Consumer communications and current events: a cross-cultural study of the change in consumer response to company social media posts due to the COVID-19 pandemic

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Abstract

The COVID-19 pandemic has changed the lives of consumers in virtually every nation. Based upon the theory of psychological reactance and psychoevolutionary theory of emotion, we hypothesize how such lifestyle changes affect consumers perceiving and responding to companies' communications messages. The theories also suggest that consumers in different cultures may respond to COVID-19 differently. To test our hypotheses, we implemented a Python scraper to collect companies' Instagram posts pre- and during the COVID-19 lockdown. A machine learning algorithm was applied on the collected post photos to automatically identify certain photo characteristics, such as indoor versus outdoor, and with a single person versus many people; a text mining and sentiment analysis was implemented on the collected post captions to identify the salient emotion each caption exhibited, such as joy and anticipation. After that, we conducted a regression discontinuity analysis of photo characteristics or caption emotion on number of likes or comments to identify consumers' response change due to the COVID-19 pandemic. The estimation results supported our hypotheses and suggested tactics that could improve consumer communications effectiveness in this changed time. Viewing COVID-19 as an example of a current event in the ever-changing world, this paper suggests that such events could impact consumer response and behavior, and that companies' marketing and advertising strategies should be responsive to such events.

Keywords COVID-19 · Consumer communications · Social media marketing · Cross-cultural study · Machine learning · Sentiment analysis · Regression discontinuity analysis

"Today, if you get the tone wrong, it's an unforgivable sin... The ability to reach audiences is unparalleled right now, but their willingness to accept marketing messages is limited to the right messages."

Harris Diamond, Chairman and Chief Executive Officer of McCann Worldgroup.

In his interview by *The New York Times* (April 3, 2020), Mr. Harris Diamond, Chairman and CEO of McCann Worldgroup, a leading global marketing solutions network, pointed out one of the biggest challenges marketers are facing—constructing the *right* communications messages for consumers. The new marketing challenge largely stems from our world's transformation to digital first (Sheth 2021). Consumers using their cellphones and laptops first to gain information and make purchases significantly affects their behavior, including how they process and respond to marketing messages. For example, the information overload brought forth by the Internet and social media leads to consumers having a low willingness to accept a marketing message. As a result, consumers only accept the "right" ones.

What makes building a "right" message more challenging is that it is a dynamic concept. The endless new events and ever-changing hotspots in today's fast-moving world keep reshaping how consumers perceive and respond to companies' communications messages, and consequently, what a

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right message is. At the same time, the Internet and social media bring an explosion of real-time data (Petrescu and Krishen 2021). How can we apply analytics on the real-time data to help marketers dynamically and swiftly identify the right and effective marketing message in response to the current events is an important and present topic in marketing analytics.

The COVID-19 pandemic we have been experiencing is a notable example of such an event that could reshape what a right marketing message is. The COVID-19 pandemic has changed consumers' lives to a great extent in virtually every community and nation in the world. In 2020, many countries and districts, including all 50 states in the United States, implemented the "stay-at-home" order. Among other requirements, many of the "stay-at-home" types of orders specifically required residents to remain home at all times unless engaging in essential activities (Mendelson 2020). The stringent restriction of consumers' activity space can influence their perception and response to companies' communications messages to them. In this study we aim to apply state-of-the-art analytics methods on data readily available from the social media platform to test if that is indeed the case. Specifically, we measure the possible impact of the COVID-19 lockdown on how favorable certain message elements are to consumers, such as the surrounding of a message photo (e.g., indoor vs. outdoor) or the emotion of a message caption (e.g., surprise or anticipation). Drawing on the theory of psychological reactance (Brehm 1966) and the psychoevolutionary theory of emotion (Plutchik 1962), we hypothesize that in a Western society such as the United States, the restrictive activity space activates feelings of confinement, which are apt to be perceived as a threat to one's freedom. The threatened individuals are likely to exhibit reactance by favoring or engaging more with the messages that could allow them to psychologically regain their freedom. By contrast, the theories suggest that the threat resulting from the COVID-19 lockdown confinement is arguably smaller in Eastern societies, and as such, Easterners may not change their message response to the same degree as Westerners might.

We use Instagram data to test our hypotheses. The entire process of collecting companies' Instagram posts, identifying the post photo characteristics, and determining the emotion that post captions may carry was all completed automatically, through machine learning and text mining methods. We then applied regression discontinuity analysis, an increasingly popular non-experimental causal inference approach (cf. Goldfarb and Tucker 2014), on the 22,930 posts we collected from company Instagram accounts in the United States and in Asian countries. Our results showed that U.S. consumers have responded more favorably to depictions of social gatherings and the outdoors in post photos during COVID-19 than before. We also found that U.S.

consumers have responded more favorably to the emotion of anticipation and less favorably to the emotion of surprise in post captions during COVID-19 than before. Compared to the U.S. findings, the dampening results for Asian consumers from COVID-19 speak to the cultural differences that exist between the two global regions.

