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Essays on Marketing for Social Good

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ESSAYS ON MARKETING FOR SOCIAL GOOD

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the AYAN GHOSH DASTIDAR's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

ESSAYS ON MARKETING FOR SOCIAL GOOD

BY

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The two essays in this dissertation examine the role of Marketing in advancing social good. One of the essays focuses on behavioral outcomes in the context of a global health crisis while the other essay investigates the impact of residents' sentiments on the competitiveness of cities.

The first essay examines whether TV advertising can affect societal outcomes beyond traditional marketing outcomes (e.g., sales, demand). We investigate this in the context of social distancing behavior during the COVID-19 pandemic by analyzing daily advertising and mobility data across 204 Designated Market Areas in the US. By employing a border identification strategy that exploits discontinuities across television markets, we find a significant positive causal relationship between COVID-19 related brand advertising and social distancing while controlling for government policy interventions (e.g., shelter-in-place, mask mandates). The estimated effects are almost 11 times larger in counties without government policy interventions (compared to counties with policy interventions). We find the effects to be heterogeneous across several brand and demographic variables. However, the government ad effect is negative (positive) in counties with (without) policy interventions and in predominantly rural counties. The study's findings underscore the critical role that brand-sponsored TV ads can potentially play during major health crises, including mitigating the lack of policy interventions from local governments and people's reactance to government-sponsored communications.

The second essay investigates the relationship between city-related citizen sentiments and key drivers of a city's competitiveness, namely, the economic performance of a city and in-migration and visits to a city. Using a combination of in-depth interviews, topic modeling, text classification, and a Panel Vector Autoregression model we demonstrate the relationships between the sentiment of city-related Twitter conversations and the drivers of a city's competitiveness. Further, we use BERT to classify relevant Twitter conversations (88% accuracy) and the sentiment of these relevant conversations (best-in-class accuracy of 85%) for six major cities in the US. Finally, using Impulse Response Functions we show that citizen sentiments have a positive and significant effect on all three drivers of a city's competitiveness. The findings highlight the need for city managers to focus on the well-being of citizens.

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INTRODUCTION

Traditionally, the role of Marketing has been primarily explored as an avenue for achieving brand-level outcomes. However, the vast array of theories, concepts, and tools at the disposal of the Marketing discipline may also be used to positively influence societal outcomes. The potential of Marketing to be used for social good is being increasingly recognized by practitioners (e.g., Balch 2014; Rodríguez-Vilá and Bharadwaj 2017) as well as by academics (e.g., Chandy et al. 2021). Building on this new focus, the objective of this dissertation is to investigate the role of Marketing in positively influencing societal outcomes. Particularly, we focus on two marketing levers – advertising and social listening – as avenues for advancing social good.

In Essay I of this dissertation, we investigate whether TV advertising can affect societal outcomes beyond traditional marketing outcomes such as sales and demand. Of particular interest is people's adoption of socially beneficial behaviors aimed at mitigating the harmful effects of public health crises. As such, we conduct this study in the context of the COVID-19 pandemic which has had a catastrophic impact on public health and the economy (Cutler and Summers 2020). The role of social distancing in reducing the COVID-19 growth rate and the number of associated deaths have been firmly established (Andersen 2020; Courtemanche et al. 2020). However, there were varying degrees of compliance with such critical social distancing measures (e.g., Brzezinski et al. 2021; Dave et al. 2021; Painter and Qiu 2021). Additionally, COVID-19 related communications and policy interventions at the local (i.e., state and county) government level were inconsistent and often chaotic (Haug et al. 2020), further contributing to lower adoption of social distancing practices. Furthermore, there exists evidence of people exhibiting reactance to government messaging and regulations (e.g., Clee and Wicklund 1980; Grossman et al. 2020; Irmak, Murdock, and Kanuri

2020). Therefore, given the critical nature of the societal outcome (i.e., social distancing) and the challenges enumerated above, we investigate the role of TV advertising from brands that contain COVID-19 related narratives (not necessarily aimed at promoting social distancing) in influencing people's adoption of social distancing practices. We assemble longitudinal data from Nielsen, SafeGraph, and several other sources to analyze the causal relationship between COVID-19 related advertisements and the social distancing behavior of individuals while controlling for various fixed effects and other related factors. Specifically, we exploit sharp spatial discontinuities along television markets for exogenous variations in advertising, otherwise known as the "border identification" strategy (Shapiro 2018b) to estimate the advertising effects. We also explore the heterogeneity in the ad effects for government policy interventions and several brand and demographic variables.

The second essay investigates the relationship between city-related citizen sentiments and key drivers of a city's competitiveness, namely, the economic performance of a city and in-migration and visits to a city. Cities compete to attract residents, visitors, investments, and jobs (Darchen and Tremblay 2010; The World Bank 2015). A prosperous city is better equipped to invest in the well-being of its residents. The competitiveness of cities ultimately depends on the implementation of effective strategies by city authorities. The use of insights from citizens, especially insights obtained from a large number of citizens, has been limited in the formulation of such city-level strategies with the primary tool of data collection being surveys and interviews (Oguztimur and Akturan 2016). As such, the opinions and sentiments of citizens are not adequately accounted for in the decisions of city managers. This may result in several negative outcomes such as citizen dissatisfaction, inadequate actions to address the well-being of citizens, and the formulation of suboptimal strategies that may adversely affect the competitiveness of

cities. Therefore, we focus on social listening as an avenue for gathering insights from citizens and demonstrate the value of citizen sentiments for the growth and competitiveness of cities. We collect data from multiple sources including Twitter and Google Trends, and using a multi-method approach consisting of in-depth interviews, topic modeling, text classification, and a Panel Vector Autoregression model, we demonstrate the relationships between the sentiment of city-related Twitter conversations and the drivers of a city's competitiveness. We also propose and execute an efficient method of collecting and classifying large volumes of unstructured city-related conversations that may be beneficial to often resources constrained city authorities for gaining actionable insights from citizens.

We conclude both the essays with a discussion on wide-ranging implications for policymakers and managers as well as for academic literature.

ESSAY I: SOCIETAL SPILLOVERS OF TELEVISION ADVERTISING – SOCIAL DISTANCING DURING A PUBLIC HEALTH CRISIS

INTRODUCTION

The primary objective of brands when they advertise is to influence brand-related outcomes such as market share, awareness, sales, loyalty, firm value, and competition (e.g., Assmus, Farley, and Lehmann 1984; Ataman, Van Heerde, and Mela 2010; Köhler et al. 2017; Percy and Rossiter 1992; Sethuraman, Tellis, and Briesch 2011; Tellis 1988). However, the effect of advertising from brands can also spillover to influence non-marketing outcomes such as public health and social good – an aspect that has been the focus of recent works in economics and marketing. While the demand implications of advertising have been widely studied (e.g., Alpert, Lakdawalla, and Sood 2015; Sinkinson and Starc 2019), a limited number of studies have explored its impact on non-marketing (societal) outcomes (e.g., Kim and KC 2020; Shapiro 2021). We contribute to this emergent stream by focusing on the positive spillover effects of advertising from brands on societal outcomes during public health emergencies.

Our focus on societal spillovers of advertising is motivated by two factors. First, a large majority of consumers want brands to play a more active role in tackling societal problems. For example, a report by Ipsos (2013) found that 77% of the respondents believed that companies should "do more to contribute to society" while the Edelman Trust Barometer Special Report (2019) found that for 81% of the respondents, being able to trust a brand to "do the right thing" was the deciding factor in purchase decisions. Second, among marketing researchers, there is a growing focus on understanding how Marketing can be used to create a positive impact on society. For example, in the "Better Marketing for a Better World" special issue by the Journal of

Marketing, the editorial team urges researchers to judge the relevancy of problems marketing aims to solve "in the context of true life and death issues" and points out that the major challenge for businesses today is to "meet the societal needs of a changing environment" (Chandy et al. 2021a). Further, the need for research on topics related to social outcomes becomes particularly pronounced in the face of public health emergencies, and other crises wherein marketers may play an important role in influencing individual behaviors. Public health emergencies or crises are broadly defined as situations whose health consequences can potentially overwhelm routine capabilities needed to address these consequences (Nelson et al. 2007). Such situations include but are not limited to pandemics, epidemics, terrorist attacks, and both man-made and natural disasters (Lurie et al. 2013). In this research, we use a public health crisis related to an infectious disease, particularly the COVID-19 pandemic, as the empirical setting. During major health crises, governments and public authorities typically intervene with communication and/or policy measures and the success of these measures is largely contingent upon attitudinal and behavioral changes of the public at large (Mizrahi, Vigoda-Gadot, and Cohen 2021). Therefore, our research setting also allows us to understand the relative efficacy of TV advertising from brands in influencing attitudinal and behavioral changes compared to government-imposed policies and interventions. Further, the setting of our study is important beyond the current context as well given that occurrences of major epidemics and pandemics are becoming increasingly likely (e.g., Marani et al. 2021; Reuters 2021) and the initial response is crucial to mitigating the impact and spread of such health crises (e.g., Bump 2021; Lewis 2021).

In the United States, the toll of the COVID-19 pandemic has been catastrophic. By January 31st, 2022 the US had recorded around 76.3 million cases of infection and 912,193

deaths[1]. In addition to the colossal impact on public health, the pandemic has had wide-ranging effects on the economy with Cutler and Summers (2020) estimating that the economic impact of the pandemic in the US "far exceeds conventional recessions" to the tune of $16 trillion lost in economic productivity, health losses, etc. This significant impact on society with "life and death" consequences motivated our choice of using the COVID-19 pandemic as the study setting. During the early stages of the COVID-19 pandemic in the United States, the spread of the virus was rapid with no available vaccines. Local governments predominantly used non-pharmaceutical policy interventions such as mask mandates and stay-at-home orders to prevent the rise in infections. In particular, social distancing has been shown to have played an important role in reducing the COVID-19 growth rate and hence the number of deaths (Andersen 2020; Courtemanche et al. 2020; Kissler et al. 2020; Thunström et al. 2020). However, the associated communication and interventions at the local (i.e., state and county) government level were inconsistent and often chaotic (Haug et al. 2020). This, along with other factors such as people's belief in science (Brzezinski et al. 2021) and political beliefs (Painter and Qiu 2021), contributed to the varying degrees of compliance with critical social distancing norms required to contain the spread of COVID-19 across the United States (Courtemanche et al. 2020; Dave et al. 2021).

Firms, however, were nearly immediate in their (marketing) response. Even in the early days of the pandemic, brands had started incorporating COVID-19 related narratives in their TV advertisements (as early as 27th February 2020). Some of these advertisements directly or indirectly promoted social distancing measures such as Burger King's "*Stay Home of the Whopper*" ad campaign and "*Contactless Delivery*" ads from Domino's which urged people to

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[1] https://www.worldometers.info/coronavirus/country/us/

order food through their contactless delivery service. There were also several other COVID-19 related advertisements that did not explicitly promote social distancing measures. Examples include McDonald's "*Most Important Meals*" ad which talked about feeding first responders for free, Kraft Heinz's "*We Got You America*" ad which focused on making their products available to people in difficult times, and NBA's "*Staying healthy takes teamwork*" ad which asked people to wash hands with soap regularly. In fact, certain brands adopted narratives that could be perceived as promoting behaviors contrary to social distancing (e.g., BMW's "*Rejoin the road*" ad and Infiniti's "*Back into the world*" ad, first aired on 12th and 15th May 2020 respectively). In summary, there was a wide variety in the COVID-19 related narratives that were adopted by brands with the narratives not necessarily aimed at promoting social distancing. While COVID-19 related advertisements seemed to garner more attention (Lumen Research 2021) and brands seemed to enjoy a public perception of being more 'reactive' to the pandemic (Edelman Trust Barometer 2020), it is unclear how – if at all – such advertising led to socially beneficial outcomes. This paper takes the first step toward understanding and documenting the role of advertising from brands in influencing socially beneficial behaviors in the context of a global public health crisis, even if it were unintended. Specifically, we ask: (1) Can TV advertisements that include COVID-19 related narratives influence societal outcomes such as social distancing? If so, does the source (government vs. private brands) matter? (2) Does the effect vary depending on the presence or absence of public policy interventions (such as stay-at-home mandates)? In other words, can brands "fill the void" in the absence of government policy interventions? (3) What are the potential mechanisms that may be driving this effect?

To address these questions, we assemble longitudinal data from multiple sources and analyze the causal relationship between COVID-19 related advertisements and the social

distancing behavior of individuals while controlling for various fixed effects and other related factors. We exploit sharp spatial discontinuities along television markets for exogenous variations in advertising, otherwise known as the “border identification” strategy (Shapiro 2018b) to estimate the advertising effects. We find that exposure to COVID-19 related advertisements from brands significantly affected aggregate social distancing behavior (operationalized as the percentage of mobile devices staying completely at home) in a region. However, the effect is moderated by local-level government interventions. More specifically, in the presence of government interventions, a 10% increase in the percentage of COVID-19 related ad Gross Rating Points (from brands) from the mean leads to a 0.74% increase in aggregate social distancing behavior in the region. However, the impact on social distancing increases by almost 11-fold (i.e., 8.32%) in the absence of local government interventions thereby offering empirical evidence of the extent to which brand advertising can offset/mitigate lapses in local government policies during a public health crisis. We also find that the source of advertising matters. Overall, brand advertising has a positive and significant effect on social distancing while government ads do not. Interestingly, government ads have a positive and significant effect on social distancing behavior in the absence of government policy interventions and a negative and significant effect in the presence of these interventions. We propose and empirically test potential mechanisms through which the effects may be explained. Specifically, we focus on the role of salience underlying the effectiveness of brand ads. Lastly, we also find heterogeneous advertising effects based on various brand, category, and demographic variables. For instance, the results indicate that the effect of advertising on social distancing behavior is amplified among more educated populations but attenuated for more conservative counties which tend to be white. Overall, our findings bear substantive implications for the power of brand advertisements to

affect important societal outcomes and for government communication strategies. We discuss the implications of our findings for other public health emergencies (e.g., climate change) as well.

THEORETICAL BACKGROUND

Extant research on advertising can be broadly classified based on whether the outcome of interest is brand-related (e.g., sales, demand, vote share, awareness) or societal (e.g., drunk driving, birth rate, work absenteeism) and whether the advertising effect on the outcome is a primary effect or a spillover. Figure 1 lists representative studies based on this broad classification of extant research.

-- Insert Figure 1 about here --

A majority of studies from extant research are related to analyzing the primary impact of advertising on brand-related outcomes (e.g., Aaker and Biel 2013; Lodish et al. 1995; Meenaghan 1995; Shapiro, Hitsch, and Tuchman 2021). Fewer studies in comparison have investigated the impact of advertising on social-behavioral outcomes, with mixed results. For example, some researchers find significant effects of TV advertising on smoking cessation (Emery et al. 2012) and drunk driving (Niederdeppe, Avery, and Miller 2017) while others find modest (Atkin 1990) to non-significant effects (Levy, Compton, and Dienstfrey 2004; Wakefield, Loken, and Hornik 2010). Additionally, a growing stream of research has focused on studying the ‘spillovers’ of advertising on brand-related outcomes (e.g. Danaher, Bonfrer, and Dhar 2008; Fossen, Mallapragada, and De 2021; Shapiro 2018b). Particularly, ad effects that influence other outcomes not related to the focal brand are referred to as spillover effects. Our research aims to investigate the spillover effects of TV advertising that could potentially contribute to a societal outcome. This area of research is represented by the bottom-right cell of

Figure 1. A scan of literature in this domain indicates only a handful of empirical studies. This includes the work of Kim and KC (2020) and Shapiro (2022). Using antidepressant drug advertising as context, Shapiro (2022) finds that the impact of direct-to-consumer ads on new prescription behavior is positive and can lead to reductions in workplace absenteeism. Kim and KC (2020) study the impact of erectile dysfunction (ED) drug advertising on birth rates and find that ED drug advertising led to a significant increase in birth rates in the United States.

We contribute to this emerging stream of research by investigating whether and to what extent TV advertising from brands positively affected an important antecedent of a public health outcome during a global pandemic, namely social distancing behavior. Furthermore, our research takes place in the context of a major public health emergency where government-led policy interventions are expected to play a role. Consequently, unlike prior studies in this domain, our context allows us to estimate the effect of TV advertising while accounting for heterogeneous policy interventions from the local governments that were often inconsistent and uncoordinated. Our work is uniquely different from studies in this stream of literature in at least two important ways. First, to the best of our knowledge, ours is the first study that examines the socially beneficial spillover effects of advertising in the context of a global public health crisis. Second, we demonstrate the critical role that brands can play during an emergency when government policy interventions are absent or inadequate i.e., we show that advertising from brands can help mitigate (to some extent) lapses in policy measures from local governments in dealing with emergencies.

Our study also contributes to the fast-growing and critical body of literature related to compliance to social distancing practices in response to the COVID-19 pandemic. Studies have identified several factors such as access to the internet (Chiou and Tucker 2020), viewership of

conservative news programming (Simonov et al. 2021), belief in science (Brzezinski et al. 2021), economic status (Wright et al. 2020), and political ideology (Barrios and Hochberg 2020; Painter and Qiu 2021) influencing people's social distancing behavior. However, extant research has not investigated the role of brand advertising – in the context of social distancing. To the best of our knowledge, this is the first study that looks at social distancing with a marketing lens and causally establishes COVID-19 related advertising from brands as another factor that influences people's social distancing behavior.

The remainder of this article is organized as follows: First, we discuss in detail the data sources used in our analyses and provide descriptive evidence to motivate further empirical investigations of our research questions. This is followed by a discussion of our empirical approach and identification strategy. Next, we discuss our findings, robustness analyses, potential mechanisms underlying the effects, and heterogeneity analyses. We conclude with a summary of our findings and discuss implications, limitations, and future research opportunities.

DATA

Given our objectives, we obtain data from multiple sources and choose an observation period of January 1 to May 31, 2020, for our analyses. This timeframe represents the onset of the pandemic and a time when some brands started broadcasting COVID-19 related ads. It also represents the period when there was considerable confusion and inconsistency in terms of policy-related mandates from local governments, thereby offering rich variance in the data for empirical analyses. The relevant data is not available in a single publicly accessible dataset. Therefore, we collect and assemble a dataset from eleven different sources as summarized in Table 1. A detailed description follows.

--- Insert Table 1 about here ---

Social Distancing Behavior

Social distancing data was obtained from *SafeGraph*, a data company that aggregates anonymized location data from numerous applications to provide insights about physical places. We use the *Social Distancing Metrics v2.1* dataset which is built using a daily panel of GPS pings from around 45 million anonymous mobile devices. The default option on the tracked mobile phones is 'opt-in' with an option for manual opt-out. The panel of devices in the data are geographically and demographically representative, and the correlation between the panel's and the US Census's population density at the county level is 97% (Brzezinski et al. 2021). SafeGraph determines the common nighttime location (i.e., home location) of each mobile device over a 6-week period to a 'home area' of approximately 153m x ~153m. Each device in the dataset has a specific home location area. When the data is made available to researchers (such as in our case), SafeGraph aggregates the home location for each device at the Census Block Group[2] (CBG) level. For sparsely populated CBGs, *SafeGraph* adds a Laplacian Noise[3] to variables representing device counts, and all CBGs with fewer than five devices are omitted. Some mobile phones may get dropped from the sample if location tracking apps are deleted, or the phone is permanently switched off. In our data, we observe 18.83 million devices daily across the US (approximately 5,848.3 devices in a county). We additionally collect the data for the corresponding period in the year 2019 for de-seasonalizing the data.

We consider people's tendency to stay at home as an indicator of their social distancing behavior (e.g., Brzezinski et al. 2021; Grossman et al. 2020; Painter and Qiu 2021; Weill et al.

[2] A Census Block Group is designed to contain around 600-3,000 people (Link).
[3] https://docs.safegraph.com/docs/social-distancing-metrics

2020; Yan et al. 2021). This choice is based on the rationale that when people stay at home (either completely or for an increased amount of time) they automatically come in lesser contact with other people and thus are more socially distant. Prior research has validated SafeGraph's mobility data in the following ways:

Validation with consumer data. Extant studies have validated the extent to which SafeGraph data can help explain social distancing by correlating it with available consumer data. For example, Kang et al. (2020) assess the mobility data from SafeGraph with the American Community Survey (ACS) commuting flow data and report a high correlation (Pearson's r greater than 0.93). In another study, Kupfer et al. (2021) find that the SafeGraph mobility data is significantly correlated (R-square greater than 0.8) with the monthly visitation numbers at six national parks in the western U.S. in 2019 and 2020. Similarly, Parolin and Lee (2021) infer school closures and distance learning estimates based on SafeGraph's social distancing data and verify the results with five validation checks employing observed real-world data. Koren and Pető (2020) use the SafeGraph data during the COVID-19 pandemic to understand business disruption from social distancing. They find that the social distancing implied from the SafeGraph data is consistent with the reduced number of customer visits and employment assessed from the American Time Use Survey data. Also, Jay et al. (2020) find that the social distancing implied by the SafeGraph data align with Gallup Survey data on physical distancing practices.

Comparison with other sources of mobility data. Huang et al. (2022) find that the mobility of individuals captured by geotagged Twitter data in 2019 correlates strongly with the mobility of individuals documented by SafeGraph (Pearson's r=0.86). Other studies have found that the mobility trend of SafeGraph data is consistent with the Descartes Labs' COVID-19

mobility dataset (Kang et al. 2020) and the Google COVID-19 Community Mobility Reports workplace data (Jay et al. 2020; Weill et al. 2020).

Some of the other major studies in this domain have relied upon and trusted the face validity and reliability of SafeGraph measures like the *number of devices staying completely at home* and *median dwell time of devices at home*. For example, Painter and Qiu (2021) state that "…*higher percentage of % Completely at Home indicates more residents in the area are complying with the social distancing order*". Further, Simonov et al. (2021) justify using SafeGraph's stay-at-home variables as measures of social distancing behavior by relying on the CDC's recommendations about social distancing (e.g., do not gather in groups, stay out of crowded places, avoid mass gatherings) and on the fact that numerous government agencies (local, state, and federal) issued stay-at-home and shelter-in-pace orders and advisories to ensure compliance with social distancing practices.

Panel A and B in Figure 2 plot the temporal variation in the social distancing across the counties. Panel A reports the daily proportion of devices staying completely at home, while Panel B reports the median home dwell time (in minutes) for a county on a given day. The grey lines describe the completely stay-at-home behavior for each county in the data, and the (thick) purple lines denote the mean completely stay-at-home behavior. A few patterns are noteworthy. We see that the general trend in panels A and B are remarkably similar, suggesting that these two variables may be capturing the same behavior – social distancing. There is a notable increase in completely stay-at-home behavior after March 13, 2020, when the federal government declared a national emergency for COVID-19. Further, there is significant variation across counties. Some counties display higher completely stay-at-home behavior (perhaps due to increases in COVID-19 cases or stay-at-home policies), while others are at lower levels. We also see from Panel A in

Figure 2 that there seem to be day-level peaks and troughs in completely stay-at-home behavior. Since our subsequent analysis is at the day level, we also account for these differences.

We alternatively specify social distancing as people's out-of-home travel behavior, specifically travel to points of interest (POIs) such as grocery stores, restaurants, etc. We use SafeGraph's *Patterns* dataset to obtain the *daily number of visits* to various POIs. This data is created by SafeGraph using a process similar to that of the *Social Distancing Metrics v2.1* dataset. In Figure 2 Panel C, we plot the number of visits to different points of interest at the county level. We see that there was a significant decrease in footfalls during mid-March when a national emergency was declared for the COVID-19 pandemic. From Panel A-C in Figure 2, it is evident that there was a clear behavioral response (in terms of social distancing) to the pandemic.

--- Insert Figure 2 about here---

From a measurement standpoint in our main analyses, we operationalize social distancing as people's completely stay-at-home behavior (SD_{ct}) and calculate it as the percentage of mobile devices staying completely at home on a given day in a county. Our measure (complete-stay-at-home behavior) is a conservative measure of social distancing because it only considers devices that completely stayed at home[4] on a day. To account for seasonality (e.g., holidays, seasons), we focus on the difference between completely stay-at-home behavior on a given day in our observation window (SD_{ct}^{2020}) and its corresponding date in the year 2019 (SD_{ct}^{2019}). SD_{ct}^{2019} can be thought of as a base period against which social distancing behavior is being compared. As such, we define our dependent variable (ΔSD_{ct}) as follows,

[4] In the robustness section, we replicate our findings using alternative measures as well. Specifically, we demonstrate robustness of the results using the median home dwell time (from the SafeGraph Social Distancing Metrics v2.1 data) as well as the number of visits to points of interest (from the SafeGraph Patterns data).

$$\Delta SD_{ct} = SD_{ct}^{2020} - SD_{ct}^{2019} \tag{1}$$

Television Advertising

We obtain DMA level data for every spot TV advertisement from Nielsen's Ad Intel database for the period starting 1st January to 31st May 2020[5]. The data includes advertising occurrences across the United States which is segmented into 210 Designated Market Areas (DMAs). Specifically, for each advertisement, we observe the day and time of ad occurrence, number of exposures (units), expenditures (in dollars), gross rating points (GRPs), the genre of program, the brand name, and the product category. GRP is a measure of advertisement intensity and is computed as a percentage of per capita impressions. One could also measure advertising intensity using the frequency of ad exposures (units), and ad spend (expenditure), but both of these measures suffer from certain drawbacks. For example, ad frequency fails to account for the reach of individual ads that may vary by the time of day or type of program it was shown on. Similarly, ad spending may differ by DMAs since the cost of purchasing ads varies by media market. Therefore, consistent with the prior literature (Tuchman 2019; Wang, Lewis, and Schweidel 2018) we use GRPs as our measure of advertising intensity. The data also includes an indicator to identify whether an advertisement was related to the COVID-19 pandemic. Nielsen created this indicator by identifying the presence of keywords like *Coronavirus, crisis, pandemic, social distancing, self-quarantine, we're all in this together, hard times, tough times, keep you safe, stay inside, our company is changing* in advertisements. They also identified ads

[5] We do not include advertisements that are purchased nationally (cable, network, and syndicated) because such ads are seen by everyone in the country who tune into a particular channel while locally purchased ads (Spot) are seen only by households in a specific DMA (Shapiro 2018a; b). As a result, the variation in advertisement intensity across DMAs is driven primarily by locally purchased advertisements i.e., by Spot advertisements. Therefore, given the purpose of our research of identifying causal influences of ads on social distancing at the county level, it is sufficient to consider only Spot advertisements.

where people were wearing face masks as COVID-19 related during this period. To verify the coding scheme used by Nielsen, we conducted our own (manual) analysis to verify the classification scheme. We randomly chose[6] 500 advertisements from our data and manually searched for the videos of the chosen advertisements to classify them into COVID-related vs. non-COVID-related. Specifically, we asked two raters to find and watch each advertisement (e.g., YouTube, iSpot.TV) and classify the ad based on the content. We stripped out any information regarding Nielsen's classification schema so that the rater would not be biased. A point to note here is that we had very little information with which to link the ads in our data to the actual videos of the ads. Namely, we only had the brand name and a very short description[7] of the ads. Thus, our raters were able to identify the videos of only 104 ads out of the 500 ads with a high degree of confidence. Table 2 presents the results of the classification exercise.

