID method with an instrumental variable approach to build confidence in our results.

[6] We use multiple definitions of increase. See Robustness Checks section for the definitions.

We instrument the endogenous donor group size variable with the even shock and use a 2SLS approach to estimate our results. Lastly, we use transaction-level data to estimate the effects of donor group size on the probability of cancelling a donation subscription. We focus only on cancellations in the transaction level analysis because cancellations warrant more investigation because of relatively less focus in literature, and we don't observe choice data for joiners (join/not join). We use a dynamic logit model for estimation; however, as discussed earlier, this model too suffers from a reverse causality problem. Therefore, we instrument the endogenous donor group size variable with event shock. We further complement the dynamic logit model with survival analysis; we use the Cox proportional hazard model with time-varying covariates. Across all models, we find that donor group size positively affects the joiners (new donors). This finding conforms with the extant product literature on displaying popularity as demand boosting tool. In the charitable donation context, this finding confirms the bandwagon effects. Surprisingly, we find that as more donors start donating to a cause, it hurts the probability of continuing donation for the current donors. This finding is counterintuitive from both the product and at least one strand of charitable donation literature. Therefore, in the case of subscription-based donations, donor group size can have both positive and negative effects, albeit for different types (new vs current) of donors. Specifically, the donor group size serves as a signal of quality for the new donors, leading to a higher number of new donors. In the case of cancellations, the bystander effect seems to be the plausible explanation. Specifically, as widely documented in the prosocial behaviour literature, the propensity to help a person reduces in the presence of others. Therefore, in our context, when the donor group size increases for a cause, the probability of continuing donation for an existing donor reduces. We rule out multiple other possible explanations using data and institutional information; for example, our results on cancellation can simply be explained by switching. Specifically, when more people start donating to a cause, a donor might feel that her resources are better utilised elsewhere, leading her to either donate to a more 'needy' cause on the current platform (intra) or switch to a different donation platform (inter). We rule out the intra platform switching based on evidence from the data (we don't find donors who cancel their donation to start donating to some other cause on the platform). Similarly, we rule out the inter-platform switching based on the high market share and a wide variety of causes present on the focal donation platform. Furthermore, we rule other possible explanations to build the case for our findings and explanations. To test the robustness of the results of the models, we test for parallel trends, the persistence of effects post the shock, heterogeneous treatment effects, different definitions of increase and instrument validity through placebo regressions. Our results remain unchanged, and we find the direction of estimates to be intact. We contribute to the literature in charitable donations in three distinct ways 1) We establish the impact of displaying donor group size in the context of subscription-based donations. Specifically, we find that, in the subscription-based donations context, information on donor group size helps get new donors, but this information also hurts the probability of current donors to continue donations. The net effect is a positive effect on donation when the donor group size is small (gain in new donors > loss in current donors) followed by zero effect (gain in new donors = loss in current donors) when donor group size is high. To the best of our knowledge, ours is the first paper to establish the effects of donor group size in the subscription-based donation context. 2) We bring clarity in the extant divergent literature on the effects of donor group size on donations. We do show that both (positive and negative) sides of the effect and the corresponding explanations are correct, albeit for different types of donors or in different stages of the donor-platform relationship) 3) Our findings are generalisable in that our results hold across different types of donor groups and a wide variety of causes. Extant literature has based its findings on a single cause category with a constricted donor pool, and it has been documented that donation behaviour varies by type of cause and donor (Andreoni, 2007; Liu et al., 2017).The rest of the paper is organised as follow; in the related literature section, we cover the extant literature on the effects of donor group size on donations. Specifically, we discuss papers with divergent findings. We also discuss papers that attempt at providing reconciliation on these divergent findings. Furthermore, we discuss the contribution of our paper to the extant literature. Next, we provide details on the institutional setting and data. The descriptive evidence section provides visualisation and correlation-based tests to provide model-free evidence. Identification strategy provides details on our source of exogenous variation and underlying identifying assumptions. The results and discussion section provides details on the results. The robustness checks and alternate explanations section offers more support for our findings. Eventually, we discuss the implication of our findings for the platform before concluding the paper.

1.2. Related Literature

The popularity of a product and its effect on demand has been well studied in the extant literature. Specifically, the probability of purchase of a product is higher if its popularity is displayed vs when it is not, ceteris paribus (Tucker and Zhang, 2011; Cai and Wyer, 2015; Zhang, 2010). Researchers use various terms for the phenomenon under different settings such as bandwagon effects, herding, information cascading, etc. (Anderson and Holt, 1997; Banerjee, 1992; Bikhchandani et al., 1992). Broadly speaking, all these studies suggest that consumers use popularity as a signal of quality. Extant research seems to be divided into two broad groups with divergent findings in the charitable donation context. 1) Positive effect- donation is higher for more popular causes (Cialdini and Goldstein, 2004; Frey and Meier, 2004; Reingen, 1982; Milgram et al., 1969) 2) Negative effect – donation is lower for more popular causes(Bonsu and Belk, 2003; Darley and Latane, 1968; Fischer et al., 2011; Panchanathan et al., 2013). The theoretical explanation behind the positive effect is the appropriate social norm. In particular, when more people donate to a specific cause, the potential donor thinks that donating to that cause is the right thing to do as others are doing it. However, for the negative effect, the explanation stems from bystander effects. In particular, when more people start supporting a cause, there is a reluctance towards continuing help, a phenomenon well established in the prosocial behaviour literature (Panchanathan et al., 2013; Bonsu and Belk, 2003). Alternatively, other explanations could be, when more people start supporting a cause, the donor might feel a) her resources could be better utilised somewhere else or b) her contribution no longer makes a difference as others are already supporting the beneficiary. Therefore, it is unclear if donor group size affects donation behaviour positively or negatively, creating a dilemma. Recent papers by (Lee et al., 2017; Mukherjee et al., 2020) attempts to resolve this dilemma through a series of experiments and find donor similarity and recipient resource scarcity as essential moderators for these divergent results. The limitation of these studies can be broadly classified into two categories a) inference based on one-time donation data b) lack of generalizability of results, stemming from the constricted subject pool and no variation in the type of charities. We attempt to address all these issues in this paper. Next, we expand on each of these limitations and how they can affect the inference and generalizability of findings.

One-time donation data

Papers that deal with positive or negative effects or which attempt at resolving the dilemma use one-time donation data. For instance, in (Mukherjee et al., 2020), participants must donate once for earthquake victims. Findings from one-time donations can't be applied in the subscription-based donation setting because of donors' different underlying decision processes. In particular, in subscription-based donation, there are the extra elements of a) deciding to continue or cancel the donation every month b) donor receives update on the progress/goal of the cause every month. Therefore, the effects of donor group size could be amplified in the subscription-based donation setting as the donors are more actively engaged with the cause. Furthermore, with one-time donation data, it is difficult to capture within donor differences or to understand the donor lifecycle (how donation behaviour of the same donor changes over time).

Variation in donors and causes

A standard critique on the generalizability of findings with donation behaviour is the inherently different altruistic behaviour of donors from different countries. For example, in our context, donors from India might be less generous compared to American donors because of inherently different donation culture (Ashraf and Bandiera, 2017; News, 2019). Inversely, Indian donors might feel close to the cause as the recipients are Indians and, therefore, donate more (Kessler and Milkman, 2018; Munz et al., 2020). However, to the best of our knowledge, there are no papers that consider this variation in altruistic behaviour. In our dataset, the donors are not only based in India but also from relatively more generous regions such as the US and Europe. Furthermore, findings in the extant literature are based on one cause (education or healthcare etc.). However, as documented in a few papers, the donation behaviour of individuals can be very different for different causes (**?**). Therefore, for generalised findings, it is useful to test the results across heterogenous donor groups (varied inherent altruism) and a variety of causes.

Contribution

We contribute to the extant literature by a) extending the donation literature to subscription-based donations context, b) resolving a dilemma in extant theory, and c) evaluating the impact of a commonly used strategy by donation platforms/ charities, i.e. providing donor group size information to current and potential donors. Theory on the effects of donor group size on donation behaviour is divergent. One strand of literature argues for the bandwagon effect (positive), and the other strand argues for the bystander effects (negative), thus creating a dilemma. In this paper, we resolve this dilemma (positive or negative effect), albeit in a subscription-based donation context. We show that displaying donor group size information can affect the donation positively and negatively, although at different points on the donor's donation life cycle. Our results are useful for managers in that it provides a balanced view on how others' prosocial behaviour information can affect the donation behaviour of potential and current donors. Managers can use this information to better design their platform and interact with the donors. Specifically, managers should use donor group size information to attract new donors. However, they should be careful about providing donor group size information to current donors as it might discourage their donations.

1.3. Institutional Setting and Data

1.3.1. Institutional Setting

This paper deals with charitable donations. Specifically, retail donors donating[7] (not organisational or CSR activities) to individual/group of recipients (not organisations). Charitable

[7]Retail donor refers to individual donors who donate to one or multiple causes/beneficiaries, and the size of donation (value) is generally small, unlike corporate donations.

donations are nearly USD 470 Bn in the US (GivingUSA, 2021). Ease of payment through online channels has led to the creation of many online donation platforms such as Donorbox, Double the Donation, GiveIndia, Ketto. Donation platforms serve as two-sided markets (nonprofits and donors). Donors prefer donation platforms because of ease of donation, access to a wide variety of causes and lower search costs, whereas the nonprofits enjoy access to a large donor base and low cost of raising funds (or else they would need to set up and maintain a website/app etc.). One-time and subscription-based donations are two primary modes of donations collection used by the platforms. Subscription-based donations have shown to generate higher revenues and tap into a committed and loyal donor base. Subscription-based donations turn out to be 4.4 times more valuable than one-time donations and 42% more valuable than fundraisers (Classy, 2018). Moreover, the retention rate among subscription-based donors is nearly 90% compared to 23% for one-time donors and 60% for repeat donors (Recurringgiving.com, 2019). Furthermore, donors signup for subscription- based donations because it provides them with a lower cost of giving, fewer donation asks, and a higher engagement (Appfrontier.com, 2020). We work with a subscription-based donation platform[8] based out of India for this paper. This platform is one of the biggest subscription-based donation platforms in India. The platform started in 2017 and generates donations of more than USD 5 Mn a year. Next, we explain how the subscription donation process works. A donor visits the platform and can select from nearly 300 causes, divided into four broad categories (education, health, livelihood, and nutrition). Each cause has its webpage where the donor can see detailed information about the cause (who will benefit and for what, information about the affiliated nonprofit etc.). Donors can view how many people are donating to the cause then. She can only donate in multiples of a minimum value. For example, if she wants to provide food for underprivileged kids and it costs at least USD 4 per month, she can donate in multiples of USD 4, which can help one or multiple beneficiaries. Each month the donor's payment card gets deducted with the amount of her donation. One of the unique features of the platform is that the donors receive a monthly email about the

[8]Name undisclosed due to non-disclosure agreement.

progress and impact of their donation. In particular, the monthly email contains information on, amount of donation for the month, the number of donors supporting the cause in that month and a thank you note. Each month the donor has an option to either continue or cancel the donation. Each donor can choose to donate to multiple causes too, however, we find this number to be very small (less than 5%). We also document all the major policy changes during the data span used in our analysis (2017-2020), to ensure that our results are not an artefact of any policy change. In this span there were two major policy changes a) FCRA amendment bill 2020[9] b) Donations Deductibles[10] (ClearTax, 2021). Both these policy changes don't affect our analysis and findings.

1.3.2. Data Description

We use transaction level data from the donation platform. The data ranges from Oct 2017(firm start date) to Dec 2020. It consists of nearly 64000 transaction of 9627 donors across 308 causes. Table 1 below represents the summary statistics of the data. For each transaction we observe date, amount of donation, minimum donation amount, number of beneficiaries, cause, meta category of cause, donor group size, demographic variables of donors and some characteristic variables of the cause. A donor is assumed to drop out(cancel) if she misses two transactions in a row[11].Subscription-based donations leading to repeat donation without appeal is one of the unique points about our dataset, in contrast, most other papers use one-time donation data per donor[12]. First, observe that although there are a few (24%) donors which stop donating after the first transaction (see FigureA.1 in the Appendix), the mean number of transactions per donor is 6.66 (s.d = 6.89), this translates

[9]This bill was passed in Lok Sabha (Lower House of the Indian parliament) in Sep 2020. It affects the grants from foreign sources to Indian non-profits. Our donation platform and associated non-profits had obtained all clearances in time and thus the donation activity wasn't affected by this regulation.

[10]New tax rules introduced in 2017-18 suggests that donation above Rs 2000 in cash will not considered for tax deductions. Again, this doesn't affect our case as all the transaction are made through debit/credit cards thereby making them eligible for deductions.

[11]In case of card/payment errors, both the focal firm and the payment gateway partner sends out an email to the donor to update her card details. However, if there is no response in a month and the donors fails to pay, she is assumed to cancel her donation. We find no evidence of donor restarting donation to the same cause after 2 months. However, there are a few instances where a donor comes back to the platform after a year or so start donating to a different cause.

[12](Kim et al., 2021) does have multiple donations per user however, a) the next donation comes after an appeal from the nonprofit b) low annual mean gift frequency (<1)

Variable	Mean	St. Dev.	Min	Max
Donor Group Size	114.6	172.56	1	670
Min Donation Amt	1,016.40	1,030.65	100	11,655
Total Donation	1,546.40	2,406.64	100	1,48,000
Number of Transactions	6.66	6.89	1	111
Number of causes		308		
Number of donors		9627		
Number of Observations		64080		

Note: The summary statistics are calculated using the panel structure of data. Number of donors and causes are reported as of Dec 2020. Donation amounts are reported in INR.

to nearly 7 transactions per donor in a span of 7 months without any reminder or appeal from the firm. Second, donors have not only more than 300 causes to choose from but also a wide range of donation amounts (varying from Rs 100 (USD 1.3) to Rs 148,00 (USD 2000). This variation both on type of cause and donation amount helps us to make generalized inference[13]. Donor group size varies from as low as 1 other person donating to 670. The mean donor group size is 114.6 (s.d=172.6), this variation is the core of our analysis, representing the popularity of causes. The broad distribution of a) donor demographics b) cause category are reported in Table A.1 and A.2 in the appendix respectively.