This research stands to make several contributions to the literature. One, it examines a subject that is contemporary and widely impactful and sheds light on the tactics that companies can adopt to improve communications effectiveness during the COVID-19 pandemic. It also widens our understanding of COVID-19's impact on consumer behavior (e.g., Kwon et al. 2021). Two, this research documents that current events such as the COVID-19 lockdown could substantially affect how consumers perceive and respond to companies' communications messages. As such, it suggests that in order to improve the communications effectiveness and maximize their Return on Investment (ROI), companies should constantly monitor the market and dynamically adjust their marketing messages. Three, the findings of this research show that consumers from different cultures may respond to the same global event, such as the COVID-19 lockdown, differently in terms of marketing messages. This extends our understanding of COVID-19's business impact across cultures (e.g., Ahmadi et al. 2021). Four, this research demonstrates and advocates that analytics could help a company take advantage of the real-time digital data to expeditiously identify consumers' changes to their communications message preference. While this research focuses on the COVID-19 pandemic, the idea could be applied to future events.

Theoretical background and hypothesis generation

Theory of psychological reactance (TPR)

According to *A theory of psychological reactance* (Brehm 1966), *psychological reactance* is defined as "an unpleasant motivational arousal that emerges when people experience a threat to or loss of their free behaviors." In other words, when people feel as though their freedoms have been infringed upon, they adjust their actions to re-establish their control and sense of freedom.

Freedom can be perceived in a variety of ways depending on the individual and the cultural context, including, but not limited to, the proxemic bubble (Hall 1966), personal space (Albert and Dabbs 1970), and architectural elements (Meyers-Levy and Zhu 2007). The concept of psychological reactance has seen a great deal of applications in marketing. For instance, Fitzsimons and Lehmann (2004) discovered that when consumers receive unsolicited advice while shopping, they enter a state of reactance and make choices that

contradict the recommendation. Kivetz (2005) employs psychological reactance to explain why consumers may reject incentive programs. Kivetz posits that consumers view incentive programs as limiting personal, “effort-congruent” rewards, and therefore interpret them as attempts to influence their buying behavior. Levav and Zhu (2009) found that aisle width can affect consumers’ choices in the sense that they display greater variety-seeking in their choices when shopping in narrower aisles. The finding is interpreted as the consumers’ reactance to the physical confinement activated by the narrower space, since choices, particularly unique and different choices, are viewed as ways to express one’s freedom.

The COVID-19 pandemic resulted in periods of large-scale lockdowns across the world, including in the United States. Under the nationwide stay-at-home orders, citizens were strongly encouraged, if not mandated, to physically stay in their homes, which are smaller spaces than most people are typically confined to for extended periods of time. Those orders also forbade people from gathering. Both of these elements are a major source of threats to freedom. As Clee and Wicklund’s (1980) well-known marketing review paper on psychological reactance pointed out, “Threats to freedom may stem from impersonal sources, which will be called ‘barriers.’ For example, physical distance might render a potential mate or friend unreachable” (p. 389).

Such confinements to a space and limitations on gathering, as major sources of threat to freedom, may make consumers feel “trapped,” which will evoke a state of reactance in people to help them restore their need for freedom. How might this reactance, caused by the unprecedented constraints on personal and societal freedom, influence consumer behavior? We reason that reactance will be seen in consumers’ response to companies’ communications messages to them. Specifically, we argue that consumers will demonstrate a heightened tendency to favor specific messages as a means to reassert their freedom. On the social media platform, Instagram, a message is typically a photo post. The photo can exhibit different characteristics in terms of architectural elements and spatial constraints, such as a picture of indoor versus outdoor, a picture of a single person versus one depicting many people. For our research, we conjecture that, because of the stay-at-home orders that have been in place due to the COVID-19 pandemic, consumers will attempt to regain freedom by favoring post photos with outdoor settings, as well as gatherings of people. It is reasonable to view the favorability of social media photos as a way to express one’s freedom, since (1) during the lockdown, people are isolated so that there are few ways for them to choose from to express themselves; (2) The literature has well established that in the case of barriers, choice options that threaten loss will tend to be more attractive or more sought after. Those options do not necessarily have to be

the most attractive of the available choice alternatives (e.g., Brehm 1966; Wicklund 1970). This supports our conjecture that consumers may regain freedom by favoring post photos with outdoor or people gathering settings, even generally speaking that they may not be necessarily the most attractive photos; and (3) as Clee and Wicklund (1980) pointed out, “It is important to note that the behaviors stemming from reactance arousal are not conservative, in the sense of the person attempting only to return to the prereactance state of affairs. Rather, the reactance response often entails an *over-reaction*, whereby threatened behaviors or attitudes come to be prized more than before” (p. 390). While it may seem absurd that consumers seek restoration of freedom from social media posts, this is very much in line with this over-reaction they described. Thus,

Hypothesis 1 In the United States, the COVID-19 pandemic increases the efficacy of companies’ messages that appeal to the state of reactance in consumers; specifically,

H1a The COVID-19 pandemic increases the efficacy of companies’ messages that contain photos of the outdoors.

H1b The COVID-19 pandemic decreases the efficacy of companies’ messages that contain photos of the indoors.

H1c The COVID-19 pandemic increases the efficacy of companies’ messages that contain depictions of social gatherings.