--Insert Tables 2 and 3 about here--

As we see from Table 2, the two classification approaches are highly congruent with one another. The raters' classification was in agreement with Nielsen's across 93.88% of the COVID-19 related advertisements and 96.36% of the non-COVID ads. This additional analysis provides more support for the use of Nielsen's classification schema in the model. In Table 3 we provide examples of COVID-19 related ads from Nielsen's dataset whose videos/content we manually identified.

Panel D in Figure 2 shows the temporal variation in COVID-19 related ads (GRPs) that were aired across counties in the United States. We observe that as the pandemic raged through the country, brands had modified their advertising to include messaging about the COVID-19

[6] We used disproportionate stratified random sampling to include more COVID-19 related ads in our sample.
[7] Example: "People in Restaurants/Food", "Vehicle Driven on Bridge"

pandemic. We operationalize our primary covariate of interest, COVID-19 related advertising intensity for a given county (c) on day (t) as the percentage of COVID-19 related advertising GRPs relative to overall advertising GRPs in the same county and day[8] ($\%COVIDAds_{ct}$). In a robustness analysis, we use alternative measures of advertising intensity (e.g., actual GRPs of COVID-19 related ads).

Additional Data Sources

We obtain county-level mask mandate and stay-at-home policy types (e.g., advisories, restrictions) and implementation dates across the United States from the Centers for Disease Control and Prevention (CDC) for our period of observation. These policies or interventions from local governments (e.g., state, county) varied from mere advisories and recommendations to stringent mandatory stay-at-home orders. The information was available for 3,142 counties, out of which approximately 1,696 (53.98%), 820 (26.1%), and 350 (11.14%) counties had no policies in place as of 25th March, 1st April, and 10th April 2020 respectively. Further, as of 1st April, 39.4% (1,238) of the counties did not have a government-imposed mandatory stay-at-home order in place. We also collect data on the daily number of COVID-19 infections for each county for our period of interest from The New York Times. Additionally, we obtain county-level education, race, gender, and income data from the U.S. Census Bureau and poverty and unemployment data from the U.S. Bureau of Labor Statistics. To identify bordering counties (used in our identification strategy) and to measure the distance between counties (used for robustness analyses), we use the county adjacency and county distance databases, respectively from the National Bureau of Economic Research (NBER). Finally, we collect data on county-

[8] The operationalization of this variable varies by source (brands, and government).

level vote shares in the 2020 United States Presidential election from Harvard Dataverse and pandemic-related keyword daily search interest data from Google Trends.

METHODOLOGY

The identification of advertising effects can be challenging due to endogeneity issues arising from strategic decision-making on the firm's side. For instance, the firm may target specific regions based on past sales or specific demographic/regional profiles that may lead to selection and reverse causality concerns. We address these concerns in the following section.

Empirical Strategy

We exploit the variation arising from how TV advertisement purchasing and media markets are set up. Specifically, there exist sharp discontinuities in the level of advertising at the borders of local advertising markets that create exogenous variation. The usefulness of such market-level discontinuities (or "border strategies") has been documented in the literature. For instance, the border identification strategy has been employed to study advertising effects in health insurance and pharmaceutical contexts (Shapiro 2018a; b), e-cigarettes (Tuchman 2019), as well as in political advertising (Huber and Arceneaux 2007; Spenkuch and Toniatti 2018; Wang, Lewis, and Schweidel 2018). The border identification strategy is essentially a special case of a regression discontinuity approach that leverages exogenous variation just above and below a cutoff. The cutoffs, in our context, are spatial in nature. That is, geographic borders of local advertising markets act as sharp cutoffs and create plausible exogenous variation in advertising for individuals living very close to the market boundary.

In our context, the local advertising market indicator is a Designated Market Area or DMA. A DMA is defined as a geographical area of grouped counties in which local television

viewing is measured by Nielsen. A DMA may include urban centers and suburbs, as well as surrounding counties where small towns and rural homes receive the same television signals. Local advertising spots are sold at the DMA level, so all households in a specific DMA see the same TV ads. Additionally, households on opposite sides of a DMA border may be exposed to different advertising levels due to regional variations in advertising. The effect of COVID-19 related ads on social distancing behavior is then identified by comparing the social distancing behavior (identified through pings from mobile devices) on each side of the DMA border. The identifying assumption is that the border counties are subject to the same unobserved shocks such that adjacent counties on each side of a DMA border may act as counterfactuals to one another. Consequently, in the absence of advertising, mobility patterns in both sets of counties should follow the same trend. This allows us to think about the DMA border counties as natural "experiments" consisting of two treatment groups where the variation comes from differences in advertising (treatment) levels after controlling for a host of observed and unobserved factors at the DMA, border, county, and time levels (Shapiro 2018b).

The unit of our analysis is at the border-county-day level because it is the level at which we observe both the advertising information (available at the DMA level) as well as the mobility data (available at the CBG level) without having missing or sparse data points. Out of the 210 DMAs into which the United States is divided, Nielsen categorizes 130 DMAs as 'full discovery markets' as all television advertisements in these markets are measured using monitoring devices. For the remaining markets, Nielsen reports only those advertisements that match ads airing in the full discovery markets or on National TV. Therefore, to avoid biases in our results occurring due to measurement errors (e.g., incomplete or inaccurate data on advertisements), we perform our analysis using the top 100 ranked DMAs. Our final data includes 99 DMA markets

spanning 894 counties in the United States (Honolulu is one of the top 100 DMAs but does not share any borders with other DMAs and hence is not part of the analysis). We identify 159 DMA-border county pairs (a DMA-border county pair consists of two *sets* of border counties on opposite sides of a DMA border) or 318 border county sets that serve as natural experiments to assess the advertising effect. Figure 3 provides an illustration of the border identification strategy and the construction of border county pairs for three sets of adjacent DMAs. Panel A plots the border counties for two DMAs – Boston, MA, and Portland-Auburn, ME. There are a total of 3 counties (county # 10, 14, and 15 labeled in Figure 3: Panel A) in Boston (shaded in red) that are adjacent to 2 counties (county # 25 and 26 labeled in Figure 3: Panel A) in the Portland-Auburn DMA (shaded in green), thus making them border counties of a DMA pair. By comparing the difference in mobility patterns between the border counties on each side of the DMA borders, we can estimate the causal effect of COVID-19 related ads on social distancing behavior. In Panel B, we provide more examples of border counties for two other DMAs – Lexington/Louisville and Atlanta/Chattanooga. Similar to Panel A, the border counties are shaded in red and green.

--Insert Figure 3 and Table 4 about here–

The border identification strategy relies on the fact that there is variation in COVID-19 related advertising intensity across border counties. To illustrate the variation, the top panel (A) of Figure 4 plots the COVID-19 related advertising for the border counties across two DMAs – Boston and Portland-Auburn. Panel A in Figure 4 shows that in a single day, households in one DMA may see more COVID-19 related ads than their neighbors in another DMA. For the 159 borders (318 border-county pairs), we check for the variation in advertising intensity in markets across borders by calculating the absolute differences in the GRP of COVID-19 related ads between DMAs for each of the 24,168 border-day observations. In 59.96% of these border-day

observations, the difference in advertising intensity in the markets on either side of a border was non-zero (see Table 4). The average absolute difference in daily COVID-19 related Ad GRPs (aggregated across all brands and ad exposures) across DMA borders was 68.33, indicating that there is indeed a spatial discontinuity in COVID-19 related advertising intensity. Further, the mean coefficient of variation (standard deviation of daily COVID-19 related ad GRPs divided by the mean) of 1.2 (see Table 4) shows that there is significant within DMA variation as well, which is also demonstrated in Panel A of Figure 4.

An identifying assumption is that people in border counties on both sides of the border would behave similarly on average and follow the same trend in mobility in the absence of COVID-19 related advertising. To visualize whether this common trend assumption holds, panel B in Figure 4 plots the stay-at-home behavior for the border counties for Boston and Portland-Auburn DMAs prior to and post the first known airing of COVID-19 related advertising in both markets. As we can see, the border counties follow the same 'common' mobility trends in the absence of COVID-19 related Ads airing before the airing of COVID-19 related advertising. However, post airing of COVID-19 related ads the stay-at-home behavior gradually starts varying in magnitude for the two DMAs. Additionally, we compare mobility trends (completely stay-at-home and median dwell time at home) across all border counties in our sample prior to 1st March 2020 (when COVID-19 related ads were either absent or negligible). We observe no statistically significant difference in the mobility trends between border counties in this period, further supporting the common trend assumption (see Table 5). In the subsequent empirical analyses, we evaluate whether (and to what extent) such differences in social distancing may be attributed to differences in TV advertising across border counties.

--Insert Table 5 and Figure 4 about here–

To further rule out observable differences between border counties (our identifying assumption requires border counties to be similar), we compare them across a series of socio-demographic variables and voting patterns (see Table 5). For population, race, household income, unemployment, poverty, education level, and % of Republican voters (2020 presidential elections), we find no significant difference between the sets of border counties.

Model

Our main model uses a linear specification to estimate the impact of COVID-19 related advertising on stay-at-home behavior. As mentioned earlier, the level of analysis is at the market-border county-day level resulting in 166,371 observations. Indexing c as counties, b as the border market combination, and t as time (in days), we specify the following,

$$\begin{aligned} \Delta SD_{bct} = \beta_1 COVIDAds_{bct}^{(Brand)} + \beta_2 COVIDAds_{bct}^{(Govt)} + \alpha_b + \alpha_c + \alpha_t \\ + \alpha_b \times month_t + \Theta_1 Policy_{ct} + \Theta_2 Daily\ Cases_{ct-1} + \epsilon_{bct} \end{aligned} \tag{2}$$

The main parameters of interest are β_1 and β_2 which captures the effect of COVID-19 related advertisements on social distancing behavior from brands and government respectively[9]. To identify β_1 and β_2, we supplement the border strategy with a rich specification of fixed effects to control for unobservables. α_b and α_c are border and county fixed effects that control for time-invariant unobservables and systematic differences across border markets and counties, respectively. Recall that, ΔSD_{ct} is already de-seasonalized such that we are only concerned with deviation in completely stay-at-home behavior between days in 2020 and the corresponding days in 2019. As such, the average social distancing behavior for each county is already absorbed in

[9] In our main specification, we use the percentage of COVID-19 related ad GRP ($\%COVIDAds_{ct}$). However, in the robustness analyses, we also estimated the model using an alternative measure – GRP of COVID-19 related ads. The results, reported in Table 6, remain consistent.

the dependent variable. Nevertheless, there may be systematic patterns in the differences. For instance, Lincoln County, OK (which is part of the Oklahoma City DMA) has a lower ΔSD_{ct} than Butts County, GA (which is part of the Atlanta DMA). The inclusion of county-level fixed effects would then account for these differences. Similarly, systematic differences at the border-market level (Boston/Portland-Auburn DMAs vs. Atlanta/Macon DMAs) are accounted for through the border fixed effects[10]. Given the short timeline of the data (~ 5 months), concerns regarding systematic temporal differences at the county/border-market level are not likely to be serious. Nevertheless, we include fixed effects at the day level (α_t) to address any systematic temporal factors that may be correlated with overall social distancing behavior. To account for common temporal trends at the border level, we include border–month fixed effects ($\alpha_b \times month_t$).

Lastly, we include a set of controls at the county level that may be correlated with ΔSD_{bct} as well as advertising. Notably, during the timeline of our data, there were multiple public policy interventions both at the national as well as state and county levels. These interventions typically included stay-at-home orders of various levels of stringency (advisories, stay-at-home mandates, shutdowns, etc.) and mask mandates. Policy changes at the national level are not of great concern to the focal analysis because they would affect both counties in the border experiment equally and be subsumed within α_t. County-level policy (imposed by state or local governments) differences, however, may confound the advertising effect if unaccounted for in the model. Therefore, we obtain data on county-level interventions by local governments from the CDC and include an indicator variable $Policy_{ct}$ that takes the value of 1 if the county c was under a

[10] We do not include market level fixed effects because these are subsumed within the county and border fixed effects. Any market level fixed effects are absorbed within α_c and market-border fixed effects are absorbed within α_b.

policy intervention and a value of 0 otherwise[11]. Similarly, we also control for the lagged number of COVID-19 cases ($Daily\ Cases_{ct-1}$) at the county-day level to account for county-level differences in infection spread that may be correlated with social distancing behavior. We take a one-day lag of the daily number of COVID-19 cases because the complete information on the total number of infections is generally available only towards the end of that particular day. To summarize, we have 159 DMA-border county natural experiments comprising 894 counties spanning 99 DMAs across the US. Our primary model is a linear specification of completely stay-at-home behavior at the border-county-day level and the main parameters of interest are β_1 and β_2 which capture the causal effect of COVID-19 related ads conditional on a host of county, border, and time fixed effects, as well as county-level time-varying variables (such as policy and infection spread). In the following section, we report and discuss the estimation results.

RESULTS

Effect of COVID-19 Related Ads on Social Distancing

To see if there is a relationship between social distancing behavior and COVID-19 related advertisements, Figure 5 plots stay-at-home behavior against COVID-19 related advertising intensity. As we see in the figure, there is a positive correlation between ΔSD_{ct} and COVID-19 related ad GRP offering suggestive evidence of the primary relationship. However, this does not imply a causal relationship which is the purpose of the estimation that follows.

--- Insert Figure 5 about here ---

[11] $Policy_{ct}$ includes all public policy interventions including non-pharmaceutical interventions such as mask mandates and stay-at-home advisories and orders, imposed at the county or state levels in response to the COVID-19 pandemic (Haug et al. 2020).

Table 6 reports the main estimation results as well as multiple robustness checks. Model 1 describes the main results in which the dependent variable (social distancing) is measured as the percentage of devices that stayed at the home location completely. The main independent variable in Model 1, COVID-19 related advertising, is measured as the percentage of COVID-19 related ad GRPs out of all ad GRPs aired in a day. The estimation points to an interesting pattern in the effects of brand and government-sponsored COVID-19 advertising. We see a significant positive effect (β = .031; $p < 0.001$) of COVID-19 related ads from brands on people's completely stay-at-home behavior with the effect being relatively stronger than the effect of all COVID-19 related ads (i.e., not split by source) in Model 2. Since the covariate and the dependent variable are percentages, we can interpret the effect sizes as percentage point (pp) changes. We find that a 1pp increase in COVID-19 related advertising GRP in a day leads to a 0.03 pp increase in social distancing behavior. Interestingly, we do not see any significant effect of government-sponsored COVID-19 related ads on social distancing (see Model 1 in Table 6). Taken together, the results point to an interesting phenomenon in the spillover effects of advertising on social distancing. Brands that reacted to the COVID-19 pandemic and adjusted their narratives seemed to have a positive impact on socially beneficial behaviors, even though the effect may have been unintended. Government advertisements, on the other hand, do not appear to be significantly influencing social distancing behaviors, even though changing such behaviors is likely to have been the explicit intent of the ads. In addition to analyzing the brand ad effects more elaborately, we also investigate the non-significant effect of government advertising in the following sections.

--- Insert Table 6 about here ---

Robustness Analyses

Alternative DV operationalizations. Our primary dependent variable, which captures the percentage of devices completely at home (ΔSD_{ct}), is a plausibly strict measure of social distancing behavior that may not account for other forms of less stringent but important social distancing behaviors such as the amount of time spent inside vs outdoors. To verify that the results continue to be robust to alternative measures of the dependent variable, we conduct two sets of analyses. First, given that reduction in time spent outside the home even when someone is not staying *completely* inside (e.g., for procuring essential items) could be beneficial in stemming the spread of infections, we re-estimate Equation 2 using median dwell time at home ($\Delta SDTime_{ct}$) as an alternate operationalization of the stay-at-home specification of social distancing behavior in Model 4 in Table 6. The results are consistent with our main findings i.e., COVID-19 related advertising from brands leads to an increase in the time spent at home while the effect is nonsignificant for government-sponsored COVID-19 ads (see Model 3 in Table 6 for the effect of COVID-19 related advertising not split by source). Hence, our results are robust to alternative operationalizations of social distancing specified as stay-at-home behavior.

Our second alternative measure of social distancing describes an individual's visit patterns to various points of interest within a county. Stay-at-home behavior, although widely accepted as a valid measure of COVID-19 induced social distancing (Brzezinski et al. 2021; Painter and Qiu 2021; Simonov et al. 2021; Yan et al. 2021), can potentially subsume other influences[12] such as those from school closures, unemployment, etc. Therefore, another approach for measuring social distancing could be to operationalize it as people’s out-of-home travel

[12] However, as explained in the ‘Empirical Strategy’ section, our identification strategy allows us to account for such influences in our model.

behavior i.e., travel to points of interest (POI) such as grocery stores, gas stations, restaurants, etc. We use SafeGraph's *Patterns* dataset to obtain the daily number of visits to individual POIs, which we aggregate at the county level. Similar to our other dependent variable operationalizations, we deseasonalize the daily number of visits to a POI ($\Delta SD\_POI\_Visit_{ct}$) and present the estimation results in Model 5 of Table 6. Here too, we see that COVID-19 related ads from brands significantly increase social distancing behavior i.e., for a 1 pp increase in COVID-19 related ads from brands there are 86.74 (p =.025) fewer visits on a day to a POI in 2020 as compared to 2019 on average. The effect of COVID-19 related ads from government agencies on social distancing behavior remains non-significant with this specification of the dependant variable as well.

Alternative IV operationalizations. We re-estimate the main model (i.e., Equation 2) with two alternative specifications of the independent variable. First, we use actual GRPs (instead of percentages) of the COVID-19 and non-COVID-19 related ads. Consistent with the main results, we find a positive and significant effect of COVID-19 related ads from brands on people's completely stay-at-home behavior. The results are reported in Model 6 in Table 6. We also estimate an advertising stock model where the advertising stock is a geometrically distributed lag of advertising. We replace the variable $COVIDAds_{ct}^{(Brand)}$ in Equation 2 with advertising stock, $COVIDAdStock_{ct}$ defined as:

$$COVIDAdStock_{ct} = \sum_{\tau=t-L}^{t} \lambda^{t-\tau} COVIDAds_{ct}^{(Brand)} \tag{3}$$

where λ is the advertising carryover parameter, t and c denote a unit of time (day) and county respectively, and L indicates the number of past periods (lags) from which advertisements

impact current social distancing behavior. $COVIDAds_{ct}^{(Brand)}$ represents the GRPs of the COVID-19 related ads from brands. This specification of the independent variable allows us to capture the carryover effects of past COVID-19 related ads on people's social distancing behavior. Given our relatively short window of observations, we choose a lag of 30 days. We estimate the value of the decay (or carryover) parameter, λ, using 3 different approaches: non-linear least squares, grid search[13] (Shapiro, Hitsch, and Tuchman 2021), and Koyck transformation (Franses and van Oest 2007). Consistent with our original specification of the independent variable, we find the effect of the Adstock variable on people's completely stay-at-home behavior to be positive and significant for all the 3 approaches: non-linear least squares (.00024; p<.05), grid search (.00049; p=.018), and Koyck (.00096; p=.002). There were some differences in the estimated carryover parameters across the three estimation methods. Non-linear least squares yielded the highest carryover effect (λ=.72), while the Koyck estimation yielded the lowest (λ=.38). We present the results for the non-linear least-squares, grid search, and Koyck transformation approaches in Models 7, 8, and 9 of Table 6, respectively. Figure 6 visually depicts the dynamic nature of the advertising effects. Each line in the figure denotes the impact of a 1pp increase in COVID-19 related advertising on social distancing behavior over time (assuming no additional exposure to ads). Although the decay rates are marginally different across the models, it is quite clear that the advertising effects seem to persist over time. Across all three approaches, we find that the advertising effect drop below 1% of its original value after approximately a week.

--Insert Figure 6 about here--

[13] The model with the lowest BIC yielded .4 as the value of the decay parameter (δ) in the grid search approach.

Data considerations. While our main analysis considers only the top 100 ranked DMAs for the sake of data accuracy, it limits the extent of geographical coverage. Therefore, to test whether our results are robust when including data from a larger geographic area we repeat our analyses with 204 DMAs (6 DMAs either don't share borders or are not measured by Nielsen) accounting for 498,736 observations. Although we find a small change in the relative magnitude of the main effects (the effects become weaker), the direction and significance of all the effects are consistent with our findings (in Table 6). See Table 7 for the results of the model with the augmented dataset.

--Insert Table 7 about here--

Sub-sample analyses. A concern with the border strategy employed in this research is that the estimated advertising effects are localized at the DMA borders which tend to be more rural (as opposed to urban). Urban counties tend to cluster near the center of DMAs. As such, the generalizability of the findings to urban counties may come under question. To address this concern raised by the review team, we follow the robustness analysis outlined in Shapiro (2018a). Specifically, we identified borders that are closer to the center of DMAs as "more urban" and re-estimated the models for those counties separately. In other words, borders that are closer to the centroid of DMAs are "more urban" and borders that are further away from DMA centers are "more rural". We use a median split to divide the sample into "more rural" and "more urban" sub-samples. We then estimated the brand advertisement effects separately for the "more urban" as well as "more rural" counties (Models 1 and 2 in Table 8). Across both subsamples, we see that the effect of COVID-19 related advertising from brands is positive and significant. Furthermore, the effect is stronger in urban counties than in the full border sample (Model 1 in Table 6) as well as the rural county sample. Thus, we can conclude that the results continue to be

robust for the brand ad effects and provide at least partial evidence that the findings generalize across different types of counties. Interestingly, we find the effect of government ads to be negative and significant in the "more rural" sample which includes more conservative[14] counties (see Table 5). A plausible explanation for this effect is psychological reactance. Psychological reactance is defined as a motivational state aimed at preserving and restoring threatened autonomy and freedom of choice (Brehm and Brehm 2013; Melnyk, Carrillat, and Melnyk 2021). Psychological reactance can motivate individuals to resist behavior change especially when it is perceived as curbing freedom of choice. Reactance is particularly pronounced for government initiatives (Clee and Wicklund 1980; Jo et al. 2020) and may be driven by political ideology (Irmak, Murdock, and Kanuri 2020). Even in the context of the COVID-19 pandemic, there seems to be some evidence of psychological reactance to government initiatives and messaging. For instance, Painter and Qiu (2021) find that residents in Republican counties are less likely to stay completely at home in response to a state order relative to those in Democratic counties. Similarly, Grossman et al. (2020) find that communications from state government leaders were less effective in reducing mobility in Republican-leaning counties relative to Democratic-leaning ones. Following this stream of work, we conjecture that the negative effect of government-sponsored COVID-19 ads in the "more rural" sample may be due to psychological reactance driven by conservativeness. In other words, in relatively more conservative areas, COVID-19 related messaging from government sources may engender feelings of reactance among the population leading to reduced adoption of social distancing

[14] The ideological divide between liberals and conservatives falls along partisan lines, with Republicans being more likely to be conservatives (e.g., Koetke, Schumann, and Porter 2021). This divide along party lines has become more amplified in recent years by social media and news outlets (e.g., Iyengar and Massey 2019). Therefore, we use Republican vote% as a measure of conservativeness of an area in this manuscript.

practices. However, in the absence of relevant data to test this mechanism we leave the test of this proposed mechanism to future research.

--Insert Table 8 about here--

In the border strategy approach, the ideal condition would manifest when every other factor, except the treatment (in our context, advertisements), is similar across the counties on the border thereby allowing one to estimate the effect of the treatment alone. In other words, the ideal natural experiments would occur when there is no policy in the counties on either side of the border or when both sides have policies in place. Therefore, we create two more sub-samples containing data from more ideal natural experiments; one where no county on either side of the border has any policy intervention (*no policy* sample) and one where all counties on the border have a policy in place (*all policy* sample). Models 3 and 4 in Table 8 show the results for the *no policy* and *all policy* samples, respectively. In Model 3, we find that the brand ad effects are consistent with our findings from the full sample in Model 1 of Table 6. Further, we find that the government ads also have a positive and significant effect in the absence of policy interventions. This is an interesting finding given that the effect of government ads was found to be nonsignificant in the overall sample. Further, in Model 4 of Table 8, we find that the brand ads have a non-significant effect on social distancing behavior. We propose and test a plausible mechanism underlying the observations related to brand ads for the 'no policy' and 'all policy' samples and government ads for the 'no policy' sample under the subsequent '*Potential Mechanisms driving the Effects'* section. Next, what is interesting is that the government ads have a negative and significant effect on social distancing behavior in the 'all policy' sample i.e., in the presence of COVID-19 related public policy interventions, pandemic-related government ads negatively affect people's adoption of social distancing practices.

Given the limitations of our data, we are unable to causally explain this finding. However, we conjecture that this effect is likely to be caused due to *reactance* or *annoyance* in response to government messaging. As discussed earlier, evidence exists in prior literature of government communications eliciting reactance among people, especially conservatives. For example, Irmak, Murdock, and Kanuri (2020) find that exposure to government regulation prohibiting the usage of mobile phones in cars led to higher usage of mobile phones in cars by conservatives. Similarly, Zhou (2016) finds that Republicans are resistant to messaging that encourages support of governmental action or personal engagement against climate change. Border counties tend to be more conservative on average (see Table 5) and as such when both government policies and government advertisements are present in a county, it may be perceived as excessive government interference. This may engender reactance among the population leading to reduced adoption of social distancing behaviors.