1.4. Descriptive Evidence

1.4.1. Visualizations

Consider Figure 1.1, as donor group size increases, both the joiners and cancellations increase. To ensure that our observation (positive correlation between donor group size and joiners & cancellations) isn't a category-specific phenomenon we plot the same relationship by cause category. Our results presented in Figure A.2 (Appendix) show that a positive correlation exists across all-cause categories. Similarly, we cut the data by donor demographics (see Figure A.3), minimum donation amount and donor group size, we find that the observation persists across all the data cuts. This ensures that our observation is not moderated by any of the obvious and observed variables. Furthermore, we plot the evolution of cancellations and joiners with donor group size (see Figure A.4 in the Appendix), to en-

[13]This makes our setting different. Specifically in extant literature the variety both in causes and amount is relatively less, primarily due to experiment design and subsequent choice overload constraints.

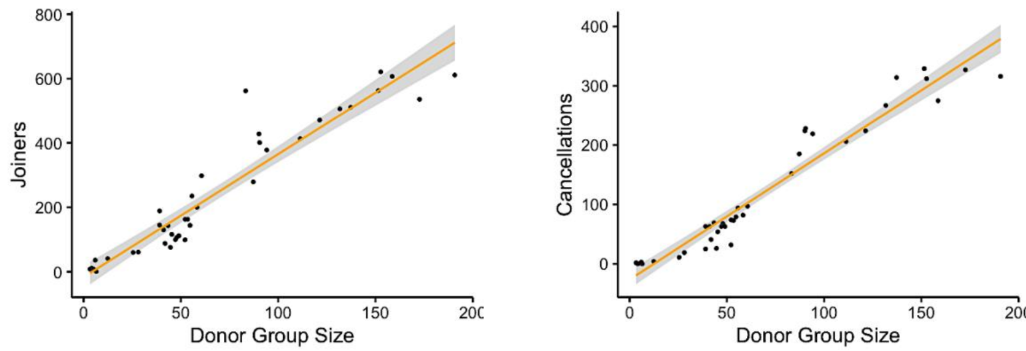


Figure 1.1: The left panel (a) shows the relationship of joiners and donor group size. The right panel (b) shows the relationship between cancellations and donor group size.

sure that the correlation between our variables of interest persists overtime.To illustrate the net impact (joiners – cancellations) of donor group size on donations we plot Figure 1.2. It shows that as the donor group size increases, the positive impact of displaying donor group size diminishes. Specifically, as the donor group size increases both joiners and cancellations increase, however, the cancellations increase more compared to joiners, thereby diminishing the benefits from displaying donor group size.

1.4.2. Correlation Based Tests

To build further confidence in our preliminary observations we run some correlation- based tests. We use panel regression models[14] with varying model specifications. We use cause fixed effects to account for omitted variable bias (preferred/appealing causes). Furthermore, we use time trends to account for platform level push (growth strategies) over time and cyclical giving behaviour of donors (List, 2011). Results for joiners and cancellations are reported in Tables 1.2 and 1.3 respectively. We find that in all model specifications, the donor group size is positively correlated with joiners and cancellations. Using visualizations and correlation-based tests, we produce preliminary evidence for our research question. We find that donor group size positively impacts the new joiners (joiners), however, surprisingly, it also positively affects cancellations. It is important to note that, the results from these

[14] We estimate $Y_{ct} = \beta_1 DGS_{ct} + T + \alpha_c + \varepsilon_{ct}$ where Y_{ct} can be joiners or cancellations, DGS_{ct} is the donor group size for cause c at time t. T represents time trend. c is cause and t represents month year indicator.

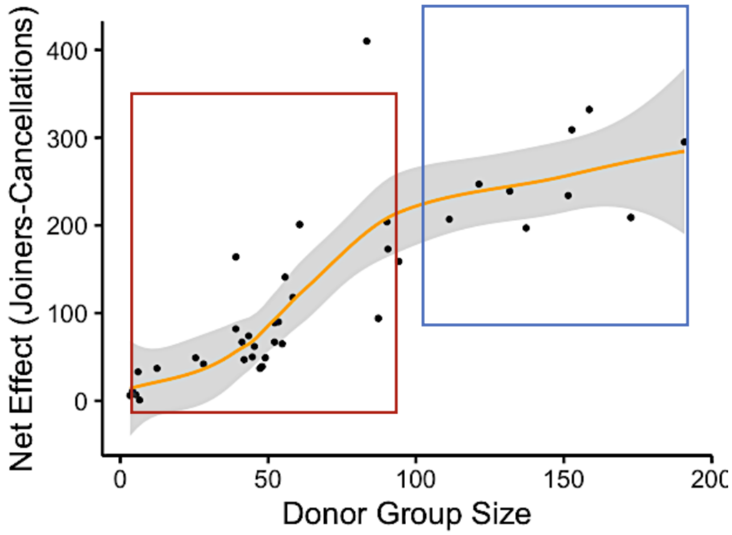


Figure 1.2: This figure represents relationship between net effect (joiners-cancellations) with donor group size. Transition from red to blue box represents the diminishing marginal benefits of displaying donor group size.

tests are not reliable because of simultaneity which is explained in detail in the next section.

1.5. Identification Strategy

Correlation-based tests presented above suffer from another form of endogeneity i.e., reverse causality. For illustration, consider Eqn (1). Y is the dependent variable which can either be the number of joiners in a cause at time 't' or it can number of cancellations in a cause at time 't'. We are interested in causally establishing the effect of donor group size DGS_{ct} on Y_{ct} . As the donor group size changes, it will change the Y_{ct} , based on extant literature, however, if Y_{ct} changes it will lead to a different donor group size in the subsequent period[15]. Therefore, both these relationships together create the reverse causality problem.

$$Y_{ct} = \beta_1 DGS_{ct} + \alpha_c + \delta_t + \varepsilon_{ct} \tag{1.1}$$

[15]For example, if cancellations increase on increase in donor group size, it will lead to a lower donor group size in the subsequent periods.

	Dependent Variable			
	Joiners			
	(1)	(2)	(3)	(4)
Donor Group Size	0.167**	0.248 ***	0.167***	0.259 ***
	(0.004)	(0.008)	(0.004)	(0.009)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R2	0.436	0.551	0.437	0.554

Note: The dependent variable is the number of joiners, standard errors are reported in parenthesis. We run four panel regression models with different model specifications. In the first two columns cause fixed effects are not included, whereas in the last two columns cause fixed effects are included. Cause level control variables are absorbed in the cause fixed effects.

	Dependent Variable			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.08**	0.108 ***	0.08***	0.110 ***
	(0.004)	(0.008)	(0.004)	(0.009)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2,556	2,556	2,556	2,556
R2	0.770	0.883	0.770	0.835

Note: The dependent variable is the number of cancellatoins, standard errors are reported in parenthesis. We run four panel regression models with different model specifications. In the first two columns cause fixed effects are not included, whereas in the last two columns cause fixed effects are included. Cause level control variables are absorbed in the cause fixed effects.

To resolve the above endogeneity concerns we use an exogenous shock to the platform. First, we will provide information on the shock and why it is exogenous. Second, we demonstrate the true randomness of the shock. In October 2019, the focal platform collaborated with many Indian firms to bring their employees and customers on the donation platform. Due to this event, there was a sharp uptick in the number of donors for many causes on the platform. Figure 1.3 depicts this event and a corresponding increase in donors. In the extant literature (Farronato et al., 2020; Natan, 2021) mergers have been used as an exogenous shock to estimate the causal effect. In our context, this event is equivalent to a merger, however, in mergers, the increase is not only to the customer base but also to the product offerings. Interestingly, in our context, due to the event there was an increase in the number of donors but not in the number of product offerings. To elaborate further consider a toy example. Consider two causes A and B, assume for cause A there was an increase in donor group size after the event whereas for cause B there was no increase in donor group size. The event comes as a shock to the donors who were donating to cause A because these donors didn't anticipate the donor group size to suddenly increase, and therefore any change relative to the control group can be attributed only to the sudden increase in donor group size. Next, to demonstrate the impact of exogenous shock, we use the evolution of donor group size with time and use it to predict the counterfactual, i.e. in the absence of the event shock what would have been the donor group size and compare it to the real data. Using pre-event data we use optimized ARIMA to predict the donor group size after the event. Our results present in Figure 1.3 indicate that there is a substantial change in the donor group size (see green line in the Figure 1.3) compared to what one would expect (see red line in the Figure 1.3). To ensure that the shock wasn't only in a particular, we plot the shock by category (see Figure A.5) and we find that although the intensity of the event shock varies by category, it is present in all the cause categories. Furthermore, to ensure that donors which join before the shock are similar to donors who join after the shock, we compare donors on all the observed donor characteristics such as location, gender, donation amounts, choice of cause category etc. Results for this analysis are reported in Table A.3. We find that donors

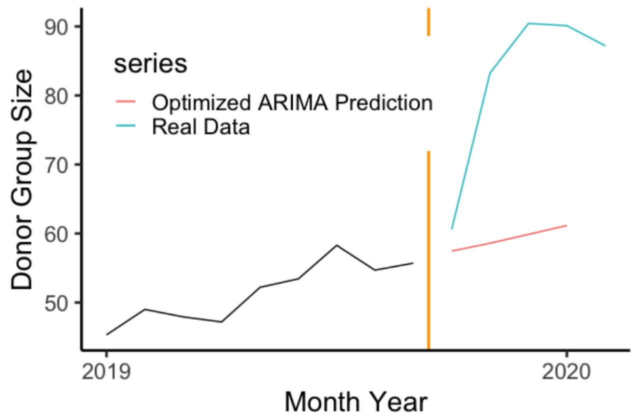


Figure 1.3: Real vs Prediction using pre-event data to illustrate shock on donor group due to event.

pre and post-shock aren't systematically different. Therefore, the donor behaviour pre and post-shock are comparable.

1.6. Empirical Strategy

We are interested in estimating the effect of donor group size on a) the number of joiners and b) cancellations. Our main empirical model employs a DID (difference in difference) panel estimator. To deploy the DID estimator we first present the data as an experiment. Specifically, we use the event shock as an intervention. The causes which experience an increase in donor group size are labelled as treatment group and the others as control group. The data is aggregated at cause month year level. We estimate the equation of the following form.

$$Y_{ct} = \alpha_c + T + \beta_1 Increase_c + \beta_2 Event_t + \beta_3 Increase_c \times Event_t + \varepsilon_{ct} \tag{1.2}$$

Where, c and t represent cause and month year respectively. Y_{ct} can be either number of joiners or number of cancellations for a cause c in the month year 't', T represents the time trend effects and $Increase_c$ is a dummy which takes value 1 if a cause (c) experiences an increase in DGS after the event or 0 otherwise. $Event_t$ is a dummy variable which takes value 1 on or after (Oct 2019) the event and 0 before the event. We are interested in β_3 which represents the difference in difference coefficient. Next, to build confidence in our inference we use the same data setup however, employ an instrumental variable approach to causally establish the effect of donor group size on our outcomes of interest. We estimate the equation of the following form.

Where, c and t represent cause and month year respectively. Y_{ct} can be either number of joiners or number of cancellations for a cause c in the month year 't', T represents the time trend[16] and DGS_{ct} is the donor group size. We have earlier illustrated that, this equation suffers from reverse causality problem. We instrument the donor group size variable with the event shock and we use a 2SLS approach to resolve the reserve causality problem. Lastly, we use individual transaction level data to estimate the effect of donor group size on probability of cancelling a donation subscription. We put focus on cancellation in individual level data analysis for two reasons a) lack of joiners choice data (join/not join data) and b) relative silence in the literature about the negative effects of donor group size information. We use a dynamic logit model. Specifically, we estimate the equation of the following form. Where $Cancel_{ijt}$represents the decision of donor 'i' for cause 'j' at time 't' to continue or cancel her subscription, it is a dummy which takes value 1 if donor decides to cancel and 0 otherwise. α_c and $\delta_t$are the cause and time fixed effects respectively.T represents donor jt ij level time trend variable which takes linearly increasing value with each month a donor remains on the platform. T captures the probability of churning, specifically a donor is more likely to cancel subscription as her tenure increases. f can either be a linear or a logit function. As demonstrated earlier, this model setup also suffers from reverse causality. We address the endogeneity problem with the 2SLS approach where we instrument the donor group size with the event shock. To build further confidence in our results, we use the same transaction-level data setup but we deploy a survival analysis approach. In particular, we estimate a Cox

[16]For example, if cancellations increase on increase in donor group size, it will lead to a lower donor group size in the subsequent periods.

