ESSAYS ON BRAND ACTIONS AND LOVE-HATE RELATIONSHIPS WITH CONSUMERS

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ABSTRACT

This dissertation, composed of two essays, uses multidisciplinary theories and methods to investigate two aspects of consumer polarization in today's increasingly opinionated and often aggressive social landscape. The first study investigates online firestorms and their impact on brand perceptions through the lens of a novel measure of random walk controversy which takes inspiration from the network science literature and encapsulates the level of insularity and echo-chamberness of brand-detractor and brand-supporter conversations on social media. A differences-in-differences event-study approach on a cross-industry sample of ~300 events (~40 Mn tweets) over the period 2012-19 shows that echo-chambers and filter-bubbles during a brand crisis negatively impact brand perceptions. 'Controversy scores' of Twitter retweet and mention networks witness higher abnormal increases during functional crises than values-based crises, which subsequently results in a greater dip in average brand perceptions during such crises as well as long-run consumer attitudes. The study further illuminates de-escalation tactics through relatively inexpensive network-level interventions – e.g., by optimally seeding a small number of influencers or conversation topics that mitigate echo-chambers and their harmful consequences. The second essay quantifies marketplace risks for brands participating in socio-political activism through partisan advertising or controversial celebrity endorsements. It uses multiple data sources – news articles, political partisanship data, Nielsen Retail Scanner and Consumer Panel records – to build a 10-year panel of county-level purchases of activist consumer brands. Average Treatment

Effects estimated from an Augmented Synthetic Controls Method suggest that: (1) activist brands' revenues in US counties are significantly affected by their political ideology; (2) this impact is greater for more divisive issues (support for Donald Trump, immigration etc.) than less divisive issues (feminism, gender equality etc.); and (3) conservative counties react more to CSA than liberal counties, so, brand revenues at a national level see a positivity bias for conservative brand activism and a small negativity bias for liberal activism. Finally, the change seems to be driven by consumer acquisitions and consumer attritions from aligned and misaligned counties respectively rather than volumes of SKU purchases or consumers' willingness to pay price-premiums.

THIS DISSERTATION IS DEDICATED TO MY GRANDPARENTS

MRS. MEENA DEY

LATE MRS. SOVA GUPTA

LATE MR. ANIL KUMAR DEY

LATE MR. SUDHANGSHU RANJAN GUPTA

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PREFACE

This dissertation document is a product of five eventful years of love and labor – as is the case with the fruition of any ambitious dream. It is only fair that I take a moment to reflect upon the support I have received during this process and thank everyone who made this possible. I must start by thanking my advisor and dissertation committee members. I am beyond grateful to my advisor Dr. Vanitha Swaminathan for being by my side through the entirety of this roller-coaster and for championing my research through thick and thin. Thank you, Vanitha, for your patient guidance through these last five years. I hope to keep learning from you, and I promise to stay inspired by you. I probably wouldn't have applied to a PhD program had it not been for the fortuitous events leading up to my working as a Research Associate with Dr. Sundar Bharadwaj, who again obliged me by agreeing to be part of my dissertation committee. Thank you so much for being my metaphorical gateway into marketing academia and for having my back throughout the PhD journey. Dr. Esther Gal-Or's long history of impactful research was a key reason for my excitement about joining the PhD program at Katz. I feel so honored to have you as part of my dissertation committee. You have been such a wonderful teacher, mentor, and guide to me – and I am so grateful for the generosity you have shown me over the course of my PhD program. Thank you, Dr. Jeff Inman, for your always-constructive suggestions on my research topics, for opening up my mind toward numerous research directions through your seminar, and for infusing every session with the little tidbits of wisdom I am going to cherish for the rest of my career. One of these days, I am going to start working on a multi-method research project and it is because you ingrained the value of triangulating a research question from all possible angles. Thank you, Dr. Mina Ameri, for your tremendous help and encouragement with my research projects, and

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1.0 BRAND ACTIONS AND LOVE-HATE RELATIONSHIPS WITH CONSUMERS

Looking back, I can retrace the genesis of my dissertation topic to my first research project at the University of Pittsburgh. Born out of my interest in the marketing-finance interface, my first semester term paper found its way into a publication (Swaminathan et al. 2022) which reviewed literature linking core brand-related actions to firms' financial valuations with the aim of identifying gaps and ambiguities in prior research findings. It took a closer look at the brand value chain framework that delineates the process of value generation with investments into the brand transforming into consumer actions, product marketplace outcomes and capital market valuations. The investigation suggested that our collective academic knowledge related to proactive and positive marketing actions far outweighs that of reactive brand actions – i.e., actions typically performed in response to unexpected negative events such as brand crises. Even in the limited literature that has investigated negative brand actions, the focus tends to be on tactical post-event responses from the firm and not on preparedness and strategic planning for such eventualities. So, while research has paid due attention to the 'love' between brands and consumers, this dissertation tries to investigate the 'hate' aspect of the same relationship and the risks arising from it – with a keen eye on the repercussions in the era of digital and social media marketing.

The essays therefore look at two contemporary phenomena – online firestorms and corporate socio-political activism – that have the potential to spark outrage against a brand. Both tend to be fueled by social media and the empowerment it provides consumers to speak their mind. They are both examples of momentous events in the life of a brand that have negative consequences on the firm's financial valuations, but have not been studied in sufficient detail in marketing literature. And they are both brand events that tend to elicit polarizing reactions from consumers depending on whether they are brand-lovers or brand-haters, whether they support the brand's position on a socio-political issue or stand opposed to it. They provided the opportunity to dive deep into two aspects of consumer polarization – social media echo-chamberness in the wake of online firestorms and politicization of consumer purchase behavior in the aftermath of firms' political engagement.

An online firestorm, the object of my first essay, is defined in marketing literature as "a sudden discharge of large volumes of negative word of mouth and complaint behavior against a person, company or group in social media networks." A prominent example would be news coverage of United Airlines' mistreatment of its passenger which got caught on camera, went viral on social media, developed a life of its own, and garnered a lot of hatred for the brand. These events form a new variety of crises that are especially challenging for brands because of social media's unpredictability, information diffusion rates and instantaneously large impacts. Additionally, they could be functional or values-based. For instance, the firestorm involving exploding Samsung Galaxies would be a prime example of a functional crisis as it deals with defective products and makes consumers question the brand's competence at delivering them the core functional benefits expected out of it. On the other hand, a values-based crisis such as the backlash against Pepsi for the BLM commercial with Kendall Jenner makes consumers question the brand's core values and their own self- and social-image for consuming that brand.

The first essay investigates such online firestorms and their impact on brand perceptions through the lens of a novel measure of social media echo-chamberness between brand-supporters and detractors — random-walk controversy. By looking at brand filter-bubbles, it adds to previous literature that has mostly dealt with Word-of-Mouth impacts of brand crises in the form of volume or valence of conversations. What makes brand echo-chamberness really interesting from a research point of view is the inherent duality of it – while it may seem like a potent segmentation strategy to have a loyal brand community and build positive brand attitudes by keeping them away from the negativity of the haters, there is something about social media and its filter bubbles that tends to make these polarized conversations toxic and full of negativity, as is evident on several brand fan (and hater) pages. This study allows me to tease these two aspects of brand echo-chambers apart and empirically identify the net effect of these contradictory possibilities in the context of brand crises.

In order to so, I analyze ~40 million historical tweets corresponding to a cross-industry sample of ~300 brand crisis events over 2012-2019 in a quasi-experimental differences-in-differences event-study. The findings show an increase in Twitter controversy scores in the immediate aftermath of brand crises. Further, functional crises, when compared against values-based crises, lead to greater echo-chamberness of brand-supporter and brand-detractor Twitter conversations – which subsequently drives greater dips in average brand perceptions, the effects of which persist into the long-run. Specifically, the findings suggest that the greater echo-chamberness of Twitter conversations following functional brand crises translates into a greater intensity and proportion of negative social media posts, which combine to produce a greater dip in average brand perceptions. A longitudinal analysis of these metrics shows the persistence of the immediate perception after-effects for merely a period of four days, but they have longer-run consequences as well – on lapsed consumers, brand preference, total brand users and brand asset values. These insights hold true across multiple robustness checks, including multiple criteria for crisis classification, analysis of alternative echo-chamberness metrics, and comparisons with a k-nearest-neighbor-matched control group of brands. Finally, the study provides an algorithmic demonstration of how brands can reduce echo-chamberness by creating a small number of bridges across opposing sides — that is, by proposing brand-positive content from social media influencers to members of the anti-brand community, with the hope to create a critical mass of endorsement edges in the form of likes, retweets, mentions, or other types of engagement. Managers are thus encouraged to track brand echo-chambers on a daily, or even hourly basis, and take actionable steps to curb it using the digital capabilities they possess.

The second essay takes a deep dive into brands participating in socio-political activism through partisan advertising or controversial celebrity endorsements. Just like online firestorms, corporate sociopolitical activism is an upshot of empowered social media users and potential consumers who expect their brands to not just provide them the functional benefits but be more expressive about their morals and values and be actively involved with the society and community they are operating in. In contrast to other brand actions involving societal and community outreach, the phenomenon of corporate sociopolitical activism is characterized by: (1) a brand advocating towards an ideological perspective and actively educating society on what is right and what is wrong, (2) the brand deciding to always publicize such actions because of its educational purpose (as opposed to other political actions such as lobbying or donations), and (3) most importantly, the brand communications being controversial and divisive because they advocate or endorse one side of a conversation that hasn't reached societal consensus, and hence, subject to risk of alienating consumers and social media users who do not agree with the brand.

This study investigates the long and short-term repercussions of such politically polarizing brand actions on brands' revenues and their drivers as a function of the ideological composition of markets. It performs the first large-scale quasi-experimental analysis of real marketplace data (from Nielsen scanner and consumer panel purchases) to quantify the revenue-stream riskiness induced in the wake of firm activism across multiple product categories. Using a 10-year panel of

US county-level data, I compare consumer purchases of activist brands. against a synthetically created control group of brands and estimate these impacts across markets with varying ideological and religious compositions over multiple event windows. Findings from this study suggest that brands' revenues in different markets (US counties) are significantly affected by the alignment of the activism with the dominant political ideology of the counties. There is heterogeneity in this observation – as expected, the impact is significantly greater for more divisive issues as compared to less divisive issues. Also, conservative counties tend to react more to firms' activism event compared to liberal counties. At an overall level, the national brand revenues do not seem to be significantly affected in either direction, although there is a positivity bias in the case of conservative activism and a negativity bias in the case of liberal activism. Finally, the change is driven by more (fewer) consumers in aligned (misaligned) brands, rather than through changes in average household spendings or willingness to pay price premiums. The study thus aims to contribute to mental models governing firms' political activism (Moorman 2020) which could be viewed as double-edged interventions. It extends and complements the limited marketing literature on the topic – Bhagwat et al. (2020)'s examination of stock market performance, Hydock et al. (2021)'s experimental demonstration of consumer purchase intentions, and Liaukonytė et al. (2022)'s empirical analysis of Goya's political campaign. The CMO surveys point out that marketing managers are reluctant to pursue such actions and will probably continue to do so in the absence of thorough findings on the subject. This study hopes to fill this research gap.

The dissertation thus tackles some of the prevailing substantive issues facing brands and uses multiple event study techniques and methodologies to answer a few questions pertaining to them. The findings are aimed at firms trying to come up with contingency plans in the event of consumer disapproval whether it is because of product and service failures, inadvertent moral transgressions that the brand gets embroiled in, or more deliberate attempts of the brand being controversial with political statements and advocacy. Hopefully, these studies will become part of solutions that firms are seeking to these questions, and will also encourage future research to investigate and answer more of such burning questions related to the domain of consumers' 'love-hate' relationships with brands.

2.0 ESSAY-1: DOUSING A SOCIAL MEDIA FIRESTORM: STUDYING AND MITIGATING IMPACTS ON SOCIAL MEDIA ECHO-CHAMBERNESS AND BRANDS' ONLINE REPUTATION

2.1 INTRODUCTION AND MOTIVATION

Brand reputation is constantly tracked and measured within organizations because of its impact on financial performance, both short-term and long-term. Interbrand's 'Best Global Brands', Forbes' 'The World's Most Valuable Brands', Kantar Millward Brown's 'BrandZ Top 100 Global Brands' and Young & Rubicam's 'Brand Asset Valuator' are just a few examples of global firms and agencies dedicated to the measurement of brand reputation and its multiple facets. Reputational capital – an organization's stock of perceptual and social assets that is reflective of stakeholder value (Fombrun et al., 2004) – is critical to a brand's long-term competitive advantage (Swaminathan et al. 2020). Social media has been a crucial enabler for brands in the reputation building process by allowing them the opportunity to establish their connection and footprint with consumers (Fossen and Schweidel 2019; Hewett et al. 2016; Kubler, Colicev, and Pauwels 2020). Rust et al. (2021) therefore makes a case for real-time tracking of online reputation through mining of social media data. This advice is not lost on practitioners as almost all the Fortune 1000 companies track consumer conversations through specialized social media listening platforms either through own subscriptions or through subscriptions with market research and consulting firms (Nguyen et al. 2020).

Evidently, in this digital age of consumer empowerment, there is intense scrutiny of brands' actions (Swaminathan et al. 2020). Social media has democratized the brand-building process to such an extent that it has slowly and steadily taken away brands' ability to control online communication surrounding them, thus leaving them vulnerable to undetectable online attacks. Prominent examples such as #deleteUber[1], United Airlines' 'Fight Club' incident[2], or Volkswagen's emission scandal[3] often go viral and damage the firm's reputation, causing it to lose customers and experience significant declines in firm valuations (Dunphy 2012; Tirunillai and Tellis 2014). Pfeffer, Zorbach, and Carley (2014) defined such online firestorms as "a sudden discharge of large volumes of negative word of mouth and complaint behavior against a person, company or group in social media networks." Online firestorms are a specific type of brand crises that tend to be catastrophic for brands because of the unpredictability and information diffusion rates of social media (Wang et al. 2019). Evidence of the growing impact of social media is the #unitedfightclub incident in 2017 where a United Airlines passenger being dragged out of their overbooked flight was caught on camera, and went viral garnering over 7 Mn YouTube views in one single day (~10 times the number of views on the music video of the hit single 'Levitating' on its best day). To further put that into context, this is a third of the views received over the entire lifetime of the decade-older 2008 'United Breaks Guitars' video about a similar brand crisis – which had an inherently higher entertainment and virality quotient but wasn't aided by the uncontrolled explosiveness of social media like in 2017. Social media listening estimates suggest that nearly 73 Mn social media users saw or read United Airlines-related tweets the day of the incident, about 60% of which were negative, causing an abnormal dip of 2.5% on United's market capitalization. Despite their widespread nature, social media firestorms have only recently been the subject of scholarly inquiry, including research focused on antecedents, such as complaint and complainant characteristics (Herhausen et al. 2019) and their harmful downstream impacts on brand perceptions and stock market returns (Hansen, Kupfer, and Hennig-Thurau 2018). Prior brand crisis research has

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[1] https://www.nytimes.com/2017/01/31/business/delete-uber.html

[2] https://www.nytimes.com/2017/04/10/business/united-flight-passenger-dragged.html

[3] https://www.theguardian.com/business/2015/dec/10/volkswagen-emissions-scandal-timeline-events

examined various forms of brand crises such as deceptive advertising reports (Wiles et al. 2010), product recalls (Borah and Tellis 2016; Chen, Ganesan, and Liu 2009; Liu, Shankar, and Yun 2017; among others), and negative news articles (Xiong and Bharadwaj 2013). However, there are unique circumstances and effects that surrounding these social media crises that warrant a deeper exploration of their diffusion mechanisms in order to guide mitigation efforts.

One of the well-established characteristics of social media discourse is the existence of echo-chambers and filter bubbles largely driven by the precision of online targeting capabilities and efficiency of matching users with information they agree with (Gilbert et al. 2009, Gromping 2014, Edwards 2013; among others). Echo chambers refer to situations where people "hear their own voice" — or, particularly in the context of social media, situations where users consume content that expresses the same point of view that users themselves hold or express (Garimella et al. 2018). Algorithmic bias and personalization accentuate these effects by providing tailored content based on a user's opinions, thus further isolating the user from a holistic view on a topic. It leads to a vicious cycle where users are exposed to a very narrow worldview, developing intolerance to opposing voices. These users tend to become more polarized, often without even being aware that they are in an echo-chamber created by opaque and sophisticated personalization algorithms.