H1d The COVID-19 pandemic decreases the efficacy of companies’ messages that contain depictions of an individual.

Applying TPR to the Asian culture

The discussion above mainly focuses on the Western culture and the United States setting, which is where TPR originated. A common dimension for comparing and contrasting cultures is individualism and collectivism (Aaker and Maheswaran 1997). The Western culture is an individualistic culture, which is characterized as valuing freedom, competition, individuality, and independence (Hofstede 1980, 1991). This view of independence leads Westerners to expect relatively large proxemic bubbles and relatively high degrees of personal space, and consequently, they may be more likely to view the activity space confinement due to the COVID-19 stay-at-home order as a perceived threat to freedom. The Eastern culture in Asian countries is a collective culture, placing importance on interdependence, peace, social hierarchies, and adherence to others (Moon and Franke 2000). In many Asian countries, for example, the self is viewed as an interdependent entity fundamentally connected by

relationships to others (Miyamoto et al. 2018). This view of interconnection reduces the expectation of personal space for an individual. This can cause the people in the culture to react differently to situations such as the COVID-19 stay-at-home order in the sense that the space confinement created by those orders is less threatening. As a result, we expect that the efficacy improvement of messages that appeal to the state of reactance in consumers due to COVID-19 lessens in Asian countries. Thus,

Hypothesis 2 In Asian countries, the COVID-19 pandemic's impact on the efficacy of companies' messages that appeal to the state of reactance in consumers is lesser than in the United States.

Psychoevolutionary theory of emotion (PTE)

In his psychoevolutionary theory of emotion (1962), Robert Plutchik posits the existence of eight primary emotions, anger, anticipation, disgust, fear, joy, sadness, surprise, and trust, that serve as the basis for all other emotions. Given that how COVID-19 has impacted some of them, such as anger, fear, and joy, are pretty obvious, our focus in this study is a pair of emotions that Plutchik considered "opposite" (Plutchik 1988), anticipation and surprise. *Anticipation* is defined as an emotion involving pleasure (and sometimes anxiety) in considering some expected or longed-for good event, or irritation due to having to wait. To the contrary, *surprise* is an emotion experienced by animals and humans as the result of an unexpected event. Miceli and Castelfranchi (2015) explain the difference between these two emotions as anticipation being the implication of future events and surprise being a momentary interpretation of a present occurrence, which can be in the form of "disconfirmation of previous anticipation."

In referring more specifically to the feeling of anticipation, we can see that it is closely related to the concept of hope. Figlio (2009) defines *hope* as an "unfulfilled anticipation, which expresses a tension in the gap between the ego and ego-ideal." Similarly, de Mello and Macinnis (2005) define hope as "a positive emotion that varies as a function of the degree of yearning for a goal-congruent, future-oriented outcome appraised as uncertain, yet possible."

De Mello and Macinnis's definition also reveals several fundamental factors about the concept of hope. *Yearning* is one of them, which is defined as the degree of longing for a goal-congruent outcome (Lazarus 1991). The fundamental factors that affect yearning include desire, importance of an outcome, and deficiencies. *Desire* is defined as an intensely passionate positive emotional experience steeped in fantasies and dreams rather than an experience involving reasoned judgments (Belk et al. 1997). Yearning is also related to the *importance* of an outcome. While a consumer may not

have a desire to join the military, doing so may be important to his self-concept and, hence, stimulate his yearning to enlist (Macinnis and Chun 2007). Finally, yearning is related to *deficiencies*. As Lazarus (1990) pointed out, "A fundamental condition of yearning and hope is that our current life circumstance is unsatisfactory—that is, it involves deprivation."

We expect that COVID-19 activates consumers' strong yearning. Desire for socialization is a strong stimulator of yearning for being back to normal. Consumers also appraise being back to normal as important, given the negative impact of COVID-19 on human society, both in scope and in degree. In addition, the COVID-19 lockdown and the movement restrictions have deprived people of accessing society's resources, which makes their life circumstance unsatisfactory. As such, COVID-19 activates consumers' yearning from all three fundamental factors, which make the yearning and its resulting hope very strong.

The hope literature also shows that hope, in particular that from strong yearning, could affect consumers' decisions, including their choice of products (e.g., Averill et al. 1990; McCracken 1990; Belk 1996; Macinnis and Chun 2007). As Belk (1996) wrote, "perhaps for all of us in one way or another, some of our strongest and most readily available hopes for transcendent and transformational experiences lie in consumer goods and services ... People need nourishment for their fantasies and many of use need reified artifacts that act as symbols of these hopes" (pp. 102–103). Although the marketing message is not one of the "products" that the literature has evidenced, we conjecture that the intensive hope and the emotion of anticipation (they are two very close concepts, as discussed) caused by the strong yearning' activated by COVID-19 could also affect consumers' reaction to messages in the sense that consumers would engage more with messages that show hope and the emotion of anticipation. As a result, they may like more messages that appeal to the feeling of anticipation. Given that surprise is the opposite of anticipation, we also conjecture that consumers will engage less with messages that show the emotion of surprise. Those conjectures, in collaboration with the psychological reactance that consumers feel and evoke in the time of COVID-19, lead us to the following hypothesis:

Hypothesis 3a In the United States, the COVID-19 pandemic increases the efficacy of companies' messages that appeal to the feeling of anticipation; specifically, the COVID-19 pandemic increases the efficacy of companies' messages that contain the emotion of anticipation.