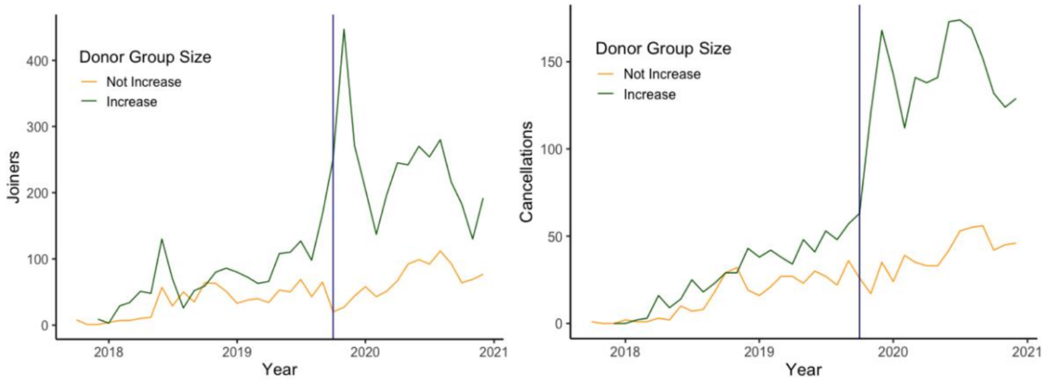


Figure 1.4: DID - The left panel (a) shows the comparison of joiners across causes which experienced an increase vs which didn't. The right panel (b) shows the comparison of joiners across causes which experienced an increase vs which didn't.

regression with time varying covariates. In summary, we use a multi method approach with varying data granularity (aggregated vs individual) to ensure that our results persists and our not driven by a particular model setup.

1.7. Results

1.7.1. The difference in difference model

Before presenting the formal results of the DID model. We report the DID visualization in Figure 1.4. Note that, for both the outcomes of interest i.e. joiners and cancellations we find the treatment and control group to move in sync before the even shock. However, after the shock the difference between two groups increase and persists over time.

We report the results of our DID analysis (estimates from Eqn (2)) on joiners and cancellations in Table 1.4 and 1.5 respectively (Complete results reported in Table A.4 and A.5 in the appendix). Consider, Table 1.4 for joiners. The DID coefficient (β_3) in Eqn (2) turns out to be positive. This indicates causes which experience an increase in donor group size gets more joiners compared to causes that didn't. In particular, after the shock, the treated causes got nearly 1.7 (see column 4 in Table 1.4) more new donors compared to the control group. Similarly, consider Table 1.5 representing the results for cancellation (estimates of Eqn (2)), in this case too, the treated causes experienced nearly 1.3 more cancellations compared to the control group causes.

	Dependent Variable			
	Joiners			
	(1)	(2)	(3)	(4)
Increase x Event	1.301***	1.316 ***	1.727***	1.727 ***
	(0.348)	(0.348)	(0.278)	(0.278)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5059	5059	5059	5059
R2	0.024	0.024	0.440	0.440

Note: The dependent variable is the number of cancellatoins, standard errors are reported in parenthesis. We run four panel regression models with different model specifications. In the first two columns cause fixed effects are not included, whereas in the last two columns cause fixed effects are included. Cause level control variables are absorbed in the cause fixed effects.

	Dependent Variable			
	Cancellations			
	(1)	(2)	(3)	(4)
Increase x Event	1.043**	1.033 ***	1.334***	1.312 ***
	(0.188)	(0.188)	(0.140)	(0.140)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5059	5059	5059	5059
R2	0.032	0.033	0.517	0.519

Note: The dependent variable is the number of cancellatoins, standard errors are reported in parenthesis. We run four panel regression models with different model specifications. In the first two columns cause fixed effects are not included, whereas in the last two columns cause fixed effects are included. Cause level control variables are absorbed in the cause fixed effects.

1.7.2. Instrument Variable Approach

We report our results for instrument variable approach (estimates from Eqn(3)) in Table 1.6 and 1.7 for joiners and cancellations respectively. Consider, Table 1.6 for joiners. The coefficient for donor group size varies from 0.146 to 0.392. This translates to, if the donor group size increase by 10, it could attract nearly 1.5 to 4 new donors for a particular cause. Furthermore, the true value would be closer to 4, because the model with full specification (column 4) would be more trustworthy[17]. Given the size of effect, it is not much of a surprise, that many donation platform display donor group size to attract new donors. Next, consider Table 1.7 for cancellations. In this case the coefficient of interest caries from 0.083 to 0.114, implying, an increase in donor group size by 10 would lead to 0.8 to 1.1 cancellations.

	Dependent Variable			
	Joiners			
	(1)	(2)	(3)	(4)
Donor Group Size	0.230**	0.392 ***	0.146***	0.382 ***
	(0.043)	(0.220)	(0.035)	(0.184)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2556	2556	2556	2556
R2	0.373	0.352	0.521	0.514

Note: This table reports the results from estimation of Eqn (3). The dependent variable is number of joiners. Donor group size is instrumented with event shock and 2SLS approach is used for estimation. The first two columns don't have cause level fixed effects but contain cause level control variables. The last two columns have cause level fixed effects and corresponding cause level covariates are absorbed.

	Dependent Variable			
	Cancellations			
	(1)	(2)	(3)	(4)
Donor Group Size	0.096**	0.114 ***	0.083***	0.107 ***
	(0.010)	(0.042)	(0.008)	(0.039)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	2556	2556	2556	2556
R2	0.737	0.629	0.820	0.835

Note: This table reports the results from estimation of Eqn (3). The dependent variable is number of cancellations. Donor group size is instrumented with event shock and 2SLS approach is used for estimation. The first two columns don't have cause level fixed effects but contain cause level control variables. The last two columns have cause level fixed effects and corresponding cause level covariates are absorbed.

[17] Column 4 reports the results of two-way fixed effects. In this we control for cause level effects and time trend which parses out the effect of donor group size better compared to other model specifications.

1.7.3. Individual-level models

We report the estimates of Eqn (4) in Table 1.8 (see Table A.6 in the appendix for complete results). Recall, for this analysis, we use only the donors who were donating before the event shock (haven't cancelled their subscription). We find that, if the donor group size increases by 10 the probability of cancellation increases by 0.04[18] (see column 4 in Table 1.8). Two of our control variables, namely, donation amount and donor location provides sanity check of our results. Donation amount estimates imply, higher the donation amount, higher is the cancellation probability. Similarly, Indian donors might be less altruistic due to culture and income compared to their American and European counterparts. We find our results consistent with these predictions. To build further confidence in our results, we deploy the survival analysis approach with time varying covariates. First, we report the visualization from a simple survival model (see Figure A.6 in the Appendix) with a median split on donor group. The visualization indicates that for higher donor group the survival probability is lower or the cancellation rate is higher. We empirically, test this with a) log-rank test, to compare survival probabilities between two groups b) cox proportional hazard model with time-varying covariates with multiple model specifications (see Table A.7) . We find the results from empirical tests to be consistent with the visualization. In particular, the coefficient on donor group size (in both w/o and with covariate models) is positive, indicating a higher probability of cancellation. In summary, the results from dynamic probability models and survival analysis indicate conform and are in line with our findings from aggregate models. Specifically, the probability to continue donation reduces when the donor group size increase.

1.8. Ruling out alternative explanations

1.8.1. Switching Behavior

An explanation for the increase in cancellations with donor group size could be the switching of donors. Specifically, when more donors (higher donor group size) start supporting a cause,

[18]These estimates are from the linear probability model. We report the results from logit model in the Appendix.

	Dependent variable:			
	Cancel			
	(1)	(2)	(3)	(4)
Donor Group Size	0.004*	0.006*	0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)
Time Trend	N	N	Y	Y
Cause FE	N	Y	N	Y
Observations	7,368	7,368	7,368	7,368
Weak Instrument	40.41 (<2e-16)	69.86 (<2e-16)	7.39 (0.006)	16.339 (0.0005)
Wu-Hausman	95.88 (<2e-16)	111.98 (<2e-16)	5.87 (0.015)	8.917 (0.002)

Note: This table reports the results from estimation of Eqn 4. The dependent variable is a binary variable that takes value 1 when a donor cancels her subscription, 0 otherwise. Female is the baseline for gender. Location is classified into 3 categories. – India (base), US and Others (mostly – UK, Canada, Australia, UAE etc.). Single Beneficiary (only one recipient of donation) is the baseline for no of beneficiary segment.

the focal donor might feel that her resources can be better utilized elsewhere. This could lead to two types of switching a) Intra-platform switching b) Inter- platform switching. Intra-platform switching refers to donors switching to a different cause on the platform. We don't find any evidence of this. Of all the donors who cancelled, we found very few donors who restarted their donations to a different cause on the platform[19] within 6 months of cancelling. Therefore, we can rule out intra-platform switching. Inter-platform switching refers to switching to a different donation platform. Although this can't be observed, we argue that this is implausible because the focal donation platform has a disproportionately high market share. Alternatively, it could be argued that donors might not find the 'right cause' (fit) to donate to on the focal platform, however, this is unlikely, because compared to competitors the focal donation platform has a much higher variety of causes. Furthermore, donors might have to bear switching costs. Therefore, inter- platform switching is also unlikely. Lastly, the donor might want to switch to a different mode (offline, one-time donation event) of donation or stop donating. In both these scenarios, the donor has stopped donating using subscription-based donation. In summary, our claim, that change in donor group size affects the underlying altruistic behaviour holds and the change in cancellations

[19]We track donors by their personal information. If a donor changes her contact information (both email and phone number) when she restarts the donation, we will not be able to track the donor and miss out on such cases.

due to donor group size is not a mere diversion of resources.

1.8.2. Minimum Donation Amount

The minimum donation amount refers is the minimum monthly amount to be paid for supporting a cause. Causes with lower minimum donations might experience higher joiners (more people can afford lower donation amounts). Similarly, cancellations would be lower for lower minimum donation amount as compared to higher minimum donation amount because of budget/expenditure constraints of donors. We control for minimum donation amounts by using it as a control variable in the models where we don't have cause fixed effects and using fixed effects. Moreover, we plot (see Figure A.7) joiners vs donor group size and cancellation vs donor group size by minimum donation quartile split. We find relationships to hold in both high and low minimum donation amount cases.

1.8.3. Act of Churning

Churning is a part of subscription-based/ repeat transaction businesses, and more cancellations for a cause overtime might be a simple act of churning because of a) better outside options b) donor doesn't want to donate anymore or c) budget constraints. We control for churning by using the individual donor time trend variable as a control. This variable linearly increases with each month the donor is a member of the platform. For robustness, we also use tenure (how long the donor is member of platform). Our results persist even after controlling for churning.

1.8.4. Position Effects

Higher joiners for a cause could be driven by the position of the cause on the donation platform website. In particular, the platform could strategically position a cause based on its fundraising objective. Therefore, the position of a cause could drive both the donor group size and the number of joiners for the cause leading to an omitted variable bias problem. We were informed by the platform that the position of causes on the website was not manipulated or strategically used. Furthermore, the landing page for each category of cause is a recommended page. On the recommended page, there are only 3-4 causes listed, therefore position effects don't play much of a role here. Specifically, causes are listed in 1x3 or 2x3 matrix and the user doesn't need to scroll down (for visualization see Figure A.8 in the Appendix). Moreover, we include cause level fixed effects in all our model specifications to control for any position effects if present.

1.9. Robustness Checks

1.9.1. Parallel Trends Assumption

Our main empirical strategy uses a widely accepted DID approach. Parallel trends assumption is the critical assumption for DID model identification. To test for the parallel trends in our context, we follow (Angrist and Krueger, 1999). We conduct a pre trend test with varying pre trend windows, namely, 3, 6 and 9 pre periods. Specifically, we estimate equation (5) below.

$$Y_{ct} = \alpha_c + \mu_t T + \Omega_c T \times I_{treatment} + \varepsilon_{ct} \tag{1.3}$$

Where c and t are cause and time subscripts respectively. α_c are the cause fixed effects, μ_t is the common trend parameter and Ω_c represents the deviation of the treatment group from the common trend. T is the time trend variable and $I_{treatment}$ is an indicator variable which takes value 1 for all the treated (Increase) causes and 0 for all the untreated (Not Increase) causes. Y_{ct} can be the number of joiners or cancellations by cause and time. Results are reported in Table 1.9 below. The parameter of interest, Ω_c for both cancellations and joiners turns out to be insignificant for all the pre trend window sizes, supporting our assumption of parallel trends. Next, to further confirm parallel trends and persistence of the effects of interest. We estimate the interaction of time indicator variables with the treatment group (Autor et al., 2003). Specifically, we estimate the interactions of the month indicator variable with the treatment indicator, the base level is 5 months or before the treatment. The results are presented in Figure 1.5. Note that, for both cancellations and joiners the estimates before the event turn out to be no different from 0. Furthermore, at and after the event the effect seems to persist for a long time (even 5 months after the shock). Therefore, from both the approaches we confirm that the parallel trends assumption holds.