There also exists evidence of marketing communications leading to annoyance and negative behaviors from consumers. For example, Li et al. (2021) find that early delivery of retargeting ads can cause annoyance to customers leading to a lower likelihood of purchase as compared to when no ad is served to them. Similarly, Todri, Ghose, and Singh (2020) find that persistent display advertising beyond a certain threshold can lead to customer annoyance and lower purchase intentions. In addition to purchase intentions, studies have found that annoyance with ads can lead to several other negative outcomes for brands such as lowering of trust and reputability of the brand among consumers (McCoy, Everard, and Loiacono 2009) and website abandonment (Goldstein et al. 2014). Thus, in the context of the pandemic, government advertising (which is likely to be more front and center with the COVID-19 narratives) on top of

existing pandemic-related government policies may cause annoyance among the population and lead to lower adoption of social distancing practices.

Simultaneity. A potential source of bias in our estimates may arise from simultaneity or the co-occurrence of COVID-19 related advertisements with the social distancing behavior of individuals. For example, advertisers may strategically target markets with higher levels of social distancing so that more people would see their ads. Usually, media buying of television advertisement slots for different DMA markets occurs as upfront purchases (i.e., several months/weeks in advance) or as non-preemptible buys (i.e., purchased one quarter before airing and guaranteed to run by the respective networks). Ad inventory that remains unsold can be bought by advertisers at discounted rates in the remnant market and can be bought up to the day before the airing if available. In either circumstance, advertisers may strategically include COVID-19 narratives in their ads in response to the prevailing social distancing behavior in a market. To evaluate the extent to which advertisers may have acted strategically, we estimate three models: a 14-day, 7-day, and a 1-day lagged completely stay-at-home behavior (ΔSD_{bct}) as the independent variable and the % COVID-19 related ad GRP (from brands) as the dependent variable. We assume that with the rapidly changing situation with respect to the pandemic in the initial phases, any information related to people's social distancing behavior older than two weeks would be outdated and would not provide accurate information to advertisers. We do not find significant effects for any of the 14-day (-.064; p=.53), 7-day (-.147; p=.14), and the 1-day (.07; p=.47) lagged versions of the social distancing variable on COVID-19 related advertising (for full estimation results see Models 1, 2, and 3 of Table 9). These results support the fact that advertisers did not change their strategies in response to COVID-19 mitigation measures at the

county level at least in our window of observation, thus alleviating concerns about reverse causality.

--Insert Table 9 about here--

Alternatively, advertising GRPs in general (including COVID-19 related ads) could naturally go up in markets with higher levels of social distancing as more individuals may stay at home and hence watch more TV. To address this concern, we regress stay-at-home behavior on an alternative (non-viewership-based) measure of advertising – the percentage of COVID-19 related ad exposures at the county-day level. The results (reported in Model 4 of Table 9) demonstrate the robustness of our main findings – the effect of COVID-19 related ads from brands on social distancing behavior is positive and significant. To rule out the possibility of temporal ordering issues in Equation 2, we also ran the regression with a 1-day lag of % COVID-19 related ad GRP (as opposed to the contemporaneous effect in Equation 2). The results remain virtually unchanged and are reported in Model 5 of Table 9. Collectively, the above analyses offer strong evidence that the main findings are robust to concerns related to simultaneity.

Alternative model specifications. We also check for the robustness of our results with different functional forms of the model. The objective is to test whether the focal positive relationship of the % of the COVID-19 related ad GRP from brands on the social distancing behavior holds for alternative functional forms while controlling for the local government interventions, lagged daily number of COVID-19 infections, and county, border, day, and border-month fixed effects. Consequently, we treat Equation 2 as our benchmark model and re-estimate this model as linear-log (Model 1), log-linear (Model 2), and log-log (Model 3) regression models, respectively, and report the findings in Table 10. We find that the focal relationship between brand TV advertisements and social distancing behavior is positive and

significant for all alternative functional forms of the model. Additionally, given that we have operationalized our dependent variable as a percentage concerns may arise regarding the validity of normality assumptions in our model. Therefore, as a robustness test, we estimate Equation 2 using a logit transformation (see Model 4 in Table 10). We find that in this instance as well, our findings related to the brand ad effects are replicated.

--Insert Table 10 about here—

[**Note on Effect Sizes**: *Please note that the coefficients reported in the above table and throughout the manuscript are unstandardized. Although both the brand and government ads are on a percentage scale, brand ads have a much larger range of values (range~0-40%, mean=9.22%) while government ads have a narrower range (range~0-6%, mean=.36%). So, a 1 percentage point increase (say from the average=.36) in the % government ad GRP is a relatively much larger increase compared to a 1 percentage point increase (say from the average=9.22%) in the % brand ad GRP. Therefore, the unstandardized coefficients of brand and government ads cannot be compared. Across all the models in the manuscript, we find that the standardized brand ad coefficients are always greater in magnitude than the standardized government ad coefficients*.]

ADDITIONAL ANALYSES

Potential Mechanisms driving the Effects

Salience of the Pandemic. During the pandemic, several brands started incorporating COVID-19 related contexts in their advertisement narratives. From the advertising literature, we know that frequent or recent exposure to a brand increases its salience which is defined as the prominence or “level of activation” of the brand in memory (Alba and Chattopadhyay 1986). Consequently, this increased prominence or level of activation of the brand in memory serves to influence attention to and recall of product attributes included in the ad narratives (Alba, Hutchinson, and Lynch 1991). In the context of the COVID-19 pandemic, people may be aware of the pandemic and its seriousness given its pervasiveness, but this awareness may not always

translate into behaviors (e.g., social distancing) because the seriousness and consequences of the pandemic may not be prominent or salient in the minds of people. Therefore, advertisements making references to the COVID-19 pandemic in their ad narratives are likely to increase the prominence of the pandemic in the minds of the people and consequently draw attention to various attributes and consequences of the pandemic.

Empirically, we exploit the variation in salience of the pandemic across counties to understand how COVID-19 related advertising affects social distancing behaviors. Literature on priming and salience (specifically in health communications) provides us with some direction. That is if individuals already understand the (health) risks of specific behaviors, then repeated messaging will yield diminishing returns even when the advocated behavior is efficacious (Pechmann 2001; Pechmann and Ratneshwar 1994). Applying this logic to our context, we would expect that COVID-19 related advertising effects would be attenuated for counties where the salience levels of the pandemic are already high. In other words, COVID-19 ads would not increase salience when salience is already high. We conduct analyses that allude to the potential mechanism by exploring heterogeneous advertising effects through moderation analyses (Goldfarb, Tucker, and Wang 2022). We use two measures of salience at the county level: county-level government policy interventions and lagged (and cumulative) pandemic-related search interest (Google Trends).

First, we leverage county-level policy interventions (such as mask mandates or stay-at-home advisories or orders) to assess the heterogeneity in COVID-19 salience. Specifically, we expect that, in the presence of government policy interventions, the salience of the pandemic is likely to have been higher among residents of a focal county (compared to counties with no government policy in place). As such, if the salience mechanism is at play, the effectiveness of

ads in influencing social distancing behavior would be lower in counties under a policy mandate because pandemic salience would already be high in those counties. Conversely, in the absence of any policy interventions, the salience of the pandemic is likely to be lower among people leading to stronger advertisement effects on people's social distancing behavior. To test this, we include $\%COVIDAds_{bct}^{(Brand)} \times Policy_{ct}$ and $\%COVIDAds_{bct}^{(Govt)} \times Policy_{ct}$ interaction terms in Equation 2, where $\%COVIDAds_{bct}^{(Brand)}$ and $\%COVIDAds_{bct}^{(Govt)}$is the percentage of COVID-19 related ad GRP from brands and government, respectively. If salience (or the lack thereof) is a potential mechanism of the advertising effect, then we would expect the interaction term coefficients to be negative. As expected, we find a significant negative interaction between $COVIDAds_{bct}^{(Brand)}$ and $Policy_{ct}$ and between $COVIDAds_{bct}^{(Govt)}$ and $Policy_{ct}$ (see Model 1 in Table 11). The results indicate that the effect of COVID-19 related ads on completely stay-at-home behavior weakens significantly in the presence of government interventions. Further, we find that in the absence of any policy, COVID-19 related ads from brands have a stronger effect (as compared to the effect in Model 1 in Table 6) on completely stay-at-home behavior (.1056; $p< .001$). This is also true of COVID-19 related ads from government sources. Further, we find that when the proportion of COVID-19 related ads from *brands* increases by 10% from the mean (median), people's completely stay-at-home behavior increases by 0.74% (0.85%) and 8.32% (8.51%) in the presence and absence of government policy interventions, respectively. Thus, in addition to providing evidence in favor of the salience mechanism, these findings highlight the critical role advertising from brands can play in influencing socially beneficial behavior among consumers in the absence of government policy interventions.

Further, as an additional robustness check, we consider the brand ad effects on social distancing behavior for varying degrees of policy severity. The severity of government policy

interventions should strongly correlate with people's salience of the cause underlying the interventions (i.e., the pandemic). Thus, if our proposed mechanism is true then the ad effectiveness should weaken progressively with the increasing severity of the interventions. We created a $PolicySeverity_{ct}$ variable with three categories: 0- 'No Policy'; 1- 'Masking and/or Shelter-in-place Advisory/Recommendation'; 2- 'Masking and/or Mandatory Shelter-in-place for at-risk persons' and 'Masking and/or Mandatory Shelter-in-place for all persons', with 2 being the strictest intervention level and 0 being the absence of any policy intervention. We reestimate Equation 2 by adding an interaction term between the severity of government policy interventions ($PolicySeverity_{ct}$) and $\%COVIDAds_{bct}^{(Brand)}$(see Model 2 in Table 11). We find that the effect of COVID-19 related ads (from brands) on people's completely stay-at-home behavior progressively weakens (-.05148 to -.10397; $p < .01$) with increasing severity of policy interventions (relative to no policy interventions being in place in a county).

--- Insert Table 11 about here ---

Second, we consider Google Trends search interest as an alternative indicator of how prominent the pandemic is within a county. Our rationale for using Google Trends search interest is that when individuals actively search for pandemic-related information, the pandemic and its consequences are likely to be prominent or have a higher level of activation in their minds. This aligns with Alba and Chattopadhyay's (1986) "prominence" definition of brand salience. Specifically, one of the ways in which the salience of a topic may manifest itself is through people's search for information related to the topic. In fact, extant research has shown the efficacy of Google Trend as a reasonably good proxy for capturing the salience of specific issues that are of concern to a wide range of people (Mellon 2014). Other researchers studying the

impact of media on behavior have also used Google Search data as a mechanism check (e.g. Kearney and Levine 2015; Kim and KC 2020).

We obtain daily search interest data (indexed from 0-100) at the DMA level for search terms containing the following keywords: *COVID-19*, *Coronavirus*, and *Social Distancing*. The search interest data is normalized to the time (*day* in our context) and location (*DMA* in our context) of the search query. In particular, the search volume of a specific query is divided by the total searches in a given geography and unit of time. This number is then converted to a 0-100 scale with 100 representing the peak popularity of the search query in the given geography and unit of time. A score of 50 would indicate that the term is half as popular compared to its peak popularity. Given the search interest score is for the entire DMA and not at the county level, we use county population as a weight to approximate search interest for the border counties in our dataset. If the salience mechanism is at play, then we would expect the effect of COVID-19 related advertising to be attenuated for counties where the pandemic-related search interests are high. We re-estimate Equation 2 by including $\%COVIDAds_{bct}^{(Brand)}$ x $Cumulative\ Search\ Interest_{ct-1}$ and $\%COVIDAds_{bct}^{(Govt)}$ x $Cumulative\ Search\ Interest_{ct-1}$interaction terms, where $Cumulative\ Search\ Interest_{ct-1}$ is the 1-day lag of the county level cumulative search interest (see Model 3 of Table 11). Taking the lag of the cumulative search interest allows us to alleviate concerns of reverse causality between interest/salience and social distancing behavior. We find that the effect of COVID-19 related ads from brands on people's social distancing behavior weakens significantly (-.0001; p< .001) with higher search interest providing further evidence of salience being the mechanism underlying the effectiveness of COVID-19 related ads.

The salience mechanism allows us to explain the observations related to brand ads for the ‘no policy’ (Model 3 in Table 8) and ‘all policy’ (Model 4 in Table 8) samples and government ads for the ‘no policy’ (Model 3 in Table 8) sample. In the ‘no policy’ sample, the relatively higher magnitude of the brand ad effect (compared to the full sample) and the significant (and positive) effect of government ads align with the salience mechanism argument that the ad effects have a bigger role to play in increasing the salience of the pandemic in the absence of policy interventions. The non-significance of the brand ad effect in the ‘all policy’ sample can be attributable to the role of brands being limited in raising the salience of the pandemic in the presence of policy interventions.

COVID-19 cases as DV. We conducted additional analyses with COVID-19 cases as an additional outcome variable of interest. We do not use COVID-19 cases/infection rates as our main variable/behavior of interest because the case reporting data was particularly noisy and unreliable early during the pandemic. There were significant delays in the reporting of actual numbers (Banco 2021), scarcity in test kits which may have led to inaccuracies (Parshley 2020), delays in the processing of test results (Barone 2020; Courage 2020), as well as significant issues with testing accuracy in the initial stages of the pandemic (Lee et al. 2021). Furthermore, given the significant variability in incubation periods for COVID-19 (3 – 14 days after exposure), it becomes much more difficult to estimate a causal effect of advertising on infection rates, especially when individuals were being tested only after the onset of symptoms and contact tracing initiatives were ineffective. For these reasons, we restrict our primary analysis to studying an important behavioral precursor (social distancing) to reducing infection rates (Courtemanche et al. 2020; Kissler et al. 2020; Thunström et al. 2020). However, it may still be

interesting to study if at all there is any effect of COVID-19 related advertising from brands on the number of COVID-19 cases.

In our first set of analyses, we investigate whether COVID-19 related advertising[15] has a direct effect on the number of COVID-19 cases in a county. As with our main analyses, the regression includes fixed effects and all other controls (including the number of tests conducted daily). We do not find any significant effect of COVID-19 related TV advertisements from brands (with 14, 21, and 28-day lags) on the daily number of COVID-19 cases for any lagged period (see Models 1, 2, and 3 in Table 12). We exercise caution in interpreting these estimates as being 'causal' because of the noisy nature of the dependent variable, which may be measured with error as described above. In our second set of analyses, we conduct a mediation analysis to test whether social distancing behavior (our main dependent variable) mediates the relationship between COVID-19 related ads and COVID-19 cases. We use the *product of coefficient* approach (Fairchild and MacKinnon 2009; MacKinnon, Fairchild, and Fritz 2007) for testing mediation, which involves estimating the following equations:

$$Y = \alpha_1 + c'X + bM + e_1 \qquad (4)$$

$$M = \alpha_2 + aX + e_2 \qquad (5)$$

Where α_1 and α_2 are the intercepts, Y is the dependent variable (COVID-19 cases), M is the mediator (Social Distancing behavior), X is the independent variable (COVID-19 related ads), and e_1 and e_2 are the residuals. In the above equations, the product of the estimates $\hat{a}$ and $\hat{b}$ represents the indirect effect of X on Y (through M). To test the statistical significance of $\widehat{ab}$, we use a bootstrapping method to compute its confidence intervals. We ran three regressions with

[15] Lagged by 14, 21, and 28 days to allow for variability in virus incubation periods.

14-day, 21-day, and 28-day lags for the COVID-19 ads to allow for the virus incubation period (CDC 2020). The results are inconclusive (see Models 4,5, and 6 in Table 12). The 14-day lag regression suggests a weakly positive indirect effect of COVID-19 ads on the number of cases, while the effects are non-significant for 21-day lag. We find evidence of a negative and significant indirect effect with the 28-day lagged model.

We do not think that these results are an indication of a causal effect, especially given the measurement error in the case count as well as potential (unobserved) confounders in the incubation periods (14, 21, and 28 days after the COVID-19 ad was aired). For example, during the initial months of the pandemic, there was considerable variation in the time elapsed between a test and a confirmed result. The delays in getting the test results were driven by the large increase in the number of (symptomatic) cases and the lack of commensurate testing infrastructure (Barone 2020; Courage 2020). Additionally, there were delays in the reporting of actual case numbers due to limited tracking infrastructure (Banco 2021). Such delays in confirmation and reporting of test results and the associated inaccurate assignment of such cases to a later date (due to the delay) would make it difficult to cleanly capture any effect of advertisements and social distancing on COVID-19 cases. Further, in the initial phases of the pandemic, testing was prioritized for patients with severe illness, health care workers, or patients involved in a known illness cluster due to the lack of testing capacity (Parshley 2020). This would lead to a higher positivity rate (# positive cases divided by the total number of tests) since people with a relatively lower likelihood of testing positive were not being tested.

In sum, although the number of COVID-19 infections is an appealing outcome measure to use, resource constraints and other practical limitations at the time of the onset of the pandemic render the measure noisy for empirical analyses as indicated by our results above. In

comparison, the social distancing measure is a relatively more reliable measure, especially at the early stages of the pandemic.

Heterogeneity in Advertising Effects

While we had no a priori hypotheses regarding the effects, our goal was to highlight descriptive differences in advertising effects (if any) across different brand, category, and demographic variables.

Brand category. To explore heterogeneity at the brand category level, we estimate the model with the percentage of COVID-19 related ads within each major brand category (e.g., Entertainment, Politics, etc.) observed in the data. The advertising brands are categorized by Nielsen into 32 distinct brand categories. For sake of parsimony, we combined similar categories to form 14 brand categories. We also clubbed certain smaller categories to create an ‘Other’ brand category (see Table 13 for details). We got our categorization independently verified by a marketing graduate research assistant. As with all our models, we controlled for the policy indicator, the 1-day lagged number of COVID-19 cases in a county, and COVID-19 related ads from government sources along with all the fixed effects described earlier. We find significant effects for 8 of the 15 brand categories. Furthermore, we see from Figure 7 that the effects are heterogeneous. In particular, we find that COVID-19 ads from brands related to *Entertainment* (-.1928; p<.001), *Alcohol & Tobacco* (-.7143; p<.05), and *Politics* (-.1299; p<.001) have a negative effect on social distancing behavior. The advertising effects are significantly positive across five other categories: *Food & Beverages* (.8626; p<.001), *Household products* (.7691; p<.001), *Insurance & Real Estate* (.2037; p<.001), *Automobiles & Automotive Products* (.0479; p<.001), and *Services* (.0925; p<.001).

--- Insert Table 13 and Figure 7 ---

The negative effect of political COVID-19 related ads is not surprising given that there exist reports of the then US president, Donald Trump, making misleading claims about the pandemic and downplaying its severity (e.g., Paz 2020; Summers 2020). The President was also found to have misrepresented facts about his response to the pandemic in ads sponsored by his campaign (Rieder 2020). Additionally, in the context of the pandemic, Republicans, in general, have focused on “pro-Trump” messaging in their advertisements (e.g., King and Arkin 2020; Pereira 2021). Such ads may have helped build credibility for Trump and his claims that downplayed the severity of the pandemic. On the other hand, COVID-19 related ads from Democrats have focused mostly on “anti-Trump” messaging and highlighted his struggles in dealing with the pandemic (Pereira 2021). Evidence exists of negative political advertising having a backlash or boomerang effect (e.g., Garramone 1984; Haddock and Zanna 1997). For the border counties in our sample, which tend to be more conservative on average, the attack ads by Democrats may have had a stronger boomerang effect, further strengthening their beliefs in President Trump’s claims.

Entertainment, Alcohol, and Tobacco products are often structured around social enjoyment and group activities and are experienced in out-of-home environments. Examples include smoking and drinking at bars, going to the movies, going to sporting events, and eating out with family and friends. Further, alcohol advertising messages have focused on social success as one of its major themes (e.g., Jones and Donovan 2001). Therefore, in addition to increasing the salience of the pandemic, exposure to advertisements from these product categories may have also increased the salience of social enjoyment, leading to reduced social distancing behaviors. In comparison, the product categories that were found to have a positive

effect on social distancing behavior (Food & Beverages, Household products, Insurance & Real Estate, Automobiles & Automotive Products, and Services) have a relatively less prominent social aspect related to their consumption. Food, beverages, and household products are purchased mostly for personal and family consumption. Similarly, the use of services and automobile, real estate, and insurance products are predominantly centered around personal (including family) consumption. Additionally, many of these product categories (including automobiles) either introduced or increased their focus on home delivery services (e.g., Arm, Miller, and Tucker 2022; Gorzelany 2020). Our data does not contain information on ad content, however, it may be reasonable to conjecture that advertisers in these product categories may have highlighted such home delivery services in their advertisements. These factors may have contributed to the positive and significant ad effects on social distancing behavior in these product categories.

Brand value/equity. To explore heterogeneity at the brand equity level, we use Kantar BrandZ's Most Valuable Global Brands[16] report to identify 100 brands with the highest brand equity. These brands are ranked based on a combination of financial value and brand equity. We identify these 100 brands in our sample and create two variables: COVID-19 related ad GRP from the top 100 brands (high brand equity) and COVID-19 related ad GRP from other brands (low brand equity), which we include in the regression. We find that COVID-19 related ads from brands with high brand equity have a significant and positive effect (.01231; p<.001) on social distancing behavior while COVID-19 related ads from brands with low brand equity have a non-significant effect (.00001; p=.876). These findings are congruent with the conventional wisdom

[16] https://www.kantar.com/en-cn/inspiration/brands/2021-kantar-brandz-most-valuable-global-brands-report

that brand equity is considered a relational market-based asset reflecting the relationship between consumers and the brand and is often preceded by brand trust (Srivastava, Fahey, and Christensen 2001).

--- Insert Figure 8 about here ---

Demographic variables. We also explored heterogeneity in the *brand* advertising effects across several county-level demographic variables (see Figure 8). Like the previous analyses, our goal here is primarily descriptive. We find that advertising effects are more pronounced for counties that are more densely populated and have higher levels of education. Interestingly, we also observe significant heterogeneity in the ad effects based on race. Ad effects are attenuated in counties with a high percentage of people who are white. Several factors could be underlying these observations. For example, population density is generally higher in more urban areas which tend to be more educated (Parker et al. 2018) and therefore likely to have greater belief in science and higher compliance with social distancing measures (e.g., Brzezinski et al. 2021). Additionally, urban areas tend to have higher per capita income (Parker et al. 2018) which increases the likelihood of people owning televisions and being exposed to and influenced by COVID-19 related TV ads. On the other hand, prior research has found conservative ideology to be correlated with psychological reactance (e.g., Irmak, Murdock, and Kanuri 2020; Taylor and Asmundson 2021). Psychological reactance can motivate individuals to resist attempts at persuasion especially when it is perceived as curbing freedom of choice and can lead to denials of the existence of threats (Brehm 1966). In the US, people who are white identify as conservatives more than other races (e.g., Saad 2020). This may elicit reactance in areas with a higher percentage of whites leading to the attenuation of COVID-19 related band ad effects.

Collectively, these results indicate that the relative effectiveness of TV advertising on social distancing behavior can vary due to factors related to differences in brand categories, brand equity, and county-level demographic factors. Later, we discuss the implications of these results for optimizing communication strategies.

POI visits by NAICS category. SafeGraph aggregates the number of daily visits to around 4.5 million points of interest (POI) in the United States. We combine this data with SafeGraph's *Places*[17] to identify the categories under the North American Industry Classification System (NAICS) to which individual POIs belong to. NAICS codes can be decomposed into 2 to 6 digits, with 2 representing the most general category and 6 representing the most granular classification within the category. We use the 2-digit NAICS categories (e.g., Educational Services, Accommodation, and Food Services) to look at how advertisements may have affected footfalls at POIs belonging to some of these major categories. Figure 9 shows how the number of visits to POIs declined from March 2020 during the pandemic.

--- Insert Figure 9 and Table 14 about here ---

In Table 14 we report the results from re-estimating Equation 2 with (deseasonalized) number of visits to POIs ($\Delta SD\_POI\_Visit_{bct}$) belonging to Education (Model 1), Entertainment and Recreation (Model 2), Food and Lodging (Model 3), and Retail and Wholesale (Model 4) categories as dependent variables in four separate models. We find a significant negative effect of COVID-19 related ads from Brands on visits to POIs for three of the four major categories that we study. However, advertisements do not have a significant effect for the Education category. This is somewhat expected since visits to Education-related POIs are primarily

[17] https://docs.safegraph.com/docs/core-places

determined based on whether such places remain open and as such individuals have less flexibility with their decisions regarding travel to such places. Consistent with our main findings, ads from government sources do not have a significant effect for any of the four POI categories.

DISCUSSION AND CONCLUSION

In this paper, we examine whether non-brand-related elements in the narratives of brand advertisements can unexpectedly influence societal outcomes. Specifically, using the COVID-19 pandemic as an empirical setting and without making any assumptions about the supposed intent of brands, we set out to investigate the spillover effects of COVID-19 related advertising on social distancing behaviors. Leveraging natural experiments resulting from advertising discontinuities along DMA borders, we show that brand ads that include COVID-19 narratives have a positive effect on people's social distancing behavior. We show that the ads influence people's adoption of social distancing behavior by increasing the salience of the pandemic. A 1 pp increase in COVID-19 related brand advertising leads to a .03 pp increase in social distancing behavior. While the percentage change estimates may seem small, they are quite substantial when considering the size of the DMAs[18]. For example, a 1 pp increase in COVID-19 related advertising leads to an average of 466 additional people (compared to 2019) staying completely at home *per* day. This effect is much more pronounced for larger DMA markets such as New York and Los Angeles where the predicted effect leads to 6,527 and 5,612 additional people staying at home completely *per day*, respectively. Taking into account the cost of advertising, we can compute the (unintended) social returns on investment (ROI) for a 1pp increase in COVID-19 related advertising. The average ROI across DMAs was found to be .33 (with a range of .06 –

[18] Similar effect sizes are reported by others in the literature as well. For instance, Kim and KC (2020) find that a 1% increase in erectile disfunction (ED) drug advertising leads to a 0.04-0.08% increase in total births.

1.27) i.e., for every dollar spent on COVID-19 related ads social distancing increased by .33 pp. In other words, the spillover effects can prove to be very cost-effective for certain DMAs (e.g., Los Angeles, New York) but less cost-effective for others (e.g. Helena, Binghamton, Charlottesville). Surprisingly, we do not find significant effects for government ads overall in our sample. However, on a deep-dive analysis, we find that the effect of government ads is positive and significant in the “no policy” sample while the effect becomes negative and significant for the “all policy” and “more rural” samples. We conjecture that this negative effect is likely due to psychological reactance and/or annoyance. We also find heterogeneous ad effects across a host of brand, category, and demographic variables. Taken together, this study not only highlights the social impact of advertising, but also takes the first step toward a new model of designing advertising strategy – one which considers not just brand-related outcomes, but also the social spillovers. Below, we discuss the implications of our findings for managers and policymakers.