Hypothesis 3b In the United States, the COVID-19 pandemic decreases the efficacy of companies' messages that appeal to the feeling of surprise; specifically, the COVID-19

pandemic decreases the efficacy of companies' messages that contain the emotion of surprise.

Applying PTE to the Asian culture

Cultures and emotions are highly interrelated (Izard 1980). As such, emotions are subject to cultural differences. Emmerling and Goleman (2003) discuss differences between Western and Asian cultures. The authors argue that the greater individualism of Westerners leads them to experience emotions somewhat differently than Asians. For example, Westerners seem to experience more "positive" emotions than do Asians in interpersonal conflict situations—the latter are more likely to view these as negative phenomena (Emmerling and Goleman 2003).

In the same vein, we conjecture that Asians are less optimistic than Westerners in responses to the COVID-19 pandemic, and are less hopeful for the future beyond lockdowns. This leads us to the following hypothesis:

Hypothesis 4a In Asian countries, the COVID-19 pandemic's impact on the efficacy of companies' messages that appeal to the feeling of anticipation is lesser than in the United States.

Hypothesis 4b In Asian countries, the COVID-19 pandemic's impact on the efficacy of companies' messages that appeal to the feeling of surprise is lesser than in the United States.

Methods

In order to test our hypotheses, we collected Instagram posts from company accounts, identified post photo characteristics and post caption emotions, and built a statistical model to examine if and to what extent consumers are influenced differently by certain photo characteristics or caption emotions, before and during COVID-19.

To demonstrate and advocate that analytics could help the company take advantage of the real-time digital data to expeditiously identify the consumers' changes to their communications message preference, we tried to automate the data collection and processing. The entire process of collecting companies' Instagram posts, identifying the post photo characteristics, and determining the emotion that post captions may carry was all completed automatically through machine learning and text mining methods.

Once the data was collected and processed, we performed a regression discontinuity (RD) analysis on it to identify the impact of the COVID-19 pandemic on consumers' response to Instagram posts. The RD analysis is a rigorous non-experimental approach that can be used to generate causal

inference (Goldfarb and Tucker 2014). The logic behind using this method is that, by comparing observations lying closely on either side of a cutoff, it is possible to estimate the treatment effect without randomized assignments. First proposed in educational psychology (Thistlethwaite and Campbell 1960), the RD approach has become increasingly popular in recent years, and has been applied in many disciplines such as economics (e.g., DiNardo and Lee, 2004), marketing (e.g., Busse et al. 2009), and epidemiology (e.g., Bor et al. 2014). The rest of this section discusses the data collection and modeling details.

Data source collection planning

To gain insight into the influence of the COVID-19 pandemic on consumer response to marketing messages, we decided to focus on social media, since that is one of the main source of real-time data available to marketers. Of all the social media platforms, we chose Instagram as our data source for two reasons. First, Instagram is one of the most rapidly growing platforms with one billion monthly users, and is ranked first as the most common company choice for social media marketing. Second, Instagram is also user-friendly when considering data collection. It not only allows public data collection from all non-private accounts, but it also provides an Application Programming Interface (API) to assist users in doing so. Specifically, Instagram offers a matched API to each account. For example, regular Instagram users can access the PepsiCo Instagram account "@pepsico" via www.instagram.com/PepsiCo, and programmers/marketing analysts can access and obtain all the post and metadata of the account via the API: https://www.instagram.com/PepsiCo/?__a=1.

On Instagram, we focused on posts on company-owned accounts. We first manually created a list of Instagram accounts to analyze. In this process, we tried to collect a balanced list with a healthy mix of large, multinational accounts (e.g., Coca-Cola, Rolex, Apple, etc.) as well as smaller, regionally-based companies (e.g., regional gas stations, grocery stores, boutiques, etc.), and those in between ranges in size and reach. We also tried to obtain Instagram accounts of companies from various industries. Our final list of 299 accounts included those of industries such as consumer packaged goods, energy, cosmetics, clothing and textiles, food services, accounting services, banking, and universities, among others. This level of diversity in our collection set allowed us to analyze the appeal of a wide range of Instagram posts to a wide range of consumer types.

Data collection procedure

The data collection procedure was conducted automatically using computer programs. Throughout the entire project,

the Instagram account generation discussed in the previous sub-section was the only manual component.

The first phase of the data collection process involved obtaining the Instagram post data from the accounts in our account list. In this process we examined photo posts and ignored video posts. For a “swipe post” (a post that contains more than one photo), we considered the first only. The process was done by writing and using a customized Python scraper. The scraper was able to provide data variables including date posted, caption, number of likes, number of comments, photo URL, etc., for all posts from each Instagram account for any date range we specified. In the current study, we use the number of likes and number of comments as DVs in our models to measure consumers’ favorability or engagement.