	Pre Trend Window Size					
	9 month		6 month		3 month	
	# Cancel	# Joiners	# Cancel	# Joiners	# Cancel	# Joiners
	(1)	(2)	(3)	(4)	(5)	(6)
Trend	0.004	-0.023	-0.014	-0.016	-0.016	-0.094
	(0.012)	(0.020)	(0.019)	(0.035)	(0.033)	(0.065)
Trend X Treatment	0.002	0.028	0.043	0.077	0.039	0.032
	(0.016)	(0.028)	(0.026)	(0.049)	(0.046)	(0.093)
Cause F.E.	Y	Y	Y	Y	Y	Y
Observations	1,365	1,365	977	977	679	679
R2	0.735	0.772	0.760	0.751	0.825	0.799
Adjusted R2	0.694	0.737	0.704	0.693	0.760	0.725
Residual Std. Error	0.736 (df =1180)	1.246 (df =1180)	0.685 (df =792)	1.267 (df =792)	0.659 (df =494)	1.318 (df =494)

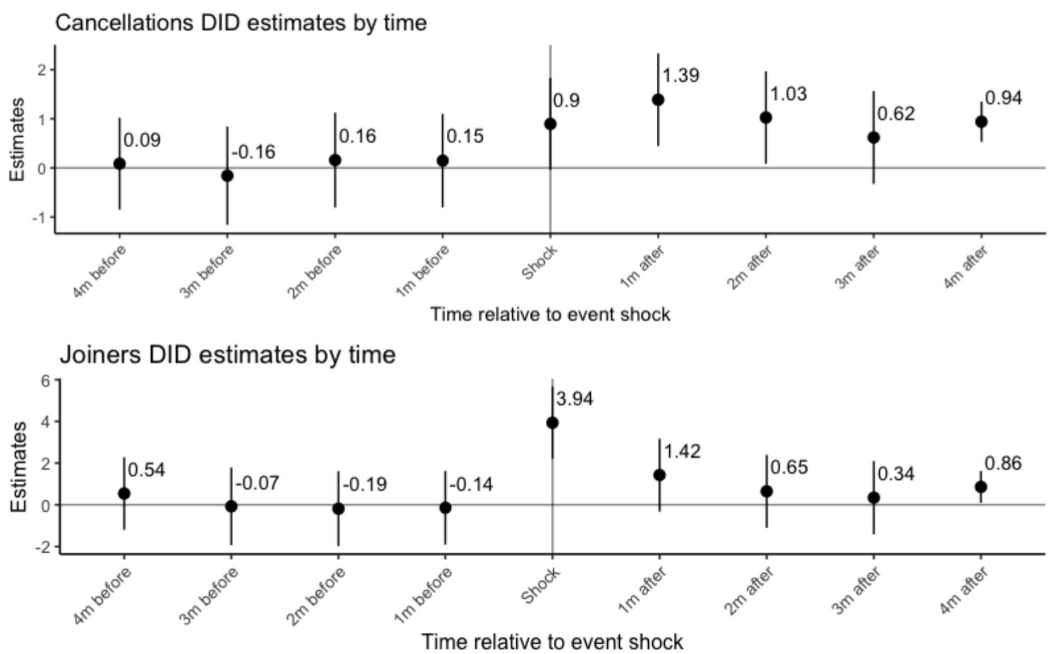


Figure 1.5: Pre and Post Event Estimate Trend. The top and bottom panels report the DID estimates overtime for cancellations and joiners respectively.

1.9.2. Instrument Validity

To test the validity of our instrument (event shock) we do multiple placebo tests. We do this to show that the variation explained by our instrument is due to the event shock and not due to some spurious correlations. To show that, our instrument (event shock) is relevant and the conditional differences between the treated and untreated causes are due to the event and not a persisting difference, we use placebo regressions. We operationalize this by creating a placebo dummy variable which turns on one month prior to the real event. Specifically, the true event shock takes value 1 on or after Oct 2019 and 0 before it, whereas the placebo dummy takes value 1 on or after Sep 2019 and 0 before it. We find the coefficient corresponding to placebo & treatment group, interaction to be insignificant, however, the true event interaction with the treatment group turns out to be significant. The results for the placebo regressions are reported in Table A.8. The first two columns are results for cancellations as the dependent variable. Specifically, the first column reports results without placebo dummy and column 2 reports results with placebo dummy. Note, that the coefficient of interaction between placebo and treatment group is insignificant. Similarly, the last two columns (Columns 3 and 4) report the results of joiners as the dependent variable. In this case, the placebo, treatment group interaction is insignificant.

1.9.3. Different Definitions of Increase

Our core empirical strategy utilizes a diff-in-diff panel estimator. We use the word 'increase' and 'not increase' to address treatment and control groups. To ensure that our results are not an artefact of a particular definition of increase we use multiple definitions of increase such as pure increase, median increase, and unexpected increase. Next, we elaborate on the definitions of increase.

Pure Increase: $DonorGroupSize_{Post} \geq DonorGroupSize_{Pre}$.The treated group variable takes value 1 for causes which have higher donor group size, post event and 0 otherwise.

Median Increase: We calculate percentage increase for each cause and if the percentage increase in donor group size for cause is higher than the median of percentage increase in

	Dependent Variable					
	Joiners	Cancellations	Joiners	Cancellations	Joiners	Cancellations
	(1)	(2)	(3)	(4)	(5)	(6)
PureIncrease x Event	1.976***	1.379***				
MedianIncrease x Event	(0.263)	(0.132)	1.997***	1.337***		
UnexpectedIncrease x Event			(0.264)	(0.132)	1.603***	1.087***
					(0.262)	(0.131)
Time Trend	Y	Y	Y	Y	Y	Y
Cause F.E.	Y	Y	Y	Y	Y	Y
Observations	5,014	5,014	5,014	5,014	5,014	5,014
R2	0.442	0.522	0.442	0.521	0.440	0.518
Adjusted R2	0.420	0.503	0.420	0.502	0.417	0.499
Residual Std. Error (df = 4822)	4.431	2.218	4.430	2.220	4.439	2.227
F Statistic (df=191;4822) =	19.982***	27.545***	19.990***	27.467***	19.806***	27.103***

all the causes, we label the treated variable group as 1 and 0 otherwise.

Unexpected Increase: For each cause, we predict the donor group size post the event using only pre-event data (using linear regression). If the donor group size after the event is higher than the predicted donor group size, then it is considered as increase (takes value 1) else not increase.

We run our difference in difference model for both joiners and cancellations. Our results reported in Table 1.10 indicate that donor group size positively effects number of joiners and cancellations across all the definitions of increase.

1.9.4. Heterogeneity

Donation behaviour of individual is dependent on the type of cause (appeal framing) they donate to (Lindauer et al., 2020). For example, probability to donate for saving a child's life might be higher than probability to donate to rebuild a community center. To illustrate the heterogeneity of the effect of donor group size we evaluate treatment effects across cause category. Our results in Figure 1.6 show that relative to education, the impact (for both joiners and cancellations) of donor group size is more for Nutrition and Livelihood related causes. However, the donor group size has less of an effect on healthcare related causes compared to Education. Implying, that the treatment effects persist across categories, albeit at different intensity.

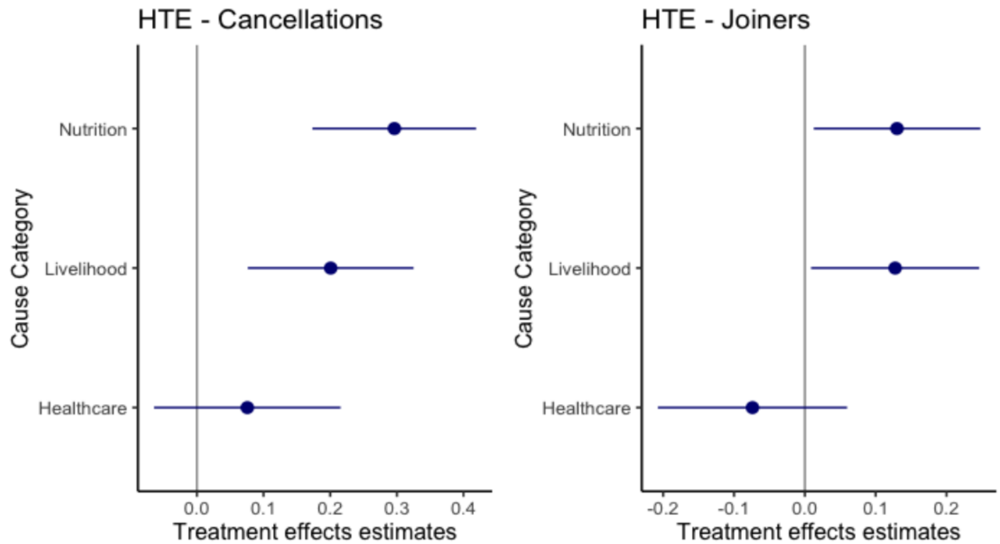


Figure 1.6: Heterogeneous Treatment Effects by cause category. Left and Right Panel report the DID estimates by cause category on cancellations and joiners respectively, relative to Education (base). The confidence band is at a 90% interval.

1.10. Discussion

The goal of this paper is to investigate the effect of donor group size on donation behaviour in a subscription-based donation context. We are interested in studying this question because a) in practice there is a shift towards adopting subscription-based donations and displaying donor group size is believed to improve donations b) the extant literature seems to be divided on the direction of effect and c) the extant research is based on one-time donation data, therefore, the findings might not be relevant in the subscription case. We found that overall, the donor group size positively impacts the donations. Specifically, higher the donor group size for a cause, more donors start donating to a cause. However, higher the donor group size, more donors cancel their subscription. Our analysis suggests that if the donor group size for a cause increase by 10 donors, it get could attract nearly 2 new donors, however, it might also lose nearly 1 existing donor. We add to the extant literature in three broad ways 1) we are one of the first studies in the subscription-based donation context and we evaluate the impact of a commonly used strategy i.e., displaying donor group size on donation behaviour

2) we provide resolution to the apparently divergent findings in the extant literature albeit in the subscription-based donation context. Specifically, we show that donor group size can have both positive and negative effects on donation behaviour albeit at different points in the donor lifecycle. 3) Our data has a high variety of donors and causes. In particular, the extant literature has based its findings on constricted pool of subjects and causes. Therefore, our findings are more generalizable compared to the previous studies. Limitations of our studies come from its setup, in that, our findings can't be generalized for every donor. For instance, donors in our context, self-select themselves into subscription- based donations, therefore, these donors could be systematically different from one-time donors. Furthermore, our findings couldn't be generalized to offline donations because the altruistic behaviour of people who donate online could be different from people who donate offline stemming from in-person interactions in offline donation settings. Future research could possibly conduct a randomized control trial to establish the effect of donor group size on donation behaviour to improve confidence in the results. Moreover, the same question can be studied in the offline donation context, as offline donation has elements of physical interaction of donor with a) other donors b) beneficiaries and c) platform. Furthermore, researchers could look at the effect of buyer group size and purchase behaviour of customers in subscription-based product markets such as magazines, phone plans etc. Based on our analysis, we suggest donation platforms be careful about the use of donor group size information. Specifically, donation platforms should provide information on the donor group size to the potential donors who might join the platform, however, the same information can cause the current donors to churn not only from the cause but also from the platform.

1.11. Conclusion

Displaying the popularity of a product has been shown to be an important tool to increase demand (purchase intention). In the charitable donation context, some papers show that higher the donor group size (popularity) of a cause higher is the probability of donation. Recently, subscription-based donations have emerged as an important tool for fundraising because of their higher donor lifetime value. In this paper, we work with one of India's largest subscription-based donation platforms. Specifically, we study the effects of cause popularity (donor group size) on donation behaviour in the context of subscription-based donation. We use an exogenous shock to the platform as our main identification strategy. We find that causes with higher donor group size attract more new donors to donate to a cause. This is documented as a bandwagon effect both in product and charitable donation literature. Surprisingly, we find that causes with higher donor group size also experience higher cancellation rates for current donors. This phenomenon is documented as a bystander effect in the extant literature. We contribute to the literature by estimating the positive and negative effects of displaying donor group size for subscription-based donation platforms. Furthermore, we bring together the divergent findings in the extant literature and show that in fact, both strands of literature are correct albeit for different donor types (joiners vs cancellations). Our findings can be useful for donation-based platforms, in that, we suggest platforms be judicious about when to use the donor group size information. Specifically, platforms should use donor group size information to bring new donors on the platforms, however, sharing the donor group size information with existing donors could be harmful due increase probability of cancellations.

CHAPTER 2

Regulatory Warnings and Endorsement Disclosure

2.1. Introduction

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). 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 (Hub, b) 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 and Fiorella) 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). 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.. 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). According to some reports, most top celebrity social media endorsements violate FTC endorsement disclosure guidelines (Mediakix). Considering these practices, FTC sent notices to 90 influencers (Commission). Figure B.1 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; Fainmesser and Galeotti; Amy and Dina) 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 et al.; Campbell et al.) 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 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.

[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/

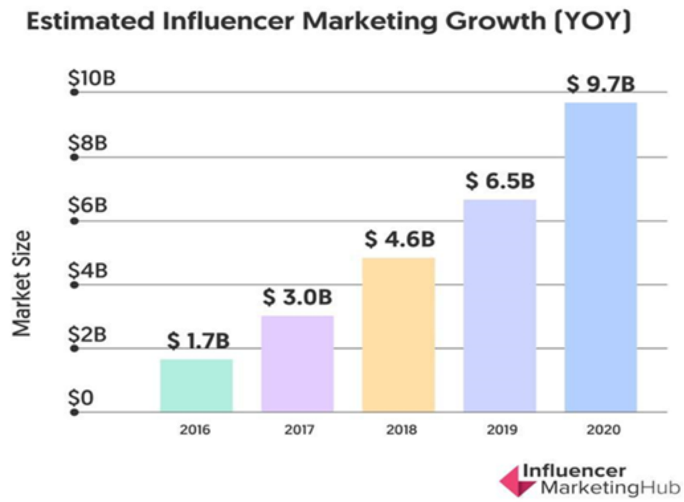
2.2. Institutional Background

2.2.1. 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). Moreover, influencers can create trends and encourage their followers to buy products they promote. (Hub, a). 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). As of 2020, the influencer marketing industry has been estimated to be nearly USD 9.7 Bn (Hub, b). From 2016 to 2020, the industry size has grown six times (see Figure 2.1). 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 2.2). 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).