Such filter bubbles can be evidenced in brand fan pages and communities which aim to bring together like-minded consumers of the brand and allow them to share their positive experiences about the brand, engage with each other and build a strong identification with the brand (Marzocchi et al. 2013; Chan et al. 2014) through repeated exposure to its content (Lambrecht et al. 2021). These communities help keep brand lovers away from negative information about the brand and allow them to stand together in solidarity towards the brand in the face of any negativity. Brands expect that encouraging brand lovers to stay within these filter bubbles should end up reinforcing the brand's goodwill and improving the brand's net promoter scores. Having clear demarcations between brand-lovers and brand-haters also seems like an efficient segmentation strategy as evidenced from the tendency of news media outlets to get increasingly polarized in terms of their content, and brands increasingly endorsing politically biased campaigns (Bhagwat et al. 2020; Liaukonytė et al. 2022; among others). But there are significant downsides to brand echo-chambers as well. For one, they tend to be hotbeds for misinformation and rumors (Shore et al. 2018), as evidenced in the case of MacRumors and brand-dedicated Reddit threads. Additionally, two-way communications and dynamic interplays between brands and consumers within social media can lead to complaint publicization (Golmohammadi et al. 2021) and strong negativity spirals (Dhaoui and Webster 2021). Another undesired consequence of the unconditional loyalty of some brand-lovers within brand social media pages is that it encourages and increases participation in anti-brand conversations (Dessart et al. 2020). These anti-brand participants, often fans of a rival brand, launch attack-posts and make managers of both brands unsure about how they should tackle negative comments on their owned social media touchpoints (Ilhan et al. 2018). These observations hint at the underlying tendency of social media filter bubbles to breed toxicity and negativity into these conversations. The incentives of social media platforms to exploit this by promoting angry and emotional content turns it into a vicious cycle, often forcing brands to reconsider their social media presence. Celebrity and person-brand Naomi Osaka, for instance, quit social media to avoid these consequences because “it takes a toll on your well-being”.

This duality in the potential consequences of filter bubbles sets up an opportunity to empirically examine the role of echo-chamberness of brand-related conversations on downstream brand perceptions following a crisis. Brand crises divide opinions in the brand echo-verse (Hewett et al. 2016) and force social media users to take sides, as brand-detractors jump on the brand-hate bandwagon while brand-supporters are expected to show continued solidarity for the brand (Dawar and Pillutla 2000). This study aims to determine whether the net effect of social media echo-chamberness serves or harms the brand during such crises. The other reason for studying echo-chamberness is that strategically seeding influencers and planting conversations have proved to be successful in influencing social media filter bubbles, as demonstrated in Garimella et al. (2018) (among other network science papers). So, if echo-chambers in brand-supporter and brand-detractor communities indeed impact brand perceptions, brands could use them as instruments to influence conversation negativity during a brand crisis and potentially limit the damage to their reputation. It would be in the firms' interests to develop and hone such digital capabilities so that they can make use of the network effects of social media to deescalate these crises.

In an effort to generate insights pertaining to echo-chamberness of these two critical consumer groups, we turn to a growing stream of literature in the network science and mathematical sociology domains (Conover et al. 2011; Garimella et al. 2018; Guerra et al. 2013; Morales et al. 2015; Ruan et al. 2013). These studies focus on 'controversy scores' — a measure of echo-chamberness and insularity in conversation graphs — that helps quantify these interactions at a granular level. To compute it, they build network graphs around brand-related conversations using engagement patterns (retweets, mentions, replies, likes, friendships and so on), then partition them to identify the two sides of the discussion (liberals vs conservatives in the case of some of the aforementioned papers; brand-supporters vs detractors in our case), and, finally, compute the probability of a brand-detractor to be exposed to an opinion of a brand-supporter and vice versa. So, inward-looking or echo-chamberlike social media graphs in which these opposing groups show a propensity to avoid conversations from each other have higher controversy scores, while inter-group engagement diminishes these values. Figure 2-1 provides examples of pre- and post- firestorm conversation patterns on Twitter – while the pre-event conversations have blurred boundaries between anti-brand (red) and pro-brand (green) conversations, post-event conversations tend to be more echo-chamberlike with prominent boundaries and structural distances between these groups. These studies also demonstrate specific online strategies of influencing such conversations by tactically seeding influencers and conversation topics (e.g., Garimella et al. 2017). These network-level interventions aim to induce engagements within social media participants geared towards optimizing the expected controversy scores while accounting for their opinions and influence levels within their respective communities.

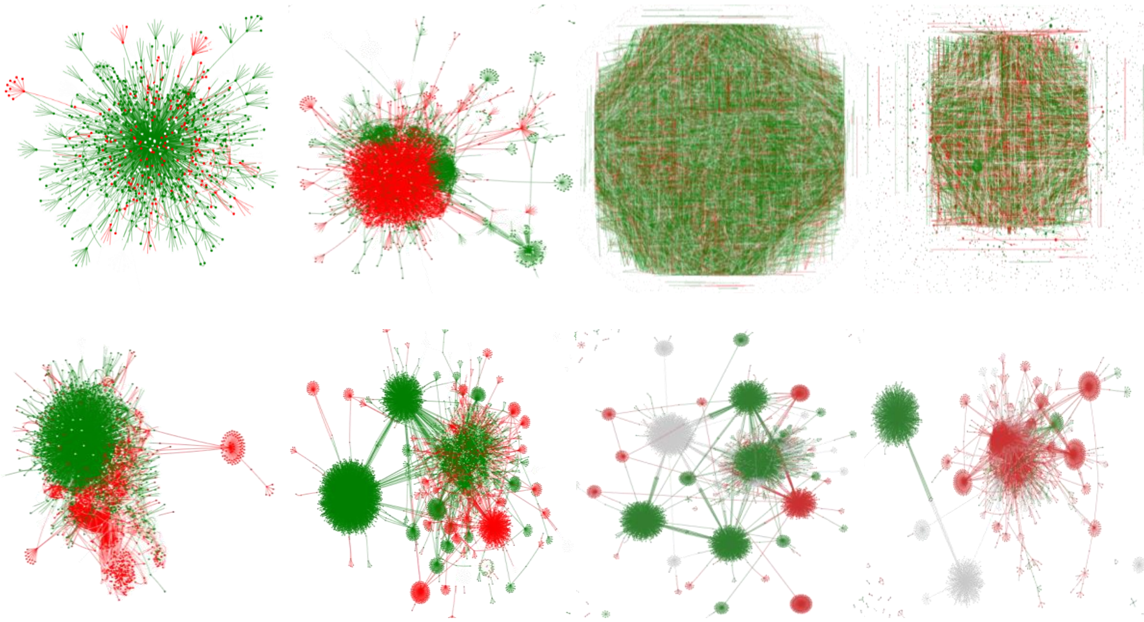

Figure 2-1: Twitter graphs are classified as high (bottom) or low (top) on echo-chamberness based on between-group engagement

In summary, we investigate brand echo-chambers in the aftermath of a brand crisis event. Using a large dataset of Twitter posts, we investigate post-firestorm Twitter retweet, mention and other engagement patterns and answer the following research questions:

RQ1: How do different categories of brand transgressions affect the controversy scores of brand-related conversation graphs in social media? Does social media echo-chamberness help develop a framework for better understanding (and mitigating) the harmful impacts of digital brand crises?

RQ2: What firm responses at the social network level can manage and mitigate negative brand perceptions in the aftermath of social media firestorms?

Empirically, we treat social media firestorms as special cases of brand crises and analyze them using event studies – i.e., by treating the crisis outbreak as an exogenous shock to the social media platform. Specifically, we investigate abnormal changes in Twitter controversy scores and average brand perception levels on social media after consumers become aware of a brand transgression or crisis. We investigate this for a cross-industry focus group of ~300 social media firestorm events (and a pairwise matched control group for robustness checks) during the period 2012-2019. We use historical tweets — from an event window starting one month before each incident and ending one month after — to compute controversy measures (Garimella et al. 2018) across multiple event windows, while aggregating brand perception scores over those intervals from Atlas Infegy's social media-listening platform. Finally, we run a three-stage least squares (3SLS) system-of-equations path analysis to show that social media echo-chamberness indeed mediates the impact of different kinds of brand crises (functional vs. values-based) on the ensuing dips in short-run and long-run brand perception. We show evidence of an increase in Twitter controversy scores in the immediate aftermath of brand crises, which is exacerbated further when these crises are functional in nature. Furthermore, we find that that the differential levels of an increase in postcrisis Twitter echo-chamberness explains to a significant extent the variance in brand perception levels observed on social media. Overall, the findings suggest that the greater echo-chamberness of Twitter conversations following functional brand crises translates into a greater intensity and proportion of negative social media posts, which combine to produce a greater dip in average brand perceptions. A longitudinal analysis of these metrics shows the persistence of the effects for a period of four days. These insights hold true across multiple robustness checks, including multiple criteria for crisis classification, analysis of alternative echo-chamberness metrics, and comparisons with a k-nearest-neighbor-matched control group of brands. Finally, we provide an algorithmic demonstration of how brands can reduce echo-chamberness by creating a small number of bridges across opposing sides — that is, by proposing brand-positive content from social media influencers to members of the anti-brand community, with the hope to create a critical mass of endorsement edges in the form of likes, retweets, mentions, or other types of engagement.

We contribute to the marketing literature by quantifying an understudied impact of online firestorms – echo-chamberness of brand-related conversations – and highlighting its role in explaining some of the harmful consequences on brand reputation. Whereas previous studies have shown how online negative WOM affects marketplace (Hansen et al. 2018) and financial (Hsu and Lawrence 2016) outcomes, our framework complements and adds to extant marketing knowledge (Figure 2-2) by demonstrating that reducing filter bubbles during crises is a promising crisis management tactic that can mitigate both these harmful effects. Our research shows how managers can work to deescalate social media firestorms through network-level interventions that reduce filter bubbles by connecting opposing viewpoints (Garimella et al. 2017).

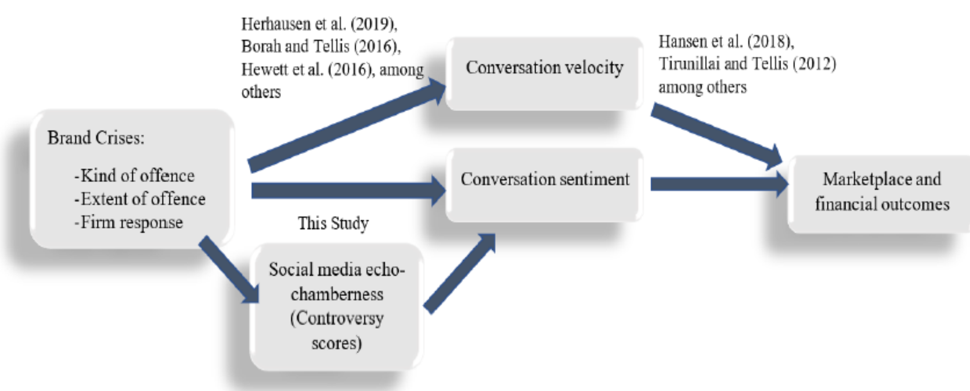

Figure 2-2: Indicative Literature review of social media firestorms and intended contribution of this study

2.2 CONCEPTUAL FOUNDATIONS AND HYPOTHESES

Online firestorms and digital brand crisis researchers have come up with conceptual models of consumer brand sabotage and collaborative social media attacks (Pfeffer et al. 2014; Kahr et al. 2016; Rauschnabel, Kammerlander, and Ivens 2016). Empirical scholarship on these phenomena, though relatively scant, includes Hansen et al. (2018) who use these conceptual frameworks to provide evidence for the impact of 'shitstorms' on short- and long-term brand perceptions in Germany. Herhausen et al. (2019) further examine the characteristics of social media messages and relationships that prove favorable to the spread of negative WOM. From a methods perspective, empirical demonstrations of social media firestorms employ event studies that have previously been extensively used to investigate multiple brand crisis types, ranging from deceptive advertising (Wiles et al. 2010), to product recalls (Borah and Tellis 2016; Chen et al. 2009; Liu et al. 2017), to bad news reports (Xiong and Bharadwaj 2013). Existing brand crisis frameworks in marketing and public relations research indicate that the impact on brands depends not only on the extent of damage caused by the brand transgression but also on the nature of said damage, i.e., on whether it committed a functional transgression (e.g., Samsung recalling its exploding cell phones) or a values-based transgression (e.g., Pepsi recalling its Black Lives Matter commercial featuring Kendall Jenner). While the former influences perceptions of a brand's product or service offerings (i.e., its core competencies) (Keller and Swaminathan 2020), the latter primarily affects a brand's symbolic and psychological perceptions (Coombs 2007). This is also true for mitigation strategies that enjoy differing levels of success with different kinds of brand crises; some of the strategies investigated include apology, compensation, denial, and justification (Coombs 2007; Coombs and Holladay 2008; Dutta and Pullig 2011; Hegner et al. 2014). While values-based crises have remained relatively unexplored in empirical marketing research, functional crises have received due attention (Cleeren et al. 2017 provide an exhaustive review). This nuanced understanding of brand crisis dimensions and firm responses is especially relevant in today's social media landscape in which brands have sophisticated digital tools to observe and act, but also face more threats in the form of boycotts, callouts and cancellations (Haskell 2021).

2.2.1 Main effect of social media firestorms on brand echo-chambers

Extant brand crisis literature (Dawar and Pillutla 2000; Ahluwalia et al. 2001), which has, for the most part, been limited to functional crises (product harm crises and service failures) suggest that these events are divisive and capable of inducing an ingroup-outgroup mindset. As consumers try to reconcile the new piece of information with their existing brand associations, the ones who hate the brand use this opportunity to reinforce their loathing for the brand by publicly expressing their rage and distaste for the brand, while the brand-lovers and brand-loyalists experience a deep cognitive dissonance. It elicits comments in defense and solidarity from these brand-supporters even at the cost of discounting factual evidence, in an exhibition of coping behaviors such as convincing themselves of the brand's innocence, trivializing the issue, or communicating self-affirming viewpoints (Perloff 2017). The starkly opposite opinions of the two groups are expected to devolve into an avoidance-generalization effect (Meleady and Forder 2019) where they surround themselves with like-minded people and deliberately avoid conversations from the other side of the discussion in a display of confirmation bias. Social media's targeting capabilities only serve to fuel this echo-chamberlike mindset further, thus:

H1: Brand echo-chamberness increase in the aftermath of online firestorms.

2.2.2 Moderation effect of nature of crisis (functional vs values-based) on brand echo-chambers

Functional transgressions differ from value-based transgressions in the extent to which they increase consumer risks associated with the brand. The latter lead to a much higher increase in social and psychological risk assessments of the brand – i.e., they make a consumer question their self- and social-image for consuming the brand – as compared to performance risks (chances of unsatisfactory outcomes from the product). The opposite is true for functional crises. The differential impact of these crisis characteristics on brand echo-chamberness, if any, needs contemplation. One might argue that values and morals are more personal to social media users and hit closer to the heart, and thus the associated social and psychological stress could make users more insular and more prone to pursue conversations in alignment with their worldview, as a sterner manifestation of the avoidance-generalization effect (Meleady and Forder 2019), than in the case of a functional crisis.

However, we hypothesize an opposing viewpoint, i.e., values-based crises should be more potent in reducing echo-chamberness in brand-supporter and brand-detractor conversations, because the relatively limited literature on moral transgressions indicates that the strength of the in-group versus out-group identity salience (Escalas and Bettman 2003; Hogg et al. 2004; Iyer and Leach 2008) should be lower for such crises as compared to functional crises. Two forces are expected to be at play here. First, functional crises are more likely to invite conversations from consumers with strong prior associations about a brand – i.e., strong love or hatred for the brand (Dawar and Pillutla 2000). In contrast, values-based crises appeal to a more universal audience because the social risks associated with a brand's ethical or moral scandal or a brand's political campaign are much more universal in nature. This should invite participation from a whole host of relatively brand-neutral or brand-moderate social media participants who are interested in the issue but are not as heavily invested in their feelings or associations towards the brand. This should have a moderating effect on the ingroup-outgroup salience of the two commenting groups as they each try to make more sense of the brand's involvement in the values-based crisis. In addition, we expect this relatively brand-moderate group of commentators to process the event more peripherally (Hansen et al. 2018) which makes their attitudes towards the brand relatively temporary and more susceptible to counter-persuasion (ELM, Petty and Wegner 1999). Second, Xu et al. (2021) point out that consumer reactions to moral transgressions are driven by empathy as opposed to dissonance-coping mechanisms in the case of functional transgressions. This should make social media participants more likely to engage with the other side of the discussion and be empathetic to their counter-arguments even when they disagree with them and argue about the legitimacy of their viewpoint (Gervais 2015). In the absence of these forces (universality, commonness of ground and empathy), functional crisis conversations are likely to be limited to the respective brand-supporter and brand-detractor groups, owing to their starkly disparate and staunch mindsets about the brand, further bolstering the perceived distinction between the in-group and out-group in consumers' minds. Thus:

H2: Increase in brand echo-chamberness is greater during a functional than values-based crises.