In our data collection process, we decided to scrape photos from two separate time periods: first, from January 1 to February 29, 2020, and second, from March 24 to May 23, 2020. This decision was made based on the COVID-19 lockdown timeline. In the United States, 28 states had issued a formal stay-at-home, shelter-in-place, or similar order in the week of March 24 (March 22–28). Virtually all 50 states had issued a formal order by the first week of April (Mendelson 2020). In Asia, Instagram is not available in China. India is the country with the largest Instagram audience size in the region (Statista 2020), where lockdown started on March 25. Thus, March 24 is a reasonable date to identify as the marker for when the daily lives of consumers changed due to COVID-19. These two periods identified for modeling purposes exclude the dates March 1, 2020 through March 23, 2020. We justify this by arguing that, although the virus was spreading and causing concern in the US during that period, it was a period when most Americans were aware and cautious but still going about their normal routines, attending school and work, and having social gatherings. Because of these reasons, we divided our data into two main time periods, as stated previously: January 1–February 29, 2020 (Regime 1) and March 24–May 23, 2020 (Regime 2). See Table A.1 in Supplementary Appendix for a summary statistic of the posts we collected, as well as a breakdown of the number of posts in each of the regimes. As a robustness check, we also collected the same data from January to May of 2019 and performed a difference-in-difference analysis. The conclusion is very similar.

Instagram photo characteristic extraction

Once we had collected all of the post data from our Instagram accounts, two data processing tasks were employed to analyze post content, one for photos and one for captions. Such processing allows us to convert photos or text to structured data so that we could use them to build models.

We first extract photo characteristics by using Microsoft Azure Computer Vision machine learning algorithm, through which 16 photo characteristics (variables) are identified for each photo: abstract, animal, building, food, indoor, outdoor, object, people.baby, people.crowd, people.face, people.group, people.hand, people.many, plant, sky, text, and transportation. Each variable is a dummy variable, indicating if a photo exhibits certain features of a surrounding or architectural element.

There are a few things worth pointing out about this process. First, the Microsoft Azure Computer Vision machine learning algorithm assigns a characteristic tag with a confidence score to each photo. For example, the tag [{ “name”: people.baby,” “score”: 0.98828125 }] on a photo means the algorithm believes the photo has a baby with 98.83% confidence. For our analysis, we only used photos for which the categorization had at least 50% confidence. We also ran our models using other confidence thresholds (e.g., 70%) and received similar results. Two, it is possible for a photo to be classified into more than one characteristic. For example, a photo can be tagged both [{ “name”: “people_baby,” “score”: 0.98828125 } and { “name”: “outdoor,” “score”: 0.390625 }]. In our analysis, we focused only on the category with the highest confidence score (again, if larger than 50%) to reflect the thought that this characteristic is the most salient one in regards to impact on customers. Three, we used a granular level of categorizing for people, but not for other content. Take the category “outdoor” for example. With the machine learning algorithm, it was possible to assign some outdoor photos to more specific levels of subcategories such as outdoor_mountain or outdoor_street. However, we aggregated all of the outdoor-related categories into one category. For “people,” on the other hand, we maintained the most granular levels of distinction, since many of them are directly related to our hypotheses and we wanted to test all of their individual effects. Most specifically, we are interested in people_crowd, people_group, and people_many. The variables crowd, group, and many are all slightly different—“crowd” indicates a large number of people in a large space, “group” represents a group of people touching each other, and “many” represents a large number of people in a smaller space than “crowd.”

The Azure Computer Vision algorithm also provides us with variables regarding foreground and background color, which we also incorporated in our models. Available colors in the Azure Computer Vision algorithm included black, blue, brown, green, gray, orange, pink, purple, red, teal, and yellow.

Instagram caption characteristic extraction

An Instagram post may have an accompanying caption. To extract caption characteristics, we wrote another customized

Python program. The first part of the program scanned each caption to extract the word count and check for the presence of emojis. After that, a sentiment analysis was performed to collect data about the eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. The program made use of the NRC Word-Emotion Association Lexicon (Mohammad and Turney 2013) to identify the presence of these eight emotions in each caption. Again, the emotion with the strongest degree of presence in the caption was used in our modeling. Some of the captions from Asian accounts were in non-English languages. To be able to analyze those as well, we used a Google Translator API to convert them to English before conducting the sentiment analysis on them.

Model 1: Instagram photo analysis

In our first model, we analyze how consumers' response to photo characteristics changed due to the COVID-19 pandemic, by estimating the following specification (Model 1):

$$Y_{ijt} = \alpha + \beta_0 s_t + X_{ijt} \beta_1 + (X_{ijt} \bullet s_t) \beta_2 + Z_{ijt} \beta_3 + \epsilon_{ijt}$$

in which Y_{ijt} is the log of the number of likes on the Instagram post j that company i sends at day t . On the right-hand side, the variable s_t is binary and equals to one if day t is in Regime 2 (representing the COVID-19 lockdown period) and zero otherwise (i.e., Regime 1). The variable X_{ijt} is a vector of binary variables that represents photo characteristics (e.g., outdoor) or photo background/foreground color. An interaction between X_{ijt} and s_t is also included in the model. The (vector of) coefficient β_1 measures the overall impact of individual photo characteristics or photo background/foreground color on consumers' favor to the post, while the (vector of) coefficient β_2 measures the *additional* impact of photo characteristics or photo background/foreground color, if there is any, due to the COVID-19 lockdown ($s_t = 1$). We use a vector of observables, Z_{ijt} , to control other possible effects that may influence a consumer's likeness to a post. Included in Z_{ijt} are account's number of followers and followees (to control for the company size), monthly dummies, weekday (Sunday through Saturday), and portion of the day when a post is posted (morning: 5 am to 12 pm; afternoon: 12–5 pm; evening: 5–9 pm; night: 9 pm to 5 am).