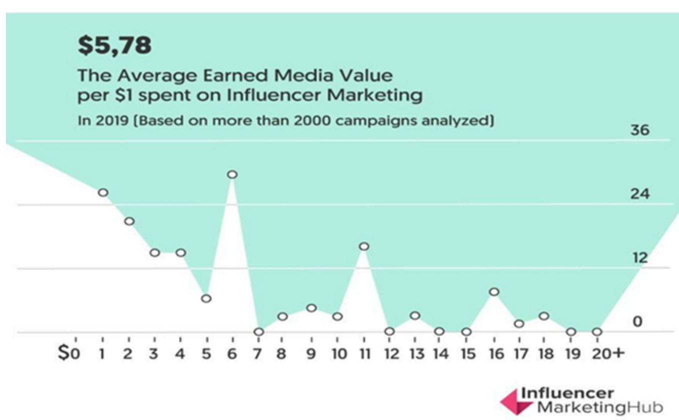
However, this industry is also prone to certain malpractices. Non-disclosure of advertising posts is one of them. Regulators are getting increasingly concerned about non-disclosures on social platforms, to the extent that regulators in the US and UK are cracking down on undeclared ads. (Practice) According to some reports, almost all top celebrity social media endorsements violate FTC endorsement disclosure guidelines (Mediakix). Apart from a few lawsuits (Fed), FTC in the US sent out notices to 90 influencers (Onl). The Commission

Figure 2.1: Influencer Marketing Industry market size and growth trend



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 (**?**). 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 2.2: ROI on influencer marketing



2.2.2. 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 citepd the notice and brought the influencer's endorsement disclosure malpractice to the public (Glenday; Lee; Mediakix).

2.3. 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.; Tips 2). 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.).

2.3.1. 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; Fainmesser and Galeotti; Amy and Dina) and Empirical work by (Ershov and Mitchell) argue for milder endorsement disclosure regulations. Specifically, (Mitchell) argues that regulators should have an opt-in disclosure policy compared to a mandatory disclosure policy. Similarly, (Fainmesser and Galeotti) argue that a mandatory disclosure policy could backfire and not serve its primary purpose. (Amy and Dina) show that a detailed disclosure policy may hurt the consumers. (Ershov and Mitchell) 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.

2.3.2. Consumer Response to Undeclared Advertising

Marketers have tried to establish the effects of undeclared, deceptive, and covert advertising on consumer response. For example, (Darke et al.) 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.) 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.; Knittel and Stango; Rao and Wang)establish that a celebrity or a firm is caught in a scandal consumers respond negatively.

2.3.3. 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 countrywide. We confirm the findings of (Darke et al.; Campbell et al.) and extend the literature by establishing the deterrence effect through spillover.

2.4. 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. 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.

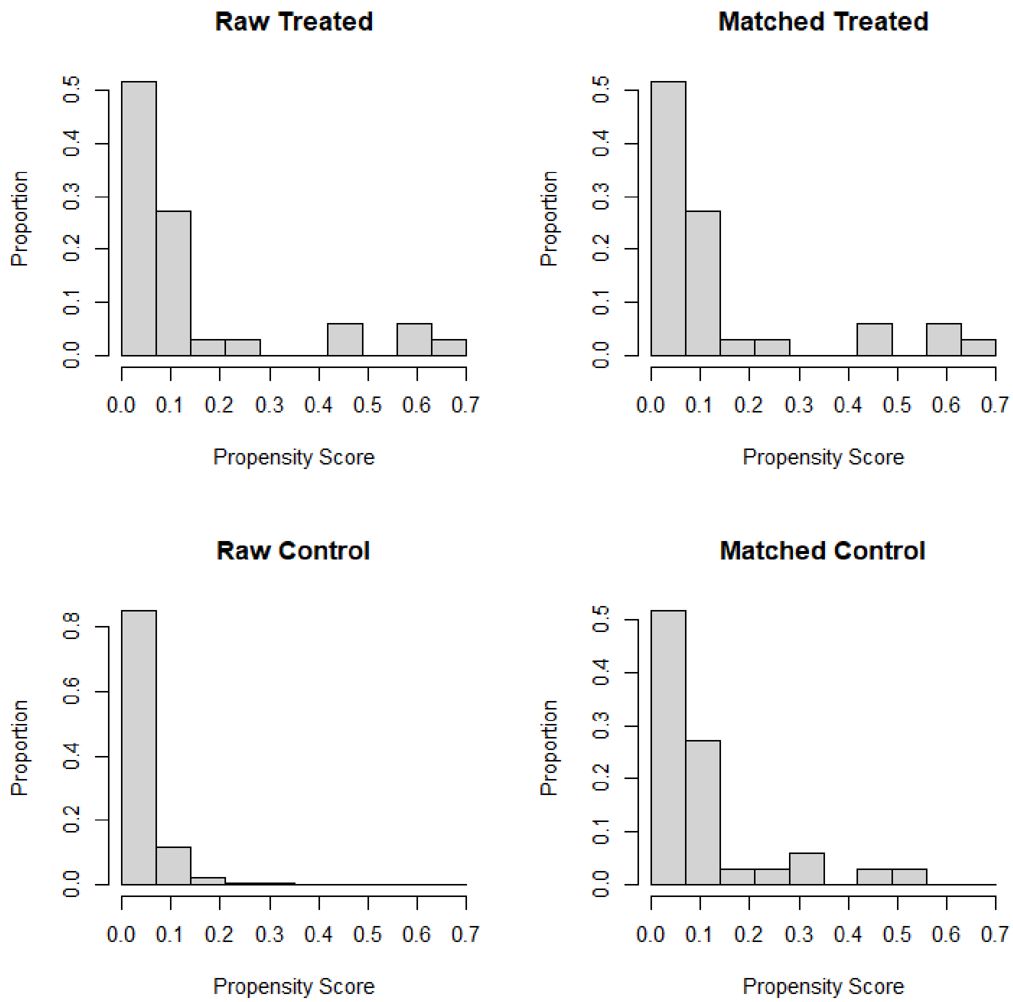
2.4.1. Finding comparable control group

Firms primarily use three criteria: Followers, Authentic Engagement, and Product Category to identify and engage with an influencer (Vodak et al.). We use the same three variables for propensity score matching to identify similar influencers from the list of remaining 970 influencers in the 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 B.1 in the Appendix provides the summary of the balanced data after propensity score matching. Figure 2.3 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. 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 influencers' 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 B.2 in the Appendix and the count of influencers by location is present in Table B.3 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.[3] Table 2.1 compares the descriptive statistic of notified and not notified influencers before and after the notice was sent. 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

[3] $DisclosurePercent_{it} = \frac{TotalAdPost_{it}}{TotalPosts_{it}}$ for influencer 'i' for a month 't'. Likes and comments are mean likes and comments in that month. For example, if an influencer makes 3 posts in a month 't' likes/comments are mean likes/comments across 3 posts

Figure 2.3: Raw vs. Matched Treatment and Control Groups



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.

2.4.2. Model Free Evidence

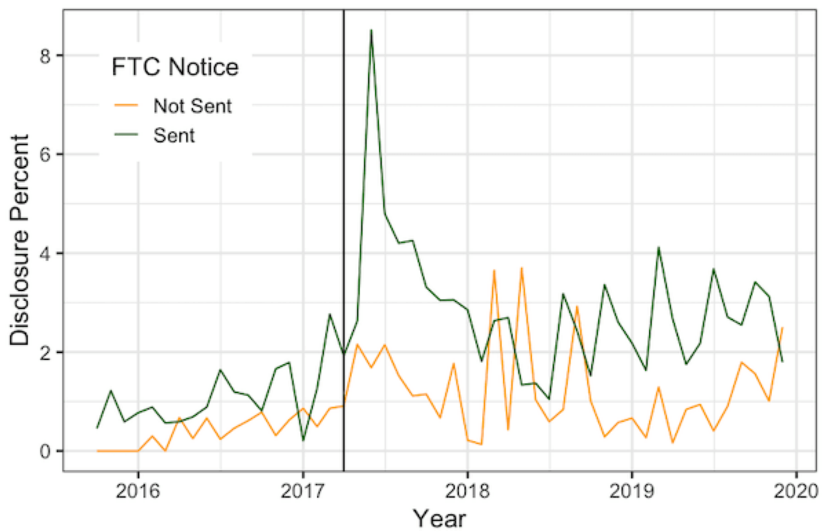
Figures 2.4, 2.5, and 2.6 represent trends of disclosure percent, log likes, and log comments.

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

	Notified Influencers		Not Notified Influencers	
	Pre Notice	Post Notice	Pre Notice	Post Notice
Disclosure Percent	1.06	2.86	0.394	1.24
Likes	4,37,286	9,13,453	2,92,626	6,67,725
Comments	11,794	11,906	4,067	5,314

Table 2.1: Pre and Post Notice Means of Notified & Not Notified Influencers
Note : This table reports the mean of outcome variables i.e. disclosure percent, likes and comments pre and post notice across notified and notified influencers

Figure 2.4: Disclosure Percent Trend – Notified vs. Not Notified Influencers

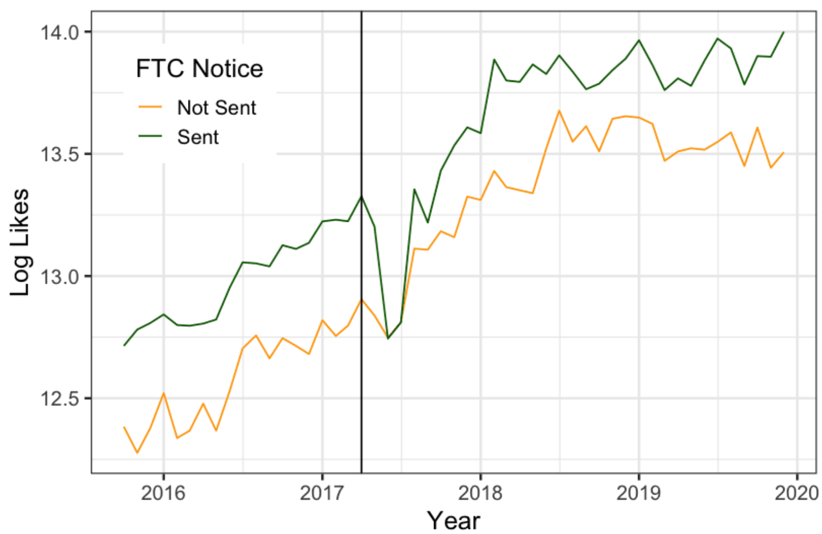


percentage in Figure 2.4, near the time when FTC notices were sent. Third, the follower engagement (likes and comments) seems to be increasing over time across both groups in Figures 2.5 and 2.6, respectively. However, the follower engagement appears to get a substantial reduction after the notice was sent for both the groups.

2.4.3. 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

Figure 2.5: Log Likes Trend – Notified vs. Not Notified Influencers



(DID) model setup (see Eq.1).

$$\begin{aligned} Y_{it} = \alpha_i + \delta_t + \beta_1 InfluencerNotified_i + \beta_2 NoticeSent_t \\ + \beta_3 InfluencerNotified_i \times NoticeSent_t + \epsilon_{it} \end{aligned} \tag{2.1}$$

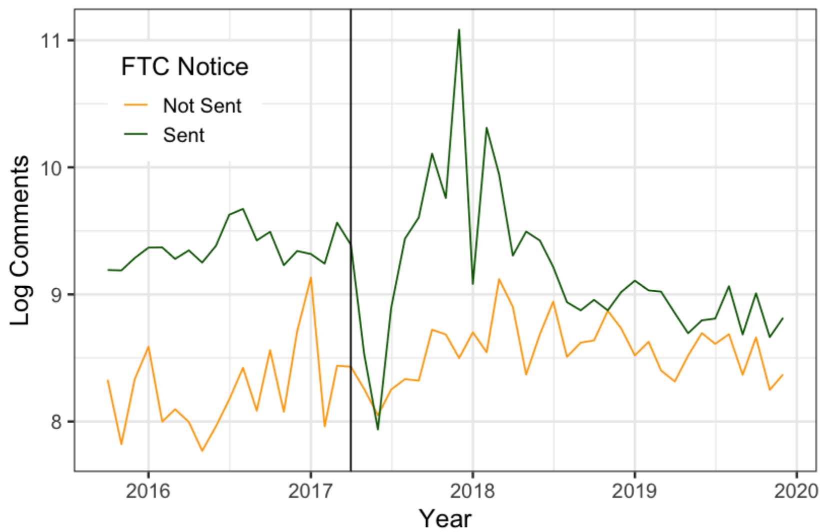
In the Eq. 1 (Y_{it}) represent disclosure percent. The $InfluencerNotified_i$ is a dummy variable that represents influencers who were sent notices and the $NoticeSent_t$ is a time dummy variable that takes the value 0 before the notice was sent (March 2017) and value 1 after the notice was sent. The 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 2.2 compares the change in disclosure percentage of influencers after receiving the notice.

In all model specifications in table 2.2, 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%

	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

Table 2.2: Comparison of disclosure percent - notified vs. not notified influencers
Note : This table reports DID estimates, comparing notified and not notified influencers. The dependent variable is disclosure percent. Standard errors are reported in parenthesis. The first two columns are model specification without influencer fixed effects, whereas the last two columns have model specifications with influencer fixed effects.

Figure 2.6: Log Comments Trend – Notified vs. Not Notified Influencers



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 B.4 and B.5 in the Appendix) has decreased for the notified influencers.[4]

2.4.4. 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 2.3.