2.2.3 Brand echo-chambers as a mediator to brand perception

Empirical exploration of online firestorms, though relatively scant, seems to suggest that functional crises cause greater dips in brand perceptions (Hansen et al. 2018) as functional crises are likely to be objectively negative in nature (Coombs 2007) and also, because directly and personally affected consumers are more likely to lash out in the aftermath of functional. We posit that differences in echo-chamberness of social media conversations should at least partially explain these findings. Network scholars (e.g., Conover et al. 2011; Garimella et al. 2018) consistently find that more filter-bubbles on social media tend to produce more passionate conversations that escalate in their use of high-intensity and high-arousal emotions in the absence of an opposing narrative to appease or counter them. A more insular group on social media is also more likely to interpret any disagreement directed at the in-group as a personal attack and generate more hostile responses (Mackie et al. 2008). This increased intensity of the more dominant negative postcrisis conversations should drive a vicious loop of generating more attention to the issue and further drawing in larger numbers of brand-detractors. With the increase in both these components of brand perceptions (i.e., intensity and proportion of negative tweets), brand perceptions on social media should suffer to a larger extent in echo-chamberlike conversations. Additionally, we expect such echo-chambers to have long-run damages for the brand. We should expect higher consumer attrition and greater decreases in brand-usage, brand-preference and brand reputation over longer time-horizons after the event.

H3: Dip in average brand perception is greater in the aftermath of functional vs. values-based crises

H4: Increase in brand echo-chamberness mediates the impact of online firestorms on average brand perceptions – i.e., higher social media echo-chamberness produces greater dips in brand perceptions in the short run and brand reputation in the long run.

2.2.4 Mitigating social media echo-chamberness and brand perception dips

A corollary to Hypothesis 4 is that it intuitively seems like a reasonable strategy to try and reduce brand echo-chamberness to mitigate these negative effects – especially since network scholars have proposed convenient algorithmic approaches for avoiding filter bubbles. One simple way to do this is to expose individuals to opposing viewpoints, an idea that has been adopted by several studies; for example, Liao and Fu (2013, 2014) find a strong correlation between users' exposure to multiple stances of public opinion and the extremity of their own position on the matter. Other studies include those of Vydiswaran et al. (2015), who investigate the role of source credibility in influencing the persuasive power of communication presentation efforts, and Munson et al. (2013), who investigate biases in users' news-reading habits and document how showing users their bias nudges them to read articles of opposing views. Similarly, Graells-Garrido et al. (2014) demonstrate the use of "intermediary topics" in alleviating polarization. Garimella et al. (2017)'s demonstration of a resolution to this issue involves exposing social media users to contrary opinions of commentators across the aisle and hoping that a small number of engagement bridges (through retweets, replies, shares or mentions) can be formed. They highlight that the decrease in echo-chamberness is effective if these engagement connections could be built between high centrality users within both communities, subject to the condition that these users' opinions have some commonality so that there is a non-zero possibility of the connection fructifying in actuality. It suggests that extreme recommendations don't work, and that people 'in the middle' are easier to convince. We propose that an algorithmic approach of connecting optimally selected edges should also improve brand perceptions during an online firestorm. Firms today have access to several digital tools that involve influencer-seeding and online targeting capabilities – so, recommending positive content from brands' influencers to targeted brand-haters could be a potential mitigation tactic for both echo-chamberness and brand perception. Previous studies in marketing have extolled the virtues of influencer seeding in positive brand contexts (Hinz et al. 2011; Lanz et al. 2019), so it is reasonable to expect that such approaches could be leveraged in brand crisis situations as well. Thus,

> Corollary Proposition P1: Optimizing network-level interventions (such as influencer-seeding) should mitigate social media echo-chamberness and negative brand perceptions during online firestorms.

2.3 QUANTIFYING AND MITIGATING SOCIAL MEDIA ECHO-CHAMBERNESS

A growing stream of literature in the computer science and mathematical sociology domain is dedicated to quantifying social media echo-chamberness using Twitter graphs $G(v, e)$ constructed by representing participants as nodes v and the communications among them (retweets, mentions, friendships etc.) as edges e (Conover et al. 2011; Guerra et al. 2013; Morales et al. 2015; Ruan et al. 2013). For example, Conover et al. (2011) employ the concept of modularity and graph partitioning to identify echo-chamberlike conversation graphs from political discussions on Twitter, whereas Guerra et al. (2013) propose an alternative graph-structure measure based on the boundary between two potentially polarized communities. Morales et al. (2015) quantify it through the estimation of propagation velocities of opinions of influential users on Twitter using a case study from Venezuelan politics. In a similar vein, Garimella et al. (2018) quantify echo-chamberness using community detection techniques by building a social media conversation graph about the topic, partitioning the conversation graph to identify potential sides of the controversy, and then computing a random-walk controversy score (RWC) that's indicative of how inward-looking or echo-chamberlike these groups are. We use RWC as the primary measure of echo-chamberness within brand-supporter and brand-detractor conversations because among all the other alternatives, it is the most generalizable one, i.e., it can be applied to almost every domain of social media conversation that has participants on both sides of the issue. Specifically, we follow Garimella et al. (2018)'s three-stage pipeline in which a 'mentions' network and a 'retweets' network is first constructed for each pre-event and post-event set of tweets. The network is then partitioned into brand-supporters and brand-detractors based on the users' average sentiment, followed by the construction of thousands of complete random walks originating from centrally located brand-haters and brand-lovers till an asymptotically convergent value of controversy score can be estimated. RWC is then computed as per its definition – 'Consider two random walks, one ending in partition X and one in partition Y, RWC is the difference in probabilities of: (i) both random walks starting from the partition they ended in and (ii) both random walks starting in a partition other than the one they ended in.' Mathematically,

$$RWC = P_{XX}P_{YY} - P_{XY}P_{YX} \tag{1.1}$$

$$P_{AB}: A, B \in \{X, Y\} = P\left(node_{partition\ A} \rightarrow node_{partition\ B}\right) \tag{1.2}$$

We also compute the *E/I index*, *Betweenness Centrality Controversy (BCC)*, *Embedding Controversy (EC)* and *Boundary connectivity-based modularity (GMCK)* (see Table 2-1) as alternate measures of social media echo-chamberness for robustness checks.

Table 2-1: Alternate measures of social media echo-chamberness and their definitions

E/I index: It is a less computationally demanding proxy for RWC. Lower E/I indicate higher levels of insularity and higher echo-chamberness). $$\boldsymbol{E/I\ index = \frac{EL - IL}{EL + IL}}$$ where ***EL:*** # external links within a network and ***IL:*** # internal links within a network (Krackhardt and Stern 1988)
Betweenness Centrality Controversy (BCC): The intuition here is that in the case of high echo-chamberness – i.e., when the two partitions X and Y are well-separated – the cut between the two partitions (C, let's say) will consist of edges that bridge structural holes (Burt 2009). So, the shortest paths connecting vertices of the two partitions pass through the edges in the cut C with greater probability, leading to inordinately high betweenness values for these edges. Given the distributions of edge betweenness on the cut C and the rest of the graph, I compute the KL divergence $\boldsymbol{d_{KL}}$ of the two distributions and BCC as: $$\boldsymbol{BCC = 1 - e^{-d_{KL}}}$$
Embedding Controversy (EC): Like the Davies-Bouldin Index (Davies and Bouldin 1979), I compute $\boldsymbol{d_X}$ and $\boldsymbol{d_Y}$ (the average embedded distance among pairs of vertices in the same partition, say X and Y) and compare them with $\boldsymbol{d_{XY}}$ (the average embedded distance among pairs of vertices across the whole unpartitioned network) to calculate EC as: $$\boldsymbol{EC = 1 - \frac{d_X + d_Y}{2d_{XY}}}$$
Boundary connectivity-based modularity (GMCK): Proposed by Guerra et al. (2013), this is based on the notion that if the two partitions represent two sides of a echo-chamberlike network, then boundary vertices will be more strongly connected to internal vertices than to other boundary vertices of either partition. It is given by: $$\boldsymbol{GMCK = \frac{1}{\lvert B \rvert}\sum_{u \in B}\frac{d_i(u)}{d_b(u) + d_i(u)} - 0.5}$$ where $\boldsymbol{d_i(u)}$ is the number of edges between vertex *u* and internal vertices *I*, while $\boldsymbol{d_b(u)}$ is the number of edges between vertex *u* and boundary vertices *B*.

These studies further highlight optimization of echo-chamberness mitigation tactics suggesting that the greatest change in echo-chamberness $\delta RWC_{u_i \to v_i}$ should be expected when engagement edges are built between higher centrality users u_i and v_i, although it is tempered by the edge-acceptance probability $p(u_i \to v_i)$ which is inversely proportional to the polarity difference between the nodes (given that it is near-impossible to connect users with polar-opposite opinions). This translates into a k-edge recommendation problem within a network – say, graph $G(v, e)$ with vertices partitioned into two disjoint sets $X$and Y – such that addition of the k edges generates a new graph $G'(v, e')$ designed for largest expected change in controversy score. In Proposition P1, we propose that a similar algorithmic approach of connecting optimally selected edges should also improve brand perceptions during an online firestorm. A stylized analysis in Appendix A.1.1 suggests that improvements in brand perception are optimized if these edges are built from nodes that were originally connected to high-centrality negative-sentiment nodes provided that they can be induced to endorse positive users with high eigenvalue centrality, i.e., these influential users on either side are sufficiently brand-neutral for them to probabilistically engage with each other (Figure 2-3). These engagement or edge-acceptance likelihoods should depend primarily on the polarity of these users. Firms today have access to several digital tools that involve influencer-seeding and online targeting capabilities – so, recommending positive content from brands' influencers to targeted brand-haters could be a potential mitigation tactic for both echo-chamberness and brand perception.

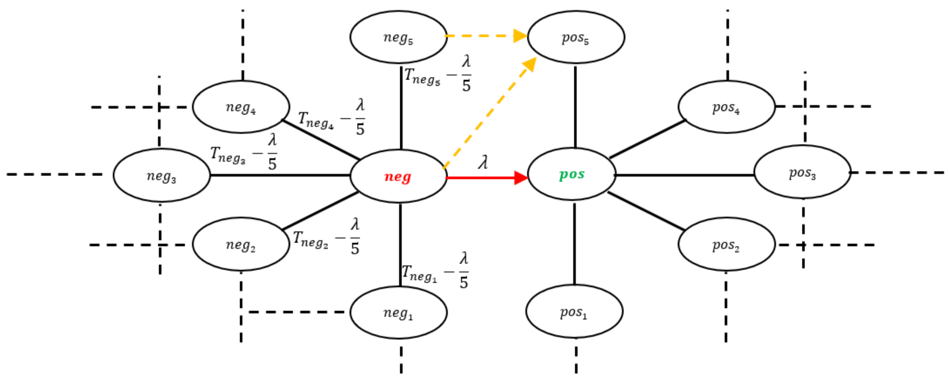

Figure 2-3: Edge between high eigenvalue centrality nodes neg → pos is more effective than neg → $\mathbf{pos_5}$ or $\mathbf{neg_5}$ → $\mathbf{pos_5}$, provided their polarities are sufficiently 'middle-of-the-road'. That changes influence of neg's neighbors by $\boldsymbol{\delta T_{neg_i} = -\lambda/d_{neg}}$

2.4 EMPIRICAL STUDY AND METHOD

2.4.1 Events Data Set (and Control Group)

Social media is replete with content creators, multipliers, and activists who are quick to pick up on interesting news stories (Moe and Schweidel 2012), thus causing brand crises to blow up into social media firestorms. Online firestorms, by their definition, are therefore epicenters of social media attention and cause significant increases in volumes of brand-related conversations, thus making their identification possible using listening platforms and Google search volumes. The process of building a repository of brand crisis events involved a combination of manual searches on LexisNexis for negative brand-related news and cross-cataloguing them with the volume of Twitter conversations filtered out using queries for keywords (brand-related), language (English), and location (United States) on Atlas Infegy's social media-listening platform. Specifically, we began with the list of the best-known brands in the United States (BAV database from 2012 to 2019) and then accessed the volume of negative social media posts on Twitter related to these brands (measured by Atlas Infegy and supplemented by the Google Search Volume Index). At the same time, two research associates manually browsed through pertinent negative news stories on LexisNexis and identified potential firestorm events from their headlines. Finally, we isolated online firestorms and the specific dates of their onset by systematically observing whether social media conversation volumes spiked in the vicinity of these news stories. We used the Atlas Infegy's topic modeling tools to ensure that the brand crisis was the predominant topic being discussed on social media to eliminate other causes of the volume spikes. The process left us with 574 events from the period 2012-2019 across 261 BAV brands representing 84 BAV product categories. Some of these events could, however, not be included in the analysis of random walk controversy scores because the number of tweets in the small post-event intervals were not adequate to compute the RWC scores reliably to the point of convergence . Finally, we used a k-nearest-neighbor matching procedure on the brands' BAV dimensions (77 attributes, e.g., brand knowledge, differentiation, relevance) to first identify control brands belonging to the same industry as the focal brand. We then verified with LexisNexis to create a pairwise matched control group of “nonevents” (i.e., dates that are not associated with negative news articles about control brands).

2.4.2 Classification of events

Business students recruited as research assistants independently responded to survey questions based on Dutta and Pullig (2011), and rated events after reading their descriptions from news articles. Respondents indicated (on a scale of 1 through 7) their agreement to whether the event concerns the organization's values and beliefs, a specific problem with the brand's product, and the level of performance, social and psychological risks associated with them, along with other dimensions of the event (See Appendix Figure A-1.1 for the questionnaire used). We then used a Principal Components Analysis of their responses to reduce these characteristics of each event down to two orthogonal dimensions which explained 80% of all variances in these variables (Figure 2-4). The factor loadings on these two dimensions suggest that the first dimension identifies the ‘$\boldsymbol{Crisis\ type_i}$’ by positively weighting the functional or performance elements of a crisis, and negatively weighting the values-based or social elements of the crisis. This component (after scaling) takes up values in the range of -6 (representing a predominantly values-based crisis) to +6 (representing a predominantly functional crisis). The second dimension identifies the additive component of all risks – i.e., the overall extent of damage caused by the crisis to the brand by loading positively and almost equally on all elements of the crisis. We classify our events based on whether they are high (top 30%), low (bottom 30%) or medium (remaining) on both these dimensions and use these categorical variables as moderators in our analysis[4].