Implications

Advertising for social good. A myriad of opportunities exists for firms to move from being predominantly profit-centered to addressing issues pertaining to consumer and social welfare (Chandy et al. 2021a; Porter and Kramer 2011). We demonstrate that marketing mix variables (such as TV advertising) can lead to social good, especially during public health crises. Specifically, we show that firms have tremendous opportunities to disseminate socially relevant messages embedded in the narratives of their TV advertisements and ultimately impact the desired societal outcome. In the context of public health emergencies (such as infectious outbreaks) or long-term crises (such as climate change), brand advertising has a stronger effect on societal outcomes (.11 pp increase in social distancing for a 1 pp increase in COVID-19

related ad GRP), especially in the absence of a cogent public policy response. This, in addition to the overall ineffectiveness of government-sponsored messaging, underscores a non-trivial role for brands during public health crises. Our findings also have broad theoretical implications for the role of brand equity in the effectiveness of the marketing mix. Specifically, we find that ads from brands with high brand equity have a stronger effect on people's social distancing behavior relative to brands with lower brand equity.

Rethinking messaging and communication strategies from government agencies. Research examining reactance suggests that public sector campaign messages directed at restricting an undesirable choice or behavior, often end up achieving the opposite effect (Wright and Palmer 2008). Consistent with this stream of literature, we find that COVID-19 related TV ads from government agencies have a significant negative impact on the social distancing behavior of individuals when such ads are shown on top of existing government policy interventions. This may be caused by reactance or annoyance due to the perception of excessive government interference on account of people being exposed to both policy mandates and government advertisements. Further, government ads have a negative effect on social distancing behavior in more rural and conservative areas. Consequently, government agencies may need to rethink their communication strategies in terms of how they are implemented and the expected reactance it is likely to elicit from the target audience. This is especially important when government agencies are engaged in mitigating major public health crises such as the COVID-19 pandemic where the compliance of the public to safety guidelines such as social distancing and wearing a mask is critical to saving lives. In such scenarios, government agencies may benefit from adopting alternative means of communication to minimize reactance and annoyance. This may involve initiatives such as collaborating with well-known, trusted public figures and social

media influencers or offering incentives to firms (selling certain categories such as food and beverage, household products, etc. and having relatively high brand equity) to incorporate relevant social welfare narratives in communications and advertisements directed at their followers and consumers, respectively. Additionally, in the absence of public policy interventions, COVID-19 related government ads have a positive and significant effect on people's social distancing behavior. This is an important finding since the implementation of public policy mandates in response to public health crises often faces headwinds due to several factors such as public opinion, lack of political will, and insufficient resources. As an example, if local-level authorities refuse to implement restrictive measures to deal with a health crisis, federal-level authorities may leverage advertising avenues to influence public behavior towards beneficial social outcomes.

Opportunities for targeted 'social' advertising. Our results indicate that several factors at the county, brand, and local government levels influence the extent to which TV advertisements affect social distancing behavior. Consequently, there is scope for marketers to leverage such information to implement more effective and targeted TV ads directed at influencing major social outcomes during public health crises. For example, we find that effect of advertising on social distancing behavior is amplified among more educated and densely populated areas but is attenuated for counties that tend to be more white. With the increasing penetration of digital set-top boxes and connected TVs, there is tremendous scope for advertisers to apply such heterogenous insights to design highly targeted and differentiated TV ad campaigns with the overarching goal of maximizing the impact on social outcomes in addition to brand-related outcomes, by spending the least amount of ad dollars.

Thinking beyond social distancing. While our observations relate to social distancing in the context of the COVID-19 pandemic, the substantive nature of the findings and the underlying mechanisms i.e., salience and psychological reactance, make them generalizable to other contexts as well. First, major epidemics and pandemics are becoming increasingly likely (Marani et al. 2021). The primary mitigation steps to all of the above outbreaks are typically quarantining and social distancing. Our research is a first step in understanding how (if at all) marketing (in the form of ad narratives from brands) can play a role in encouraging these behaviors during such crises. Brand managers and policymakers could use the findings from this study to devise more efficient communication strategies to deal with such future health crises. Second, our findings are generalizable to other public health crises as well such as the steadily worsening climate crisis. In the context of climate change, people currently engage in behaviors considered harmful to the environment due to the lack of salience of the adverse consequences of their actions. Indeed, studies have found that people with heightened concerns about climate change are more likely to adopt pro-environmental behaviors (Semenza et al. 2008). Similarly, Goldstein, Cialdini, and Griskevicius (2008) find that the salience of social identities and associated norms influence the adoption of pro-environmental behaviors. Brand advertisements with relevant narratives may help increase the salience of the crisis and influence desired behaviors (such as recycling or switching to clean energy) critical for mitigating the crisis.

Limitations and Opportunities for Future Research

This study is not without limitations. From a methodological standpoint, the border strategy identification approach estimates a local treatment effect (advertising effect) and may not generalize to all contexts and regions. Although we show that the effects are robust in more urban counties, our analysis is restricted to urban/rural border counties. In the same vein, the

implications of this study are most pertinent to public health crises, especially epidemics and pandemics which tend to be longer-term events. We acknowledge, however, that given the lag in TV advertising strategies to adjust narratives, the results may not directly apply to sudden short-term public emergencies (such as natural disasters, etc.)[19]. Perhaps in such emergencies, messaging from brands through other forms of media such as social media may be more feasible. From a theory standpoint, we shed light on some potential mechanisms that may be driving the effect. Of course, there may be other competing mechanisms at play that we are unable to test due to data limitations. A formal investigation into the theoretical underpinnings of the effects (perhaps through experimentation) may be an exciting avenue for future work in this domain. Finally, although we can reliably estimate the effect of COVID-19 related advertising on social distancing, we do not explore the various content-related aspects of ads that may/may not influence such behaviors (due to data constraints). We hope that future research can study ad content/narrative effects such as tone, visuals, etc. We recognize that ours is just the first step (among hopefully many) in understanding the profound manners in which brands can create social value. We believe that there are many more promising avenues for research in this domain, such as investigating individual-level ad viewing behavior, sentiment, activism, etc.

[19] We note, however, that brands seem to be becoming increasingly agile with respect to changing their TV ad narratives. Within 2 weeks of the pandemic declaration, more than 60 brands nationally aired COVID-19 related TV ads (Bain & Company 2020). Within the first 100 days of the pandemic, 797 brands aired a total of 1,701 COVID-19 related TV ads (iSPOT.tv 2020). These numbers indicate the agility and ability of brands to speedily pivot their TV ad narratives in a relatively short period.

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TABLES AND FIGURES

Table 1: Data Sources

	Data	Description	Source	Use
1	Social Distancing Metrics v2.1	Anonymized daily population movement data representing 45 million smartphone devices in the United States	SafeGraph	Dependent variable
2	Ad Intel	Spot-time-DMA level data for every advertisement on television	AC Nielsen	Independent variables
3	Government imposed COVID-19 prevention policies	County-level daily data on government-imposed mask mandates and stay-at-home policies	CDC	Control variable, Understanding mechanism
4	Covid-19 case count data	County-level daily data on the number of COVID-19 cases in the United States	NYT	Control variable
5	Demographic data	County-level education, race, gender, and income data	Census Bureau	Comparison of county characteristics
6	Unemployment data	County-level unemployment data	BLS	Comparison of county characteristics
7	2020 US Presidential Election Vote %	County-level party-wise vote share	Harvard Dataverse	Comparison of county characteristics
8	County Adjacency data	Data on the list of counties geographically adjacent to a given county	NBER	Identifying border counties
9	Pandemic-related Search Interest	Daily search interest around the list of pandemic related keywords on a scale of 0-100	Google Trends	Understanding mechanism
10	Point of Interest visits	Daily number of visits to different points of interest such as grocery stores, restaurants, etc.	SafeGraph	Dependent Variable
11	County Distance Data	Data of distance between county centroids	NBER	Robustness

Table 2: Manual Classification of COVID vs. non-COVID ads

		Nielsen Classification		Total
		COVID	Non-COVID	
Rater Classification	COVID	46 (93.88%)	2 (3.64%)	48
	Non COVID	3 (6.12%)	53 (96.36%)	56
Total		49	55	104

Table 3: Examples of COVID-19 Related Ads

	Brand	Ad Description (from Nielsen)	Ad Title	Link
1.	Coors Light Beer	COVID-19/old footage/woman with sign	America Could Use a Beer	https://www.ispot.tv/ad/nn_x/coors-light-america-could-use-a-beer
2.	Kroger Supermarket	COVID-19/notebook & pen/man/mask	No Instruction Manual	https://www.ispot.tv/ad/n6mi/the-kroger-company-no-instruction-manual
3.	Ashley Homestore	COVID-19/woman/dog/kids/furniture	Enjoy Home	https://www.ispot.tv/ad/nkRP/ashley-homestore-covid-19-enjoy-home
4.	DSW Shoe Warehouse Store	COVID-19/woman/storefront/shoes/url	DSW is Open! The Hunt for the Best Shoe Store is Over	https://www.youtube.com/watch?v=OJIgP22HTTY
5.	Hersheys Candy	COVID-19/woman & man/kid/hands/text	Heartwarming at Home	https://www.ispot.tv/ad/nIt3/hersheys-heartwarming-at-home

Table 4: Variation in COVID Advertising Intensity (GRP) Between Border DMAs

	N	Min	Median	Mean	Max
Coefficient of Variation (All)	97	1.10	1.20	1.20	1.32
Absolute Difference in GRP (All)	24,168	0	12.76	68.33	913.53
Coefficient of Variation (Brands)	97	1.10	1.20	1.20	1.35
Absolute Difference in GRP (Brands)	24,168	0	12.79	67.72	851.87
Coefficient of Variation (Govt.)	97	1.16	1.63	1.70	3.35
Absolute Difference in GRP (Govt.)	24,168	0	0	7.41	191.76

Table 5: Comparison of Observed Characteristics of Counties on Opposite Sides of DMAs

	Mean1	Mean2	Difference	t-statistic	p-value
Population	100,787.60	105,174.30	-4386.70	-.25	.80
Female %	49.70	49.91	-.20	-2.26	.02
Hispanic %	10.75	10.65	.10	.11	.91
Black %	8.83	9.04	-.21	-.26	.79
Poverty %	15.27	15.29	-.02	-.06	.95
Median Household Income ($)	53,347.12	53,066.18	280.94	.40	.69
Unemployment %	7.13	7.12	.01	.08	.93
Bachelor’s Degree or Higher %	20.05	19.99	.06	.14	.89
Republican Voter % (2020 Presidential Elections)	66.15%	65.17%	.01	.88	.38
Proportion of Devices Completely at Home	.246	.247	-.001	-.23	.82
Median Dwell Time at Home (Minutes)	615.87	607.33	8.54	1.35	.18

Table 6: Estimation Results

	Main model		Alternative DV measures			Alternative IV measures			
Sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full Sample	Full Sample
DV operationalization	Stay-At-Home %	Stay-At-Home %	Median Home Dwell Time (minutes)	Median Home Dwell Time (minutes)	# of POI visits	Stay-At-Home %	Stay-At-Home %	Stay-At-Home %	Stay-At-Home %
Main IV operationalization	%GRPs	%GRPs	%GRPs	%GRPs	%GRPs	GRPs	Adstock GRP (NLS)	Adstock GRP (Grid Search)	GRPs (Koyck)[a]
Model #	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)	(Model 8)	(Model 9)
COVID-19 related advertising (Brands)	.0310*** (.0084)			.3594* (.1461)	-86.742* (38.6540)	.0007* (.0003)	.0002* (.0001)	.0005* (.0002)	.0006** (.0002)
COVID-19 related advertising (Govt)	-.0514 (.0444)			1.094 (.8181)	-339.67 (299.1700)		-.0000 (.0016)	-.0001 (.0016)	.0000 (.0012)
COVID-19 related advertising (All)		.0292*** (.0084)	.3758** (.1453)						
Non COVID-19 Ad GRP						-.0000 (.0001)	-.0000 (.0001)	-.0000 (.0001)	.0001 (.0001)
Stay-At-Home % (1-day lag)									.3773*** (.0069)
Policy (= 1)	2.021*** (.1846)	2.0251*** (.1843)	24.364*** (2.9556)	24.4010*** (2.950)	-3,724.5 ** (1,176.5)	2.0266*** (.1844)	2.0043*** (.1848)	2.0021*** (.18332)	1.3745*** (.119)
Daily Cases (1-day lag)	.0093*** (.0020)	.0093*** (.002)	.1186*** (.0297)	.11849*** (.0297)	-225.5*** (44.232)	.0093*** (.002)	.0086*** (.0016)	.0086*** (.0017)	.0055*** (.0012)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	165,268	165,268	165,268	165,268	165,268	165,268	133,281	133,281	164,165
R^2 Adj.	.849	.849	.807	.807	.656	.849	.84	.84	.871

Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. "Main IV operationalization" denotes the operationalization of the COVID-19 related advertising variable (Brand and Govt). 'All' denotes the COVID-19 related advertising variable NOT split by source. Policy = dummy variable capturing county-level interventions such as shelter-at-home and mask mandates. Govt. = Government. a – The total advertising effect for Koyck Transformation is given by [coefficient of 'COVID-19 Ad GRP (Brands)'/ (1- coefficient of 'Completely stay-at-home (1-day lag)'] = .0006/(1-.377) = .00096.

Table 7: Main Effects of COVID-19 Related Ads for 204 DMAs

DV operationalization	Stay-At-Home %	Stay-At-Home %	Median Home Dwell Time (minutes)	Median Home Dwell Time (minutes)
Model #	(Model 1)	(Model 2)	(Model 3)	(Model 4)
% COVID-19 Ad GRP (All)	.01459*** (.00382)		.16297+ (.08315)	
% COVID-19 Ad GRP (Brands)		.01528*** (.00394)		.1806* (.08384)
% COVID-19 Ad GRP (Govt.)		.00037 (.01634)		-.20074 (.33242)
Policy (= 1)	1.5246*** (.13584)	1.5235*** (.13586)	19.937*** (2.2283)	19.909*** (2.2289)
Daily Cases (1-day lag)	.00971*** (.00181)	.00971*** (.00181)	.12665*** (.02765)	.12667*** (.02767)
County FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes
N. Obs	495,427	495,427	495,427	495,427
R^2 Adj.	0.795	0.795	.751	.751

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level non-pharmaceutical interventions such as shelter-at-home and mask mandate. Govt.= Government. c= county, b= border, and t= day. All' denotes the COVID-19 related advertising variable NOT split by source.

Table 8: Estimation Results from Sub-Sample Analyses

Sample	Sub-Sample Analyses "More Rural" Counties	 "More Urban" Counties	 "No Policy" Counties	 "All Policy" Counties
DV operationalization	Stay-At-Home %	Stay-At-Home %	Stay-At-Home %	Stay-At-Home %
Main IV operationalization	%GRPs	%GRPs	%GRPs	%GRPs
Model #	(Model 1)	(Model 2)	(Model 3)	(Model 4)
COVID-19 related advertising (Brands)	.0297* (.0124)	.046*** (.0115)	.066* (.0269)	-.0044 (.0073)
COVID-19 related advertising (Govt)	-.1440* (.0659)	.0266 (.0589)	.8093*** (.1804)	-.2233*** (.0356)
Policy (= 1)	1.8028*** (.2508)	2.2541*** (.2679)		
Daily Cases (1-day lag)	.0123** (.0039)	.0077*** (.002)	.1015*** (.0241)	.0017*** (.0005)
County FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes
N. Obs	90,671	74,597	93,029	64,236
R^2 Adj.	.812	.894	.775	.777

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. "Main IV operationalization" denotes the operationalization of the COVID-19 related advertising variable (Brand, and Govt).

Table 9: Robustness Checks for Simultaneity, Ad Exposure, & Lagged IV

DV operationalization	%GRPs (Brands)	%GRPs (Brands)	%GRPs (Brands)	Stay-At-Home %	Stay-At-Home %
Model #	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
Stay-At-Home % (1-day lag)	.07043 (.09779)				
Stay-At-Home % (7-day lag)		-.14743 (.1007)			
Stay-At-Home % (14-day lag)			-.06441 (.10356)		
% COVID-19 Ad Exposure (Brands)				.0314** (.01099)	
% COVID-19 Ad Exposure (Govt.)				.09382^{+} (.0548)	
% COVID-19 Ad GRP (Brands 1-day lag)					.03298*** (.00828)
% COVID-19 Ad GRP (Govt. 1-day lag)					-.00779 (.04443)
Policy (= 1)	31.369*** (3.616)	31.577*** (3.5931)	31.493*** (3.5743)	2.0307*** (.18433)	2.0168*** (.18459)
Daily Cases (1-day lag)	-.00157 (.03063)	-.00141 (.02966)	.00129 (.02906)	.00929*** (.00197)	.00929*** (.00197)
County FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes	Yes
N. Obs	165,268	157,547	150,929	165,268	165,268
R^2 Adj.	.932	.930	.928	.849	.849

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level non-pharmaceutical interventions such as shelter-at-home and mask mandate. Govt.= Government.

Table 10: Regression Results from Different Model Specifications

Functional Form	Linear-Log	Log-Linear	Log-Log	Logit
DV operationalization	Stay-At-Home %	log(Stay-At-Home %)	log(Stay-At-Home %)	Log Odds (Stay-At-Home %)
Model #	(Model 1)	(Model 2)	(Model 3)	(Model 4)
% COVID-19 Ad GRP (Brands)		.00046*** (.00014)		.0015*** (.0004)
% COVID-19 Ad GRP (Govt.)		-.00072 (.00073)		-.0024 (.0021)
log (1+ % COVID-19 Ad GRP (Brands))	.4294*** (.0895)		.00689*** (.00158)	
log (1+ % COVID-19 Ad GRP (Govt.))	-.04137 (.09551)		-.00053 (.0016)	
Policy (= 1)	2.0142*** (.1837)	.03194*** (.0029)	.0318*** (.0029)	.0938*** (.0088)
Daily Cases (1-day lag)	.0093*** (.00197)	.00012*** (.00003)	.00012*** (.00003)	.0005*** (.0001)
County FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes
N. Obs	165,268	165,268	165,268	165,268
R^2 Adj.	.849	.829	.829	.837

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level non-pharmaceutical interventions such as shelter-at-home and mask mandate. Govt.= Government.

Table 11: Potential Mechanism Underlying COVID-19 Related Advertising from Brands (& Government)

DV operationalization	Stay-At-Home %	Stay-At-Home %	Stay-At-Home %
Model #	(Model 1)	(Model 2)	(Model 3)
% COVID-19 Ad GRP (Brands)	.1056*** (.0168)	.1069*** (.015)	.0457*** (.0087)
%COVID-19 Ad GRP (Govt.)	.4323*** (.12)	-.0593 (.0438)	-.0477 (.0513)
% COVID-19 Ad GRP (Brands) × Policy (= 1)	-.086*** (.0162)		
% COVID-19 Ad GRP (Govt.) × Policy (= 1)	-.5475*** (.1244)		
% COVID-19 Ad GRP (Brands) × Cumulative Search Interest (1-day lag)			-.0001*** (.0000)
% COVID-19 Ad GRP (Govt) × Cumulative Search Interest (1-day lag)			.0001 (.0001)
% COVID-19 Ad GRP (Brands) × Policy Severity (= 1)		-.0517** (.0159)	
% COVID-19 Ad GRP (Brands) × Policy Severity (= 2)		-.1043*** (.0151)	
Policy (= 1)	3.2256*** (.2676)		2.0059*** (.1836)
Policy Severity (= 1)		1.1186*** (.3143)	
Policy Severity (= 2)		3.77*** (.2523)	
Cumulative Search Interest (1-day lag)			.0033*** (.0004)
Daily Cases (1-day lag)	.0094*** (.002)	.0097*** (.0018)	.007*** (.0018)
County FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes
N. Obs	165,268	165,268	165,268
R^2 Adj.	.849	.85	.85

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level non-pharmaceutical interventions such as shelter-at-home and Govt.= Government.

Table 12: Estimation Results with COVID-19 Cases as Dependent Variable

	Effect of COVID-19 Ads from Brands on COVID-19 Cases			Mediation Analysis: Social distancing mediating the effect of COVID-19 ads on COVID-19 cases		
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)
% COVID-19 Ad GRP (Brands) 14-day lag	.12112 (.0929)					
% COVID-19 Ad GRP (Brands) 21-day lag		.00842 (.07492)				
% COVID-19 Ad GRP (Brands) 28-day lag			.03074 (.06149)			
% COVID-19 Ad GRP (Brands) 14-day lag	-.94747 (.63201)					
% COVID-19 Ad GRP (Brands) 21-day lag		-.99376 (.78865)				
% COVID-19 Ad GRP (Brands) 28-day lag			-1.2475 (.86551)			
Mediation (a*b) 14-day lag				.00178 [.0003, .0032]		
Mediation (a*b) 21-day lag					-.00128 [-.003, .0002]	
Mediation (a*b) 28-day lag						-0.00272 [-0.0046, -0.0014]
Policy (=1)	4.4055 (2.7228)	4.4062 (2.7227)	4.358 (2.6984)			
Test Count	.10284*** (.0252)	.10286*** (.02522)	.10102*** (.02526)			
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R Sq.	.656	.656	.66			

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level interventions such as shelter-at-home and mask mandates. Govt. = Government.

Table 13: Brand Category Mapping

Original Brand Category	**Final Brand Category**
Beer & Wine	Alcohol & Tobacco
Cigarettes, Tobacco & Accessories	Alcohol & Tobacco
Automobiles, Accessories & Equipment	Automobiles & Automotive Products
Gasoline, Lubricants & Fuels	Automobiles & Automotive Products
Soaps, Cleansers & Polishes	Cleaning & Cosmetics
Toiletries & Cosmetics	Cleaning & Cosmetics
Drugs & Remedies	Drugs & Other Remedies
Computers, Office Equipment & Stationery	Other
Electronic Entertainment Equipment & Supplies	Electronics
Optical Gadgets & Cameras	Electronics
Entertainment & Amusements	Entertainment
Confectionary, Snacks & Soft Drinks	Food & Beverages
Foods & Food Products	Food & Beverages
Building Materials, Equipment & Fixtures	Household Products
Household Equipment & Supplies	Household Products
Household Furniture Supplies & Materials	Household Products
Insurance & Real Estate	Insurance & Real Estate
Business, Proprietorship & Employment, Recruitment	Other
Freight, Industrial & Agricultural Development	Other
Horticulture & Farming	Other
Industrial Materials	Other
Miscellaneous, Not Elsewhere Classified	Other
Pets, Pet Foods Supplies	Other
Political	Political
Publishing & Media	Publishing & Media
Apparel, Footwear, & Accessories	Retail
Retail	Retail
Sporting Goods, Toys, & Games	Retail
Business & Consumer Services	Service
Airplanes, Aviation, Servicing & Equipment	Travel
Travel, Hotels & Resorts	Travel

Table 14: Effects of COVID-19 Related Ads on Visits to Points of Interest

	(Model 1: Education) $\Delta SD\_POI\_Visit_{bct}$	(Model 2: Entertainment & Recreation) $\Delta SD\_POI\_Visit_{bct}$	(Model 3: Food & Lodging) $\Delta SD\_POI\_Visit_{bct}$	(Model 4: Retail & Wholesale) $\Delta SD\_POI\_Visit_{bct}$
% COVID-19 Ad GRP (Brands)	-1.9689 (5.3404)	-15.388* (7.757)	-23.351* (9.4693)	-19.443* (7.7897)
% COVID-19 Ad GRP (Govt.)	-26.157 (35.177)	-59.504 (59.251)	-95.513 (72.639)	-95.245 (57.869)
Policy (= 1)	-483.33*** (128.42)	-447.94* (208.21)	-788.27** (278.09)	-912.28*** (245.49)
Daily Cases (1-day lag)	-27.4040*** (3.6006)	-33.827*** (7.467)	-55.516*** (12.855)	-45.566*** (8.2836)
County FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
DMA Border x Month FE	Yes	Yes	Yes	Yes
N. Obs	165,268	165,268	165,268	165,268
R^2 Adj.	.454	.617	.654	.639

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Policy = dummy variable capturing county-level non-pharmaceutical interventions such as shelter-at-home and mask mandates. Govt. = Government. c= county, b= border, and t= day.