Using this design, we are able to recover the true effect of notices on disclosures, likes, and

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

	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

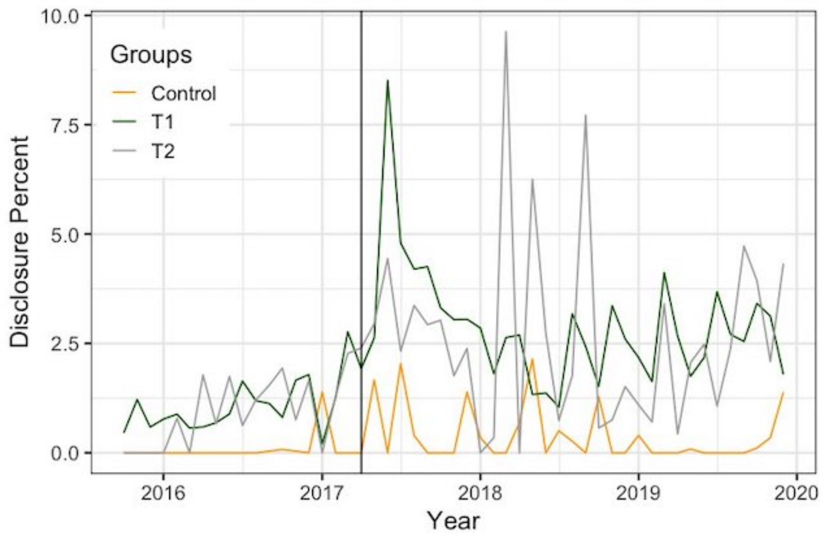
Table 2.3: Pre and Post Notice Means of T1, T2, and C groups
Note : This table reports the mean of outcome variables i.e. disclosure percent, likes and comments pre and post notice across T1 (got notice), T2 (didnt get notice but are US based) and Control (outside US) set of influencers.

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.

2.4.5. Model Free Evidence after SUTVA resolution

First, we present model-free evidence to get a preliminary idea of our results. Figure 2.7 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 2.8 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

Figure 2.7: Disclosure Percent Trend – Across Treatment & Control Groups



or T2) experienced a more significant decline in likes. Figure 2.9 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.

Figure 2.8: Log Likes Trend - Across Treatment & Control Groups

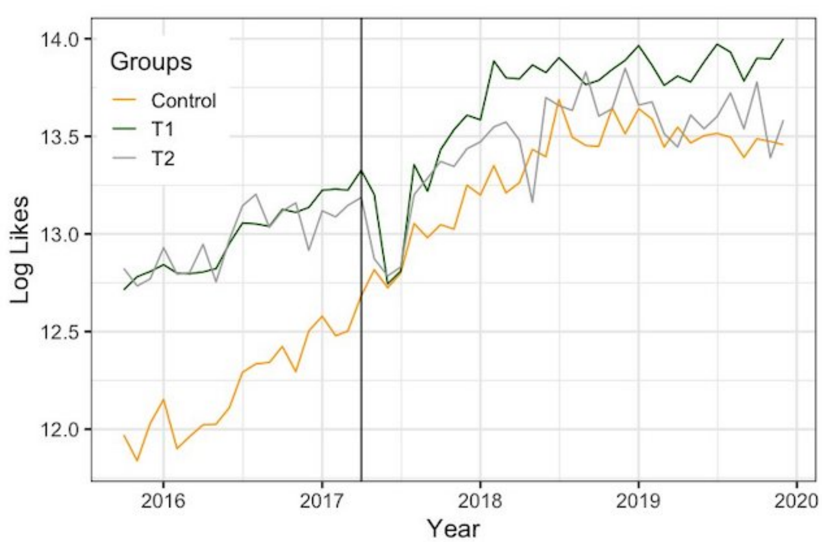
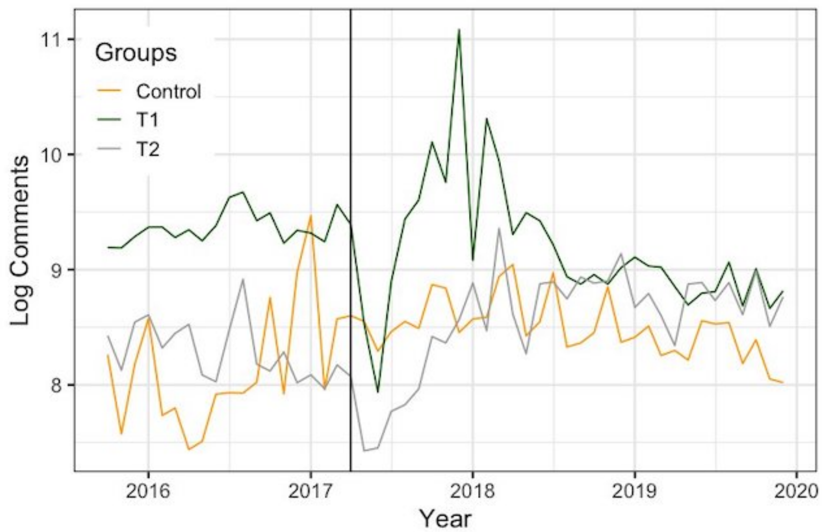


Figure 2.9: Log Comments Trend - Across Treatment & Control Groups



2.4.6. 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.

$$\begin{aligned} DisclosurePercent_{it} &= \beta_0 + \beta_1\ NoticeSent_t + \beta_2 NoticeUS_i + \beta_3 NoNoticeUS_i \\ &+\beta_4 NoticeUS_i \times NoticeSent_t + \beta_5 NoNoticeUS_i \times NoticeSent_t + \epsilon_{it} \end{aligned} \tag{2.2}$$

where $DisclosurePercent_{it} = \frac{TotalAdPost_{it}}{TotalPosts_{it}}$ 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 2.4.

Variable	Definition
$DisclosurePercent_{it}$	Disclosure percent of influencer 'i' over a period 't'.
$NoticeSent_t$	Dummy for a time of notice
$NoticeUS_i$	Dummy for influencers in the US who got the notice
$NoNoticeUS_i$	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'

Table 2.4: Variable Definition

2.5. DID Results and Discussion

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

The results of our estimated DID model (Eq. 2) are present in Table 2.5. Firstly, observe that coefficient on both Notice Sent and Notice Not Sent in the US (β_2 andβ_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. 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).

2.5.2. 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

	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

Table 2.5: Direct and Spillover effects of notice on disclosure percent

Note : This table reports DID estimates, comparing T1,T2 and Control set of influencers. The dependent variable is disclosure percent. Standard errors are reported in parenthesis. The first two columns are model specification without influencer fixed effects, whereas the last two columns have model specifications with influencer fixed effects.

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.

$$\begin{aligned} log(Likes_{it}) = \beta_0 + \beta_1 NoticeSent_t + \beta_2 NoticeUS_i + \beta_3 NoNoticeUS_i + \beta_4 \\ NoticeUS_i \times NoticeSent_t + \beta_5 NoNoticeUS_i \times NoticeSent_t + \beta_6 \\ log(DisclosurePercent_{it}) + \beta_7 Comments_{it} + \epsilon_{it} \end{aligned} \tag{2.3}$$

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

$$\begin{aligned} log(Comments_{it}) = \beta_0 + \beta_1 NoticeSent_t + \beta_2 NoticeUS_i + \beta_3 NoNoticeUS_i + \beta_4 \\ NoticeUS_i \times NoticeSent_t + \beta_5 NoNoticeUS_i \times NoticeSent_t + \beta_6 \\ log(DisclosurePercent_{it}) + \beta_7 Likes_{it} + \epsilon_{it} \end{aligned} \tag{2.4}$$

We report the results for two measures of follower engagement, i.e., the likes and comments in Table 2.6 and Table B.6 (in the Appendix), respectively. Results of DID estimates on likes are reported in Table 2.6. 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 behaviour which in turn might lead to different likes. DID estimates (NoticeUS $\times$ 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

	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

Table 2.6: Direct and Spillover effects of notice on likes

Note : This table reports DID estimates, comparing T1,T2 and Control set of influencers. The dependent variable is likes (follower engagement). Standard errors are reported in parenthesis. The first two columns are model specification without influencer fixed effects, whereas the last two columns have model specifications with influencer fixed effects.

'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 B.6 (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.

2.5.3. 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 2.5, the interaction coefficient (No NoticeUS $\times$ 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 (NoNoticeUS $\times$ NoticeSent) in Table 2.6 and Table B.6 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 $\times$ NoticeSent vs. NoNoticeUS $\times$ 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.

2.6. 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.

2.6.1. 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.). 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.

2.6.2. 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 behaviour 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 behaviour 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).

2.6.3. 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) .

2.6.4. 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 and Stango) 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.) finds adverse spillover effects for suppliers and competitors in the Volkswagen emission scandal. Therefore, spillover effects are driven by consumers' belief that other influencers may also be involved in similar non-disclosure malpractice.

2.7. Limitations and Robustness Checks

In the results presented above, we have aggregated data at the monthly level and used 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

	Data Span (Local Effects)						Clustering	
	Full		Local		Highly Local			
	Direction	Order	Direction	Order	Direction	Order	Direction	Order
Disclosure	Y	Y	Y	Y	Y	N	Y	Y
Likes	Y	Y	Y	Y	Y	Y	Y	Y
Comments	Y	Y	Y	Y	Y	Y	Y	Y

Table 2.7: Model variations for robustness check
Note : This table reports various model specifications and corresponding results. All models are TWFE specified. Direction corresponds to negative or positive impact of notice. For disclosure direction is positive for both direct and indirect effects. For likes and comments direction is negative for both direct and indirect effects. Order refers to degree of impact on T1 vs T2 set of influencers.

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 2.7 for summary and Table B.7 to B.12 in the Appendix) [5]. 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 2.7, and complete results are available in Tables B.13 to B.15 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

[5]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.

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 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.

2.8. 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.

APPENDIX

Popular or Crowded: Subscription Based Donations

A.1. Tables

Category	Education	Healthcare	Livelihood	Nutrition
Count	114	56	77	60
Percentage	37.1	18.2	25	19.5

Table A.1: Broad distribution of causes by category

Location	India	US	Others
Count	6614	1964	1043
Percentage	68.7	20.4	10.8

Table A.2: Broad distribution of donors by location

	Dependent variable: Donor Join Pre vs Post Event
Healthcare	0.073
	(0.201)
Livelihood	0.045
	(0.271)
Nutrition	0.133
	(0.191)
Education	0.130
	(0.276)
Other Locations	-0.091
	(0.201)
US Location	-0.193
	(0.156)
Male	0.086
	(0.103)
Log (Min Donation Amt)	-0.405
	(0.667)
Observations	906
Log Likelihood	-547.761
Akaike Inf. Crit.	1,111.521

Table A.3: Comparing Donors characteristics pre and post event

	Without Controls			With Controls		
	slope	coef	se(coef)	slope	coef	se(coef)
Intercept	0.132	2.05E-04	4.64E-06	1.47E-01	5.28E-04	2.93E-05
Donor Group Size	0.000581	4.51E-07	2.67E-08	1.90E-04	1.17E-06	2.61E-07
Male				-2.20E-02	-6.91E-05	2.65E-05
Others-Location				1.56E-02	3.49E-05	4.32E-05
US-Location				2.86E-03	-1.17E-05	3.06E-05
Donation Amt				1.16E-06	-2.08E-09	1.16E-08

Table A.4: Survival Probabilities using time varying covariates

	Dependent Variable			
	Cancellations		Joiners	
	(1)	(2)	(3)	(4)
Increase	0.973	0.906	2.829	2.653
	(1.189)	(1.191)	(2.374)	(2.379)
Event	-0.343	-0.206	-0.025	0.179
	(0.129)	(0.224)	(0.259)	(0.343)
Placebo		-0.147		-0.152
		(0.227)		(0.350)
Increase $\times Event$	1.379	1.022	1.976***	1.186**
	(0.132)	(0.340)	(0.263)	(0.498)
Increase $\times Placebo$		0.394		0.960
		(0.345)		(0.566)
Constant	-0.282	-0.230	0.284	0.430
	(1.116)	(1.117)	(2.228)	(2.230)
Placebo	N	Y	N	Y
Observations	5,014	5,014	5,014	5,014
R2	0.522	0.522	0.442	0.442

Table A.5: Placebo Regressions

	Dependent variable:			
	Joiners			
	(1)	(2)	(3)	(4)
Increase	1.002	0.988	2.940*	2.942**
	(0.257)	(0.257)	(1.270)	(1.270)
Utsav	0.188	0.508	0.278*	0.260
	(0.196)	(0.317)	(0.157)	(0.248)
Increase X Utsav	1.301	1.316"	1.727	1.727**
	(0.348)	(0.348)	(0.278)	(0.278)
Constant	0.733	1.106	0.129	0.105
	(0.146)	(0.326)	(0.948)	(0.981)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059
R2	0.024	0.024	0.440	0.440

Table A.6: Joiners vs Donor Group Size (DID - Inc vs Not Inc)

	Dependent variable:			
	Cancellations			
	(1)	(2)	(3)	(4)
Increase	0.378	0.387	1.136*	1.176*
	(0.138)	(0.138)	(0.638)	(0.636)
Event	0.214**	0.003	0.285**	-0.166
	(0.105)	(0.171)	(0.079)	(0.124)
Increase $\times Event$	1.043	1.033*	1.334*	1.312***
	(0.188)	(0.188)	(0.140)	(0.140)
Constant	0.307	0.061	0.033	-0.557
	(0.079)	(0.175)	(0.476)	(0.492)
Time Trend	N	Y	N	Y
Cause FE	N	N	Y	Y
Observations	5,059	5,059	5,059	5,059
R2	0.032	0.033	0.517	0.519

Table A.7: Cancellations vs Donor Group Size (DID - Inc vs Not Inc)

A.2. Figures

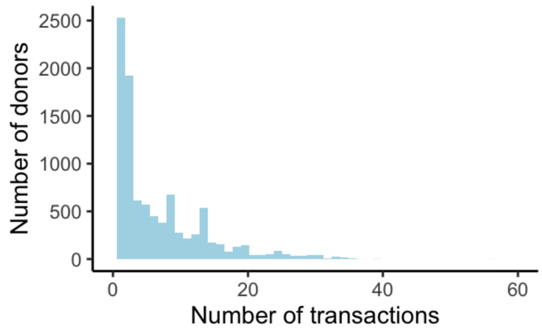


Figure A.1: Distribution of the number of transactions

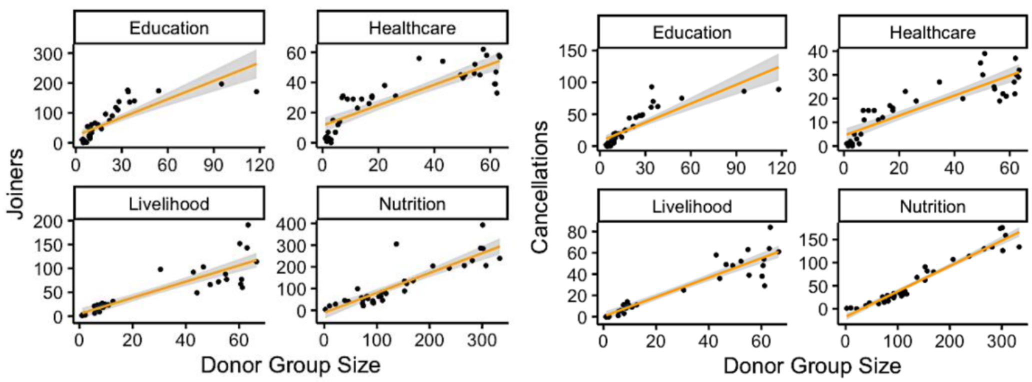


Figure A.2: The left panel (a) shows the relationship of joiners and donor group size by category. The right panel (b) shows the relationship between cancellations and donor group size by category.