[4] We also provide analysis results using the continuous moderator variables in the web appendix …. for robustness checks

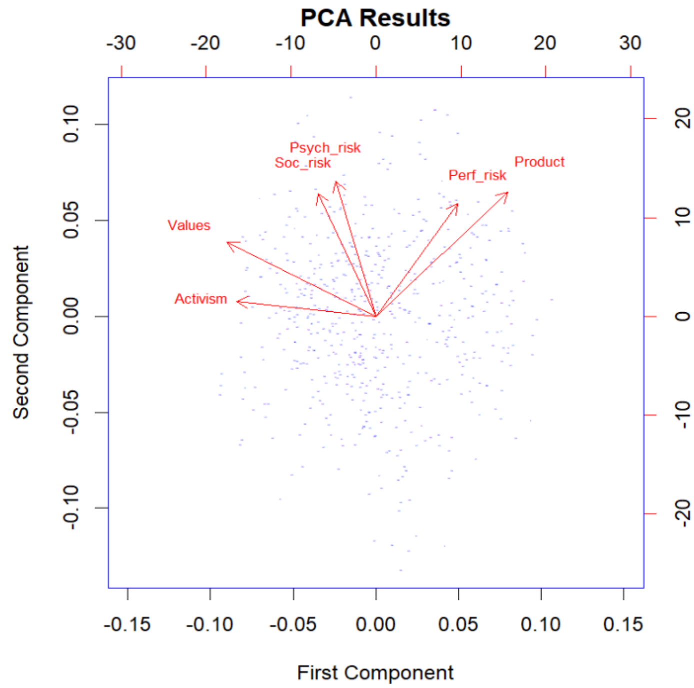

Figure 2-4: Orthogonal Principal Components help classify events on the dimensions of Crisis Type (PC-1) and Extent of Crisis (PC-2)

2.4.3 Short-run Brand perception

We used Atlas Infegy's platform to calculate daily brand perception levels for an event over a period of 30 days before the event and 30 days after the event, by filtering queries for keywords (brand-related), language (English), and location (United States). We then averaged them over different pre- and post-event windows as an estimate of brand perceptions and extent of abnormal changes as a consequence of the social media firestorm. The formula used for daily average brand perception[5] is:

$$Brand\ Perception_{day\ i} = \frac{Pos.intensity_i * Pos.mentions_i - Neg.intensity_i * Neg.mentions_i}{Total\ mentions_i} \qquad (2)$$

[5] The social media-listening platform provides day wise aggregated values of positive (negative) intensity indicating the average "strength of score for positive (negative) tweets, ranging from 0 to 100." We assume the intensity of neutral mentions to be zero.

2.4.4 Long-run Brand Perception

We used Young and Rubicam's BAV database for estimating long-run impacts of the brand crises. They use their proprietary measurement tools to provide annual estimates of 'Brand Asset' composed of the four BAV pillars – brand differentiation, relevance, knowledge, and esteem. In addition, they provide other consumer-specific estimates such as consumer preference (Brand-I-Prefer percentage), consumer attrition (Lapsed User percentage) and Total Users. Multiple studies have found the BAV measures to be strong indicators of a firm's long-run performance (Mizik and Jacobson 2008).

2.4.5 Impact Analysis (for H1-H4)

We investigate the impact of the nature of brand transgression by calculating the difference in the mean brand perceptions and controversy scores across multiple pre- and post-event time intervals, which corresponds to the abnormal change in these social media measures corresponding to a brand crisis. This is given by:

$$\Delta RWC_{focal}(-30, n) = RWC_{focal}(n\ days\ post\ event) - RWC_{focal}(30\ days\ pre\ event) \tag{3}$$

$$\Delta Perc^{n}{}_{focal}(-30, n) = Perc^{n}{}_{focal}(n\ days\ post\ event) - Perc^{n}{}_{focal}(30\ days\ pre\ event) \tag{4}$$

The parenthesized expression $(-30, n)$; $\{n \in N : 1 \leq n \leq 30\}$ represents the window over which we measured all dependent variables. After calculating these deltas, we probed statistical evidence for H1 (main effect) by estimating the coefficients of the constant terms and H2 and H3 (moderating effects comparing the impact of values-based crises and functional crises) by estimating the coefficients of the $\boldsymbol{Crisis\ type_i}$ variable in regression Equations 5, 6 and 7. The corresponding abnormal change in the long-run BAV measures is computed by subtracting their three-year moving average before the event from the corresponding value the year after the event. Finally, we controlled for the extent of damage (second principal component), brands' brand value, industry, and year- and quarter-fixed effects, along with the possibility of errors being correlated at the industry level.

$$\Delta RWC_{focal}(-30,n)_{ijt} = \beta_0 + \beta_1 Crisis\ type_i + \beta_c Controls_{ijt} + \varepsilon_{ijt} \tag{5}$$

$$\Delta Brand\ Per^n{}_{focal}(-30,n)_{ijt} = \alpha_0 + \alpha_1 Crisis\ type_i + \alpha_c Controls_{ijt} + \xi_{ijt} \tag{6}$$

$$\Delta Brand\ Per^n{}_{focal}(\text{long} - \text{run})_{ijt} = \alpha_0 + \alpha_1 Crisis\ type_i + \alpha_c Controls_{ijt} + \xi_{ijt} \tag{7}$$

For robustness and endogeneity checks, we further analyzed a control group and computed the double-difference for abnormal changes in the same set of dependent variables (Equation 8, which, when injected into Equations 5-7 as DVs, become equivalent to the triple differences-in-differences specification in Equation 9 with α_{did} and $\alpha_{cr,did}$ as the coefficients of importance, indicating the main and moderating effects, respectively. The intent of the difference-in-differences identification strategy (Angrist and Pischke 2008) is to capture the online firestorm's effect by comparing the RWC and brand perception metrics in the aftermath of the event with those of the same brand before the event (i.e., a within-brand effect) as well as with brands that did not experience the crisis in the same period (i.e., a between-brand effect). Adding matched control brands eliminates selection bias from observables and aids in averaging out pairwise differences between the dependent variables across events. We also perform an event-horizon generalized diff-in-diff analysis as an additional robustness check (See Appendix A.1.2)

$$\begin{aligned} \Delta\Delta RWC(-30,n)_{event} &= \Delta RWC_{focal}(-30,n)_{event} - \Delta RWC_{control}(-30,n)_{event} \\ &= RWC_{focal}(\text{n days post event}) - RWC_{focal}(\text{30 days pre event})\} \\ &\quad -\{RWC_{control}(\text{n days post event}) - RWC_{control}(\text{30 days pre event})\} \end{aligned} \tag{8}$$

$$\begin{aligned} DV_{it} &= \alpha_0 + \alpha_c Controls_{it} + \alpha_{did}(Post_{it} * Focal_{it}) + \alpha_{post} Post_{it} + \\ &\quad Crisis\ type_i * \left\{\alpha_{cr,did} Post_{it} * Focal_{i,t,T} + \alpha_{cr,post,T} Post_{i,t,T}\right\} + \eta_{it} \end{aligned} \tag{9}$$

Finally, we used Hayes' mediation estimation (Hayes 2017) to validate the proposed mediation mechanism. For the short-run mediation in the immediate aftermath of the crisis, we estimated a 3SLS system-of-equations with bootstrapped standard errors (10.1-10.3) (Cameron and Trivedi 2009) to avoid any simultaneity bias arising from the immediate short-run brand perception measures and controversy scores being computed from the same data source simultaneously. We allowed the errors from the two regression equations to covary without restriction. Doing so helps us quantify the extent to which the proposed mediating variable (RWC) explains the abnormal changes in the brand perception measure. The coefficients of interest are λ_0, λ_1 and λ_2. A successful mediation effect would be implied if the inclusion of the $\Delta RWC(-30,n)_{ijt}$ variable reduces the significance of the coefficients λ_0 and λ_1, in comparison with those obtained in the main- and moderation-effect findings (α_0 and α_1 in the estimation of Equation 6). Statistically nonsignificant coefficients would indicate complete mediation, while partial mediation would leave behind a significant coefficient with lower magnitude. We would then be able to conclude that the controversy score can explain away the effects of the crisis on brand perceptions.

$$\Delta RWC(-30,n)_{ijt} = \theta_0 + \theta_1 Crisis\ type_i + \theta_c Controls_{ijt} + \eta_{ijt} \tag{10.1}$$

$$\Delta Brand\ Perc^n.(-30,n)_{ijt} = \lambda_0 + \lambda_1 Crisis\ type_i + \lambda_2\ \Delta RWC(-30,n)_{ijt} + \lambda_c Controls_{ijt} + \nu_{ijt} \tag{10.2}$$

$$Cov\left(\eta_{ijt}, \nu_{ijt}\right) \neq 0 \tag{10.3}$$

2.4.6 Simulation of Network Level Interventions (for Corollary Proposition P1)

We simulated Garimella's (2018) approach to demonstrate whether connecting a few optimal edges within Twitter conversation networks can significantly mitigate the harmful impacts on social media echo-chamberness and brand perceptions. We calculated the two critical network-related components that affect the expected improvement in RWC and sentiment: (1) eigenvalue centrality of each user and (2) polarity of each user based on his or her average brand sentiment during the social media firestorm. For each crisis event in our sample, we ranked unconnected edges in the post-event Twitter conversation network, first in a decreasing order of average eigenvalue centrality of the two nodes it connects and then in an increasing order of polarity differences between the nodes; in the process, we shortlisted k^k edges between the k-highest eigenvalue centrality nodes on either side of the discussion.

We then incrementally constructed edges beginning with the most optimal (the one with the highest centrality of nodes on either side, provided that their polarity difference is less than the 25th-quartile threshold among the potential k^k connections), until a network was constructed with 5% additional edges as compared with the original. We computed the social media echo-chamberness metrics at different levels of this edge-addition process and estimated the change in brand perceptions predicted by the corresponding coefficients of Equation 10.2.

2.5 RESULTS

2.5.1 Test for Event Identification

Figure 2-5 plots the coefficients of the event dummies (with Day "-1" as the baseline) in Equation 11, thus establishing the precision of the chosen event dates and providing evidence for the adequacy of the event study analysis for analyzing social media firestorms.

$$DV_{i,t,Group} = \alpha_0 + \sum_{T=-30}^{T=+30} \alpha_{post,T,Group} Post_{i,t,T} + \eta_{i,t}; Group = \{Focal, Control\} \tag{11}$$

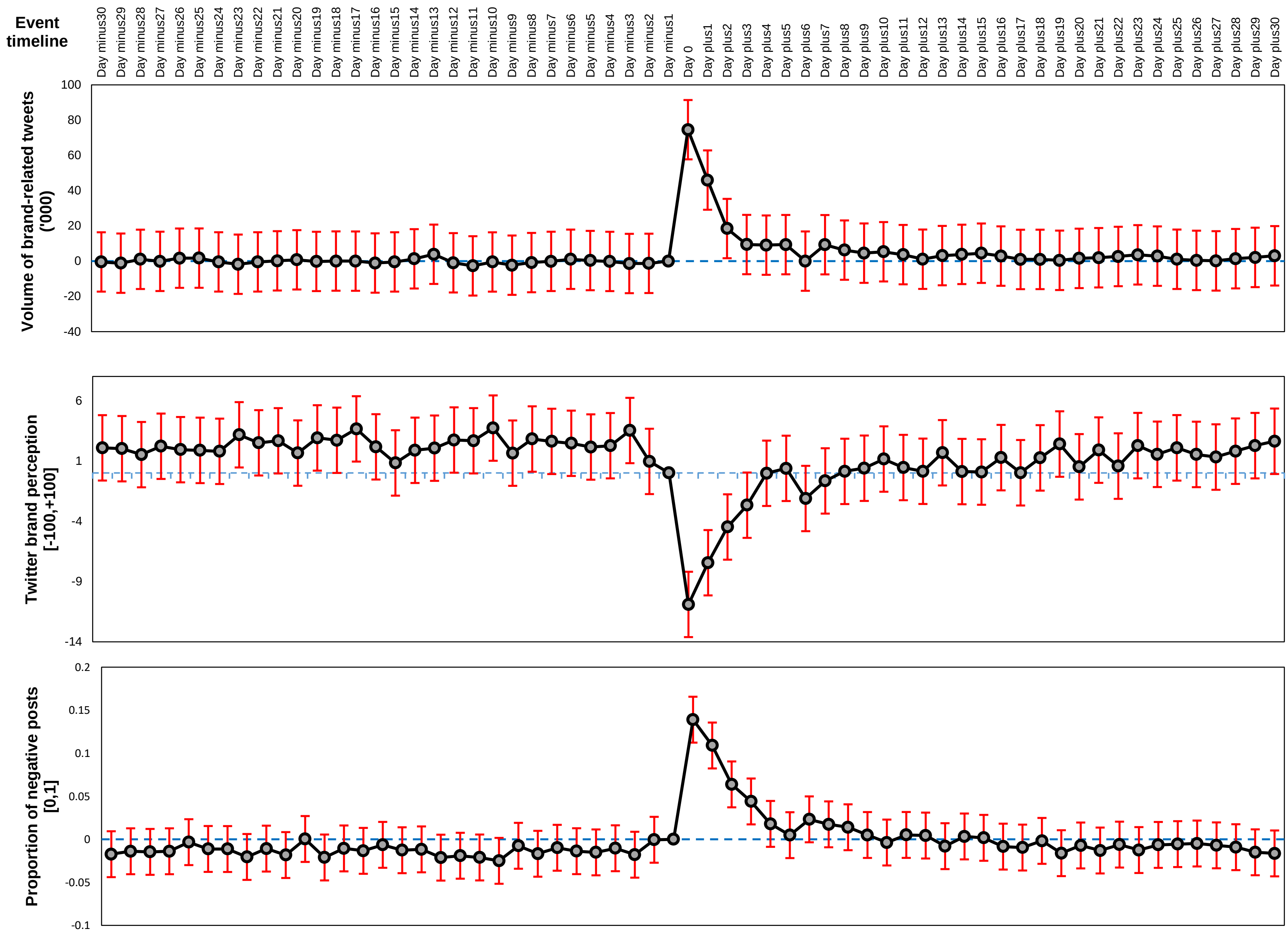

Figure 2-5: Test for identification of firestorms using event timeline of social media conversation characteristics

The plots in Figure 2-5 show the onset of the online firestorm on Day 0 through the significant change in the three social media conversation characteristics — volume of brand-related tweets, brand perception among social media users, and its primary driver (i.e., proportion of negative tweets related to the brand) — for both the focal events and the control group of nonevents. The plots show the relatively short-lived nature of these firestorms, the changes remaining significant for four days (Days 0-3) while regressing to the mean levels by the fifth day of the brand crisis becoming public. The plots also show the validity of the chosen control group of nonevents by providing evidence for the parallel trends assumption and setting up the possibility of a differences-in-differences analysis for providing necessary robustness and endogeneity checks for our findings. As demanded by the parallel trends assumption, the social media conversation characteristics of the chosen nonevents show no significant deviation in their preevent patterns (i.e., Day -30 to Day -1) from the focal group of events. In addition, Appendix Table A.1-1 shows how the treatment and control groups match up against each other on the critical BAV metrics. The comparison indicates that the distribution of these metrics, with the exception of Brand Knowledge, do not differ significantly at the 95% CI, thus providing evidence for a well-matched control sample.

2.5.2 Characteristics of brand crisis types

Consistent with extant marketing literature, functional crises and values-based crises in our sample differ significantly on the dimensions of performance and social risks associated with them. Values-based crises have significantly higher levels of social risk and significantly lower levels of performance risks associated with them. Figure 2-6 (Panels A and B) demonstrates this by comparing and contrasting between crises that can be unambiguously classified as functional (crises that ranked in the top 30 percentile of the continuous $\boldsymbol{Crisis\ type_i}$ variable) or values-based (crises that ranked in the bottom 30 percentile of the continuous $\boldsymbol{Crisis\ type_i}$ variable). We also used this classification to test our expectation that the universality of social risks prevalent in values-based crises should draw in a larger population of brand-moderate social-media users. For this measure, we used Infegy's estimation of 'neutral tweets' as a proportion of the total volume of conversations. Figure 2-6 Panel C further demonstrates this to be true, as nearly 27% of tweets in the aftermath of values-based crises can be classified as 'neutral' as compared to 16% of tweets in the case of functional crises. We also tested these values for the brand-activism events in our sample (sub-category of values-based crises which were rated in the top 70 percentile on the $Brand\ Activism_i$ variable by our survey respondents) – see Appendix Figure A.1-2. We find that brand activism events are even further-removed from functional crises on the dimensions of performance and social risks, although not significantly different from values-based crises. So, they seem to demonstrate a stronger manifestation of these features of values-based crises.