Figure 1: Representative literature

	Brand-Related Outcomes (Sales, Demand, Loyalty etc.)	Societal Outcomes (Health Outcomes, Drunk Driving etc.)
Primary Advertising Effects	Keller (1987) Lodish et al. (1995) Meenaghan (1995) Rubinson (2009) Aaker and Biel (2013) Tuchman (2019) Shapiro, Hitsch, & Tuchman (2021)	Atkin (1990) Levy, Compton,& Dienstfrey (2004) Henriksen et al. (2006) Wakefield, Loken,& Hornik (2010) Emery et al. (2012) Niederdeppe, Avery,& Miller (2017)
Spillover Advertising Effects	Danaher, Bonfrer, and Dhar (2008) Sahni (2016) Shapiro (2018a) Kim (2019) Fossen, Mallapragada, and De (2021)	Kim and KC (2020) Shapiro (2021) **This Study**

Figure 2: Mobility & Advertising patterns

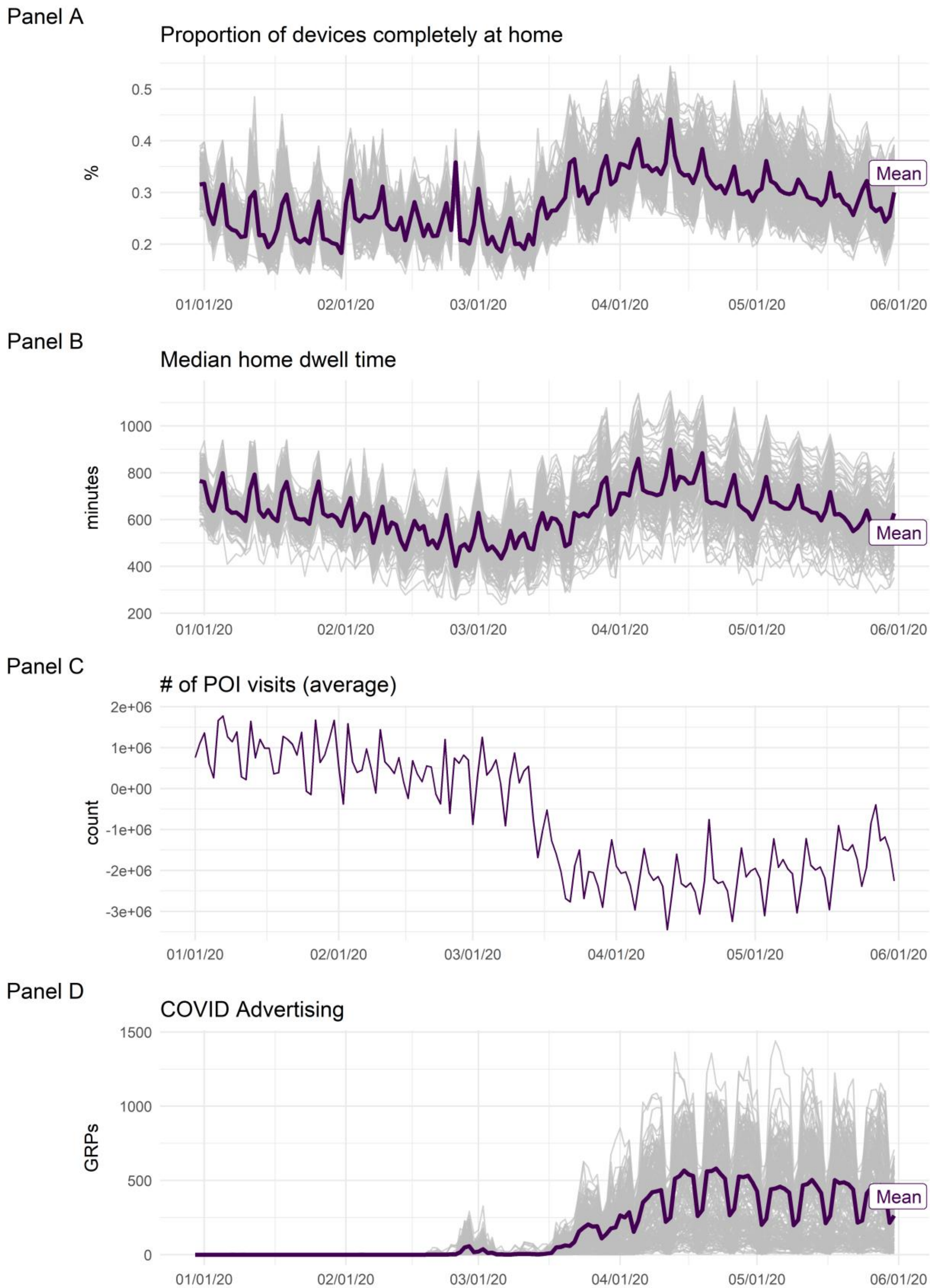


Figure 3: DMA Border Counties (an illustration)

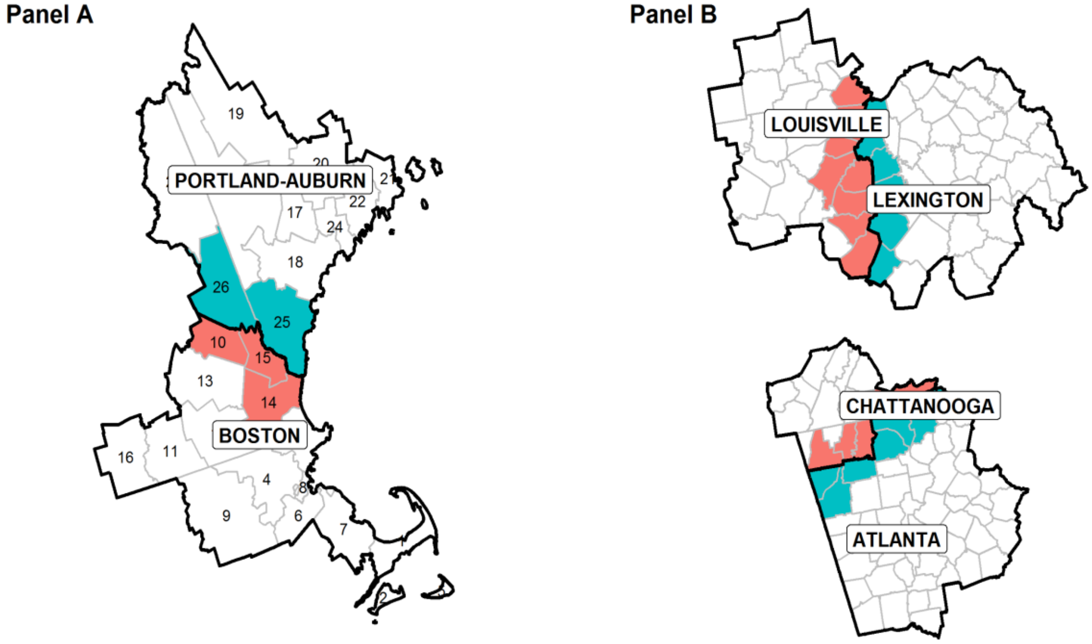


Figure 4: COVID-19 Related Advertising and Stay-at-home behavior in Boston and Portland-Auburn DMA Border counties

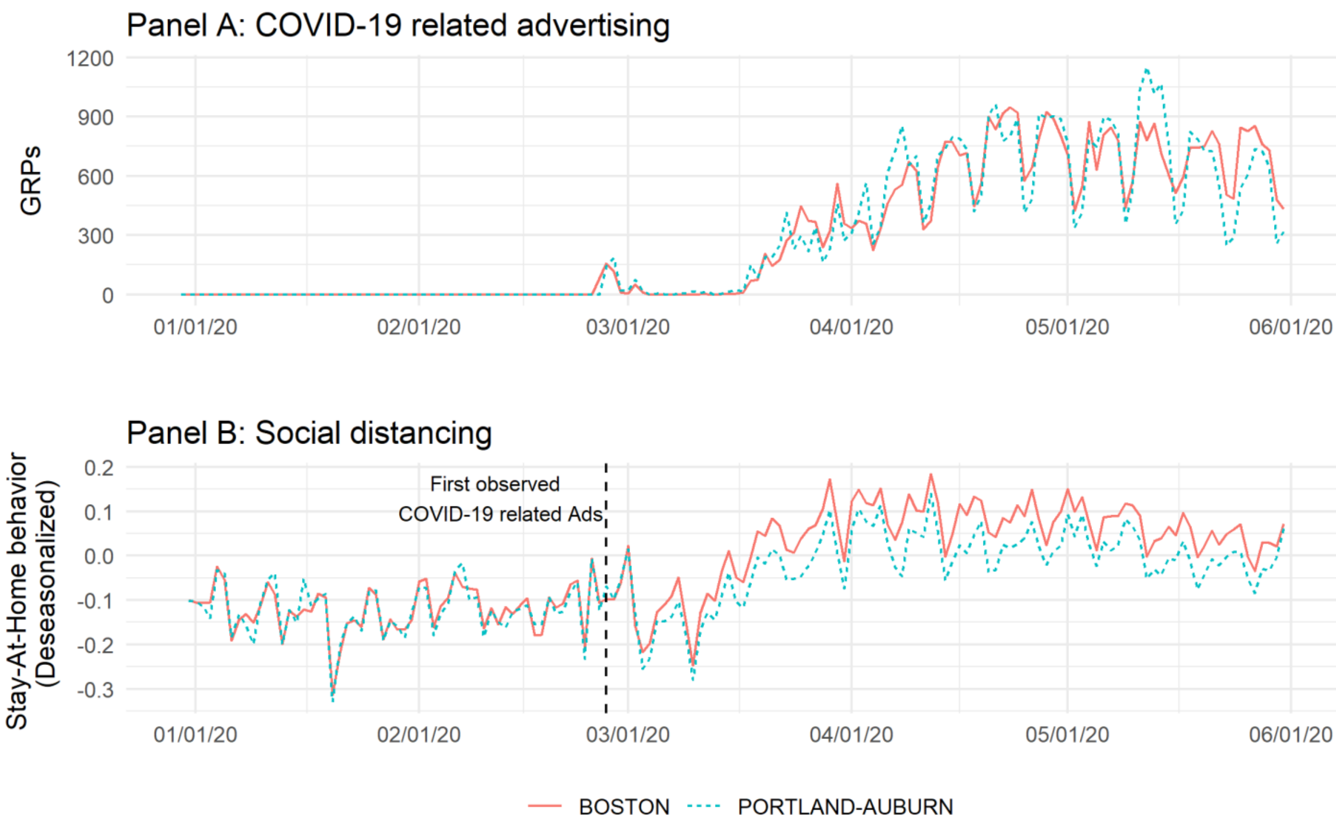


Figure 5: Correlation between ΔSD_{ct} and COVID-19 related ad GRP

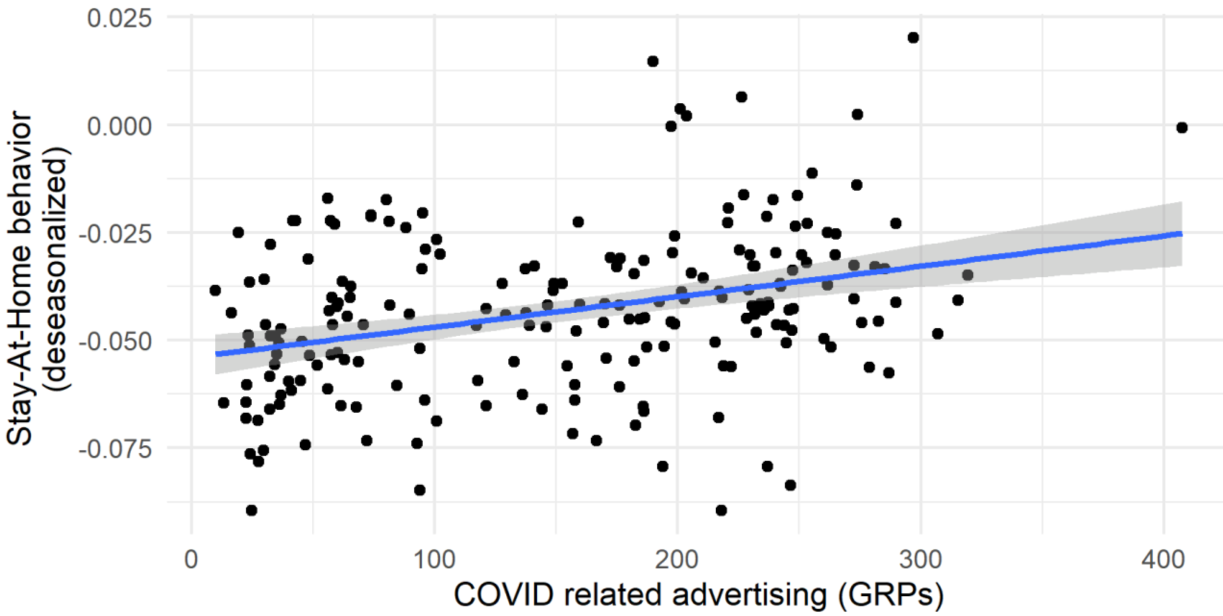


Figure 6: Impact of 1pp Increase in COVID-19 related Ads from Brands on Social Distancing Over Time

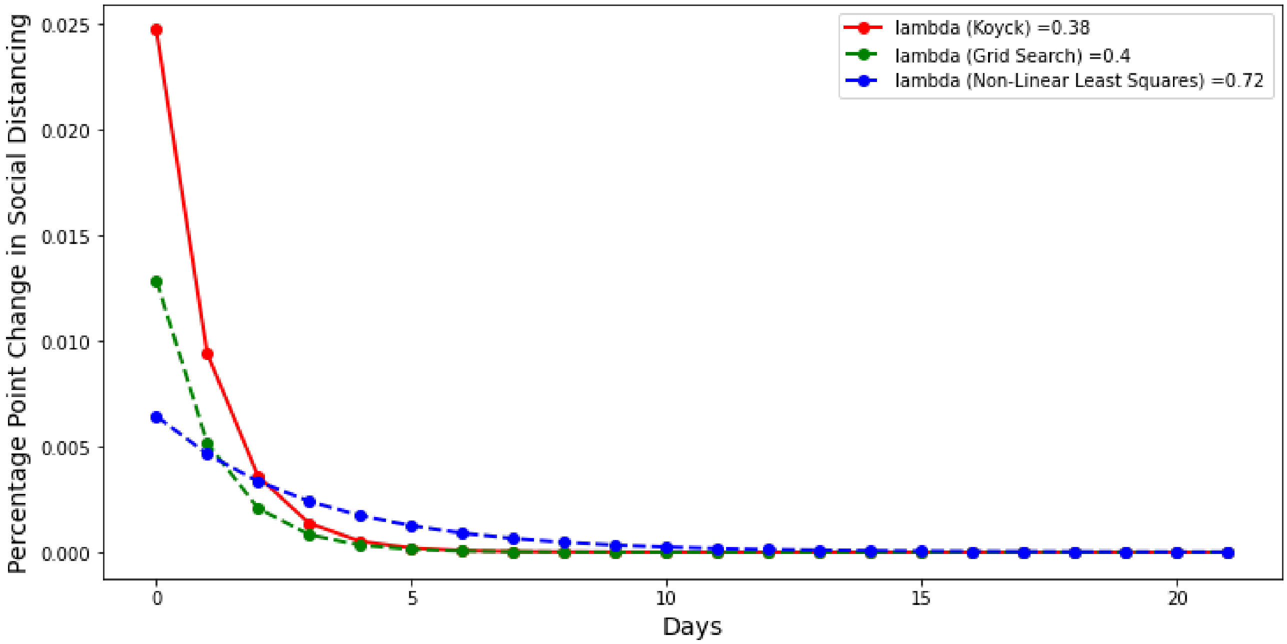


Figure 7: Heterogeneous COVID-19 Ad Effects (Brand Category)

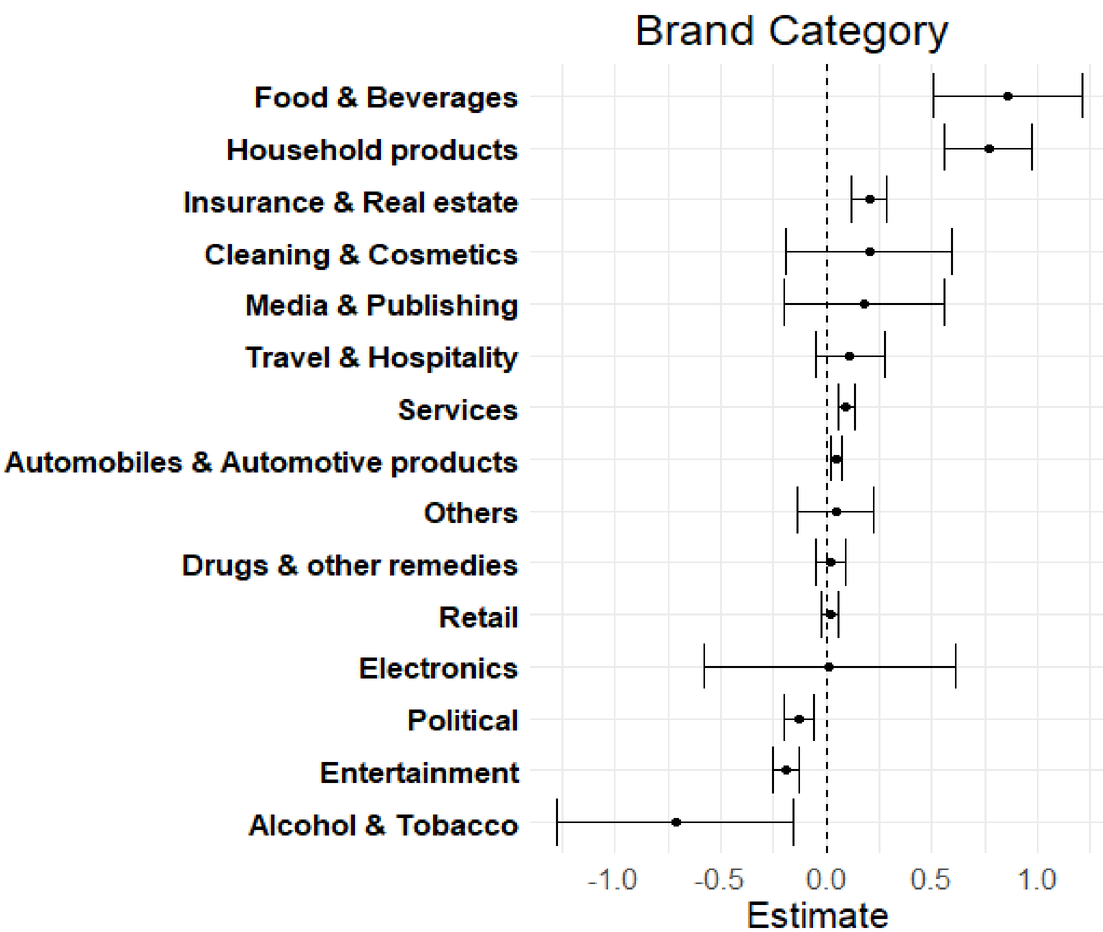


Figure 8: Heterogeneous COVID-19 Brand Ad Effects (Demographic Characteristics)

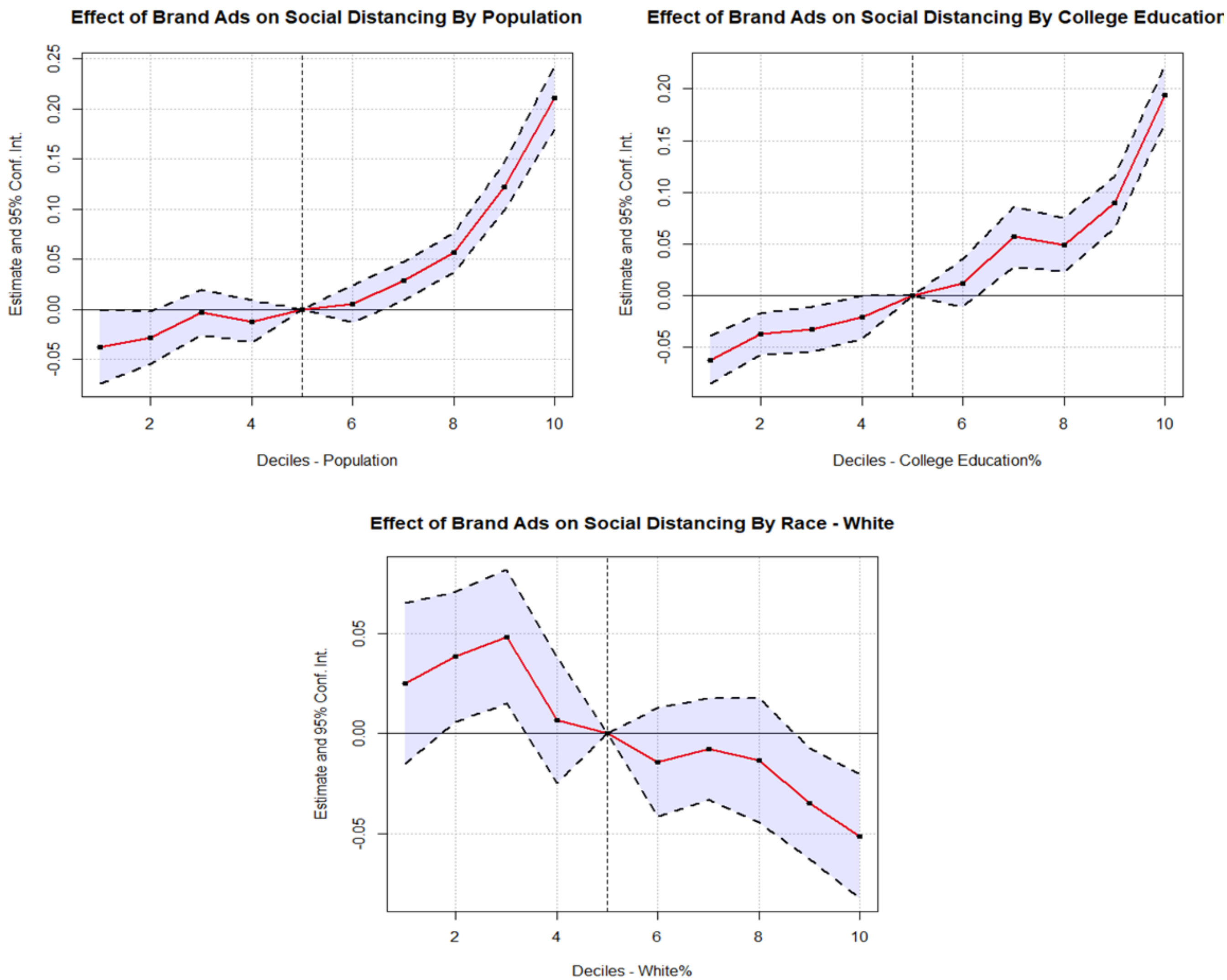
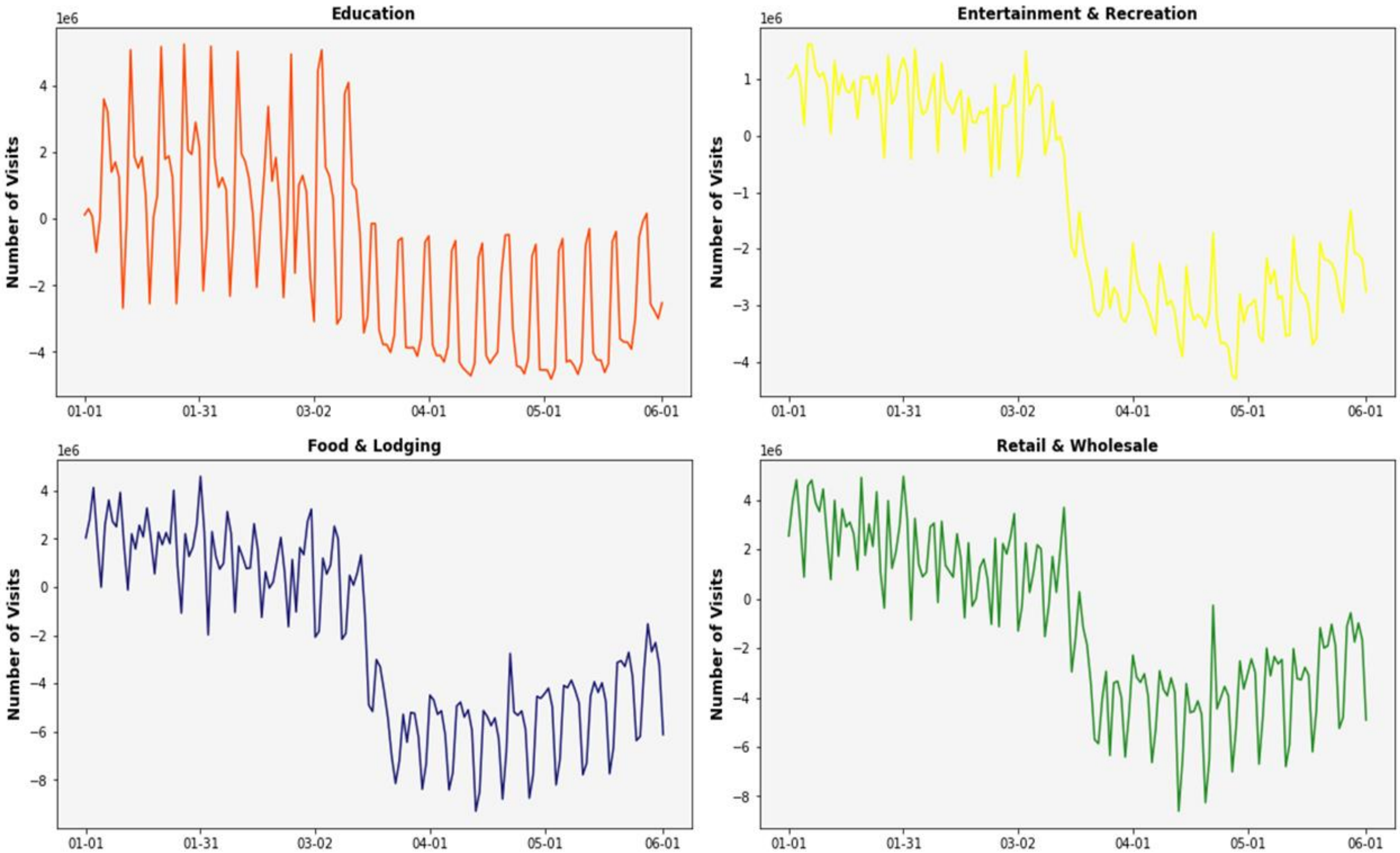


Figure 9: Change in POI Visits in 2020 Compared to 2019



ESSAY II: CITIZEN-CENTRIC SOCIAL LISTENING FOR CITIES – CITIZEN SENTIMENTS AND CITY COMPETITIVENESS

INTRODUCTION

When Amazon announced its plan for a second headquarter worth $5 billion in investments and 50,000 jobs, city governments across the US and Canada lined up with attractive proposals filled with incentives often running into billions of dollars to woo Amazon (Jensen 2019). However, these proposals often failed to take into account the concerns of residents of these cities. For example, while some New Yorkers were excited by the promise of jobs that the Amazon project was touted to generate, others questioned the magnitude of the incentives being provided to Amazon in addition to the adverse effects that it may have on the city's cost of living, environment, etc. (Goodman 2019). The resulting protests forced Amazon to abandon plans to have New York as one of its two new headquarters locations. There are several other instances of seemingly panacean business investments leading to adverse effects. For example, while it brought prosperity to the city of Seattle, the presence of Amazon also led to unaffordable housing, terrible traffic, inequality, and erosion of urban identity (Roberts 2017). Similarly, among several other problems, the prosperous Silicon Valley has rents that are 227% higher than the national average leading to a severe affordable housing crisis while also lacking vibrant public places (Harris 2017). A common theme among these examples is the failure of city authorities to adequately account for the opinions and sentiments of their citizens.