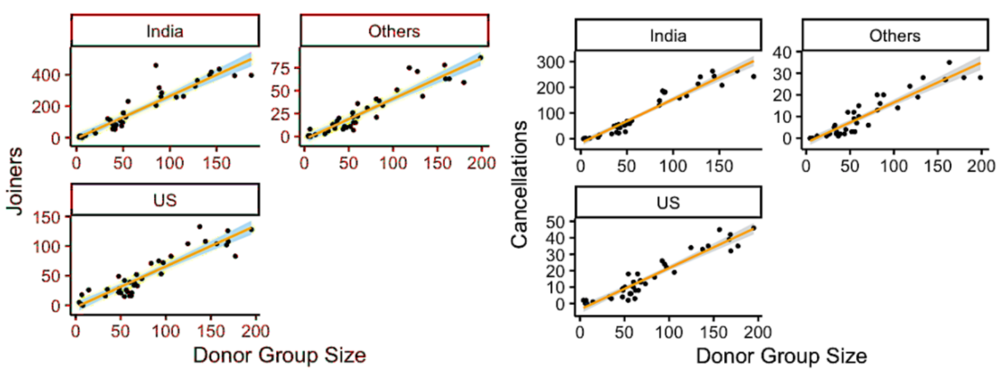


Figure A.3: The left panel (a) shows the relationship of joiners and donor group size by location. The right panel (b) shows the relationship between cancellations and donor group size by location. Others includes mostly developed countries such as UK, Canada, Australia etc.

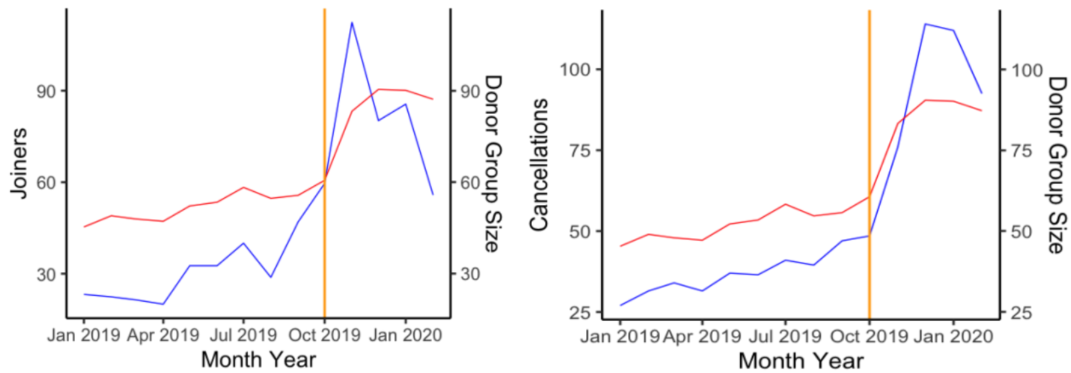


Figure A.4: Raw Trends Around the Event: The left panel (a) shows raw trend of joiners and donor group size. The right panel (b) shows raw trend of cancellations and donor group size. (Not drawn to scale to present on same graph for comparison and coincidence) (Red lines are donor group size trend, and blue lines can be joiners or cancellations)

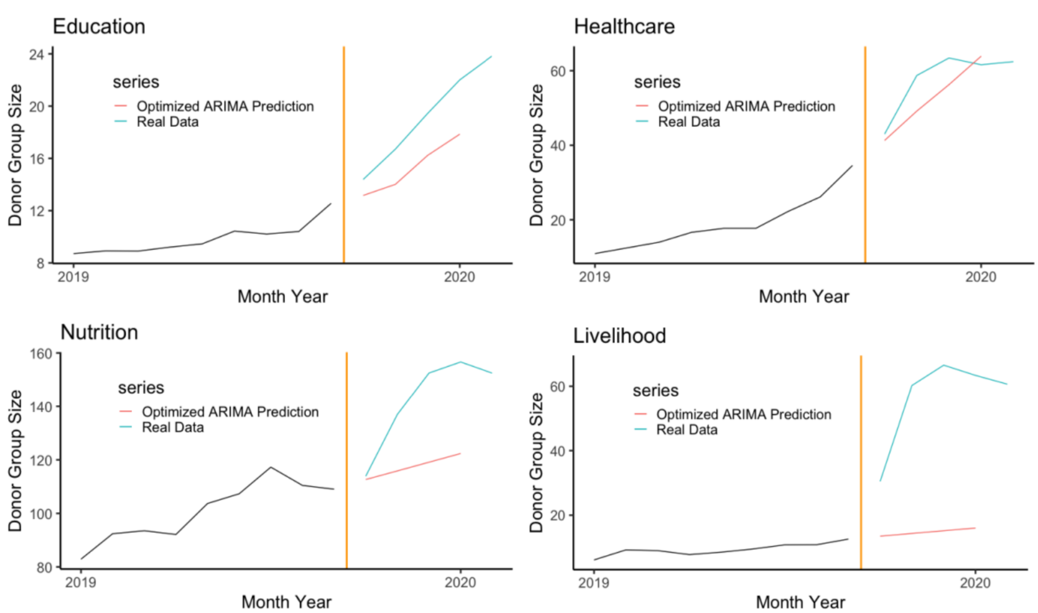


Figure A.5: Event shock by cause category

Figure A.6: This figure reports the Kaplan Meir survival probabilities (1-Pr (Cancel)) for donors with high and low (median split) donor group size. It also reports the p-value from log rank test, indicating clear statistical difference between the two groups.

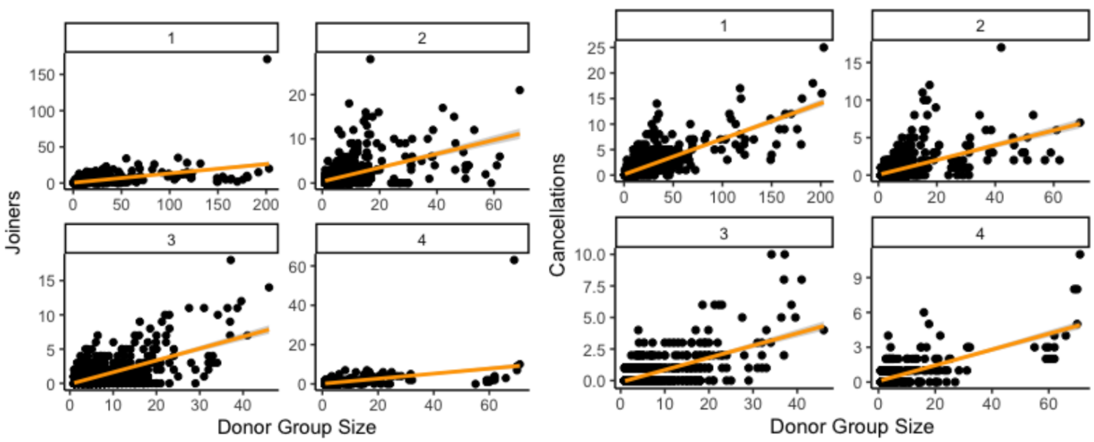


Figure A.7: Outcomes vs donor group size by minimum donation amount quartile split. The left panel shows the relationship of joiners donor group size and right panel shows the relationship between cancellations donor group size. 1-4 top legend indicates quartile number.

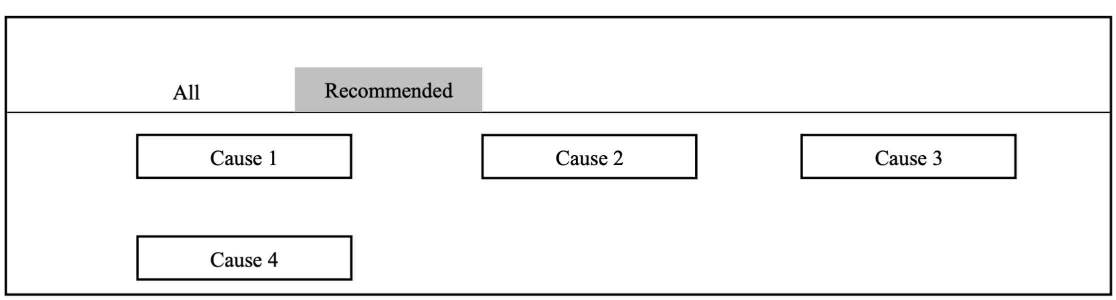


Figure A.8: Position effects - This figure illustrates the landing page of the website.

APPENDIX

Regulatory Warnings and Endorsement Disclosure

B.1. Tables

	Mean Treated	**Mean Control**	**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
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 B.1: Summary of balance matched data using propensity score matching
Note : This table reports the comparison of treatment and control groups. This table shows after propensity score matching the treatment and control group, pre-treatment were comparable.

Notice Sent - U.S.	Notice Not Sent - U.S.	Notice Not Sent
(Treatment 1)	**(Treatment 2)**	**(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 B.2: List of Influencers - Treatment and Control Group

Note : This table reports the name of influencers by treatment groups and control.

Count of Influencers			
	Notified	Not Notified	
Country	**Notice Sent (T1)**	**Inside U.S. (T2)**	**Outside U.S. (C)**
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 B.3: Influencers by location and group

Note : This table reports count of influencers by location.

[H]

Table B.4: 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 × 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

[H]

Table B.5: 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 × 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)
Constant	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

[H]

Table B.6: : Direct and Spillover Effects – Disclosure Percent -Local Effect

	Dependent Variable			
	log(DisclosurePercent)			
	(1)	*(2)*	*(3)*	textit(4)
NoticeUS	0.320***	0.320***		
	(0.077)	(0.077)		
NoNoticeUS	0.254**	0.254***		
	(0.100)	(0.100)		
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

[H]

Table B.7: : Direct and Spillover Effects – Disclosure Percent -Local Effect

	Dependent Variable			
	log(DisclosurePercent)			
	(1)	*(2)*	*(3)*	*(4)*
NoticeUS	0.320***	(0.077)	0.320***	(0.077)
NoNoticeUS	0.254**	(0.100)	0.254**	(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

[H]

Table B.8: Direct and Spillover Effects – Likes -Local Effects

	(Dependent Variable)			
	(og(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
	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

[H]

Table B.9: : 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*** (0.200)	1.237***	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		0.769
Adjusted R^2	0.039	0.046		0.751

[H]

Table B.10: Direct and Spillover Effects – Disclosure Percent -Highly Local Effects

	Dependent Variable			
	log(Comments)			
	(1)	*(2)*	*(3)*	*(4)*
NoticeUS	0.316***(0.102)	0.316*** (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

[H]

Table B.11: 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		0.695
Adjusted R^2	0.030	0.026		0.661

[H]

Table B.12: 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

[H]

Table B.13: Clustered - Robust SE - Disclosure Percent

	Dependent Variable			
	Disclosure Percent			
	(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 × NoticeSent	1.595***	1.595***	1.595***	1.595***
	(0.284)	(0.286)	(0.277)	(0.279)
NoNoticeUS × NoticeSent	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
R^2	0.061	0.084	0.199	0.222
R^2 Adj	0.06	0.069	0.189	0.2
se_type	HC2	HC2	HC2	HC2

Table B.14: 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
R^2	0.146	0.219	0.428	0.503
R^2 Adj.	0.145	0.206	0.421	0.488
se_type	HC2	HC2	HC2	HC2

[H]

Table B.15: 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
R^2	0.083	0.144	0.491	0.553
R^2 Adj.	0.082	0.129	0.484	0.539
se_type	HC2	HC2	HC2	HC2

B.2. Figures

Figure B.1: FTC Letter to Influencers and Firms

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.

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

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

{*Influencer*}
{*Date*}
Page 2

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

*

BIBLIOGRAPHY

Federal Trade Commission. URL https://www.ftc.gov/news-events/press-releases/2016/03/lord-taylor-settles-ftc-charges-it-deceived-consumers-through.

Online Influencers Called Out in Second Letter to FTC. URL https://www.citizen.org/news/online-influencers-called-out-in-second-letter-to-ftc/.