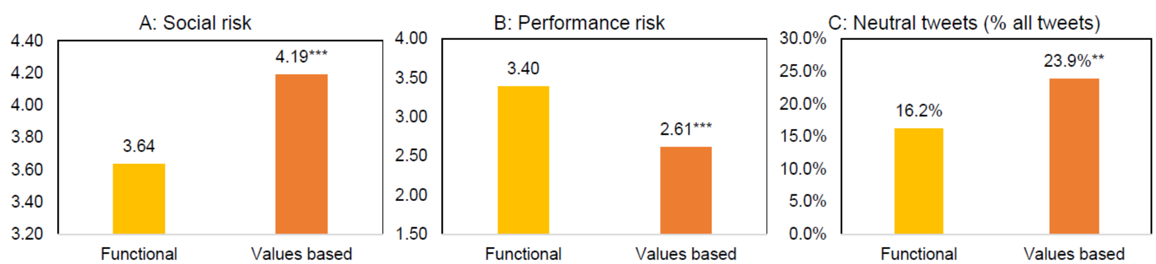

Figure 2-6: Characteristics of different firestorms

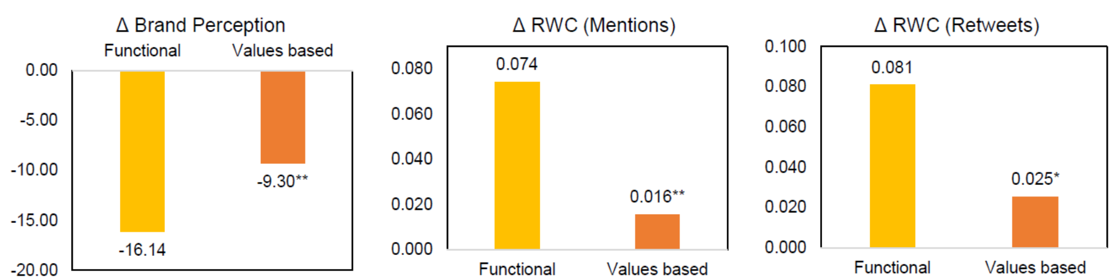

Figure 2-7: Brand Perception and Controversy Score Impact of different firestorms

2.5.3 Tests for Main and Moderation Effects

Figure 2-7 provides overall changes of controversy score and brand perception outcomes of functional crises and contrasts them against values-based crises, thus providing model-free evidence for the main and moderation effect hypotheses (See Appendix Figure A.1-3 for comparison with brand activism events).

Complementing these initial findings, Panels B and C in Table 2 catalog the regression results of abnormal changes in random-walk controversy measures in the event window (-30,1) for the retweets network and mentions network, respectively. As expected in H1, all transgressions lead to increases in brand RWC, as evidenced by the significant positive Pre−Post coefficient. We find support for moderation of $\boldsymbol{Crisis\ type_i}$ on both these dependent variables, as predicted in H2. The positive coefficient of the $\boldsymbol{Crisis\ type_i}$ variable in the 'Medium' and 'High' categories in Panels B and C provide evidence for a greater increase in RWC in the aftermath of functional than values-based crisis (i.e., the higher the perceived functional element of the crisis on consumers' minds, the greater is the social media echo-chamberness). We replicate this analysis using the continuous $\boldsymbol{Crisis\ type_i}$ variable (see Appendix Table A.1-2). We plot this moderation with the continuous variable in Figure 2-8 to demonstrate through a floodlight analysis (Spiller et al. 2013) that the increase in RWC in the postevent conversation network becomes nonsignificant at a 95% CI at values of $\boldsymbol{Crisis\ type_i} \leq -1.2$ for mentions networks, which is ≈ 0.8 standard deviations below the mean in our sample. The same happens at $\boldsymbol{Crisis\ type_i} \leq -3.3$ for retweet networks, which is ≈ 2 standard deviations below the mean in our sample. These effects persist when we add additional controls for extent of damage (second principal component from the survey results), brand size, year- and quarter-fixed effects, and other conversation characteristics such as volume of positive, negative and neutral tweets.

As expected in H3, the dip in average brand perception is greater in the aftermath of functional than values-based crises over both the short-run and the long-run. Panel-A of Table 2 illustrates the moderation effects of nature of crises on brand perceptions in the short-run. The floodlight analysis (Figure 2-8 Panel-A) illustrates that although the decrease in the short-run brand perceptions remains significant throughout the range of the moderator, values-based crises suffer this consequence to a lesser extent. We further decompose these short-run abnormal changes in brand perception into its drivers — namely, the proportion of negative posts and intensity of negative posts — and tabulate our results in the Appendix Table A.1-3. As theorized, we find that the crises affect both these components, indicated by the positive coefficients of both $\boldsymbol{Pre - Post}$ and $\boldsymbol{Crisis\ type_i}$ variables. We also tabulate the immediate brand-perception changes for event windows (-30,2) to (-30,5) — the length of persistence of online firestorms estimated in the previous section — in Appendix Table A.1-4. We find that the impacts of the firestorm are replicated across the five event windows, though the coefficients become more imprecise (larger standard errors) and the explanatory power of the regressors decreases (successively lower values of R^2). This is expected because larger event windows are likely to contaminate the event study results with a gradually increasing possibility that other factors are influencing these social media constructs. Consistent with these findings, Appendix Tables A.1-7 Panels [I] and [II] further illustrate that higher levels of performance risk further aggravate brand perceptions and social media echo-chamberness, while social risks tend to negatively moderate these relationships across multiple event windows.

We find these effects replicated for the long-run BAV measures (Table 4 Panel A). There is a main negative impact of online firestorms on Brand Stature, Brands' lapsed user percentages, Brands' preference percentages and total number of users. $\boldsymbol{Crisis\ type_i}$ moderates these effects as it did in the case of the immediate short-run brand perceptions. We find that functional crises have greater adverse impact on lapsed user percentages, brand preference percentages and brand's total number of users.

Table 2-2: Main and moderating effects of social media firestorms and Crisis type respectively on Brand Perception and Controversy Scores[6]

	A: Average Brand Perception				B: Mentions network RWC				C: Retweet network RWC			
	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors
Crisis type: Mixed		-3.657^	-3.157^	-3.157^		0.0292	0.0244	0.0244		0.00781	0.0136	0.0136
		(2.720)	(2.694)	(3.099)		(0.0319)	(0.0314)	(0.0408)		(0.0408)	(0.0383)	(0.0414)
Crisis type: Functional		-6.099**	-4.869^	-4.869**		0.0575*	0.0790**	0.0790*		0.0364^	0.0822*	0.0822**
		(2.933)	(3.047)	(2.238)		(0.0344)	(0.0355)	(0.0436)		(0.0239)	(0.0433)	(0.0324)
Pre-Post	-13.16***	-9.852***	-33.79***	-33.79***	0.0420***	0.0130^	0.107^	0.107***	0.0482***	0.0342^	0.189**	0.189***
	(1.129)	(2.080)	(5.941)	(2.533)	(0.0132)	(0.0244)	(0.0692)	(0.0280)	(0.0168)	(0.0312)	(0.0845)	(0.0230)
Observations	294	294	293	293	294	294	293	293	294	294	293	293
R-squared	0.000	0.015	0.192	0.192	0.000	0.009	0.202	0.202	0.000	0.003	0.262	0.262

Table 2-3: Path analysis showing that change in polarization explains all of the variance in Brand Perception dip in the aftermath of social media firestorms

A: Main and Moderation effect (Eq 6)		B: 3SLS Mediation with ΔRWC (mentions) (Eq 10)			C: 3SLS Mediation with ΔRWC (retweets) (Eq 10)		
Covariates	Δ Brand perception	Covariates	Δ RWC (10.1)	Δ Perc (10.2)	Covariates	Δ RWC (10.1)	Δ Perc (10.2)
Crisis type: Mixed	-3.157^	Crisis type: Mixed	0.0200**	0.191	Crisis type: Mixed	0.0214*	-0.250
	(3.099)		(0.00929)	(1.577)		(0.0116)	(1.532)
Crisis type: Functional	-4.869**	Crisis type: Functional	0.0200**	0.191	Crisis type: Functional	0.0214*	-0.250
	(2.238)		(0.00929)	(1.577)		(0.0116)	(1.532)
`		Δ RWC (mentions)		-73.00*	Δ RWC (retweets)		-46.97*
				(41.98)			(32.46)
Pre-Post	-33.79***	Main Effect	0.0586	-14.37	Main Effect	0.136	-13.44
	(2.533)		(0.115)	(13.71)		(0.120)	(15.65)
Controls	BAV, Yr., Qtr., Ind.	Controls	BAV, Yr., Qtr., Ind.		Controls	BAV, Yr., Qtr., Ind.	
Observations	293	Observations	293	293	Observations	293	293

[6] Results in the table represent 'Main Effect' and 'Moderation Effect' for the event window (-30,1) – the effects are replicated for the entire duration of the online firestorms although they decrease over time in both magnitude and significance.

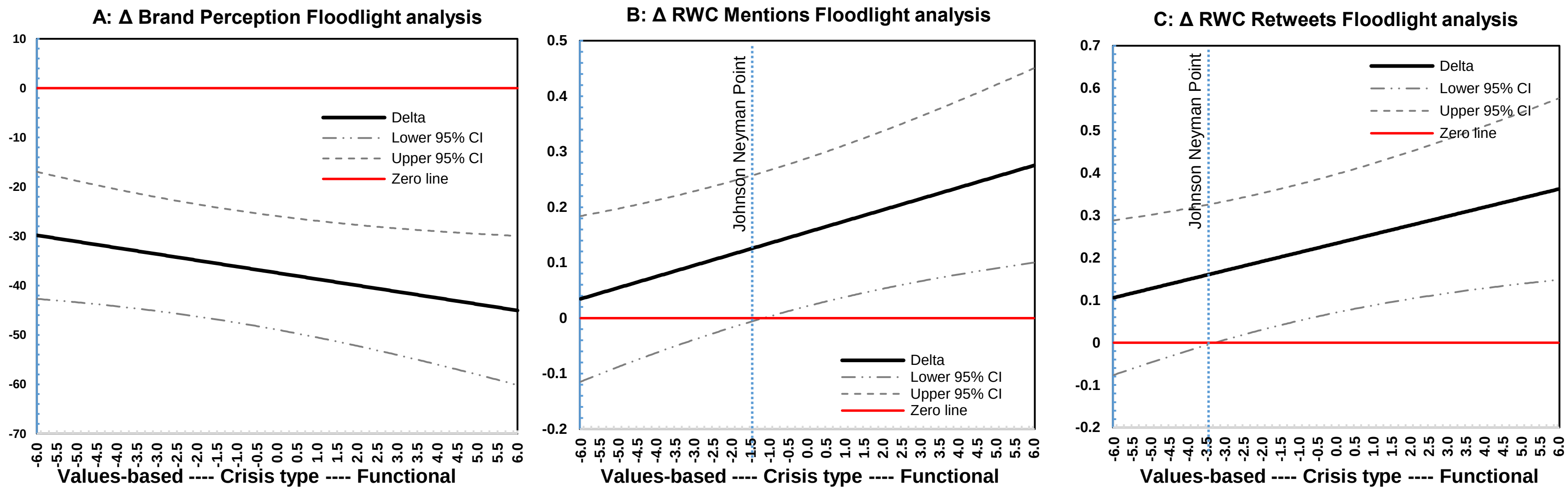

Figure 2-8: Floodlight analysis (Spiller et al. 2013) to visualize moderation effect of crisis type and Johnson Neyman point for Controversy Scores

Table 2-4: Hypothesized Main, moderation and mediation effects are replicated for long-run BAV metrics

	A: Long-run Brand Perception				B: Mediation Effect of Controversy Scores on Long-run Brand Perception>>							
	Δ Brand Stature	Δ Lapsed Users (%)	Δ User Pref. (%)	Δ Total Users	Δ Brand Stature		Δ Lapsed Users (%)		Δ User Pref. (%)		Δ Total Users	
Crisis type: Mixed	-0.0104	0.219^	-0.395^	-0.152	-0.00928	-0.0103	0.185	0.206	-0.157	-0.210	0.186	0.102
	(0.0234)	(0.117)	(0.285)	(0.525)	(0.0236)	(0.0234)	(0.319)	(0.320)	(0.291)	(0.293)	(0.555)	(0.557)
Crisis type: Functional	-0.0456^	0.609*	-0.564*	-0.234^	0.00178	-0.00181	0.550^	0.605^	-0.324	-0.361	-0.0387	-0.101
	(0.0453)	(0.355)	(0.319)	(0.187)	(0.0447)	(0.0439)	(0.358)	(0.459)	(0.325)	(0.329)	(0.622)	(0.625)
Δ RWC (mentions)					-0.0782^		0.770^		-1.324**		-1.910*	
					(0.0532)		(0.620)		(0.596)		(1.138)	
Δ RWC (retweets)						-0.0267		0.503		-0.225^		-0.0859*
						(0.0426)		(0.510)		(0.176)		(0.0606)
Pre-Post	-1.272***	2.115^	-3.569**	-5.518*	-1.244***	-1.249***	2.011	2.053	-4.558**	-4.687**	-6.439*	-6.673*
	(0.117)	(1.694)	(1.523)	(2.806)	(0.150)	(0.151)	(1.706)	(1.712)	(2.039)	(2.062)	(3.896)	(3.922)
Observations	285	281	281	281	285	285	281	281	281	281	281	281
R-squared	0.293	0.172	0.225	0.238	0.299	0.299	0.178	0.173	0.420	0.407	0.386	0.378

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.15

2.5.4 Tests for Mediation of Controversy Scores on Brand Perception

The results of the path analysis (Equations 10.1-10.3) for short-run brand perceptions in Table 3 show evidence of the proposed mediation in H4 through brand RWC. The significant, negative coefficients of mentions-RWC and retweets-RWC in the second stage of the 3SLS system-of-equations estimations show that higher values of social media echo-chamberness indeed lead to greater dips in average brand perceptions in the aftermath of these crisis events. Furthermore, these results indicate that the RWC metric completely mediates the differential impacts of nature of crises (functional vs. values-based) on average sentiment, as evidenced by the lack of significance of the $\boldsymbol{Crisis\ type_i}$ variable. We also find that the coefficient of the $\mathrm{Pre-Post}$ variable in the second-stage estimates is lower in both value and statistical significance than the main effects unearthed in the previous section (also highlighted in Panel A of Table 2), thus suggesting that a change in the RWC score explains the bulk of the variance in the average brand perception metric in the immediate aftermath of social media firestorms. These mediation effects last for the entirety of the firestorm period — that is, over event windows (30,2) - (30,4) (Appendix Table A.1-5). Finally, Appendix Table A.1-6 provides support for the theory that this effect is driven by higher RWC scores of social media conversations during a functional crisis influencing both components of the brand perception dips — that is, (1) the intensity of negative discussions (i.e., by producing more heated and high arousal discussions) and (2) the proportion of negative tweets (i.e., by drawing in brand-haters in greater numbers). Thus, we conclude that RWC provides a viable mechanism for the dips in brand perception that occur in the aftermath of a social media firestorm.

These results are replicated for the long-term brand perception measures as well. As Table 4 Panel B demonstrates, random walk controversy scores have strong predictive power on post-event BAV changes in Brand Asset, Brands' lapsed user percentages, Brands' preference percentages and total number of users, and are able to explain all of the variance in these BAV measures caused by the the online firestorm. These results hold even when controlling for all other crisis conversation measures like size of the firestorm, number of negative tweets and so on.

2.5.5 Simulation Results of Network-Level Interventions

Given the empirical evidence of H4, we proceeded to simulate multiple marginally larger networks, assuming that the concerned brand's efforts are able to create a small number of retweets or mentions between brand-supporters and brand-detractors. Six case studies (Figure 2-9) demonstrate how controversy scores decrease to a significant extent through the addition of a small number of extra edges — an additional .5% of the original number of edges within these six echo-chamberlike conversation networks decrease RWC by .036 on average (consequent improvement of ≈ 2.7 brand perception points), which goes up to .144 (≈ 11 brand perception points) with 5% extra edges. We provide results for these simulation results on the entire sample in Figure 2-10 and provide these improvement figures computed to a degree of statistical certainty. Thus, we demonstrate the strength of seeding influencers and connecting opposing viewpoints during a crisis as a potential solution to the online firestorm conundrum and advise that brands must develop capabilities to build bridges between relatively "middle-of-the-road" users with high eigenvalue centrality, thus effectively using the network effects on social media to inject and diffuse positive brand-related content.