Model 2: Instagram caption analysis

In our second model, we analyze how consumers' response to caption emotion changes with the COVID-19 pandemic by estimating the same specification as before but with different inputs (Model 2):

$$Y_{ijt} = \alpha + \beta_0 s_t + X_{ijt} \beta_1 + (X_{ijt} \bullet s_t) \beta_2 + Z_{ijt} \beta_3 + \epsilon_{ijt}$$

in which Y_{ijt} is the log of the number of comments received by the Instagram post j that company i sends at day t . On the right-hand side, the variable X_{ijt} is a vector of binary variables that represents the word count, presence of an emoji, and presence of the eight basic emotions in captions that we discussed previously. The (vector of) coefficient β_1 measures the overall impact of caption length, caption emoji presence, and caption emotion on consumers' likelihood to comment on a post, while the (vector of) coefficient β_2 measures the additional impact of the same variables, if there is any, due to the COVID-19 lockdown. The variable s_t , the vector of observables, Z_{ijt} , and the interaction between X_{ijt} and s_t have the same implications in Model 2 as they did in Model 1.

Results and Discussion

Key estimation results of Model 1 and Model 2 are reported in the left and right panel of Table 1, respectively. The full estimation results are presented in Table A.2 in Supplementary Appendix.

Model 1 results: U.S. accounts

Column 1 on the left panel of Table 1 shows the photo analysis results from U.S. accounts. The estimation results suggest that a photo from an account with more followers tends to have more likes. A photo during a weekday, compared to a photo on Sunday, receives fewer likes. These results show that our model is plausible.

For our purposes, we are most interested in the photo characteristics variables. Taking the photo characteristic outdoor as an example, “outdoor” and “outdoor.2” represent the estimate of the photo characteristic as being outdoor, for Regime 1 and Regime 2, respectively. “Outdoor” is insignificant, suggesting that overall, an Instagram photo characterized as “outdoor” is not necessarily able to generate more likes. However, “outdoor.2” is 0.6691 and is significant, suggesting that in Regime 2, i.e., during COVID-19, the number of consumers who like an Instagram photo featuring the outdoors increases by an *additional 66.91%, compared to the overall effect of “outdoor” on the number of likes*. On the contrary, the results of “indoor” and “indoor.2” suggest that overall, consumers are less likely to like an Instagram post set indoors. Their favor toward “indoor” photos decreases further by 34.79% in Regime 2. While the effect magnitudes seem large, they are very much in line with the theory of over-reaction from reactance arousal, as described in Cleve and Wicklund (1980).

The three photo characteristics about “people” show strong and consistent results, in the sense that compared to Regime 1, Instagram photos featuring people in gatherings and are characterized as “people.crowd,” “people.group,”

Table 1 Key estimation results

Model 1: Photo Characteristics (DV: Num of Like)					Model 2: Caption Emotions (DV: Num of Comments)				
	(1) U.S. Accounts		(2) Asian Accounts			(1) U.S. Accounts		(2) Asian Accounts	
	Coefficient Estimates	S. E.	Coefficient Estimates	S. E.		Coefficient Estimates	S. E.	Coefficient Estimates	S. E.
(Intercept)	6.4850***	0.0617	5.6060***	0.0907	(Intercept)	1.7270***	0.0567	0.9655***	0.0930
s	-0.1599***	0.0549	-0.1113	0.0749	s	0.2537***	0.0502	0.2459***	0.0756
followeeNum	0.0000	0.0000	-0.0002***	0.0000	followeeNum	-0.0001***	0.0000	0.0000	0.0000
followerNum	0.0000***	0.0000	0.0000***	0.0000	followerNum	0.0000***	0.0000	0.0000***	0.0000
Monday	-0.2118***	0.0508	-0.1404*	0.0749	Monday	-0.0826*	0.0485	-0.0403	0.0799
Tuesday	-0.2201***	0.0510	-0.0881	0.0751	Tuesday	-0.0891*	0.0487	-0.0713	0.0801
Wednesday	-0.2516***	0.0493	-0.1375*	0.0727	Wednesday	-0.0698	0.0470	0.0130	0.0777
Thursday	-0.2744***	0.0493	-0.1006	0.0735	Thursday	-0.0860*	0.0470	-0.0807	0.0783
Friday	-0.2893***	0.0486	-0.2537***	0.0708	Friday	-0.0881*	0.0465	-0.1130	0.0760
Saturday	-0.1311**	0.0535	-0.0613	0.0777	Saturday	-0.0647	0.0512	-0.0234	0.0831
morning	0.0598	0.0420	0.5598***	0.0620	morning	0.0217	0.0400	0.1932***	0.0667
afternoon	-0.0352	0.0387	0.3705***	0.0604	afternoon	0.0660*	0.0370	0.1536**	0.0647
evening	0.0980**	0.0430	0.4995***	0.0622	evening	0.0524	0.0411	0.1707**	0.0664
indoor	-0.4930***	0.0856	0.0774	0.1847	anticipation	-0.0354***	0.0132	0.0190	0.0179
indoor.2	-0.3480***	0.1249	-0.6060**	0.2599	anticipation.2	0.0367**	0.0166	0.0085	0.0219
outdoor	0.0870	0.1818	-0.6640**	0.3145	surprise	0.0858***	0.0187	0.0107	0.0254
outdoor.2	0.6690**	0.2615	0.0705	0.6275	surprise.2	-6.0670**	0.0238	-0.0153	0.0312
people.crowd	0.0188	0.2197	-0.0584	0.3132					
people.crowd.2	0.9570***	0.3641	0.4470	0.5920					
people.group	0.2640***	0.0833	-0.1930	0.1215					
people.group.2	0.2460**	0.1245	0.4090**	0.1879					
people.many	-0.1850	0.2046	-0.1680	0.2332					
people.many.2	0.9190***	0.3233	0.9480**	0.4159					