Pei Amy and Mayzlin Dina. Influencing the Influencers by Amy Pei, Dina Mayzlin :: SSRN. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3376904.

Lisa Anderson and Charles Holt. Information Cascades in the Laboratory. *American Economic Review*, 87(5):847–62, 1997.

James Andreoni. Giving gifts to groups: How altruism depends on the number of recipients. *Journal of Public Economics*, 91(9):1731–1749, September 2007. ISSN 0047-2727. doi: 10.1016/j.jpubeco.2007.06.002.

Joshua D. Angrist and Alan B. Krueger. Empirical strategies in labor economics. In *Handbook of Labor Economics*, volume 3, Part A, pages 1277–1366. Elsevier, 1999.

Nava Ashraf and Oriana Bandiera. Altruistic Capital. *American Economic Review*, 107(5): 70–75, May 2017. ISSN 0002-8282. doi: 10.1257/aer.p20171097.

John Atkins. Compensation Models For Influencers. URL https://tuffgrowth.com/compensation-models-for-influencers/.

David H. Autor, Frank Levy, and Richard J. Murnane. The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, 118 (4):1279–1333, November 2003. ISSN 0033-5533. doi: 10.1162/003355303322552801.

Abhijit Banerjee. A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, 107(3):797–817, 1992.

Florian Barth, Christian Eckert, Nadine Gatzert, and Hendrik Scholz. Spillover Effects from the Volkswagen Emissions Scandal: An Analysis of Stock, Corporate Bond, and Credit Default Swap Markets. URL https://papers.ssrn.com/abstract=3089897.

Sushil Bikhchandani, David Hirshleifer, and Ivo Welch. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100(5): 992–1026, October 1992. ISSN 0022-3808. doi: 10.1086/261849.

Samuel K. Bonsu and Russell W. Belk. Do Not Go Cheaply into That Good Night: Death-Ritual Consumption in Asante, Ghana. *Journal of Consumer Research*, 30(1):41–55, 2003. ISSN 1537-5277. doi: 10.1086/374699.

Danny Brown and Sam Fiorella. *Influence Marketing: How to Create, Manage, and Measure Brand Influencers in Social Media Marketing*. Que Publishing. ISBN 978-0-13-339164-0.

Fengyan Cai and Robert S. Wyer. The impact of mortality salience on the relative effectiveness of donation appeals. *Journal of Consumer Psychology*, 25(1):101–112, January 2015. ISSN 1057-7408. doi: 10.1016/j.jcps.2014.05.005.

Margaret C. Campbell, Gina S. Mohr, and Peeter W. J. Verlegh. Can disclosures lead consumers to resist covert persuasion? The important roles of disclosure timing and type of response. 23(4):483–495. ISSN 1057-7408. doi: 10.1016/j.jcps.2012.10.012. URL http://www.sciencedirect.com/science/article/pii/S1057740812001337.

Robert B. Cialdini and Noah J. Goldstein. Social Influence: Compliance and Conformity. *Annual Review of Psychology*, 55(1):591–621, 2004. doi: 10.1146/annurev.psych.55.090902.142015.

Classy. The State of Modern Philanthropy 2018 | Classy. https://learn.classy.org/state-of-modern-philanthropy-2018?sfdc_cid=7012R000000qjebQAA, 2018.

ClearTax. Donations Eligible Under Section 80G and 80GGA. https://cleartax.in/s/donation-under-section-80g-and-80gga, 2021.

Federal Trade Commission. FTC Staff Reminds Influencers and Brands to Clearly Disclose Relationship. URL https://www.ftc.gov/news-events/press-releases/2017/04/ftc-staff-reminds-influencers-brands-clearly-disclose.

Peter R. Darke, Laurence Ashworth, and Robin J.B. Ritchie. Damage from Corrective Advertising: Causes and Cures. 72(6):81–97. ISSN 0022-2429. doi: 10.1509/jmkg.72.6.081. URL https://doi.org/10.1509/jmkg.72.6.081.

John M. Darley and Bibb Latane. Bystander intervention in emergencies: Diffusion of responsibility. *Journal of Personality and Social Psychology*, 8(4, Pt.1):377–383, 1968. ISSN 1939-1315. doi: 10.1037/h0025589.

Daniel Ershov and Matthew Mitchell. The Effects of Influencer Advertising Disclosure Regulations: Evidence From Instagram. In *Proceedings of the 21st ACM Conference on Economics and Computation*, EC '20, pages 73–74. Association for Computing Machinery. ISBN 978-1-4503-7975-5. doi: 10.1145/3391403.3399477. URL https://doi.org/10.1145/3391403.3399477.

Itay P. Fainmesser and Andrea Galeotti. The Market for Online Influence. URL https://papers.ssrn.com/abstract=3207810.

Chiara Farronato, Jessica Fong, and Andrey Fradkin. Dog Eat Dog: Measuring Network Effects Using a Digital Platform Merger. SSRN Scholarly Paper ID 3727123, Social Science

Research Network, Rochester, NY, November 2020.

Peter Fischer, Joachim I. Krueger, Tobias Greitemeyer, Claudia Vogrincic, Andreas Kastenmüller, Dieter Frey, Moritz Heene, Magdalena Wicher, and Martina Kainbacher. The bystander-effect: A meta-analytic review on bystander intervention in dangerous and non-dangerous emergencies. *Psychological Bulletin*, 137(4):517–537, July 2011. ISSN 1939-1455. doi: 10.1037/a0023304.

Bruno S. Frey and Stephan Meier. Social Comparisons and Pro-social Behavior: Testing "Conditional Cooperation" in a Field Experiment. *American Economic Review*, 94(5): 1717–1722, December 2004. ISSN 0002-8282. doi: 10.1257/0002828043052187.

Werner Geyser. What is an Influencer? - Social Media Influencers Defined [Updated 2021]. URL https://influencermarketinghub.com/what-is-an-influencer/.

GivingUSA. 80+ Charitable Giving Statistics & Demographics (2021). https://www.definefinancial.com/blog/charitable-giving-statistics/, July 2021.

John Glenday. Instagram influencer Sophie Hinchliffe breaks rules with undeclared paid P&G posts | The Drum. URL https://www.thedrum.com/news/2019/06/06/instagram-influencer-sophie-hinchliffe-breaks-rules-with-undeclared-paid-pg-posts.

William C Holmes. FTC Regulation of Unfair or Deceptive Advertising: Current Status of the Law. 30:27.

Influencer Marketing Hub. Influencer Marketing Hub, a. URL https://influencermarketinghub.com/influencer-marketing-2019-benchmark-report/.

Influencer Marketing Hub. Influencer Marketing Hub, b. URL https://influencermarketinghub.com/influencer-marketing-benchmark-report-2020/.

Blackbaud Institute. Online Giving Trends. https://institute.blackbaud.com/charitable-giving-report/online-giving-trends/, 2021.

Judd B. Kessler and Katherine L. Milkman. Identity in Charitable Giving. *Management Science*, 64(2):845–859, February 2018. ISSN 0025-1909. doi: 10.1287/mnsc.2016.2582.

Sungjin Kim, Sachin Gupta, and Clarence Lee. Managing Members, Donors, and Member-Donors for Effective Nonprofit Fundraising. *Journal of Marketing*, 85(3):220–239, May 2021. ISSN 0022-2429. doi: 10.1177/0022242921994587.

Christopher Knittel and Victor Stango. Celebrity Endorsements, Firm Value and Reputation Risk: Evidence from the Tiger Woods Scandal. 60. doi: 10.1287/mnsc.2013.1749.

Dami Lee. The FTC is cracking down on influencer marketing on YouTube, Instagram, and TikTok - The Verge. URL https://www.theverge.com/2020/2/12/21135183/ftc-influencer-ad-sponsored-tiktok-youtube-instagram-review.

Seung Yun Lee, Sunho Jung, and Sangdo Oh. Others' participation rate influences an individual's charitable ...: Ingenta Connect. https://www.ingentaconnect.com/content/sbp/sbp/2017/00000045/00000010/art00003;jsessionid=3bgfg ic-live-03, 2017.

Chavie Lieber. How to make $100,000 per Instagram post, according to an agent for social media stars. URL https://www.vox.com/the-goods/2018/11/28/18116875/influencer-marketing-social-media-engagement-instagram-youtube.

M. Lindauer, Marcus Mayorga, J. Greene, P. Slovic, D. Västfjäll, and P. Singer. Comparing the Effect of Rational and Emotional Appeals on Donation Behavior. 2020. doi: 10.31234/osf.io/5wjuv.

John A. List. The Market for Charitable Giving. *Journal of Economic Perspectives*, 25(2): 157–180, June 2011. ISSN 0895-3309. doi: 10.1257/jep.25.2.157.

Lili Liu, Ayoung Suh, and Christian Wagner. Donation Behavior in Online Micro Charities: An Investigation of Charitable Crowdfunding Projects. January 2017. ISBN 978-0-9981331-0-2. doi: 10.24251/HICSS.2017.100.

MatchPro. The Top Nonprofit Fundraising Statistics You Should Know, November 2020.

Mediakix. 93% of Top Celebrity Social Endorsements Violate FTC Rules. URL https://mediakix.com/blog/celebrity-social-media-endorsements-violate-ftc-instagram/.

Zameena Mejia. Kylie Jenner reportedly makes $1 million per paid Instagram post—here's how much other top influencers get. URL https://www.cnbc.com/2018/07/31/kylie-jenner-makes-1-million-per-paid-instagram-post-hopper-hq-says.html.

Stanley Milgram, Leonard Bickman, and Lawrence Berkowitz. Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology*, 13(2):79–82, 1969. ISSN 1939-1315. doi: 10.1037/h0028070.

Matthew Mitchell. Free (Ad) vice.

Aarti Mohan, Sanjana Govil, and Ojas Malpani. Everyday Giving in India Report. page 52, 2019.

Ashesh Mukherjee, Seung Yun Lee, and Thomas Burnham. The effect of others' participation on charitable behavior: Moderating role of recipient resource scarcity. *Journal of Business Research*, 120:213–228, November 2020. ISSN 0148-2963. doi: 10.1016/j.jbusres.2020.08.016.

Kurt P. Munz, Minah H. Jung, and Adam L. Alter. Name Similarity Encourages Generosity: A Field Experiment in Email Personalization. *Marketing Science*, 39(6):1071–1091, November 2020. ISSN 0732-2399. doi: 10.1287/mksc.2019.1220.

Olivia R. Natan. *Choice Frictions in Large Assortments*. PhD thesis, The University of Chicago, 2021.

US News. Which Countries Are the Most Generous? //www.usnews.com/news/best-countries/articles/2019-12-20/the-worlds-most-generous-countries, 2019.

Zafer D. Ozdemir, Kemal Altinkemer, Prabuddha De, and Yasin Ozcelik. An Internet-Enabled Donor-to-Nonprofit (D2N) Marketplace. *SSRN Electronic Journal*, 2009. ISSN 1556-5068. doi: 10.2139/ssrn.1415386.

Karthik Panchanathan, Willem E. Frankenhuis, and Joan Silk. The bystander effect in an N-person dictator game. *Organizational Behavior and Human Decision Processes*, 120(2): 285–297, March 2013. ISSN 0749-5978. doi: 10.1016/j.obhdp.2012.06.008.

Richard W. Pollay. The Distorted Mirror: Reflections on the Unintended Consequences of Advertising. 50(2):18–36. ISSN 0022-2429. doi: 10.1177/002224298605000202. URL https://doi.org/10.1177/002224298605000202.

Advertising Standards Authority | Committee of Advertising Practice. New guidance launched for social influencers. URL https://www.asa.org.uk/news/new-guidance-launched-for-social-influencers.html.

Anita Rao and Emily Wang. Demand for "Healthy" Products: False Claims and FTC Regulation. 54(6):968–989. ISSN 0022-2437. doi: 10.1509/jmr.15.0398. URL https://doi.org/10.1509/jmr.15.0398.

Peter H. Reingen. Test of a list procedure for inducing compliance with a request to donate money. *Journal of Applied Psychology*, 67(1):110–118, 1982. ISSN 1939-1854. doi: 10.1037/0021-9010.67.1.110.

Alexander P. Schouten, Loes Janssen, and Maegan Verspaget. Celebrity vs. Influencer endorsements in advertising: The role of identification, credibility, and Product-Endorser fit. 39(2):258–281. ISSN 0265-0487. doi: 10.1080/02650487.2019.1634898. URL https://doi.org/10.1080/02650487.2019.1634898.

Shane Barker In Marketing Tips 2. What's the Difference Between Celebrities and Influencers - and Which Does Your Brand Need? URL https://smallbiztrends.com/2018/02/influencers-vs-celebrities.html.

NP Trust. Charitable Giving Statistics. https://www.nptrust.org/philanthropic-resources/charitable-giving-statistics/, 2021.

Catherine Tucker and Juanjuan Zhang. How Does Popularity Information Affect Choices? A Field Experiment. *Management Science*, 57(5):828–842, May 2011. ISSN 0025-1909, 1526-5501. doi: 10.1287/mnsc.1110.1312.

Josef Vodak, Lucia Cakanova, Miroslav Pekar, and Martin Novysedlak. Who is Influencer and How to Choose the Right One to Improve Brand Reputation? 17:149–162. ISSN 1581-6311. URL https://econpapers.repec.org/article/mgtyoumgt/v_3a17_3ay_3a2019_3ai_3a2_3ap_3a149-162.htm.

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Juanjuan Zhang. The Sound of Silence: Observational Learning in the U.S. Kidney Market. *Marketing Science*, 29(2):315–335, March 2010. ISSN 0732-2399. doi: 10.1287/mksc.1090.0500.