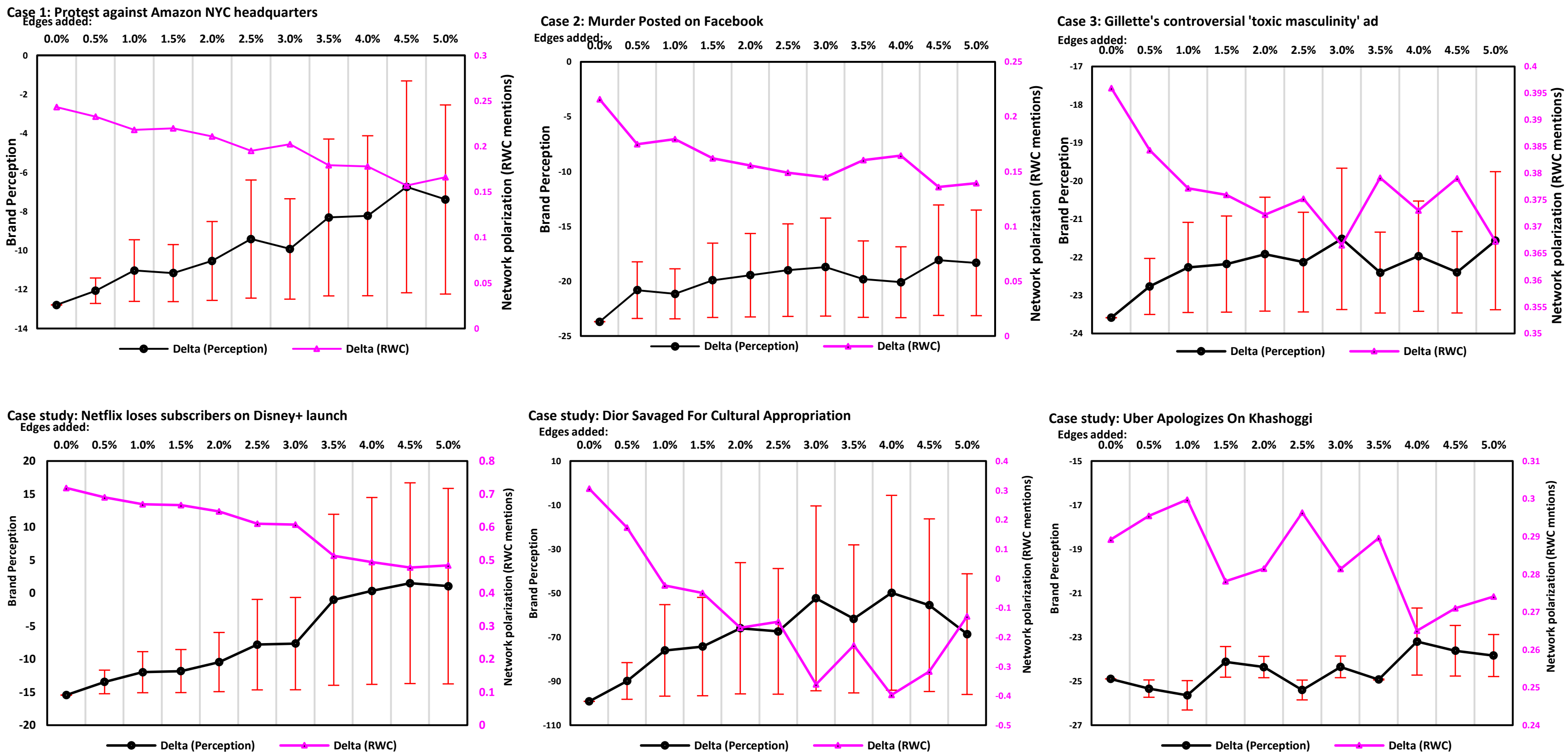

Figure 2-9: Simulation case studies show network-level interventions can be optimally designed for reducing Twitter polarization and improving brand perceptions

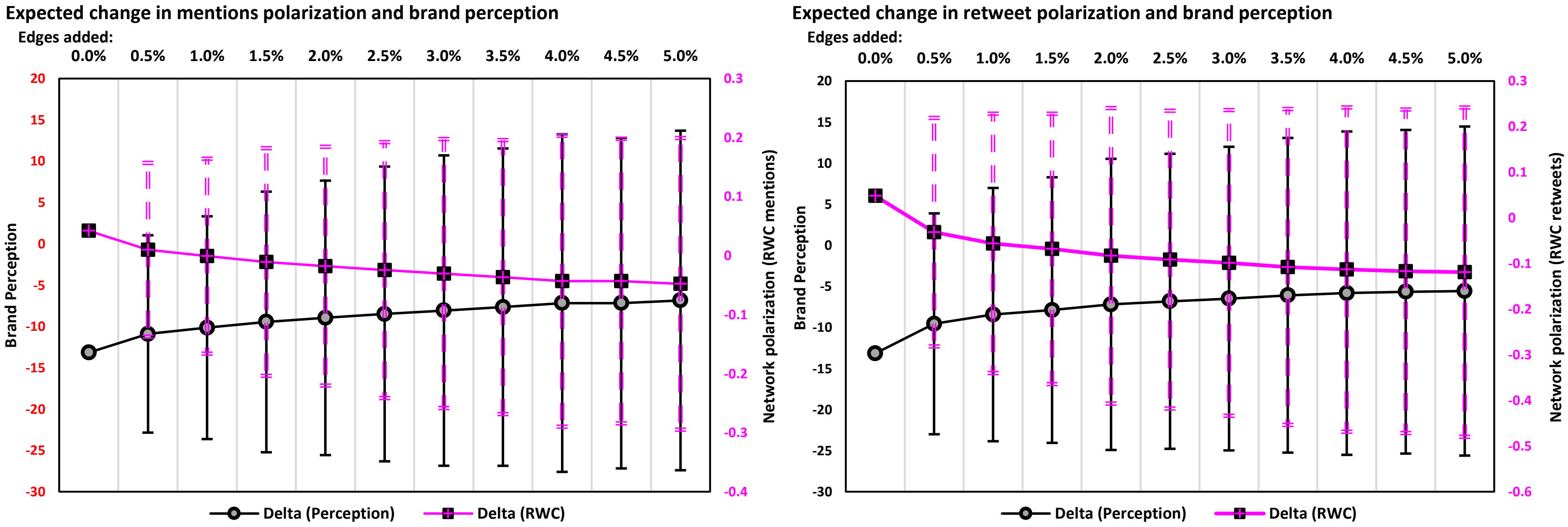

Figure 2-10: Expected change in polarization and brand perceptions from adding small number of edges within mention and retweet graphs.

2.5.6 Robustness Checks with alternate controversy scores

Finally, we tested the impact of brand crises on the alternative measures of social media echo-chamberness (see Table 1). The results in Appendix Table A.1-7 Panel [III] show that the findings of the random-walk controversy are almost completely replicated for the four other controversy scores used in our analyses. While the main effect is invariably an increase in echo-chamberness for all controversy measures, the hypothesized moderation effect of the nature of crises is also reflected directionally, albeit to a marginally significant degree. We also tested the robustness of the suggested mediation process by running the 3SLS path analysis with the alternative measures of social media echo-chamberness as the potential intervening variable. The path analysis results (Appendix Table A.1-8) provide evidence for the suggested mediation process by showing that, similar to the random-walk controversy, adding these brand echo-chamberness metrics in the second stage of the regression seems to explain away all the variance observed in the brand perception variable caused by the crisis, as evidenced by the non-significance of the $\boldsymbol{Pre-Post}$ and $\boldsymbol{Crisis\ type_i}$ variables, especially in the case of embeddedness controversy and GMCK. Furthermore, the negative coefficients of the echo-chamberness measures themselves in the second regression, further bolster our hypothesis that increases in brand filter bubbles during crises tend to aggravate brand perceptions, and thus it is in the interest of brands' social media teams to try to keep echo-chambers to a minimum in the event of a brand crisis.

2.5.7 Robustness Checks with comparison to control group

Appendix Table-A.1-9 presents the effect of adding the control-group RWC values to the analysis, using a "double-differences" abnormal change DV and running a triple-differences analysis.

These findings present further evidence of the main and moderation-effect hypotheses by replicating the results from those discussed in previous sections. The $\boldsymbol{Pre-Post}$ variable loses significance in the differences-in-differences analysis but retains its directionality. The estimates of $\alpha_{did,T}$ and $\alpha_{cr,did,T}$ which we plot in Appendix Figure A.1-4, replicate the brand perception findings.

2.5.8 Robustness checks for simultaneity bias

We further replicated these mediation results across multiple systems-of-equations models such as the Seemingly-Unrelated-Regressions, SUR-with-bootstrapped errors and Stata's GSEM estimation. In addition, we conducted the following tests:

First, we ruled out the possibility of reverse causality - i.e., the possibility of immediate short-run brand perceptions impacting the controversy scores rather than the other way round (Appendix Table A.1-10). We find that the short-run brand perception scores do not impact the controversy scores to a statistically significant extent. Also, the main and moderation effects of the online firestorm remain unchanged even when these brand perception covariates are introduced into the regression estimation.

Second, we estimated the predictive capability of controversy scores on Infegy brand perception scores over other event-windows that do not include the firestorm. Appendix Table A.1-11 tabulates abnormal changes in the Infegy brand perception metrics in the event- window (-90,60) while excluding 2 days prior to the crisis and 5 days after the crisis. Consistent with our hypotheses, RWC increases proportion of negative tweets as well as negative intensity, thus affecting brand perceptions adversely even beyond the immediate aftermath of the firestorm.

2.5.9 Do controversy scores impact abnormal stock returns?

We analyzed the predictive capabilities of firestorm brand perception and controversy scores on cumulative abnormal stock returns in the aftermath of the crises. The sample of events was limited to those involving brands that are owned by eponymous publicly-listed firms. While controversy scores marginally impact the cumulative abnormal returns on Day-1, their impact no longer remains significant beyond the first day of the firestorm. As opposed to the consumer-specific BAV measures (brand asset, lapsed users, consumer preference percentage, and total users percentage), RWC does not seem to directly impact stock returns. Instead, their impact on stock returns is felt indirectly through the changes they bring about in the firestorm brand perception measures. This makes sense because stock market analysts do not observe controversy scores during a firestorm, and make their valuations based on the more widely calculated and explicitly observed brand perception measures. We find that the higher the dip in brand-perception in the immediate short-term of the crisis, the higher the dip in cumulative abnormal returns of publicly listed firms in our sample (Appendix Tables A.1-12 and A.1-13). This effect persists for more than 15 days even if the immediate brand-perception effects of the online firestorm are much more short-lived.

2.6 DISCUSSION

2.6.1 Summary of Key Contributions

Social media filter bubbles have been an area of concern for social scientists and policy makers in the past decade and likely will remain an integral part of people's lives. Brands are no different, so now is an opportune time for marketing literature to investigate this understudied construct and its effect on brands. In this study, we begin closing this knowledge gap by investigating how social media filter bubbles in Twitter retweet and mentions graphs evolves in the aftermath of brand crises and how it influences consumer perceptions of the brand. In the process, we explore a novel construct — random-walk controversy score — as a potential underlying mechanism that explains differing levels of brand perception as online firestorms unfold. Specifically, we find that, compared with values-based crises, functional crises lead to higher controversy scores (indicating greater insularity of discussions), which subsequently lead to greater dips in average brand perception levels. This happens because insular conversations within clusters of brand-haters lead to an echo-chamber of negative opinions about the brand that are difficult to deescalate because of these people's lack of engagement with pro-brand commentators. This insularity leads to increases in the intensity and proportion of negative social media posts, both contributing to the deterioration in brand perceptions. We also identify a potential solution to this conundrum and recommend that brands try to connect opposing viewpoints by seeding influencers. As Garimella et al. (2017, 2018) suggest, this crisis management strategy involves exposing certain brand-detractors to positive brand-related content shared by the brand's influencers. Brands can try to make a significant dent in the ensuing increases in echo-chamberness levels by targeting users characterized by an optimal combination of centrality within the conversation network and probability to share that content — we demonstrate this by simulating marginally larger postcrisis conversation graphs that are effective in reducing brand echo-chamberness and thus improving conversation sentiment levels. In doing so, this study makes several novel substantive and methodological contributions. First, to our knowledge, this study is the first attempt to investigate social media echo-chamberness in a marketing context and to tackle it from a dynamic network analysis standpoint. The algorithmically computed random-walk controversy scores (and other social media echo-chamberness measures) represent metrics that brands can track on a weekly, daily, and even hourly basis with the help of any digital capabilities they possess. More important, we show that brands can take actionable steps to curb the often-undesirable outcome of brands' social media presence.

Managers could certainly use our findings to tactically plant conversations and seed social media influencers to meet their objective of mitigating online firestorms. While most brands are already aware of social media-listening platforms and their benefits, this study further encourages their usage by employing the aggregated scores of such platforms as a real-time measure of social media brand perception.

Second, we complement existing brand crisis frameworks by adopting and applying them on a large scale (i.e., by conducting surveys to classify crises under multiple dimensions). This process helps us draw out nuances in our findings that might have been overlooked or been susceptible to our own subjective interpretations if we had classified them ourselves, as do most other empirical studies in this domain. We also contribute to the literature by adding a new digital crisis mitigation strategy to the mix of traditionally explored strategies, such as apology and denial. Finally, the study opens up avenues for exploring how social media conversation networks have the ability to influence consumer opinions during a crisis. While marketing scholars have examined social learning models quite extensively in the context of product adoptions, innovation diffusion, and product ratings, we encourage the application of such models to negative brand actions in future studies.

2.6.2 Limitations and Future Research Directions

As with all early investigations, our study suffers from a few limitations that scholars could take up as starting points for future research. From a methodological standpoint, we acknowledge that our sample suffers from a bias toward larger brands because we use the BAV database as the initial shortlist for our set of brands and that qualifies our analysis to the most well-known brands in the United States. In addition, online firestorms are, by definition, brand crises that cause a stir on social media, which further restricts our sample to strong brands with high stature, while also preventing smaller crises from being picked up by our selection criteria. Although we tried to control for such biases by using BAV metrics as regressors and incorporating a well-matched group of control nonevents, we cannot eliminate the possibility of some residual selection biases. Future research could help eliminate such selection biases by building more sophisticated machine learning tools to identify smaller online firestorms.

We acknowledge that brand perceptions and RWC are seemingly related constructs, in the sense that one of the components of brand perceptions (i.e., the volume of negative tweets) should be trivially expected to influence social media echo-chamberness because the classification of social media users into brand-supporters and brand-detractors is based on their tweet sentiments. While this is a potential confound, we believe the two constructs represent distinct facets of brand-related conversations. First, Garimella et al. (2018) provide evidence that the controversy scores are unaffected by sizes of the network graphs because they are, at their core, probabilities. Second, retweet and mention network structures are formed only when one user willingly allows him- or herself to be influenced to some extent by another user's opinions. So, all tweets that form part of the brand perception calculation are not included in the controversy score calculation; only a subset of high-influence tweets make the cut. Third, other measures of brand perception, such as BAV and Equitrend measures, are not available on a daily basis, so the social media-listening platform was the best source for the brand perception measures. Future studies could try to come up with alternative real-time brand perception measures to remove such confounds.

One key area of improvement in the controversy score computation would be to incorporate friendship and followership associations as edges between social media user nodes. Tracking these relationships is more complicated going back in time for several reasons, such as deactivation of accounts, unavailability of accurate number of friends/followers at multiple periods, and the overall resource-heavy nature of the endeavor. In addition, Garimella et al. (2018) suggest that friendship and follower graphs were not good predictors of filter bubbles in their limited and politics-centric data set. Despite these difficulties and limitations, future research could still investigate these networks because they might represent methods to preemptively avoid filter bubbles and perception dips among a brand's social media followers. We also acknowledge that brand crises could be classified on the basis of multiple other dimensions. These include, for example, the stakeholder harmed (e.g., employee, consumer, society), especially for values-based crises. Future research should unpack additional crisis subclassifications and examine their differences from a theoretical perspective. Admittedly, this study is a first step in what we hope is a long line of important work that tackles the issue of social media echo-chambers. Our study suffers from a few methodical drawbacks and theoretical considerations that we leave for future research to ponder, along with the myriad unanswered questions that such a complex subject inevitably raises.