As of 2018, 55% of the total global population was living in urban areas, and the number is estimated to grow to 68% by 2050 (UN DESA 2018). Global trends and commerce point to the increasingly important role of cities in driving national and global economic growth (e.g., Katz

2011). Several studies and reports point to the growing stature of cities as autonomous centers of social and sustainable economic growth and innovation (e.g., Johnson 2008; Khanna 2016; Stucki and Tran 2021). Consequently, cities have become important platforms posing substantive research questions for marketers to explore. A report by The World Bank (2015) highlighted the need for cities to make themselves more competitive to attract more investments and create more jobs. The Economist Intelligence Unit defines the competitiveness of cities as the “ability to attract capital, businesses, talent, and visitors”. Indeed, several studies have found evidence of cities competing for investments, tourists, new residents, and a qualified workforce (e.g., Darchen and Tremblay 2010). Further, cities are increasingly investing in various marketing activities such as advertisements (e.g., Nahmias 2018), appointing CMOs (e.g., Olenski 2018; Quig 2020), and setting up dedicated customer service departments for citizens (e.g., Metro Atlanta CEO 2017). At the heart of these activities by cities are their citizens. Citizen-centric approaches have downstream positive outcomes for the city. A city that invests in its residents' social and economic welfare is also likely to attract more residents and talented workers to the city, thereby making the city an attractive prospect for business investments (e.g., Parilla and Liu 2019). In this regard, citizens’ perceptions and evaluations of various attributes related to a city could be a source of valuable insights for city management in devising more effective strategies. Such insights could also serve as a mechanism of evaluation and innovation for city services and provide valuable inputs for devising the city’s marketing campaigns. Indeed, some prior studies have suggested that the opinions of citizens could be as good an indicator of urban quality of life as conventional objective measures (Krendel 1970).

Social media have increasingly become an important platform for marketers, enabling them to gather intelligence and develop a better understanding of people’s expectations and

perceptions of brands (e.g., Fossen and Schweidel 2019; Rust et al. 2021). For example, marketers have leveraged social media for innovation (e.g., Muninger, Hammedi, and Mahr 2019), reputation tracking (e.g., Rust et al. 2021), customer relationship management (e.g., Trainor et al. 2014), and predicting consumer behavior (e.g., Erkan and Evans 2016; Kübler, Colicev, and Pauwels 2020). This process of monitoring social media channels for gathering intelligence about brands from consumers is formally known as social listening (Newberry 2021). While it has been widely adopted and explored in the context of traditional brands, there has been limited use of social listening in the context of cities. In keeping with a renewed call for exploration of Marketing's positive impact on consumers and society as a whole (e.g., Chandy et al. 2021), we investigate the role that social listening can play in identifying the sentiments and concerns of citizens and how that can influence the competitiveness of cities.

The importance of acquiring insights from citizens is further highlighted by the situation created by the COVID-19 pandemic. Housing and employment have been two of the most important drivers behind people's moving decisions (Lin, Cranshaw, and Counts 2019). However, the COVID-19 pandemic has allowed many workers to work remotely which has led many workers to reassess their decision to live in cities that are hot job markets but also have a high cost of living (e.g., Feintzeig and Eisen 2020). There exists some evidence of cities using social listening to gather insights from citizens in specific contexts. For example, the city of Houston uses social listening to understand citizens' responses to changes in city services (Hart 2019). However, there is a lack of systematic investigation into how the sentiment of citizens, as measured through large-scale social listening, can influence the competitiveness of cities.

In summary, the primary focus of this study is to understand if and how the sentiment of citizens towards a city influences key drivers of a city's competitiveness. Additionally, we

highlight the usefulness of social listening as a tool for obtaining high-frequency city-related insights on a large scale. To that end, we also focus on addressing major challenges associated with achieving an effective social listening strategy. Particularly, we address the challenges of determining what social media conversations would be relevant for cities and efficiently identifying these relevant conversations from large volumes of high-frequency data. Consequently, we ask the following research questions:

1. If and how does the sentiment of citizens towards a city influence key drivers (e.g., economic performance, migration, tourism) of a city's competitiveness?
2. How can city managers identify and efficiently collect relevant conversations on social media?
    a. What city-related attributes are considered important by people for their decision to live in or move to a city?
    b. How can city managers efficiently identify relevant social media conversations from large volumes of high-frequency data?

To answer these questions, we use a combination of qualitative methods, machine learning algorithms, and time-series models on data acquired from multiple sources. In Study 1, using extant literature, in-depth interviews, and topic modeling of conversations on city forums (CityData.com), we identify major city-related factors that people consider important while deciding to live in or move to a city. Given the vast array of conversations on social media (e.g., Twitter) that contain mentions of a city, some of which are relevant while most others are irrelevant to the city, we use the factors identified in Study 1 as a guide to manually label social media conversations that reflect people's opinions and sentiments towards the city. In Study 2,

we use a Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al. 2018), trained on the labeled data, to identify Twitter conversations relevant to cities. We find that our model achieves an 88% classification accuracy and outperforms popular machine learning text classification models. Using another BERT model with a similar architecture, trained on the Sentiment140 (Go, Bhayani, and Huang 2009) data, we classify and score the sentiment of the relevant Twitter conversations. The BERT model for sentiment classification achieves a best-in-class accuracy of 85% on Twitter data. Finally, in Study 3, we provide preliminary empirical evidence for the relationship between citizen sentiments and the three key drivers of a city's competitiveness, namely, the economic performance of a city, in-migration (operationalized as migration-related search interest), and visits to a city (operationalized as visit-related search interest). Using a panel vector autoregression (PVAR) model and Impulse Response Functions (IRFs), we show that citizen sentiments have a significant and positive effect on all three drivers of a city's competitiveness.

In the following sections, we first present a discussion on relevant literature to motivate our research. Second, we provide a detailed discussion of the different data sources used in this research followed by a discussion of the methods and findings from the three studies. Finally, we discuss the implications of this research for academics and city managers and conclude by stating the limitations and future scope of this research.

THEORETICAL BACKGROUND

Cities & Marketing

Kotler, Haider, and Rein (1993) define city marketing as the process or technique of promoting, selling, and distributing the city or parts of the city as products or services.

Competition between cities over resources such as industries, jobs, infrastructure, investments, and skilled workers has been one of the primary drivers behind the evolution of city marketing (e.g., Acharya and Rahman 2016; Florida 2002b; Florida 2002a; Kotler et al. 1999). Kavaratzis (2008) summarizes the evolution of city marketing into three phases: fragmented promotional activities, more structured marketing mix strategies, and branding of cities. In other words, city marketing has evolved from simple promotional activities aimed at attracting residents or businesses to including marketing mix strategies encompassing organizational measures, financial incentives, and product development. In the final phase, branding measures were adopted to create and manage the image of a city by influencing the emotional and psychological connections of stakeholders with the city. A significant number of recent studies in this domain have primarily focused on different aspects of city (or place) branding (e.g., Lucarelli and Olof Berg 2011; Oguztimur and Akturan 2016; Vuignier 2017). Four broad areas of research can be identified from this body of work: (1) city branding concept, processes, and measurement, (2) branding strategies, (3) branding culture and tourism; and (4) social urbanism (Oguztimur and Akturan 2016). Particularly, branding has been considered (i) as a tool by cities to enhance a city's economic, cultural, and political value (e.g., Kavaratzis 2004) and (ii) as an instrument of communicating a city's competitive advantage, quality of the place, its history, lifestyle and culture (Björner 2013). Additionally, some of the major city-related constructs explored in city marketing literature include city brand image (e.g., Altınbaşak and Yalçın 2010; Brandt and de Mortanges 2011; Gilboa et al. 2015), city reputation (e.g., Delgado-García, de Quevedo-Puente, and Blanco-Mazagatos 2018), city brand personality (Ahmad et al. 2013; Demirbag Kaplan et al. 2010), and creativity (e.g., Trueman, Cook, and Cornelius 2008).

In practice, however, city marketing efforts have been primarily limited to promotional activities with branding efforts focusing mostly on creating logos and slogans (Ashworth and Kavaratzis 2009; Kavaratzis 2008). Further, a growing industry for evaluating and ranking cities based on various scales such as *quality of life* (e.g., Quality of Life Index by Mercer), *global power* (e.g., Global Power City Index by The Mori Memorial Foundation), *sustainability* (e.g., The Sustainable Cities Index by ARCADIS), *smart city* (e.g., IMD Smart Cities Index) has emerged to measure the satisfaction of citizens with various attributes of a city. City rankings, however, suffer from many drawbacks such as insufficient attention to interrelations and causalities, lack of clarity in methodological approach, and lack of consideration towards actual behavior and preferences of citizens (Giffinger, Haindlmaier, and Kramar 2010). On the other hand, academic research has acknowledged the need for adopting a more holistic approach to city marketing (e.g., Ashworth and Voogd 1994, 1988, 1990; Kavaratzis and Ashworth 2007). The city marketing process in its refined form consists of three major steps. The first step deals with analyzing a city's current situation by assessing the city's assets, opportunities, and audiences (Kavaratzis and Ashworth 2007). Second, cities use these insights for formulating and implementing their vision and goals through marketing measures (Ashworth and Voogd 1990). The final step in this process involves monitoring and evaluation of the implemented measures (Kavaratzis 2008). Similarly, Ashworth and Voogd (1990) equate citizens to consumers and propose understanding the needs, wishes, and demands of citizens as the first step in the city marketing process. Therefore, marketing initiatives for cities must incorporate insights from citizens/residents (used interchangeably in this manuscript) of the city. The importance of citizens has been widely acknowledged in city marketing literature (e.g., Braun, Kavaratzis, and Zenker 2013; Rehmet and Dinnie 2013; Zenker and Seigis 2012). For example, Zenker and

Petersen (2010) propose that identity fit between the city prototype and the self-concept of the residents leads to strong resident-city identification which leads to higher commitment and a higher likelihood to stay in the city while Zenker, Petersen, and Aholt (2013) focus on unearthing the factors underlying citizens' satisfaction with a city. Further, Zenker and Rütter (2014) have demonstrated the relationship between citizen satisfaction and place attachment, place brand attitude, and positive citizenship behavior. However, research is limited regarding how the sentiment of citizens towards a city may affect various city-level outcomes important for the competitiveness and growth of cities.

Cities have been compared to corporate brands (e.g., Hankinson 2001, 2004) with people's understanding of brands being considered equivalent to their understanding of cities (Ashworth and Kavaratzis 2009). In marketing literature, regular insights from customers are considered essential for obtaining a competitive advantage for traditional brands (e.g., Hogan, Lemon, and Rust 2002; Mithas, Krishnan, and Fornell 2005). Further, in recent times with businesses generating vast volumes of consumer data and with technological and methodological advances allowing extraction of insights from such data (Lycett 2013), big data analyses have become essential in many marketing decision-making processes (e.g., Chintagunta, Hanssens, and Hauser 2016; Erevelles, Fukawa, and Swayne 2016). However, in the context of cities, the use of such insights, especially insights gained from citizen-related big data, has been limited in marketing decision processes. In prior literature, the primary instruments of data collection from citizens have been surveys and interviews (Oguztimur and Akturan 2016). These methods often suffer from several issues such as response, interpretation, and sample selection biases. Unsolicited organic opinions and sentiments of citizens have mostly been overlooked by researchers in the context of city marketing. Additionally, due to logistical and cost-related

issues, interviews and surveys are usually conducted infrequently and with a limited number of people. With the proliferation of digital and social media, organic and unsolicited opinions and sentiments are readily available from a significantly larger number of citizens in real-time. Additionally, research finds that text streams from social media have the potential to substitute and supplement traditional survey-based polls (O'Connor et al. 2010).

Sentiment & Consequences

In this study, we explore whether the sentiment of residents towards a city influences key drivers of a city's competitiveness such as economic performance, migration, and tourism. With regards to the relationship between consumer sentiment and future economic performance, the evidence is mixed. Evidence exists of consumer confidence being able to forecast economic activity (e.g., Golinelli and Parigi 2004) and lagged consumer sentiment having explanatory power for current household spending, a major driver of economic activity (Carroll, Fuhrer, and Wilcox 1994). Similarly, Anthony Bryant and Macri (2005) show that consumer sentiment influences variations in consumer expenditure while Fornell, Rust, and Dekimpe (2010) find that lagged consumer satisfaction changes have a significant impact on consumer spending growth. Further, Rodriguez and Soper (2020) demonstrate that the inclusion of sentiment variables significantly improves the prediction accuracy of economic outcomes. However, Ludvigson (2004) finds that the independent information provided by most consumer confidence measures can predict only a modest amount of variation in future consumer expenditure growth. In the context of cities, we argue that the sentiment of residents toward a city could have a significant impact on the future economic performance of the city. In the context of brands, satisfaction leads to higher brand loyalty, positive word of mouth, and lower search for alternatives (e.g., Bloemer and Kasper 1995; Srinivasan, Anderson, and Ponnavolu 2002). Similarly, it can be

expected that more positive sentiments around the key city-related attributes would lead to more positive word of mouth and lower willingness to move out of the city. Indeed, Zenker and Gollan (2010) find that residents' satisfaction with the place is crucial for their decision of staying or moving out of the city. Such decisions can positively impact the city's economic performance as a thriving city is likely to attract business and personal investments.

In the same vein, residents' positive sentiment around key city-related attributes, expressed through different communication channels (e.g., social media) is expected to help attract potential migrants to the city. The reverse is expected to be true as well when residents' sentiment towards a city is negative. In fact, research has found that negative word-of-mouth has a stronger effect on people's behavior (e.g., Chakravarty, Liu, and Mazumdar 2010). The role of word-of-mouth in customer acquisition is widely acknowledged in marketing literature (e.g., Nam, Manchanda, and Chintagunta 2010; Villanueva, Yoo, and Hanssens 2008; de Vries, Gensler, and Leeflang 2017). For example, Hennig-Thurau, Wiertz, and Feldhaus (2015) find a significant effect of movie-related word-of-mouth on Twitter on people's decision to watch the movie. In-migration i.e., the moving of new residents to a city, is a major area of interest to city authorities. Cities want a skilled labor force that can contribute to the growth and prosperity of the city. In the process of migration, the search for information about a place is a later stage activity with awareness and interest in the place preceding it. One such source of creating awareness and interest is promotional activities by places. However, promotions and advertisements are generally believed to be less credible than organic content in the process of developing the image of a place (Gartner 1994). Therefore, the experiences of residents can not only serve as a source of information for potential migrants (Dekker and Engbersen 2014) but can also be a source of creating awareness and interest in the place. The sentiments and

experiences of residents can also help create awareness and interest among visitors and tourists to the city. Social media serves as a platform suited to amplifying communications and sharing the experiences of locals with outsiders.

The experiences of visitors, shared through online and offline word-of-mouth, can also influence the decisions of potential migrants to a city i.e., more positive experience-related word-of-mouth from visitors should positively affect people's moving decisions to the city. Further, evidence exists of economic activity being an important factor in people's decisions to migrate to a place (e.g., Lin, Cranshaw, and Counts 2019). Therefore, the economic performance of a city is likely to have a positive effect on in-migration to a city. The reverse is likely to be true as well i.e., in-migration should have a positive effect on the economic performance of a city (e.g., Baughn, Neupert, and Sugheir 2013; Rodríguez-Pose and von Berlepsch 2014). This relationship may be attributable to factors such as the availability of skilled labor, purchase of property, and higher spending in the city's economy. Similarly, a bidirectional relationship is likely to exist between tourism and economic performance with tourism or visits to the city positively affecting a city's economic performance (e.g., Fayissa, Nsiah, and Tadasse 2008; Neuts 2020) and conversely, the economic performance of a city positively influencing people's decisions to visit a city (e.g., Antonakakis et al. 2019). The latter relationship could be attributable to factors such as business-related visits and the presence of better amenities and recreational facilities. Finally, we should also expect the economic performance of cities to positively affect the sentiment of citizens. Stronger economic performance is indicative of the presence of more economic opportunities and the availability of funds for investment in the well-being of the citizens.

--Insert Figure 1 about here--

We summarize the above arguments in a conceptual model (see figure 1) of the relationships between citizen sentiments, economic performance, in-migration, and visits to a city. We empirically test this conceptual model in study 3 using a panel VAR model. One thing to note here is that several of the proposed relationships between the three drivers of a city's competitiveness have been established in prior literature even if not in the context of cities. However, we test these established relationships simultaneously with the novel relationships between citizen sentiments and the driver of a city's competitiveness as part of a system of relationships. In addition to lending validity to our findings, estimating these established relationships also allow us to study the effects of citizen sentiments in an endogenous system. For ease of understanding, we represent the novel relationships using thicker arrows in figure 1.

Social Listening

With the emergence of social media platforms, social listening has gained prominence for brands as a tool for gathering insights from consumers. Several studies have highlighted the need for brands to monitor social media platforms for customer complaints and negative word-of-mouth, failing which could lead to negative outcomes for brands (e.g., Einwiller and Steilen 2015; Johnen and Schnittka 2019). Other studies have highlighted how leveraging social media insights can create more effective customer relationship management (CRM) strategies for firms (e.g., Greenberg 2010; Malthouse et al. 2013; Trainor et al. 2014). Insights from social media have also been used widely by firms to enhance their innovation processes (e.g., Roberts and Piller 2016). Examples include the 'My Starbucks' idea platform which has led to the implementation of more than 300 ideas that were generated from the online community (Muninger, Hammedi, and Mahr 2019). Further, Culotta and Cutler (2016) use brands' social connections on Twitter to measure brand perceptions. Social media has become an important tool

for the tourism industry with tourists relying heavily on social media for gathering information about the destination, planning trips, and sharing experiences (e.g., Leung et al. 2013). Consequently, there is a greater focus on electronic Word of Mouth (eWOM; Buhalis and Law 2008) as a source of information dissemination to influence tourists' micro and macro destination choices (e.g., Tham, Croy, and Mair 2013). Research on the use of social media in tourism has primarily focused on communication from past travelers and destination management organizations (DMOs) as sources influencing the decisions of potential tourists (Tham, Croy, and Mair 2013). There has been limited investigation of the role that social media activities of citizens of a destination can play in influencing the decisions of potential visitors. Freire (2009) shows that local people are relevant and important for a destination brand-building process. Additionally, for potential migrants, social media serves as a source of insider knowledge about places (Dekker and Engbersen 2014). In addition to private sector brands, the public sector is also increasingly adopting social listening for the development of innovations in public policies and services (e.g., Criado, Sandoval-Almazan, and Gil-Garcia 2013; Loukis, Charalabidis, and Androutsopoulou 2017). There is a growing stream of research that emphasizes the need for government and public agencies to incorporate insights from social media in policy decisions. For example, Marine-Roig and Anton Clavé (2015) utilize user-generated content from social media to derive tourism-related business intelligence for the city of Barcelona while Kavanaugh et al. (2012) investigate how social media insights can be used by governments for crisis management. Further, governments have used social media for engaging with citizens (e.g., Bonsón, Perea, and Bednárová 2019), increasing government transparency and trust (e.g., Song and Lee 2016), crisis communication (e.g., Graham, Avery, and Park 2015), and promoting their place brand (e.g., Sevin 2016).

Social media serves as a reservoir of insights into the opinions and sentiments of citizens that is difficult to collect using traditional means like surveys (Kavanaugh et al. 2012). These insights have the potential to improve services and communications with citizens (Bertot, Jaeger, and Hansen 2012). Often city marketing approaches have been criticized for being focused on attracting resources such as investments, tourists, and new residents while ignoring prevailing social and economic issues in the cities (Boland 2013). Social listening can serve as a tool for highlighting marketing's role in advancing social good. For example, social listening can help authorities identify concerns of citizens in a timely manner allowing them to devise appropriate remedial actions. Gasco et al. (2019) use Twitter to detect noise complaints and identify them by source. It can also be a source of meaningful and actionable insights to make actions from public agencies more effective, thereby having a greater impact on beneficial social behaviors. For example, Twitter conversations have been used to detect the early spread of influenza epidemics allowing policymakers to take appropriate preventive measures (Allen et al. 2016; Aramaki, Maskawa, and Morita 2011).

DATA

To address our research questions, we assemble data from multiple sources. We collect data from City-Data.com, Twitter, Federal Reserve Bank of St. Louis, and Google Trends, and also conduct in-depth interviews and review of extant literature. Table 1 lists the different data sources and their intended use. From each of these sources, we collect data for 6 major cities in the United States. These cities include Atlanta, Chicago, Detroit, Miami, Phoenix, and San Francisco. We discuss the data sources in detail in this section. Details about the in-depth interviews and review of extant literature are provided under the 'Methodology' section.

--Insert Table 1 about here--

City-Data.com

It is a "social networking and information" website that contains detailed facts and statistics about cities in the United States. It also has discussion forums where people can discuss various city-related topics. Specifically, we use Python scripts to collect text data from discussion threads where people ask and respond to questions related to specific aspects of a city. These discussions are specifically conducted in the context of 'moving' to a particular city. We collect data on all discussions originating between 1st January 2015 till 31st December 2018.

Social Media Conversations (Twitter)

Twitter is a social networking and microblogging service that allows users to post real-time messages, called tweets. Twitter had around 68 million active monthly users in the United States as of March 2019 (Clement 2019), with 22% of all US adults using it (Perrin and Anderson 2019). We choose Twitter as a platform to demonstrate the effects of social listening for the following reasons: (1) as compared to other social media platforms, most Twitter profiles are public (Rust et al. 2021) which allows for more people's opinions to be heard and has a potentially higher capacity for information disseminations related to cities; (2) approximately 26% of all urban adults use Twitter (Perrin and Anderson 2019) forming a much larger information pool than any survey-based instruments can achieve; (3) Twitter provides a publicly available Application Programming Interface (API)[1] with sophisticated search features (e.g., hashtags, mentions) with queries up to 1024 characters long; and (4) almost all major cities (and

[1] https://developer.twitter.com/en/docs/twitter-api/tweets/search/introduction

their different departments) in the United States have public Twitter profiles that citizens engage with. For each of the 6 cities in our study, we collect tweets related to individual cities over a 48-month period (years 2015 to 2018). We searched for tweets containing (i) popular hashtags associated with the focal city, and (ii) official Twitter handles of the cities and their various departments. In total, we collected 9,932,966 Tweets.

Economic Conditions Index

This index is produced by the Federal Reserve Bank of St. Louis and computed using a dynamic factor model that includes 12 variables measuring various aspects of economic activity every month in a Metropolitan Statistical Area (MSA). The 12 variables include (1) Average weekly hours worked by private-sector employees, (2) Unemployment rate, (3) Private sector goods-producing employment, (4) Private sector service-producing employment, (5) Government sector employment, (6) Real average hourly earnings, (7) Construction permits for new private residential buildings, (8) Real average quarterly wages per employee, (9) Total real personal income per capita, (10) Return on average assets, (11) Net interest margin, and (12) Loan loss reserve ratio. This index is calibrated to Gross Metropolitan Product (GMP) growth and variance to allow for comparison across metro areas (Arias, Gascon, and Rapach 2016). We use this index as a measure of the economic performance of the city.

Google Trends

Google Trends provides access to a largely unfiltered sample of actual search requests made to Google. Google Trends data has been shown to be a crucial variable in forecasting important outcomes such as tourist arrivals, and economic and financial variables (e.g. Choi and Varian 2012; Da, Engelberg, and Gao 2011). It normalizes search data (0-100) to make

comparisons between terms easier. Specifically, the search interest data is normalized to the time (*month* in our context) and location (*Metropolitan Statistical Area (MSA)* in our context) of the search query. The search volume of a specific query is divided by the total searches in a given geography and unit of time. This number is then converted to a 0-100 scale with 100 representing the peak popularity of the search query in the given geography and unit of time. A score of 50 would indicate that the term is half as popular compared to its peak popularity. In the absence of high frequency (daily/monthly) migration and tourism data at the city (or MSA) level, we use Google Trends data to create dependent variables for 'interest in migrating to a city' and 'interest in visiting a city'. To create the 'interest in migrating to a city' (or 'in-migration interest') variable, we use the search interest around keywords such as *jobs in*, *apartments in*, *houses in*, and *schools in* while the 'interest in visiting a city' (or 'visiting interest') variable is based on the interest around keywords like *hotels in* and *flights to*, for specific cities. The final variables are created for a focal city by aggregating the interest for the search terms originating in MSAs other than the focal city at the monthly level. We use the in-migration interest and visiting interest variables as proxy measures of actual in-migration and visiting behavior.

METHODOLOGY

We answer our research questions using three different studies. In study 1, we identify major city-related factors that may influence people's decisions to live in or move to a city. In study 2, we identify relevant Twitter conversations and measure their sentiment. Finally, in study 3, we provide preliminary evidence of the relationship between citizen sentiments and key drivers of city competitiveness. See figure 2 for an overview of the methodology.

--Insert Figure 2 about here--

Study 1: Identifying Major City Attributes

For cities to gather actionable intelligence from social media, the first step is to identify which social media conversations are relevant to the city. Social media users often use a city's hashtag to increase the reach of their posts even if the content of the post is not relevant to the city (see Figure 3 for examples). This makes it difficult to sift through large volumes of posts to identify conversations of value and relevance to city managers. Given the aim of this research is to explore the role of opinions and sentiments of citizens in driving the competitiveness of cities, we focus on identifying city-related factors that play a major role in citizens' decision to live in or move to a city thereby having a cascading effect on the competitiveness of cities. We use a multi-method approach consisting of a review of extant literature, topic modeling of city forum discussions, and interviews with a convenience sample.

--Insert Figure 3 about here--

Review of extant literature. We conduct a thorough review of the extant literature on Google Scholar to identify various city attributes that had been studied by academics and practitioners. Table 2 contains the list of city attributes identified from extant literature. Our review covers a wide range of studies appearing in both marketing and non-marketing journals including various indices and rankings instituted by practitioners and various think tanks. We focus on those studies that explicitly identified different city attributes and also classify the studies based on whether the attributes included in them were identified using inputs from citizens. We find that only a limited number of studies had incorporated insights from citizens when selecting a city attribute (e.g., Bonaiuto et al. 2019; Llinares, Page, and Llinares 2013) while a vast majority of them use extant literature as a guide for choosing city attributes. There were also a few studies that identified the attributes based on inputs from subject matter experts

(e.g., Foroudi et al. 2016; Zenker, Petersen, and Aholt 2013). Further, the few studies that had incorporated the opinions of citizens, did so in the context of defining specific constructs (e.g., City Image) without specifically addressing whether the identified city attributes influenced their decision to live in or move to a city. The findings from this review suggest that systematic identification of important city attributes that may influence people's decision to live in or move to a city is lacking from prior literature.