*Denote 90% confidence level

**Denote 95% confidence level

***Denote 99% confidence level

or “people.many” all generate additional numbers of likes in Regime 2. Specifically, an Instagram photo containing a large number of people in a large space (“people.crowd”), a group of people touching each other (“people.group”) and a large number of people in a smaller space (“people.many”) increases the number of likes by an additional 95.69%, 24.62%, and 91.87%, respectively.

Model 1: results: Asian accounts

The photo analysis results from Asian accounts are presented in Column 2 of the left panel of Table 1. The estimation results on number of followers and post day and time are similar to those from U.S. accounts, suggesting the plausibility of our model. As for the key variables of interest, “outdoor” is significant and has a coefficient of -0.6636, suggesting that overall, an Instagram photo characterized as “outdoor” will generate 66.36% fewer likes. However, “outdoor.2” is insignificant, suggesting that in Regime 2, the number of consumers who like an Instagram photo

characterized as “outdoor” is not incrementally affected beyond the overall effect. On the other hand, the results on “indoor” and “indoor.2” suggest that overall, Asian consumers are less likely to like an Instagram post characterized as “indoor;” their favor to “indoor” photos decreased an additional 60.63% in Regime 2.

For the Asian accounts, “people.crowd,” “people.group,” and “people.many” are all insignificant, suggesting that generally, Instagram photos characterized as any of these are not necessarily able to generate more likes. “People.group.2” and “people.many.2” are similar to what we saw with U.S. accounts. Specifically, “people.group.2” and “people.many.2” are significant with coefficients of 0.4094 and 0.9477 respectively, signifying that, in Regime 2, the number of likes on an Instagram post with those categorizations is increased by 40.94% and 94.77% compared to their overall effects. Unlike what we saw with U.S. accounts, however, “people.crowd.2” is also insignificant, suggesting that in Regime 2, the number of consumers who like an Instagram photo characterized as “people.crowd” is unaffected.

Model 2 results: U.S. accounts

Column 1 of the right panel of Table 1 shows the results from U.S. accounts. The estimation results suggest that a post from an account with more followers tends to have more comments. Compared to a post on Sunday, a post during a weekday receives fewer comments. These results show that our model is plausible.

The estimation shows interesting results on the two emotion variables that are opposite to each other, anticipation and surprise. “Anticipation” and “anticipation.2” represent the estimate of a caption with an anticipation emotion, for Regime 1 and Regime 2, respectively. “Anticipation” is significant with a coefficient of -0.0354 , suggesting that overall, an Instagram caption characterized as “anticipation” will have 3.54% fewer comments. However, “anticipation.2” has a coefficient of 0.0367 and is significant, suggesting that in Regime 2, the number of comments on a post with a caption characterized as “anticipation” increases by 3.67%, compared to the overall negative effect of “anticipation.” This tells us that the positive effect of “anticipation” during COVID-19 reverses its general negative effect.

On the contrary, “surprise” is significant with a coefficient of 0.0858 , suggesting that overall, an Instagram post with a caption characterized as “surprise” will generate 8.58% more comments. “Surprise.2” has a coefficient of -0.0607 and is significant, suggesting that in Regime 2, the number of consumers who comment on a post with caption featuring “surprise” decreases by 6.07%, compared to the overall effect of “surprise” on number of comments. This tells us that, inversely from anticipation, the negative effect of surprise during COVID-19 reverses its general positive effect.

Model 2 results: Asian accounts

Column 2 on the right panel of Table 1 shows the photo analysis results from Asian accounts. Interestingly, in contrast to the results from U.S. accounts, both “anticipation” and “anticipation.2” are insignificant, suggesting that overall, as well as incrementally in Regime 2, an Instagram caption characterized as “anticipation” is not necessarily able to generate more or fewer comments. This tells us that Asian consumers respond neither negatively nor positively to the emotion of anticipation.