3.0 ESSAY-2: WHEN BRANDS TAKE A STAND – IMPACT OF CORPORATE SOCIO-POLITICAL ACTIVISM ON POLARIZATION OF CONSUMER PURCHASE BEHAVIOR AND BRAND REVENUES

3.1 INTRODUCTION

Studies conducted at the Pew Research Center over the past several years illustrate the increasingly stark disagreement between Democrats and Republicans on the economy, racial justice, climate change, law enforcement, international engagement, and a long list of other issues. This is evident in our day-to-day social media discourse as well, where any mention of these topics seems to devolve into polarized communities and hateful counterarguments (Garimella et al. 2018). Perhaps the most dangerous facet of political polarization is the growing distrust and animosity towards the opposite party and its followers, especially in America's relatively rigid, two-party electoral system. Reasons range from the rise of activists and demagogues in political parties (Layman et al. 2006), increasingly cynical segmentation of voters, in-group biases (Iyengar et al. 2019; Layman et al. 2006) and media filter bubbles (Roose 2019). Recent political events such as Donald Trump's presidency, the COVID pandemic and the Black Lives Matter movement have additionally provided significant evidence for this phenomenon. Joe Biden's president-elect speech addressed this important issue as he pledged to look beyond red and blue to bridge the deep and bitter divisions in American society. The US is hardly the only country wrestling with deepening political divisions (case-in-point, the Brexit vote in the UK) but is certainly one of the hotbeds.

A managerial consequence of this polarization in American society and social media is that brands' existing and potential consumers have forced them into taking public stances on divisive social and political issues and signal where they stand, a practice referred to as corporate political advocacy (CPA; Wettstein and Baur 2016) or corporate socio-political activism (CSA; Bhagwat et al. 2020). A slew of real-life examples can be found from a cursory glance at major business events in the recent past. After the Parkland School shooting, Delta Airlines eliminated promotional benefits for National Rifle Association members. When the National Football League instituted a policy prohibiting players from kneeling during the national anthem, Nike endorsed Colin Kaepernick, the controversial and polarizing face of the protests, in a prominent ad campaign and lent their support to the cause of racial inequality. More recently, several firms including Meta, J.P. Morgan Chase, Amazon and Starbucks expanded health coverage benefits for employees to include travel costs seeking legal abortions outside their home state after the Supreme Court released a ruling that overturned Roe v. Wade. These examples represent spillover effects of American politics into corporate activism, whereby companies find themselves engaging on divisive sociopolitical issues in response to consumer expectations. As Liaukonytė et al. (2022) point out, the rise in political engagement among citizens has also given rise to a sharp increase in political consumerism, in which consumers appear to "vote" with their wallets and either deliberately avoid the consumption of certain products (boycott) or proactively seek consumption (buycott) for political reasons (Stolle and Micheletti 2013). Such consumers, in turn, expect their favorite brands to align with their socio-political ideologies in addition to providing them functional benefits through their products and services. Brands are increasingly giving in to these consumer demands and proclaiming their support or disapproval to hot political debates and hoping such segmentation strategies work in their favor. Not all firms agree with the need to engage with such controversial political conversations though (Gelles 2021). For example, calls for a boycott of Keurig on Twitter for pulling ads from the Sean Hannity Show prompted the company's chief executive officer to write in an apology email to the company's employees that the decision "gave the appearance of 'taking sides' in an emotionally charged debate" and "our company and brand reputations are too valuable to be put at risk in this manner" (Bromwich 2017). In a similar vein, the Chief Marketing Officer (CMO) Surveys (2018; 2020) found only 17-18% of marketing leaders responding affirmatively to the question: "Do you believe it is appropriate for your brand to take a stance on politically charged issues?"

Despite the prevailing "cancel culture" and increasing calls for action on social media to boycott or buycott a politically engaged brand, there is limited empirical evidence as to whether brand activism campaigns are effective at generating changes in actual marketplace outcomes such as revenues and market shares. As the CMO surveys point out, marketing managers are usually reluctant to pursue such actions, and will probably continue to do so in the absence of thorough findings on the subject. Marketing literature on the topic is nascent, and this study hopes to extend the collective knowledge of this phenomenon we have garnered so far – thanks to a few recent papers that have tackled it and its consequences for firms. For instance, Bhagwat et al. (2020) provide evidence that there is negative impact of CSA on firms' stock market performance which is moderated by the activism's deviation from key stakeholders' values and brand image and characteristics of CSA's resource implementation (such as source of CSA announcement). Hydock et al. (2020) look at the impact of brand activism on consumer purchase intentions and conduct experiments to show that there is a negativity bias in consumer preferences such that consumers who are against the brand's political stance are more likely to boycott the brand as compared to consumers in favor buycotting it. Liaukonytė et al. (2022)'s analysis of the positive impact of Goya brand's CEO's pro-Donald Trump comments on the revenues of the brand positively despite overwhelming social media calls for boycotts, thus extending findings from multiple previous studies on political consumerism (Jung and Mittal 2020 provide a good review). Seemingly, it happened because Trump-supporters, previously Goya non-users, decided to support the brand and became part of Goya's consumer portfolio whereas the loyal Latino consumers of the brand didn't respond to the social media protests at all. The study also points out the relatively short persistence of these effects. Bronnenberg and Dubé (2022) call for future research to build more case studies to assess the extent to which these findings generalize and to dig more deeply into the mechanisms driving these outcomes. This paper fills this research gap by expanding the scope of the analysis to a wider array of CSA events as well as making statements about long-run effects of such brand actions. To the best of our belief, this is the first study to perform a large-scale longitudinal analysis of real marketplace data to quantify these effects on actual consumer purchases in an effort to quantify the consumer portfolio risks embedded within such divisive segmentation strategies. In short, the study answers the following research questions:

- To what degree do brand activism events with varying levels of partisanship polarize consumers in their purchase decisions?
- Is there an overall bias of the direction of the brand's ideology – liberal vs. conservative? – i.e., do purchase behaviors react more sharply to liberal or conservative brand activism?
- Is there an overall bias of the direction of the county's ideology – liberal vs. conservative? i.e., Do liberal or conservative counties react more sharply to these events?

- What is the overall positivity or negativity bias of the brand action – i.e., does a brand see an overall increase or decrease in revenues at the national level?

In order to answer these questions, we perform a quasi-experimental analysis of multiple political activism campaigns originating from Consumer-Packaged Goods (CPG) brands in the Young and Rubicam Brand Asset Valuator (Y&R BAV) database, thus demonstrating and quantifying the polarization of consumer purchase behavior and the consequent brand revenues in the wake of such brand actions. We build a repository of CSA events using keyword-searched news articles from archival sources such as LexisNexis and assign the level of riskiness or partisanship associated with each activism event based on Pew Research polarization reports and legislative voting patterns over time. Using a 10-year panel of county-level purchases of these brands aggregated from Nielsen Retail Scanner and Consumer Panel records, we perform an event study by treating these brand activism announcements on traditional media as exogenous shocks to consumer markets, analyzing abnormal changes to brand revenues and their drivers – consumer acquisition, consumer attrition, volume of items purchased, number of store-trips made for said purchases, and average prices paid for the items. For each event in our sample, we compare changes in consumer purchases after a brand's participation in political activism vis-a-vis a synthetically created control group of brands (Abadie et al. 2010; Li 2021) and estimate the effects of varying ideological compositions of markets (based on counties' voting patterns and Census data) and activism partisanship over multiple event windows. Specifically, our event study analysis procedure comprises building an optimal control group composed of non-activist brands using an Augmented Synthetic Control Method (ASCM; Ben-Michael et al. 2021) that matches them on pre-trends in addition to multiple brand parameters measured by the Y&R BAV database, then estimating the average treatment effects (ATE) of each brand activism event, and following it up with a Stage-2 regression of these abnormal changes in marketplace outcomes as a function of county and brand activism characteristics.

Our findings suggest that brands' revenues in different markets (US counties) are significantly affected by the alignment of the brand activism with the dominant political ideology of the counties. A brand's participation in political activism can cause up to a 15% abnormal divergence in brands' revenues depending on how conservative or liberal these counties are. But there is heterogeneity in this observation – as expected, the impact is significantly greater for more divisive issues (such as support for Donald Trump, immigration etc.) as compared to less divisive issues (such as appeals for feminism and gender equality) which see marginal impacts on the revenues of the brand. Heterogeneity also exists depending on which direction the brand leans, as conservative counties tend to react more to brand activism events compared to liberal counties. At an overall level, the brand's revenues at the national level do not seem to be significantly affected by a positivity or negativity bias. However, the aforementioned stronger reaction of conservative counties leads to a marginal positivity bias in the case of conservative brand activism and a negativity bias in the case of liberal brand activism. Finally, the change is driven by more (fewer) consumers in aligned (misaligned) counties, rather than through changes in average household spendings or willingness to pay price premiums.

In this way, the study contributes to mental models governing firms' political activism (Moorman 2020) which are understandably double-edged interventions. Substantively, it extends and complements the limited marketing literature on the topic, and methodologically, it demonstrates the utility of the ASCM approach in precisely and reliably computing average treatment effects of rare events such as CSA communications from large consumer purchase datasets (such as the one provided by Nielsen)

The remainder of the article is organized as follows. We first briefly review prior research defining corporate socio-political activism (and corporate political advocacy) followed by marketing literaure's findings on political consumption and how it should impact brand revenues in the aftermath of CSA events. After developing our predictions regarding the effect of CSA on brand revenues and their drivers, we provide details on the empirical study conducted to test these hypotheses. We provide details of the ASCM-aided quasi-experimental field study using purchase data from Nielsen retail scanner and consumer panel database. After presenting and reporting the results of the study, we summarize our findings, highlight the theoretical contributions of this article and discuss the implications of our findings for practitioners and academics.

3.2 CONCEPTUAL FOUNDATIONS AND HYPOTHESES

3.2.1 Corporate Socio-Political Activism (CSA) or Corporate Political Advocacy (CPA)

Firms have long been expected to provide societal benefits to consumers in addition to the functional benefits they generate through the goods, services and shareholder wealth they produce. A brand's community outreach or involvement – till very recently – used to be restricted to corporate social responsibility (CSR) which is now seen as a company fulfilling its perceived societal obligations. However, as brands like Ben and Jerry's or Patagonia have shown with their success, many stakeholders now expect firms to go beyond and be more expressive about who they are and what values they hold. In today's polarized political climate, that often translates into expressing a brand's stance on Government policies, electoral issues, and moral debates. So, we find brands increasingly demonstrating public support or opposition to one side of a partisan sociopolitical issue, a phenomenon called Corporate Socio-political Activism (CSA) or Corporate Political Advocacy (CPA, henceforth addressed as equivalent to CSA). A prime example would be Nike endorsing Colin Kaepernick[7] and his controversial actions of taking the knee against racial injustice in the NFL, despite the awareness that it is a lot more divisive, risky and controversial as compared to, for instance, the rather benign CSR statement from Starbucks[8] suggesting they act in line with their triple bottom line philosophy through careful sustainable procurement processes (Figure 3-1).

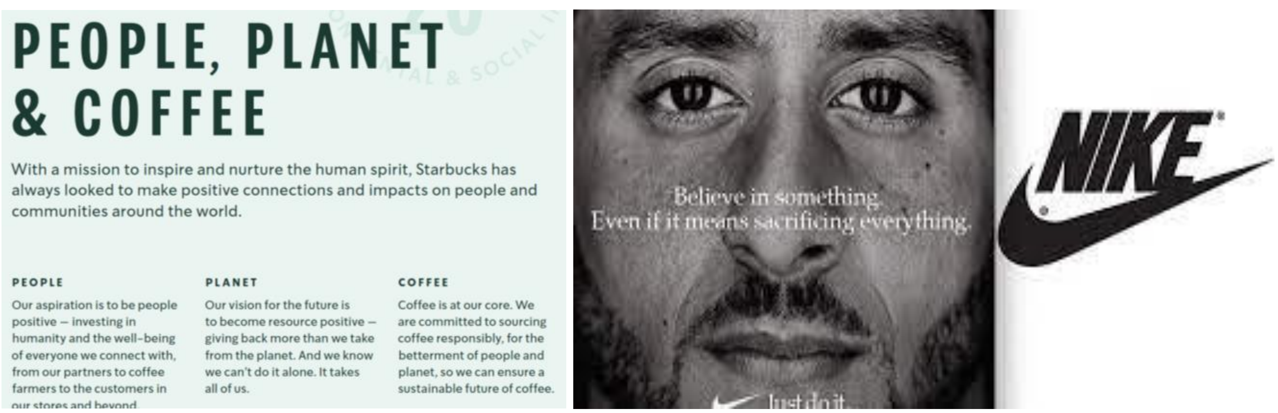

Figure 3-1: Corporate Social Responsibility (CSR; Left) vs Corporate Socio-political Activism (CSA; right)

It is helpful to think of CSR and CSA as two ends of this societal actions' spectrum, where they differ on the following key aspects. The first important distinction characterizing CSA is that

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[7] https://twitter.com/Kaepernick7/status/1037387722107830272

[8] https://www.starbucks.com/about-us/

it involves a brand or firm advocating towards an ideological perspective and actively educating society on what is right and what is wrong; whereas CSR refers to "company actions that advance social good beyond that which is required by law" (Kang et al. 2016) and constitutes the gradual formalization of cause-related marketing and corporate philanthropy aimed to "do well by doing good" through a strategic focus (Varadarajan and Menon 1988). Second, and most importantly, CSA actions are controversial and divisive because they advocate or endorse one side of a conversation that hasn't reached societal consensus (e.g., gun control, transgender rights, gender equality, racial equality), and hence, subject to risk, as they can elicit both positive and negative responses from consumers based on their ideologies, which can then lead to backlashes and boycotts from consumers who stand in opposition to the brand's political stance. There are temporal and cultural aspects to such sociopolitical issues as well, as society evolves and builds consensus over time. For example, universal women's suffrage was controversial a century ago, but is now accepted in the United States. Similarly, gay marriage would have been considered a taboo as recently as ten years back but is now legal and socially accepted in every state. CSR is low in partisanship because it involves high societal consensus issues for stakeholders and is intended to improve relationships with most of them (Mishra and Modi 2016). CSA, on the other hand, is polarizing because stakeholder responses to CSA are highly variable and depend on the stakeholders' sociopolitical values (Bhattacharya and Elsbach 2002). While it is inevitably linked with politics, it is important to note that CSA differs from other political actions such as lobbying or donations to parties in that, it is always publicized in order to serve its educational purpose and is often at odds with regulators or policy makers, thus making them even riskier from a firm performance point of view. Bhagwat et al. (2020) and Hydock et al. (2020) provide useful comparisons between CSA, CSR and Corporate Political Activity (Nalick et al. 2016).

3.2.2 Political Consumption

Marketing and political consumption literature has long established that consumers' political ideologies and deep-seated moral values play a significant role in their purchase decisions. Differences in political ideology manifest among consumers in the marketplace (Crockett and Wallendorf 2004; Jost 2017). Jost (2017) highlights that those ideological differences impact persuasion and cognitive processing, motivation, consumer choice and customer satisfaction, among others. Several findings have been crystallized in the area of political ideologies influencing consumers' consumption behaviors. For instance, political conservatism (vs liberalism) has been linked to stronger brand attachment and willingness to pay for premium brands (Chan and Ilicic 2019, consumer preference for products that can signal their superiority (vs. uniqueness; Ordabayeva and Fernandes 2018), lower propensity to report complaints and higher likelihoods to accept proposed resolution by firms when dissatisfied (Jung et al. 2017). Political conservatism has also been associated with a systematic preference for established national brands (as opposed to their generic substitutes) and with a lower propensity to buy newly launched products (Khan et al. 2013)

It is therefore no surprise that when brands openly brandish their political leanings and make these associations explicit and extraordinarily salient by engaging in sociopolitical activism (Iyengar and Westwood 2014), consumers choose products and brands that reflect their own political identities (Reed et al. 2012; Shachar et al. 2010; Ross and Shachar 2014) and reject brands with identities they wish to avoid (White et al. 2012). Hydock et al. (2020)'s investigation reveals as much, in addition to the prediction of a negativity bias that makes it more probable for a negatively aligned consumer to boycott a brand, as compared to a positively aligned consumer ‘buycotting’ it. This, however, doesn’t paint a complete picture yet – because despite copping extensive social media backlash, Nike’s ‘Black Lives Matter’ campaigns showed no signs of a negativity bias as it raked in millions of dollars in merchandise sales for the company[9]. Similarly, Goya’s CEO’s controversial comments had a positive impact on their revenues albeit for a short run despite huge calls for boycotts.