--Insert Table 2 about here--

Topic modeling of city forum discussions. City online forums provide citizens the platform to discuss city-specific topics. In particular, we are interested in discussions that revolve around topics related to moving to a city i.e., discussions initiated by people enquiring about city attributes important to them before moving to a city. These conversations between seekers and providers of information are a rich source of information about city attributes that are considered important by citizens since people are more likely to ask about attributes that are important to their decision of choosing a city to move to. Additionally, several studies have highlighted the importance of online forums for understanding people's opinions and preferences (e.g., Gruner, Homburg, and Lukas 2014; Pitta and Fowler 2005). In this study, we obtain 'moving'-related forum discussion texts from City-Data.com[2] which contains "detailed, informative profiles for every city in the United States" and has over 14 million monthly users. Apart from containing facts and statistics from individual cities, this website also contains forums where users can ask and answer queries and engage in discussions related to cities. While the discussions cover a range of diverse topics, using a Python script we extract conversations that focus on topics

[2] http://www.city-data.com/

related to people's decision of moving to a city. Specifically, we search the forum for all conversations containing variations of the keyword "move" (e.g., moving, moved) for each of the 6 cities in our study over a 4-year period (2015-2018).

To uncover the underlying topics in these conversations, we use Correlated Topic Model (CTM) which is a machine learning technique proposed by Lafferty and Blei (2005) and an extension of LDA (Blei, Ng, and Jordan 2003). LDA falls short when it is required to model the correlation between topics since the topic probabilities are drawn from a Dirichlet distribution which assumes topic proportions to be independent. CTM improves over the LDA by allowing topics to be correlated and it does so by drawing topic probabilities from a multivariate logistic normal distribution instead of a Dirichlet distribution. Before applying CTM, we prepared our data by removing stop words and punctuations, converting all words to lower case, and tokenizing each document into individual words. Next, we lemmatized the words using SpaCy 3.0[3] to convert them to their root form and removed all documents that contained less than five words. Further, we excluded words that occurred only in up to 1% of all documents (posts) because such words that occur only in a few documents do not contribute toward estimating the topic-word distribution. Finally, using a standard algorithm (Gensim package in Python) we created bigrams and trigrams to account for words that should be considered together. We refer to individual posts on the forum as a 'document' and the collection of the posts for a city as a 'corpus'. The CTM algorithm assumes that an N-word document is created from the following generative process:

1. Draw $\eta | \{\mu, \Sigma\} \sim N(\mu, \Sigma)$

[3] https://spacy.io/usage/v3

2. For $n \in \{1, \ldots \ldots, N\}$:

    a. Draw topic assignment $Z_n|\eta$ from a Multinomial $(f(\eta))$.

    b. Draw word $W_n|\{Z_n, \beta\}$ from Multinomial (β)

Where, $\{\mu, \Sigma\}$ is a K-dimensional mean and covariance matrix with K being the number of topics. β is the probability vector associated with a topic Z_n that is used to select the word W_n. Finally, the function f is a logistic transformation that maps $\eta = (\eta_1, \ldots \ldots, \eta_k)$ to the vector of topic probabilities $\theta = (\theta_1, \ldots \ldots, \theta_k)$ as follows:

$$\theta_i = f(\eta_i) = \frac{\exp(\eta_i)}{\sum_{k=1}^{K} \exp(\eta_k)} \qquad (1)$$

We use the Python package 'tomotopy'[4], which uses Collapsed Gibbs Sampling to infer topic-word distributions, to conduct our analysis. CTM requires the number of topics to be provided as an input to the algorithm which we determine using the 'UMass' topic coherence measure proposed by Mimno et al. (2011). Topic coherence measures the semantic similarities between top words in a topic and helps determine if the topic has meaning or if it is just an artifact of the statistical process (e.g., Rosner et al. 2014). We use the 'Gensim' Python package to calculate the coherence scores where lower values of UMass indicate more coherent topics. We plot the coherence scores for topic numbers ranging from 5 to 50 with increments of 5 (see Figure 4) and select the number of topics based on the lowest point on the plot. The optimal number of topics was found to be 45. The identified topics were named based on their representative words and related topics were combined under broader city-related factors. Table 4 below contains details of the identified topics.

[4] https://bab2min.github.io/tomotopy/v0.10.2/en/

--Insert Figure 4 about here--

Interviews & surveys. The large number of forum discussion posts necessitated an algorithmic approach for identifying underlying topics of discussion. This approach is partially dependent on the subjectivity of the researcher (e.g., labeling of topics) and given the unstructured nature of forum discussions, may fail to identify some topics. To ensure we account for all major topics related to city attributes, we conducted in-depth interviews with 29 undergraduate students at a large public university located in a major city in the United States and asked them about city-related attributes they consider important for living in a city and explain the rationale behind the choice of these factors. The respondents were all between 18 to 34 years of age and 51.7% (N=15) of them were female. The number of factors mentioned by each respondent varied between 3 to 6. In total, 40 unique factors were mentioned during the interviews with *employment*, *transportation*, *cost of living*, *safety*, and *diversity* being the most frequent. See Table 3 for a list of sample responses.

--Insert Table 3 about here--

From the list of unique attributes identified from the literature review, forum discussions, and interviews, we created broader and more generalizable factors by combining similar and related city attributes. Three independent coders (graduate students) categorized the unique attributes into 11 broad city-related factors (see Table 4 for details). The inter-coder reliability was .88 with differences between the coders being resolved through discussions. We also provide a definition for each of the 11 city-related factors.

--Insert Table 4 about here--

Study 2: Relevance and Sentiment Classification on Twitter

Identifying relevant conversations. To extract meaningful insights from social media conversations, city managers need to track those conversations which are relevant to their objectives. Noisy data can lead to incorrect conclusions especially when insights cannot be inferred manually. Therefore, a crucial step in social listening is the ability to separate relevant conversations from noise. In this research, our objective is to analyze conversations around city attributes that influence people's decision to live in or move to a city, which ultimately affects a city's competitiveness. Thus, we use the factors identified in Study 1 as a guide to identifying relevant city-related conversations on Twitter.

It is difficult to manually identify relevant conversations in such a large dataset. Therefore, we use Machine Learning to separate relevant conversations from the noise. However, to accurately classify a conversation as relevant (versus irrelevant), we require large volumes of labeled data to train the algorithms. In general, machine learning models perform better when they are trained on a large number of training examples. This is intuitive since the greater the number of examples a model is trained on better will it be able to learn the characteristics of the data. However, labeling is a costly and time-consuming process. Often, such large, labeled, context-specific datasets are not available. Thus, in this study we use the concept of transfer learning where models pre-trained on millions of words can be adapted to perform specific tasks by training them on a small corpus of task-specific labeled data. We use the state-of-the-art Bidirectional Encoder Representation from Transformers (BERT) NLP model developed by Devlin et al. (2018). BERT is trained on BookCorpus data (800M words) and English Wikipedia (2,500M words) for Masked Language Modeling and Next Sentence Prediction. Specifically, we use the "bert-base-uncased" version of BERT (12 encoder layers,

768 hidden units, 12 attention heads, and 110M parameters) which does not differentiate between lower- and upper-case words. This model is fine-tuned with labeled data specific to our context which allows it to *learn* how to discern between relevant and irrelevant tweets.

BERT uses transformers, an attention mechanism, that allows it to learn contextual relationships between words in a text. Transformers use an encoder for reading text inputs and a decoder for the task-specific output. Text inputs to BERT encoders are in the form of a sequence of tokens which are created using the WordPiece[5] tokenization algorithm (Wu et al. 2016). A 'CLS' classification token is attached to the beginning of each sentence and a 'SEP' separation token at the end of a sentence. For example, 'I love Atlanta! It has great people.' will be converted to [[CLS], 'i', 'love', 'atlanta', '!', 'it', 'has', 'great', 'people', '.', [SEP]]. A 768-dimensional initial embedding is learned for each token during the pre-training phase. Further, to identify the position of a token in the sentence a position embedding is added to each token. Finally, a marker (segmentation embedding) is also added to distinguish between sentences. The input embeddings are the sum of the token embeddings, the segmentation embeddings, and the position embeddings. The input is then passed through 12 sequentially arranged encoders and the representation corresponding to the first token (CLS) in the output is used for fine-tuning. BERT's pooler layer applies a linear transformation (with weights learned from the next sentence prediction task) over the representation of CLS and passes it through a 'tanh' activation function ($\frac{e^x-e^{-x}}{e^x+e^{-x}}$). For our classification task, we add our classification layer architecture on top of BERT. Specifically, we add 5 sequential dense layers with the following dimensions (768,384), (384, 192), (192, 96), (96,48), and (48,2) with ReLU activation after each layer (see

[5] https://huggingface.co/transformers/tokenizer_summary.html

Figure 5 below). The tapered nature of our architecture allows for better generalization and helps avoid overfitting while also saving the computational cost by having a lesser number of parameters for computation. We also use a dropout rate of 0.4 after the first layer to prevent the model from overfitting. Finally, we use a sigmoid activation function ($\frac{e^x}{1+e^x}$) in the output layer for our binary classification task.

--Insert Figure 5 about here--

Before the final data collection, we collected 20,000 Tweets using the previously mentioned criteria. These tweets were randomly distributed over the 48 months considered in our study. We use three graduate students to label the tweets as either *relevant* or *irrelevant*. The labelers were provided with the list of the broad city-related factors identified in study 1 along with the list of constituent attributes of each factor. They were instructed to label a Tweet as relevant if the subject of the Tweet was related to any of the broad city-related factors, otherwise, as irrelevant. The final labels were decided based on a majority decision or through discussions (in case of a non-unanimous choice). There were 4,877 (24.4%) tweets labeled as 'relevant' in our data. We further analyze the tweets labeled as 'irrelevant' to identify frequently occurring words and hashtags in these tweets. We use these words (e.g., "Enter to win", "Join us") and hashtags (e.g., #NowPlaying, #sale) as part of the exclusion criteria for the final data collection.

We split our labeled data into training (70%), validation (15%), and holdout samples (15%) and trained the model on the training sample using the Adam optimizer with weight decay (AdamW) and a learning rate of 1e-5 to update the network parameters. We use the negative log-likelihood as the loss function and use the validation sample for model evaluation during the training phase. Finally, we evaluated our model on the holdout sample. We observe a

classification accuracy of .88 and an f1-score of .88 (see Table 5 for details). For our class of interest i.e., the relevant class, the model has a recall of .96 which means that 96% of all relevant tweets were identified accurately and a precision of .81 which means that 81% of all 'relevant' classifications were accurate. We also compare our model with other benchmark text classification models like LSTM and CNN and find that BERT has higher accuracy than both these models (see Table 5 for details). In total, 1,283,648 Tweets were classified as relevant in our sample using BERT.

--Insert Table 5 about here--

Sentiment classification. Tweets have several unique characteristics due to which their sentiments are hard to infer algorithmically. Some of the major characteristics that make sentiment analysis on Tweets difficult are (1) short length and Twitter-specific communication elements, (2) sentiment class imbalance i.e., a large majority of Tweets convey neutral sentiments, and (3) dynamic nature of topics and language elements i.e., topics, sentiments, and communication elements may change over time (Zimbra et al. 2018). Popular approaches for conducting sentiment analysis include Lexicon-based and Machine Learning methods. Lexicon-based methods represent a text as a bag of words and determine the overall sentiment of the text based on the sentiment polarity of individual words. Such methods are popular due to their accessibility and ease of computation. However, their classification accuracies tend to be lower than Machine Learning (ML)-based methods (Zhang et al. 2019). Therefore, we adopt an ML-based approach to classify the sentiment of Tweets identified as relevant.

To identify the sentiment of the relevant Tweets, we train another BERT model with the same architecture with data from the publicly available Sentiment140[6] dataset. The Sentiment140 dataset consists of 1.6 million tweets with their sentiments labeled as either positive or negative (800,000 each). This dataset was created by Go, Bhayani, and Huang (2009), and the sentiment classification was conducted using distant supervised learning. Sentiment140 has been widely used for sentiment classification tasks in prior literature (e.g., Bravo-Marquez, Mendoza, and Poblete 2013; Zhang et al. 2019; Zimbra et al. 2018). We train our model with 80% of the data and split the remaining data into validation (10%) and holdout samples (10%). Our model reports an accuracy of .85 with an f1-score, recall, and precision of .85 as well. This is a significant finding since a majority of prior studies on Twitter sentiment classification have achieved accuracies lower than .84 (e.g., Chakraborty et al. 2020; Corrêa Júnior, Marinho, and dos Santos 2017; Emadi and Rahgozar 2020; Zhang et al. 2019). To the best of our knowledge, there is only one published study that achieves an accuracy of .91 (Horne et al. 2020). However, the authors state that one of the major limitations of their model (GRUBERT) is that it suffers from interpretability issues. Therefore, compared to popular ML models used in recent literature, our model's performance in the Twitter sentiment classification task is best-in-class.

Sentiment scoring. One of the primary objectives of this sentiment analysis is to create sentiment scores that can be used to study the relationship between citizen sentiments and key outcomes for cities. Since the training data consists of only two classes (positive and negative), our model executes a binary classification task. The model outputs two probabilities adding up to 1; one for the tweet belonging to the positive sentiment class (P_{Pos}) and the other for belonging

[6] http://help.sentiment140.com/for-students

to the negative sentiment class (P_{Neg}). We create sentiment scores for individual tweets by subtracting P_{Neg} from P_{Pos}. For example, if the probability of a tweet belonging to the negative class is, say, .82 (.18 for the positive class) then the sentiment score would be -.64. One thing to note here is that all tweets do not have the same impact. For example, tweets with higher engagements (e.g., replies, likes, retweets, quoted tweets) will be seen by more people and could have a stronger effect on other people's perceptions. Therefore, we weight the sentiment scores by the total engagement of individual tweets (see Equation 1 below). Finally, since the data for the outcome variables are available at the monthly level, we aggregate the weighted sentiment scores for each city at the monthly level.

$$Sentiment\_Score_{ct} = \sum_{k=1}^{n} Sentiment_k * Engagement_k \qquad (1)$$

Where 'c' represents a city, 't' represents a month, and 'k' represents a tweet. Engagement for a tweet is obtained as the sum of the number of replies, likes, retweets, and quoted tweets and Sentiment is the score obtained by subtracting P_{Neg} from P_{Pos}.

Study 3: Relationship Between Citizen Sentiments & Key Drivers of a City's Competitiveness

In this study, we undertake a preliminary empirical exploration of the relationships between the sentiment of citizens towards key attributes of a city, the economic performance of a city, and the in-migration and visiting interests of people towards a city. For each of the 6 cities considered in this study, we create the variables of Citizen Sentiments (City_Sent), Economic Performance (EC_Perf), In-migration Interest (InMig_Int), and Visiting Interest (Visit_Int) at the monthly level for 48 months. This creates a panel structure with 6 units and 48 time periods. Figure 6 plots the four variables over time in their raw form.

--Insert Figure 6 about here--

However, these variables of interest are endogenous i.e., they can affect each other both contemporaneously and across time lags. For example, the economic performance of a city can influence the sentiment of citizens in future periods. Conversely, the citizen sentiments can also influence the future economic performance of the city through more investments in the city and more people visiting and moving to the city. Therefore, to study the effects of these variables simultaneously, we employ a Panel Vector Autoregression (PVAR) Model (e.g., Holtz-Eakin, Newey, and Rosen 1988; Love and Zicchino 2006) and use the Generalized Method of Moments (GMM) approach to estimate the model. We perform a double logarithmic (log-log) transformation on our endogenous variables (e.g., Venkatesan et al. 2015). We specify our Panel VAR model as follows:

$$\begin{bmatrix} \ln(City\_Sent_{it}) \\ \ln(EC\_Perf_{it}) \\ \ln(InMig\_Int_{it}) \\ \ln(Visit\_Int_{it}) \end{bmatrix} = \begin{bmatrix} \alpha_{i,City\_Sent} \\ \alpha_{i,EC\_Perf} \\ \alpha_{i,InMig\_Int} \\ \alpha_{i,Vis\_Int} \end{bmatrix} + \begin{bmatrix} \delta_{it,City\_Sent} \\ \delta_{it,EC\_Perf} \\ \delta_{it,InMig\_Int} \\ \delta_{it,Vis\_Int} \end{bmatrix}$$

$$+ \sum_{j=1}^{J} \begin{bmatrix} \Phi_{1,1}^{j} & \cdots & \Phi_{1,4}^{j} \\ \vdots & \ddots & \vdots \\ \Phi_{4,1}^{j} & \cdots & \Phi_{4,4}^{j} \end{bmatrix} \times \begin{bmatrix} \ln\left(City\_Sent_{it-j}\right) \\ \ln(EC\_Perf_{it-j}) \\ \ln\left(InMig\_Int_{it-j}\right) \\ \ln\left(Vis\_Int_{it-j}\right) \end{bmatrix} + \begin{bmatrix} \varepsilon_{it,City\_Sent} \\ \varepsilon_{it,EC\_Perf} \\ \varepsilon_{it,InMig\_Int} \\ \varepsilon_{it,Vis\_Int} \end{bmatrix} \quad (2)$$

Where i indicates a city, t indicates the unit of time (month), j indicates the number of lags and J indicates the maximum number of lags chosen for the model. $\Phi_{i,i}^{j}$ are parameters of the lagged endogenous variables representing direct and indirect effects among the endogenous variables and ε_{it}'s are normally distributed random errors. We account for the time-invariant heterogeneity among different cities by including city-level fixed effects (α_i). Additionally, we

include common, time fixed effects (δ_t) which can account for time-varying shocks that can affect all the cities.

We use the ‘panelvar’ package (Sigmund and Ferstl 2021) in R to estimate our model. One thing to note here is that the time-invariant city fixed effects may be correlated with the lagged endogenous variables leading to biased estimates. We use a forward mean-differencing approach to address this bias (Love and Zicchino 2006). We difference out the time-varying fixed effects (δ_t) by mean centering the forward mean differenced endogenous variables with the mean of the variables across the 6 cities for each month. We use the Bayesian Information Criterion (BIC) to select the optimal lag for the model (e.g., Hewett et al. 2016). Table 6 shows the BIC values for up to 8 lags. We find that a 1-month lag provides the best fit for our model. Further, to test the stationarity of the (mean-centered and forward mean differenced) endogenous variables we run the augmented Dickey-Fuller unit root test. The null hypothesis that a unit root is present is rejected for all four variables. After estimating Equation 2, we test the stability of the model and find that all the eigenvalues of Φ are less than 1 (see figure 7).

--Insert Table 6 and Figure 7 about here--

Results. A panel VAR model allows us to study the effect of orthogonal shocks or impulses of one variable on another variable while keeping the effect of all other variables constant. This is achieved through Impulse Response Functions (IRFs). Table 7 reports the IRF mean responses and the significance based on 90% confidence intervals for 12 future periods (months). The confidence intervals are computed using bootstrapping with 1000 draws. We find that the economic performance of cities has a positive and significant effect on in-migration interest (periods 1, 2, and 3), citizen sentiments (periods 3, 8, and 10), and visiting interest (periods 3, 5, and 7). Citizen sentiments have a positive and significant effect on economic

performance (periods 4 and 6), in-migration interest (periods 3, 5, and 7), and visiting interest (periods 1, 3, 5, and 7). Unexpectedly, we also find that for a few future periods, citizen sentiments have a negative and significant effect on in-migration interest (periods 2 and 4) and visiting interest (periods 2 and 4). Further, concerning the impulse from in-migration interest, we find a positive and significant effect only on the economic performance (period 2) while visiting interest is found to have a positive and significant effect only on in-migration interest (periods 3 and 5). However, for future periods 2 and 4, we find a negative and significant effect for the impulse of visiting interest on in-migration interest. Finally, the effect of the variables on themselves is positive and significant for up to periods 3, 1, and 1 for economic performance, citizen sentiment, and in-migration interest, respectively. The self-effect of visiting interest is positive and significant for periods 1, 3, and 5.

--Insert Table 7 about here--

In summary, we find evidence of significant positive relationships between citizen sentiments and the three drivers of a city's competitiveness. Further, we also find evidence of the three drivers of city competitiveness positively influencing each other and also citizen sentiments. Therefore, we find support for all the paths proposed in our conceptual model. Surprisingly, we also find a few significant negative relationships among the variables which require further empirical and conceptual exploration.

DISCUSSION AND CONCLUSION

Cities occupy 2% of the world's surface area, but they are home to more than 50% of the World's population (Ratti 2016). In the United States, the top 25 metro areas make up more than half of the national GDP (Feldman 2019). City governments in the United States are important

economic entities containing vast populations and require intelligent allocation of resources. Further, cities compete for resources such as investments, residents, and visitors which are important for the growth and wellbeing of the city and its residents. In this research, we set out to study how the sentiment and opinions that city residents (citizens) harbor towards a city can influence key drivers of a city's competitiveness. Additionally, we demonstrate how social listening can be an important tool for city managers to acquire actionable insights from citizens.

We started by trying to understand which city-related attributes are considered important by people for their decisions to live in or move to a city. To that end, we undertake a thorough review of academic and practitioner literature to identify major city-related attributes considered in prior studies, conduct in-depth interviews with a convenience sample, and perform topic modeling on city forum discussions to identify city-related attributes considered important in people's decisions to move to and live in a city. We identify 11 major city-related attributes from this exercise. We use a transfer learning-based machine learning approach to identify large volumes of Twitter conversations around these city-related attributes that are relevant to city managers. Specifically, we use the BERT model which achieves a classification accuracy of .88 outperforming popular text classification models (e.g., CNN, LSTM). Consequently, we use another BERT model to classify the sentiment of the conversations classified as relevant and achieve a best-in-class classification accuracy of .85.

In the final study, we provide preliminary evidence regarding the relationships between citizen sentiments and the key drivers of a city's competitiveness, namely, economic performance, in-migration, and visits to the city. Using a PVAR model we find evidence to support all the hypothesized relationships in our conceptual model. Of particular interest are the

positive and significant relationships between citizen sentiments and the three drivers of a city's competitiveness. However, we also find some unexpected negative effects for certain periods.

Implications of this Research

Our research has several implications for academics as well as practitioners. Below we enumerate the contributions of our research to academic and practitioner literature.

Managerial implications. First, this research contributes to a deeper understanding of the role of citizens in the growth and competitiveness of cities. We show that citizen sentiments have a significant positive effect on the economic performance of cities, and in-migration and visiting interest towards cities. City managers may want to leverage our findings and use citizen sentiments as a lever to increase the competitiveness of the city. For example, city managers may want to communicate and advertise the achievements of the city to the residents via different channels to boost their sentiments. Additionally, they may undertake efforts to increase city-related organic word-of-mouth from residents on social media which may help attract more residents and visitors. Second, the process described in this research can be automated with relative ease to measure the sentiment and opinions of citizens regularly, enabling city managers to identify concerns and grievances of citizens and take initiatives to resolve them, leading to greater well-being for the residents. Such regular insights could also be used by city managers in other areas such as understanding the responses of citizens to city services and gauging their agreement with proposed city initiatives.

Third, our research demonstrates the efficiency of using a Transfer-learning based machine learning model to identify relevant conversations on social media. Given that data labeling is an expensive and time-consuming task, city managers may benefit from using our

proposed model by only having to label a limited amount of data. Additionally, our model achieves very high classification accuracies in identifying the relevance and sentiment of city-related Twitter conversations. Therefore, using our approach would reduce noise from social media insights which play an important role in managerial decision making. Finally, to the best of our knowledge, this is the first study that uses Google Trends search interest data to estimate the effects of in-migration and visits to a city. Google Trends data is available at a much higher frequency than actual migration and visit data. Therefore, validation of previously established relationships with this high-frequency data in our study allows city managers to use this data to predict important outcomes at more granular periods.

Theoretical implications. We propose and empirically test a conceptual model relating the sentiment of citizens towards a city and three key drivers of a city's competitiveness. To the best of our knowledge, this is the first study that empirically tests the effect of citizen sentiments on city-level outcomes. Further, we introduce the transfer-learning-based BERT model to analyze unstructured and noisy Twitter data in the context of city marketing which outperforms popular machine learning models such as CNN and LSTM. BERT also achieves best-in-class classification accuracy on the Twitter sentiment classification task. Finally, we use a systematic and multi-method approach consisting of a review of extant literature, in-depth interviews, and topic modeling of online forum discussions to identify major city-related attributes considered important by people to live in or move to a city.

Limitations and Scope for Future Research

While our study makes important contributions to both academic and practitioner literature, it also suffers from a few limitations. First, our panel consists of data from only 6 major US cities, and hence the generalizability of our findings may require more support. To

make the findings more generalizable, we would want to extend this research to more cities both in and outside the US. Second, we use Google Trends search interest data to operationalize in-migration and visiting behaviors. Search interest data could be a noisy measure of the actual behaviors. Therefore, for future research, we would want to test our conceptual model with actual in-migration and visiting data. Third, the COVID-19 pandemic has created more opportunities for remote work and has made it easier for people to move out of cities, necessitating a deeper understanding of citizen sentiments and opinions for city managers. However, the data used in this study does not include observations from the post-pandemic period. As the next step, we would want to include post-pandemic data and study how the pandemic may affect our findings. Finally, we find that for a couple of future periods, there exist some unexpected negative relationships between some of the endogenous variables, particularly those involving the variables created using Google Trends data. As one of the next steps in this research, we would want to theoretically and empirically investigate these negative effects.