The result on the emotion of surprise is also different from U.S. accounts. Both “surprise” and “surprise.2” are insignificant, suggesting that overall, as well as incrementally in Regime 2, an Instagram caption characterized as “surprise” is not necessarily able to generate more or fewer comments.

Discussion

Our Model 1 results from the U.S. accounts strongly support our Hypothesis 1. The photo characteristics that yielded more positive responses than usual since the onset of COVID-19 restrictions include the outdoors and social gatherings (groups, crowds, and many people). Because stay-at-home orders and social distance restrictions were put in place, we posit that U.S. consumers experienced a heightened sense of reactance, which, as previously stated, involved the desire to reassert freedom and control. As Americans were encouraged to stay inside their homes, their motivation to reassert their freedom caused their response to the outdoors, the opposite of “staying inside their homes,” to be positively affected. Similarly, as social distancing, defined by the Centers for Disease Control and Prevention (2020) as “limiting face-to-face contact with others” and “stay[ing] at least 6 feet (about 2 arms’ length) from other people,” was promoted, the motivation to reassert freedoms caused people to respond positively to visuals of social gatherings and crowds. To summarize, consumers preferred content that appealed to their desired state of freedom during the event of COVID-19, not the state of limitation in which they were living.

When evaluating the Model 1 results from Asian accounts, it is clear that the cultural differences described in the theory section play a role in current consumer perceptions. While several of the same photo characteristic variable types (e.g., indoor and many) cause consumers in Asia to favor in the same direction, either negatively or positively, as consumers in the U.S., all but one (group) are less significant in terms of magnitude. Further, certain characteristic variables (such as outdoor and crowd) show no significance among Asian consumers at all, which sheds light on supporting our Hypothesis 2.

In a recent paper, Kwon et al. (2021) theorized that the heightened sense of isolation, or loneliness, brought on by COVID-19 evokes a need for social connection that increases the attractiveness of “not near” offerings. The authors then used lab experiments to provide support for their theorized process. Our Model 1 results are highly consistent with theirs, and offer empirical evidence of COVID-19’s impact on consumer behavior via a big data and analytics approach.

Regarding our Model 2 results, our empirical findings suggest that, in the United States, the feeling of anticipation in captions increases user interactions in terms of comments, supporting our Hypotheses 3a and 3b. In fact, not only does COVID-19 increase the efficacy of anticipation in social media messages, but it does so even as the usual, pre-COVID-19 effect of anticipation is significantly negative. Such a switch in the direction of influence indicates that anticipation is a driving force behind consumer preferences during this time, and that the feeling encourages consumers

to comment on and interact with a post. The emotion of surprise acting in an opposite way from anticipation further supports the idea that consumers, during COVID-19, gravitate toward hope and anticipation for the future, rather than their current state.

On the contrary, results from analyzing Asian accounts show that anticipation and surprise both lack significance for post captions. While they do not directly support our Hypotheses 4a and 4b, which predicts a smaller-degree impact, the no-impact results certainly provide evidence to support our key point that the COVID-19 pandemic's impact on the efficacy of companies' messages that appeal to the feeling of anticipation or surprise varies across cultures.

Conclusion

By evaluating the content of, as well as the number of likes and comments on, Instagram posts from companies in the United States and Asian countries, this article studies the impact of the COVID-19 pandemic on consumers' response to companies' communications messages. The theory of psychological reactance and the psychoevolutionary theory of emotion suggest that the limits on daily life and freedoms imposed on consumers due to COVID-19 restrictions might influence the types of messages that are favored. However, the theories also suggest the possibility of different responses from consumers in various cultures.

Our results for both U.S. and Asian Instagram accounts have confirmed Hypotheses 1 through 4 that, due to COVID-19-related lockdowns and restrictions on travel, work, and school, consumers experienced a state of reactance. This mental state contributed to the desire for consumers to reassert their freedoms, which was clearly reflected in U.S. consumers' adjustments in attitudes toward certain messages. Generally, consumers in Asian countries exhibited responses in the same direction, but to a much a weaker degree. These results not only document that the COVID-19 lockdown could substantially affect how consumers perceive and respond to companies' communications messages, but also suggest that the impact could be significantly different across different cultures. Overall, the COVID-19 pandemic is just one example of a current event that influences the way consumers perceive, favor, and interact with advertising and marketing messages. This study implies that a crucial aspect of marketing communications is to study how such consumer preferences can be influenced by the surrounding world. Maintaining agility and responsive marketing during current events can help companies stand out in the eyes and minds of the consumers on whom they so greatly depend.

Although our data supports the hypotheses, future replication of this study using other data sources is necessary

to assist in establishing the external generalizability of the results. The current event may have various impacts on the marketing messages from different industries (e.g., grocery vs. travel vs. luxury goods), so that it would also be interesting to dive into the data to examine the possibly heterogeneous effects across industries. In addition, this study only examines photo posts and ignores video posts. Future studies on video messages could extend its applicability.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1057/s41270-021-00138-3>.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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