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TABLES & FIGURES

Table 1: **Data Sources**

	Data	Description	Source	Use
1	Forum Discussions	Moving-related discussions about specific cities.	City-Data.com	Identifying city-related attributes important to people's decision of moving to a city
2	Social Media Conversations	Tweets containing popular hashtags associated with the focal city or official Twitter handles of the cities and their various departments	Twitter	Opinion mining & Sentiment Analysis
3	Economic Conditions Index	This index is computed using a dynamic factor model that includes 12 variables measuring various aspects of economic activity every month in a Metropolitan Statistical Area	Federal Reserve Bank of St. Louis	Dependent Variable
4	Google Search Interest	Search Interest around keywords related to visiting and migrating to a city normalized to a 0-100 scale	Google Trends	Dependent Variable
5	In-depth Interviews	Factors considered important for living in a city and explanation of the rationale behind the choice of these factors	University Students	Identifying city-related attributes important to people's decision of moving to a city
6	Review of Extant Literature	Identify various city-related attributes that has been studied by academics and practitioners	Google Scholar	Identifying city-related attributes important to people's decision of moving to a city

Table 2: **Review of Extant Literature (Representative Sample)**

	Title	Author Information	Journal	Focal Construct	City-related Attributes[a]	Academic/Practitioner
1	The role of rankings in growing city competition	Rudolf Giffinger, Gudrun Haindlmaier & Hans Kramar (2010)	Urban Research & Practice	Smart City Rankings	Economy/Competitiveness, People/Social and Human Capital, Governance/Participation, Mobility/Transport, Environment/Natural resources, Living/Quality of life	Academic
2	Modelling the smart city performance	Patrizia Lombardi, Silvia Giordano, Hend Farouh & Wael Yousef (2012)	The European Journal of Social Science Research	Smart City	Economy, Mobility, Environment, People, Living, Governance	Academic
3	Strengthening the city's reputation in the age of cities: an insight in the city branding theory	Ahmadreza Shirvani Dastgerdi & Giuseppe De Luca (2019)	City, Territory and Architecture	City Image	Economic Performance, Cultural Activities, Policy Making, Media & Advertising, Urban Planning	Academic
4	The impact of IMC consistency and interactivity on city reputation and consumer brand engagement: the moderating effects of gender	Maja Šerić & Maria Vernuccio (2020)	Current Issues in Tourism	City Reputation	Integrated Marketing Communications (IMC), Interactivity, IMC Consistency	Academic
5	Antecedents of tourism destination reputation: The mediating role of familiarity	Enrique Marinao Artigas, Sonia Vilches-Montero, & Coro Chasco Yrigoyen (2015)	Journal of Retailing and Consumer Services	Destination Reputation	Infrastructure, Environment, Events, Recreation, Affective Perceptions	Academic
6	Cities and their brands: Lessons from corporate branding	Mihalis Kavaratzis (2009)	Place Branding and Public Diplomacy	City Branding	Vision and Strategy, Internal Culture, Local Communities, Synergies, Infrastructure, Cityscape and Gateways, Opportunities, Communications	Academic

7	City Reputation Indicators (CRIs): measuring inhabitants' city representation	Marino Bonaiuto, Silvia Ariccio, Stefano De Dominicis, Ferdinando Fornara, Erica Molinario, Renato Troffa, and Haoxing Wang (2019)	Psyecology	City Reputation	Quality of Life, Safety, Cost of Living, Weather, Compatibility, Landscape Quality, Care and Maintenance, Public Transportation, Food, Place Identity, Place Attachment, Inclusiveness	Academic
8	Creative dimensions for branding and regeneration: Overcoming negative perceptions of a city	Myfanwy Trueman, Diana Cook, and Nelarine Cornelius (2008)	Place Branding and Public Diplomacy	Creative Cities	Technology and Research, Innovation, Instability, Culture, Diversity, Ethnicity, Identity, Profile, Leadership, Networks, Education, Security	Academic
9	Exploring Brand Experience Dimensions for Cities and Investigating Their Effects on Loyalty to a City	Đpek Kazançoğlu and Taşkın Dirsehan (2014)	Business and Economics Research Journal	City Experience	Social Activities & Leisure Time Experience, Affective Experience, Observable Experience, Taste Experience, Disturbing Sensory Experiences, Nature elated Experiences	Academic
10	The Citizen Satisfaction Index (CSI): Evidence for a four basic factor modeling a German sample	Sebastian Zenker, Sibylle Petersen, and Andreas Aholt (2013)	Cities	Citizen Satisfaction Index	Urbanity & Diversity, Nature & Recreation, Job Chances, Cost-Efficiency	Academic
11	The Role of Place Image Dimensions in Residents' Support for Tourism Development	Dimitrios Stylidis (2016)	International Journal of Tourism Research	Place Image	Community services, Physical appearance, Social Environment, Entertainment services	Academic
12	Conceptualizing Smart City with Dimensions of Technology, People, and Institutions	Taewoo Nam & Theresa A. Pardo (2011)	The Proceedings of the 12th Annual International Conference on Digital Government Research	Smart City	Technology Factors (Digital, Intelligent, Ubiquitous, Wired, Hybrid, Information), Human Factors(Creative, Learning, Humane, Knowledge) and Institutional Factors (Governance, Policy, Regulations/Directives)	Academic

13	Antecedents of residents' city brand attitudes	Bill Merrilees, Dale Miller and Carmel Herington (2009)	Journal of Business Research	City Brand	Nature, Business creativity, Shopping, Brand, Intentions, Transport, Cultural activities, Government services, Social bonding	Academic
14	Attributes of Milan influencing city brand attractiveness	Ivan De Noni, Luigi Orsi, and Luca Zanderighi (2014)	Journal of Destination Marketing & Management	City's Attractiveness for Talent	Level of Safety, Level of Tourism Supply, Quality of Culture, Level of Internationalization, Quality of Environment/ Urban Design, Quality of Social Services, Quality of Healthcare, Quality of Education Structures, Quality of work/job opportunities.	Academic
15	Managing residents' satisfaction with city life: Application of Importance–Satisfaction analysis	Andrea Insch (2010)	Journal of Town & City Management	City Resident Satisfaction	Work/life balance; Personal and public safety; Natural environment; City's community assets; Cultural, arts and creative scene; City's vibrancy and energy; Openness of residents to new people, ideas and diversity; Sports grounds and facilities; Location relative to other destinations and accessibility to other cities; Efficient public transport	Academic
16	A summated rating scale for measuring city image	Shaked Gilboa, Eugene D. Jaffe, Donata Vianelli, Alberto Pastore, and Ram Herstein (2015)	Cities	City Image	Municipal Facilities, Security, Public Services, Leisure and Recreation, Caring, Tourism and Recreation	Academic
17	City RepTrak	Reputation Institute (2018)		City Reputation	Advanced Economy, Effective Government, Appealing environment	Practitioner
18	The Anholt-GMI City Brands Index	Simon Anholt (2006)		Anholt City Brands Index	Presence, Place, Pre-requisites, People, Pulse, Potential	Practitioner

19	Global Power City Index	Institute of Urban Studies, The Mori Memorial Foundation (2019)	City Ranking Index	Livability, Environment, Accessibility, Economy, R&D, Cultural Interaction	Practitioner
20	Global Cities Report	Kearney (2019)	City Ranking Index	Business Activity, Human Capital, Information Exchange, Cultural Experience, Political Engagement	Practitioner
21	AIRINC Global 150 Cities Index	AIRINC	City Ranking Index	Salary, Cost of living (Housing, Utilities, Transportation, Food, Drink, Recreation, Clothing, Domestic Help, Household Supplies, Communications, Home Furnishings, Personal Care, and Medical), Taxes, Quality of Living, Safety, Discomfort, Inconvenience Social Benefits	Practitioner
22	IESE Cities in Motion Index	Center for Globalization and Strategy (2018)	City Ranking Index	Human capital, Social cohesion, Economy, Environment, Governance, Urban Planning, International outreach, Technology, and Mobility and Transportation	Practitioner
23	IMD Smart Cities Index	IMD World Competitiveness Center (2019)	City Ranking Index	Health and Safety, Mobility, Activities, Opportunities, Governance	Practitioner

Note: ‘a’ - Only broad attributes listed for brevity.

Table 3: **Sample Responses from In-depth Interviews**

Respondent #	Response 1	Response 2	Response 3
1	The type of people and the area. Is it diverse? Because I appreciate diversity. I chose Atlanta because of the diversity at Georgia State University…my first choice and my only choice because of the all the different backgrounds of people. Because when I graduate, I am not just going to work with Black people or White people or Asian people, I want to have a mixture of all those types of people in one area, so that you learn how to work with all different kind of cultures and understand all cultures, because I am in International Business.	Price of living, because I don't have a job, I am student, I have to make sure that I can afford go to school, and live and eat. Most importantly is my education, that's most important to me, so if I have to come here, I have to come here because I have no other choice. I live down here. I pay in the higher prices.	May be like the area, crime, safety. I like downtown because, a lot of time it's not safe but they have people making sure that you are safe…I don't walk anywhere at night. They have the safety ambassadors from the city, they wear the red shirts and stroll around during the day…to make sure everyone's safe. I feel like it's effective.
2	Will I have many opportunities job-wise, is that a place where I can see myself growing?	Am I going to feel comfortable walking home alone at night? If I am taking public transportation, am I going to be safe, or is it kind of sketchy?	Probably if there's someone there that I know. I know I have someone here that I can fall back to. Or someone I know can introduce to people, friends; it's not like I am completely by myself in whole new city
3	Just to know that I wouldn't feel alone in the city so seeing faces that look like me and I love the excitement of seeing faces that also do not look like because then it allows me to see what type of cultures that (place) brings.	I have just always been very fond of cultures, I am always a curious person, I love to get into other cultures and try to relate it to my own.	One of the biggest reason I moved to Georgia, I am a journalism student, as a Journalism major, Atlanta is obviously a great place to network, and I feel there is a lot of options and areas that I can enter so opportunities excites me as well
4	More walking places I can walk to, close to everywhere, somewhere downtown like if I get out of my house, two minutes' walk and I go to the grocery store, instead of like driving. Living in the suburb and driving somewhere.	Has a lot of nice attractions like an aquarium, zoo, you can always stay busy.	I like a city with a nice skyline, nice buildings, clean. One of you may say New York, I really don't like New York because when I look at it. It's like not clean. Places that care about recycling take care of streets
5	I think it's very important because you cannot live in the city without money so…where everyone can find a place where they fit in and there's a lot of readily available jobs for people who either transfer from new states or just got out of college.	How the city takes care of their people, like if there's a lot of homelessness and crime. How the city finds ways to combat that and help their people out because I think tell a lot about a city by how many people are homeless or jobless or they don't have a place to go.	I like the fact that you meet a lot of different people who come from a lot of different backgrounds. And I really think it's great to get that kind of perspective, like other people, other culture, religion, and gender, sexual orientation…their perspective on living in the city or life in general.

Table 4: **City-related Attributes Identified in Study 1**

	Broad Factors	Underlying Attributes (Literature Review)	Keywords from CTM Topic Modeling (City-Data.com)	Definition
1	Growth & Opportunities	Ease of doing business, Thriving market, Jobs	growth, companies, career, employment, industry, opportunities, economy, income, work, wage, salary	This relates to the opportunities for growing one's career, business, and skills that the city has to offer.
2	Diversity	Open-mindedness, Cosmopolitanism, Inclusiveness, Ethnic Diversity	ethnicity, inclusiveness, openness	The inclusiveness, ethnic diversity, open-mindedness and cosmopolitanism of the city.
3	Governance & Leadership	Public Service, politics, Technology, Innovation	services, leadership, amenities, politics, tax, water, corruption, innovation, technology	The performance of the government in demonstrating leadership, delivering public services and amenities, formulating and implementing policies, ensuring transparency and adoption of technology.
4	Environment & Sustainability	Pollution, Sustainability, Parks, Recycling	trees, pollution	The environmental health of the city in terms of pollution, green-spaces, sustainable practices etc.
5	Social Issues	Crime & Safety	violence, drugs, safety, shootings, gang, robberies, safety, crime, homelessness, segregation, overpopulation, racism, inequality, gentrification	This consists of issues such as crime, homelessness, segregation, overpopulation, racism, gentrification, and other issues that affects the societal structure in cities.
6	Culture & Heritage	History, Vibe	History, Vibe	This relates to the history, heritage, and vibe of the city.
7	Cost of Living	Housing, Property value	cost, affordability, insurance, rent, expense, apartments, property, condominiums, housing	The cost associated with living in a city. This includes rent, property prices, insurance, housing, taxes, fuel, food, and other expenses.
8	Infrastructure	Transportation, Roads, Bridges, Airport, Access to health care	traffic, highways, public transportation, freeways, hospitals, healthcare, parking, sidewalks, healthcare, roads	Transportation (highways, public transportation, roads, parking, traffic), health (hospitals, healthcare) and education (schools, colleges,

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				universities) infrastructure of the city.
9	Beauty & Appearance	Parks/Open Spaces, Cityscape, Clean	Beauty, skyline, landscape, cleanliness, parks	The physical beauty and appearance of a city which includes the skyline, landscape, cleanliness, parks, water bodies and other features that make the city appealing.
10	Entertainment & Recreation	Restaurants, Nightlife, Theme Parks, Restaurants, Shopping	events, nightlife, music, museums, art, shopping, sports, beaches, mountains, festivals, hiking, concerts, clubs, bars, malls, theaters, monuments, walking, restaurants, cuisines	The avenues of recreation and entertainment available in the city such as museums, shopping malls, theaters, sporting events, concerts, bars, restaurants, hiking trails, walking paths, festivals etc.
11	People	Community	community, neighborhood, family, home, friends, residents, celebrities	The people who make up the city. It consists of communities, families, friends, celebrities etc.

Table 5: **Model Comparison for Relevance Classification Task**

Metric	BERT	CNN	LSTM
Accuracy	.88	.86	.42
F1-score	.88	.83	.59
Recall	.96	.96	.42
Precision	.81	.74	1.00

Table 6: **Optimal Lag Selection Using BIC**

Lag	BIC
1	-4,008.47
2	-3,970.08
3	-3,931.50
4	-3,892.72
5	-3,853.73
6	-3,814.53
7	-3,775.08
8	-3,735.39

Table 7: Impulse Response Function Results

Impulse	Period	Response			
		Economic Performance	Citizen Sentiments	Visiting Interest	In-migration Interest
Citizen Sentiments	1	--	.313	.254	--
	2	--	--	-.231	-.118
	3	--	--	.235	.125
	4	.013	--	-.205	-.165
	5	--	--	.177	.155
	6	.026	--	--	--
	7	--	--	.12	.122
	8	--	--	--	--
	9	--	--	--	--
	10	--	--	--	--
	11	--	--	--	--
	12	--	--	--	--
Economic Performance	1	.628	--	--	.129
	2	.034	--	--	.313
	3	.095	.004	.119	.048
	4	--	--	--	--
	5	--	--	.127	--
	6	--	--	--	--
	7	--	--	.096	--
	8	--	.027	--	--
	9	--	--	--	--
	10	--	.021	--	--
	11	--	--	--	--
	12	--	--	--	--
Visiting Interest	1	--	--	--	--
	2	--	--	--	-.105
	3	--	--	--	.103
	4	--	--	--	-.101
	5	--	--	--	.089
	6	--	--	--	--
	7	--	--	--	--
	8	--	--	--	--
	9	--	--	--	--
	10	--	--	--	--
	11	--	--	--	--
	12	--	--	--	--
In-migration Interest	1	--	--	--	--
	2	.025	--	--	--
	3	--	--	--	--
	4	--	--	--	--
	5	--	--	--	--
	6	--	--	--	--
	7	--	--	--	--
	8	--	--	--	--
	9	--	--	--	--
	10	--	--	--	--
	11	--	--	--	--
	12	--	--	--	--

Note: '--' signify a nonsignificant relationship. Significance is considered at 90% confidence intervals.

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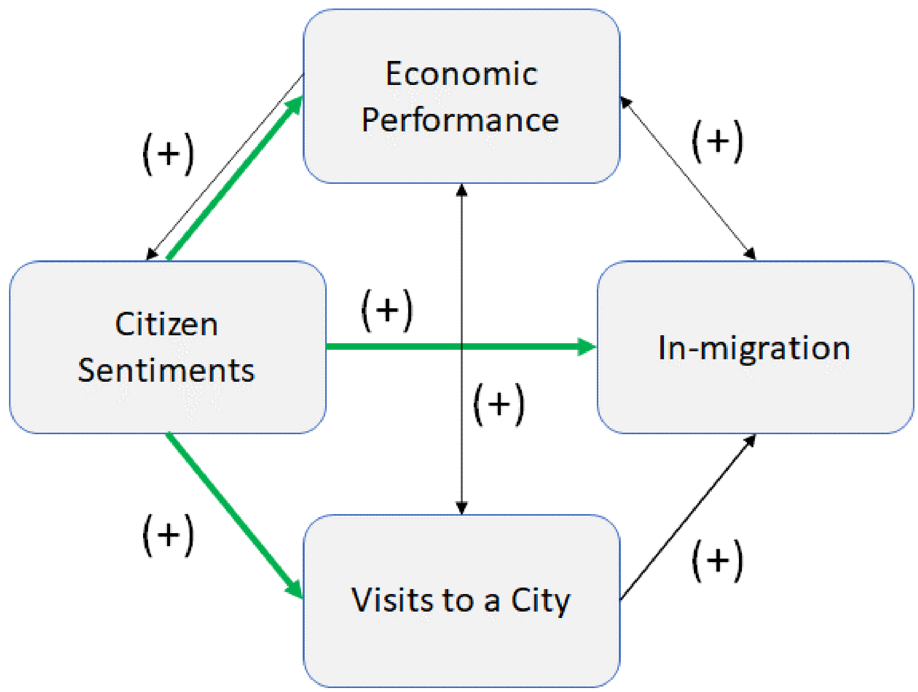
Figure 1: Conceptual Model



Note: The green and thicker arrows represent the novel relationships studied in this research

Figure 2: **Overview of Methodology**

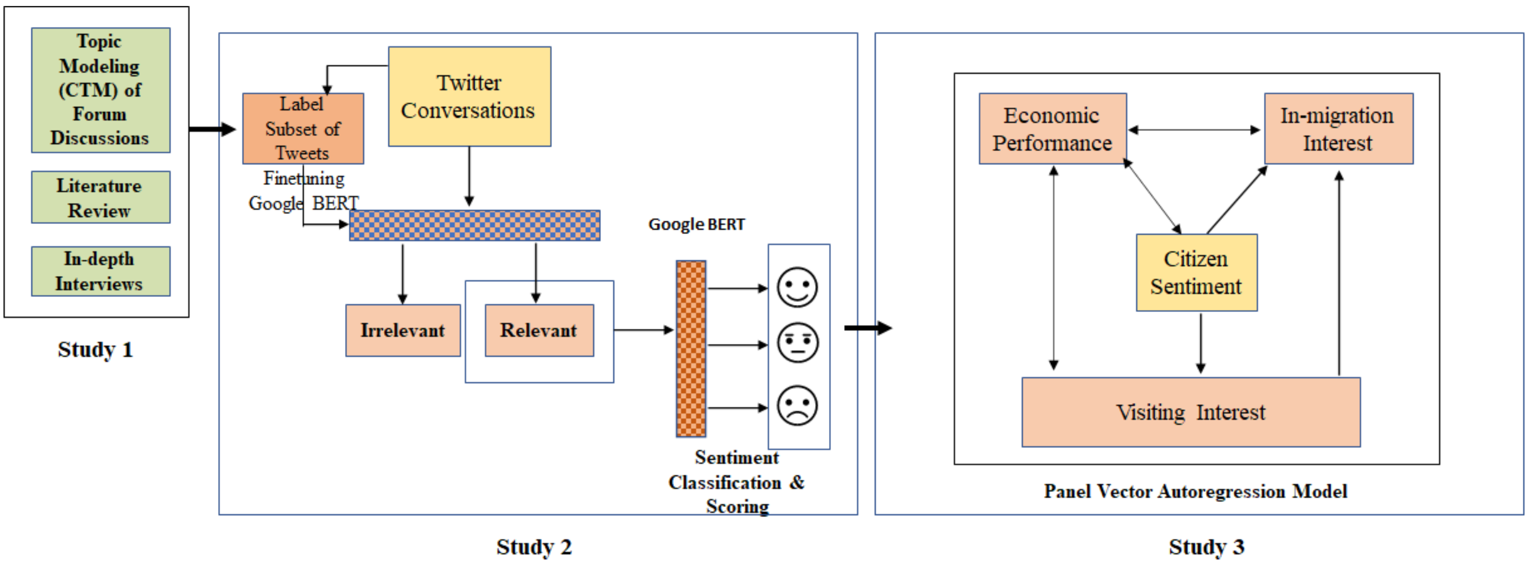


Figure 3: **Examples of Relevant & Irrelevant Tweets for Cities**

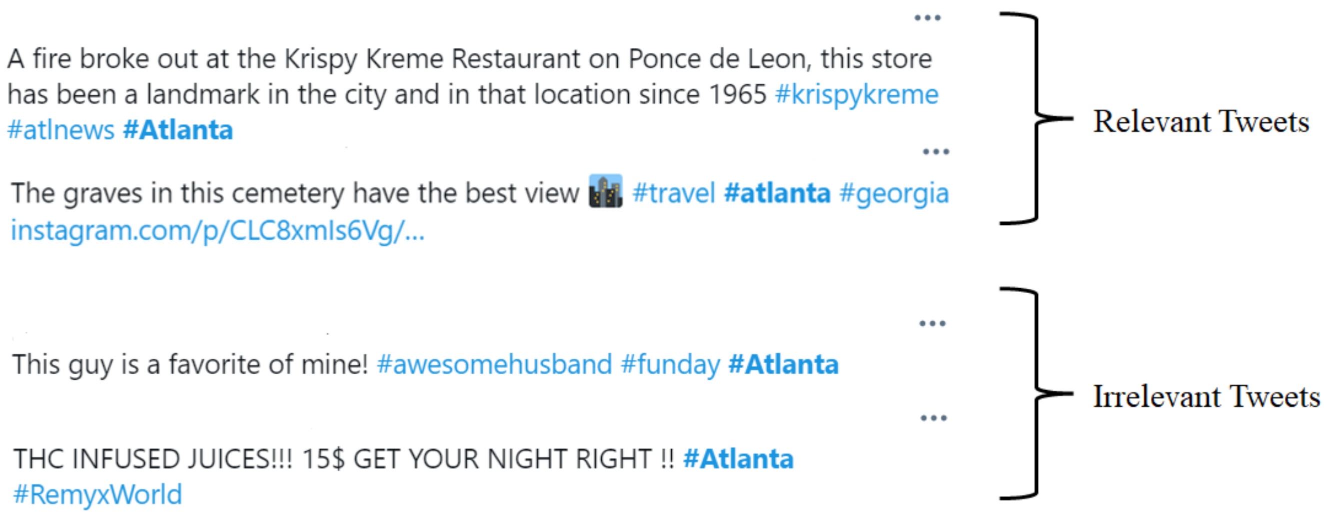


Figure 4: **Topic Coherence Scores (UMass) by Number of Topics**

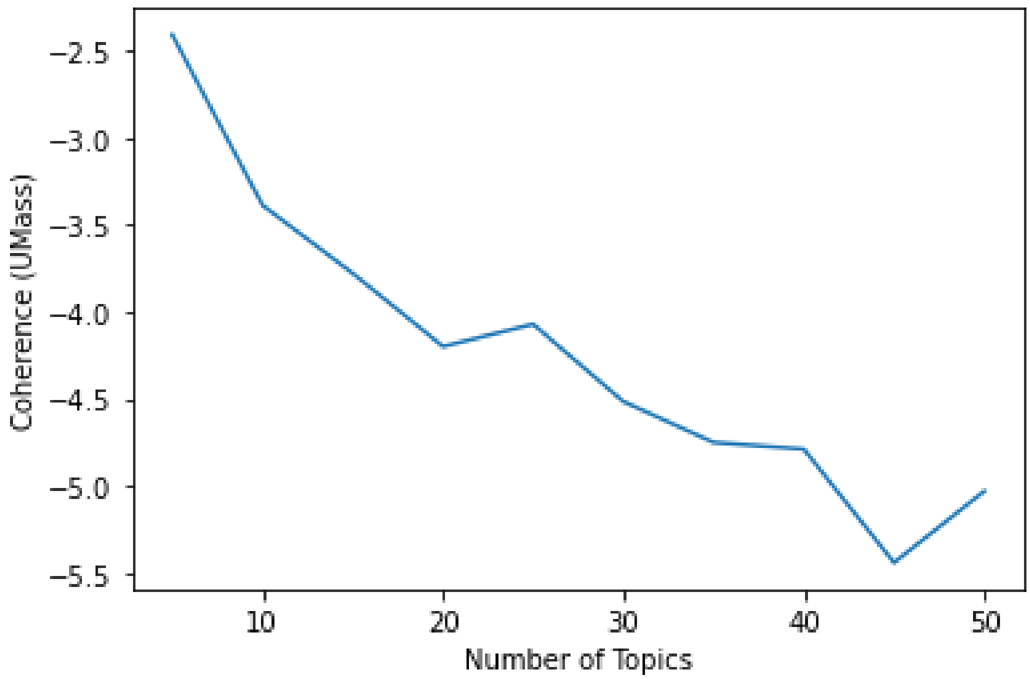


Figure 5: **Additional Layers on Top of BERT**

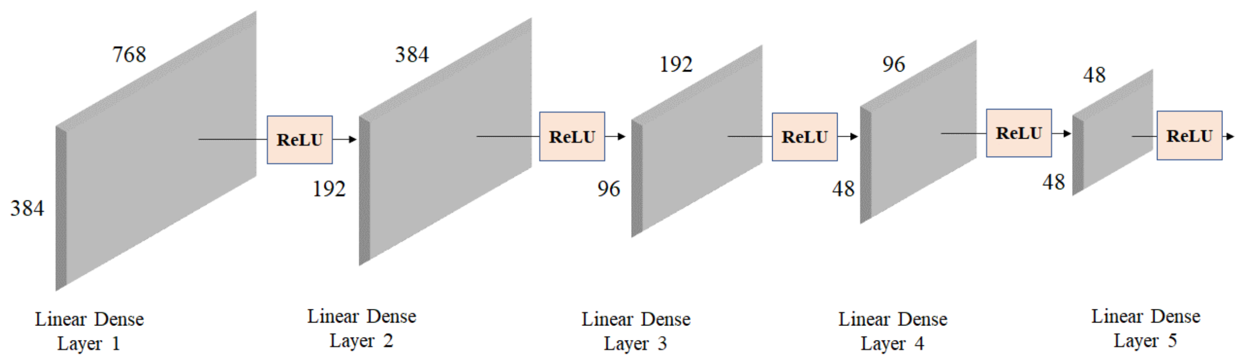


Figure 6: **(Clockwise) Time Series Plots of Economic Conditions Index, Citizen Sentiments, In-migration Interest, and Visiting Interest**

Figure 7: Stability of the Panel VAR Model