These contradictory results suggest the presence of several factors and contingencies that impact the outcomes of different forms of CSA. On account of these observations, this study proposes that all kinds of CSA cannot be treated equally as consumers should be expected to react differently to them based on their ideologies, the extent and type of activism, the product category the brands belong to, among other factors – all of which should affect consumer purchases and brand revenues differently. Next, we expound on our hypotheses and try and unearth additional insights into this evidently complex phenomenon.

3.2.3 Hypotheses

3.2.3.1 Impact of (Mis)alignment of CSA with Political Ideology

Prior research has shown that consumers choose products and brands that reflect their present and desired identities. By associating with identity-consistent brands, consumers are able to express a version of their self-concept in the physical world, which then reinforces the ephemeral sense of identity held in their minds (Reed et al. 2012). It helps them preserve their ‘self’ by signaling to themselves and to others the importance of this identity (Oyserman 2009; Oyserman

[9] https://www.vox.com/2018/9/24/17895704/nike-colin-kaepernick-boycott-6-billion

and Schwarz 2017; Legg,Tang, and Slevitch 2012). Furthermore, the self-congruity hypothesis suggests that consumers are both attracted to identity-consistent brands and repelled by brands with identities they wish to avoid (White et al. 2012). Given that people strongly equate their political views with their personal identities (Iyengar and Westwood 2014), it follows that consumers should identify with politically aligned brands and disidentify with politically misaligned brands. Firms' engagement in CSA provides consumers with an opportunity to identify with a brand by virtue of their ideological alignment with the brand's values. In fact, brands operating in today's era of public movements are relying on consumers to take note of brands' claims of having a higher purpose than just selling functionally useful products. Such brand actions garner online and offline engagement and boost brand attachment by providing a viable strategy to generate a compelling and unique market positioning e specially when it is in keeping with its core values and consumer expectations. But this effect on consumers remains challenging to manage. As brands seek to extend their reach, the increasing loudness of calls to action on social media has led to increasing backlash, with consumers turning into vociferous protesters engaging in negative electronic word of mouth (TrackMaven 2014; Mukherjee, and Althuizen, 2020). We therefore expect to find brand revenues to be correlated with the degree of ideology alignment between the brand's stance and the market ideology. Thus,

H1: Brand revenues should increase (decrease) in markets that are politically aligned (misaligned) to the CSA

3.2.3.2 Moderating Impact of CSA Partisanship

Clearly, not all socio-political activism is created equal, because of the inherent dynamism and evolution of socio-political issues. What is considered socially and politically controlversial today may no longer be classified as such in a few years. As Bhagwat et al. (2020) point out, it also depends on the form of support, announcement source stature, deviation from stakeholder values and so on. Moorman (2020) also offers different roles assumed by a brand in CSA – including brand authenticity, corporate citizen, cultural authority, calculative, brand as educator, political mission, and employee engagement. Different brands adopting different activism perspectives should expect to experience differing levels of backlash and resistance. The more controversial a brand's position, the more backlash it should experience from misaligned consumers and the higher the chances of overwhelming support from aligned consumers. As Pew Research reports point out, there are differing levels of public support and dissent for different socio-political issues if one goes by voting patterns within the republican and democratic political parties. We therefore hypothesize that:

H2: Brand revenues in the aftermath of CSA should be impacted more in high-partisanship political issues as compared to low-partisanship political issues

3.2.3.3 Moderating Impact of Direction of Political Leaning of Markets

Jost et al. (2003) used a motivated social cognition approach to systematize the association of political identity with three motivational structures: epistemic (related to seeking certainty from a world that is ambiguous and complex), existential (a desire for safety and security in a dangerous world), and relational (understanding of social reality in terms of different groups such as in-groups and out-groups). This means that first, conservatives engage in more heuristic, automatic, and stereotypical thinking due to their higher need for cognitive closure. In contrast, liberals engage in more deliberate, systematic, and effortful thinking due to their higher need for cognition and higher tolerance for uncertainty. Second, conservatives have a higher psychological need to cope with anxiety and threat which results in increasing hostility toward out-groups and support for traditional norms in the face of mortality salience (Greenberg et al.1994; Pyszczynski, Greenberg, and Solomon, 1999). Finally, relational motivations of conservatives make them promote in-group relationships and for establishing consensus among such groups. On the other hand, liberals have a higher concern for friendliness and agreeableness in relationships (Carney et al. 2008). Jung and Mittal (2020) invoke these differences to suggest key differences between conservatives and liberals in various stages of the consumer decision process. During the information and product choice stages, for instance, liberals deliberate more than conservatives when making decisions and are more open to new information (Farmer 2014). In contrast, conservatives have a lower tolerance for ambiguity and uncertainty (Jost et al. 2003),which may make it harder for them to accept novel arguments. This is consistent with Angle et al.(2017) who found that conservatives show greater resistance to change and their mental rigidity. This suggests that one should expect a higher level of connect between conservatives and a pro-conservative brand as compared to the association between liberals and pro-liberal brands. These observations also suggest that when firms use CSA to actively educate consumers and change their worldview, conservatives are more likely to show greater reaction in opposition to liberal activism than liberals when they react to conservative activism. This is consistent with Allard and McFerran (2021)'s findings that liberals punish overtly ethical brands less than conventional brand users in the event of a firm's moral transgressions. In contrast, conservatives punish them more than conventional brand users as they are less proficient in integrating the inconsistent information originating from the brand's actions. These findings suggest that conservative reactions to CSA should outweigh liberal reactions. Thus:

H3: Brand revenues in the aftermath of CSA should be impacted more in conservative-leaning markets as compared to liberal-leaning markets

3.2.3.4 Moderating Impact of Direction of Political Leaning of Activism

A corollary of hypothesis H3 should be that since conservative markets react more strongly to both conservative and liberal CSA, the overall impact of conservative activism on brand revenues should be positive while the opposite should be true for liberal activism. Additionally, Menon and Keisler (2020) tie the success of brand activism to the level of brand authenticity which is defined in literature as "the extent to which consumers perceive a brand to be faithful to itself (continuity), faithful to its customers' expectations for the brand to deliver on its promises (credibility), motivated by caring and responsibility towards the community (integrity), and reflecting values that consumers consider important (symbolism)". That, in conjunction with Mirzaei et al. (2022)'s finding that consumers are increasingly skeptical of liberal ('woke') activism and its authenticity, further suggests that liberal activism should be less effective for brands as compared to conservative activism. The significantly larger frequency of liberal activism as compared to conservative activism from brands may be one of the reasons behind this aforementioned lack of authenticity which leads to even liberals feeling disenfranchised by the overt opportunism in the case of a few CSA events. This also leads to conservative activism feeling more novel and genuine, thus allowing the conservative markets to stand in unwavering support of the pro-conservative brand which represents an inalienable in-group member.

H4: Overall (i.e., across all markets together), brand revenues should increase (decrease) in the aftermath of conservative (liberal) leaning CSA

3.2.3.5 Drivers of Brand Revenue Changes

The boycott or buycott effect on brands' revenues could be driven by two types of consumer behavior — (1) existing households who increase their purchase volume or frequency and (2) new households who had not purchased the brand before but want to enter the brand's consumer portfolio because of their ideological alignment with the brand. We hypothesize that this should be driven by both of these effects. We expect a genuine 'boycott' and 'buycott' outcome, i.e., consumers either newly buying the brand's product in expressing their support or staging a protest by completely disassociating from the brand (Jung and Mittal 2020). We also expect that the newly anointed consumers within the brand's portfolio should outbuy the existing consumers in response to the contradictory behavior from the out-group (consumers with the opposing political ideology), as was the case in Liaukonyte et al. (2022)'s analysis of Goya CEO's pro-Trump comments. Thus:

H5: Change in Brand Revenues in the aftermath of CSA should be driven by increase (decrease) in number of consumers in politically aligned (misaligned) markets

H6: Change in Brand Revenues in the aftermath of CSA should be driven by increase (decrease) in average spending of consumers in politically aligned (misaligned) markets

3.3 DATA AND METHODS

3.3.1 Empirical Context

The empirical setting for our study is the consumer-packaged goods (CPG) sector — a key economic sector in the United States, contributing ~10% of national GDP, employment, and labor income[10]. The high frequency of purchases makes it ideal to investigate consumer portfolio and behavior changes on a longitudinal timeline. The Nielsen retail scanner data and consumer panel

[10] As per https://consumerbrandsassociation.org/wp-content/uploads/2019/11/ConsumerBrands_EconImpact.pdf

data comprise almost exclusively of these fast-moving consumer goods, providing us with the opportunity to observe purchases of 2.6 million UPCs (1.4 million in the consumer panel) including dry grocery, frozen foods, dairy, deli, packaged meat, fresh produce, nonfood grocery, alcohol, general merchandise, and health and beauty aids that are aggregated into more than a thousand product categories. Similarly, the volume of transactions recorded in the retailer scanner data from ~ 40,000 stores and consumer panel data from ~80,000 consumers annually across the US provides external validity regarding the representativeness of our sample of transactions. We benefit from the richness of the data set – for example, it provides data from 2006-2020 and helps track marketplace outcomes over a long pre-event and post-event period for each brand activism event. It also provides data on multiple product categories for the same brand.

We shortlisted the top 500 brands from the Y&R BAV database in terms of their brand asset value and tracked each of their products (using their Unique Product Codes or UPCs) within the Nielsen retail scanner data (for overall brand revenues) and consumer panel data (for the drivers of brand revenues) over the period of 2011-2020.

3.3.2 Brand Activism Events

We followed the procedure outlined by Bhagwat et al. (2020) to build a list of CSA events involving CPG brands over the period 2013-2020. Specifically, we used LexisNexis' repository of news articles and manually created a list of CSA events by using brand-related keywords and keywords pertaining to controversial political topics such as immigration, racial inequality, and so on. All political keywords indicated in Bhagwat et al. (2020) ("coming from a dictionary of time-relevant search terms of partisan sociopolitical topics extracted from Pew Research Center's 2014 report") were included in our data collection process. The focal events are publicly available announcements of statements or actions by firms regarding partisan sociopolitical issues. Manual intervention was required for identifying the first mention of an activism event if a related brand action was repeated several times on different future dates. Additionally, we made sure to eliminate announcements for which another possible confounding event may have occurred within a month of the brand action so as to be able to attribute all revenue changes to the CSA event.

3.3.3 Activism Classification

We classified CSA events on the degree of how partisan they are – and we used the Pew Research Centre reports for this purpose. For instance, a 2019 Pew Research Centre[11] survey found "Gun Policy" to be the most partisan issue in terms of percentage agreement difference between the democrats and the republicans, immigration to be a moderately partisan issue, and religious views to be mildly partisan – thus helping us quantify the level of risk involved in a particular brand's activism. Clearly, a brand taking a stand on gun control invites more criticism and risk as opposed to religious freedom.

Table 3-1 provides the list of the CSA events in our sample in chronological order. They range across a large period of time (2013-2020) and product categories across food, beverages and body grooming verticals. Across the events in our sample, we cover four pro-conservative and fourteen pro-liberal activism events with varying levels of partisanship. The level of partisanship has been classified as high and low based on the 2019 Pew Research Report. Issues such as Donald Trump and Immigration have been classified as high whereas issues such as feminism, gender

[11] https://www.pewresearch.org/politics/2019/12/17/in-a-politically-polarized-era-sharp-divides-in-both-partisan-coalitions/

equality and religious freedom have been classified as low. As per the report, the differences between Republicans and Democrats on the former set of issues exceed the average party gap of 39 percentage points across all political issues – while the latter are lower than the average party gap. In addition, we took note of the temporal dimension in the case of a few events. While LGBTQ issues would be classified as 'Low' as per the 2019 report, we classified pre-2016 LGBTQ activism as 'High' because it gay marriage had not been legalized yet and the riskiness of supporting it entailed a much higher level of risk pre-2016 as compared to 2019.

3.3.4 Market Classification

We classified counties into deciles based on their democratic vs republican vote-shares in the most recent federal elections. Decile-1 in our analysis indicate the most conservative (republican) counties and Decile-10 indicate the most liberal (democratic) ones. Overall, we find that each progressive decile indicates an average increase in democratic vote-share of ~5%. Table 3-2 provides the democratic vote-shares across the county-deciles across each 4-year period in our data set.

Table 3-1: List of Corporate Sociopolitical Activism Events from CPG brands in our Sample

Event Year and Quarter	Event	Conservative or Liberal	Partisanship Classification - High vs Low	Product Category Analyzed
2013Q4	Barilla CEO anti-LGBT comments	Conservative	High	Pasta, Condiments
2014Q1	Pantene feminism ad	Liberal	Low	Hair Care
2014Q2	Heineken St. Patrick's day parade pull-out	Liberal	Low	Beer
2015Q2	Ben and Jerry's Climate Change Campaign	Liberal	Low	Ice-Cream
2015Q2	Starbucks Race Together + Renewable Pledge	Liberal	Low	Coffee
2015Q3	Doritos Pro-LGBTQ Rainbow Chips	Liberal	High	Snacks
2016Q2	Coco-Cola Pro-LGBTQ Campaign	Liberal	High	Carbonated Beverages
2016Q3	Coors Conservative Fund-raising	Conservative	Low	Beer
2016Q3	Starbucks Support for Hillary Clinton and BLM	Liberal	High	Coffee
2016Q4	Ben and Jerry's BLM Support	Liberal	High	Ice-Cream
2017Q1	Budweiser Pro-immigration Campaign	Liberal	High	Beer
2017Q1	Starbucks Pro-Immigration Anti-Trump statements	Liberal	High	Coffee
2017Q2	Pepsi Kendall Jenner BLM Ad	Liberal	Low	Carbonated Beverages
2017Q2	Red Bull CEO announces conservative media outlet	Conservative	High	Carbonated Beverages
2017Q3	Skittles LGBTQ support	Liberal	Low	Candy
2018Q4	Ben and Jerry's PeCan Resist Anti-Trump Campaign	Liberal	High	Ice-cream
2019Q1	Gillette Me-Too Toxic Masculinity Ad	Liberal	Low	Shaving Needs
2020Q3	Goya Pro-Trump Comments	Conservative	High	Canned Vegetables, Condiments

Table 3-2: Democratic Vote Share across County-Deciles by Time-Period

	Year>>					
Decile	**2000-03**	**2004-07**	**2008-11**	**2012-15**	**2016-19**	**2020-23**
1	19.32%	18.35%	19.53%	15.64%	11.69%	12.33%
2	27.19%	25.74%	26.93%	23.48%	17.10%	17.74%
3	32.09%	30.19%	31.55%	27.83%	20.41%	21.15%
4	35.45%	33.68%	35.48%	31.62%	23.35%	24.65%
5	38.32%	36.78%	39.24%	35.37%	26.67%	28.16%
6	41.03%	39.69%	42.88%	39.32%	30.44%	32.22%
7	43.91%	42.91%	46.17%	43.15%	34.88%	37.15%
8	46.99%	46.54%	50.56%	47.58%	40.14%	42.97%
9	51.24%	51.38%	55.97%	54.06%	48.09%	51.69%
10	61.69%	62.28%	67.79%	67.01%	64.97%	66.97%

3.3.5 Consumer Purchase Data

We used Nielsen data from the Kilts center to access a nationally representative sample of consumer purchases and aggregated them at the county level. These datasets provide SKU level information on a weekly basis and comprises two independent data sets – the retail scanner data which we use for market revenues and market share analysis and the consumer panel data which we analyze for consumer level metrics such as acquisition, attrition, and more granular RFM analysis. The Retail Scanner data from Nielsen claims to be "the most accurate source for volumetric or share information" helping us track what happened within the US stores in terms of sales volumes, prices and retail trade support. The Household Panel data is more diagnostic in nature, and helps understand the reasons behind store product movements by providing information about what happened in the households (who are the buyers, how often do they buy, how loyal are they, and so on).

3.3.5.1 Brand Revenues ($) from Kilts Retail Scanner Data

The Kilts retail scanner data provides information about each product that is scanned out of the ~40,000 stores that partner with them annually. Each product SKU is identified through a unique product code (UPC) and is categorized under a brand, product module and product group (which we use as product category in our analysis). The dataset also provides information about the counties in which each retail store is located and the week in which a purchase was made. We use the prices and purchase volumes of each brand's multiple SKUs and aggregate them to compute the revenues of the brand at the county- and quarter-level across multiple product categories. Finally, we further aggregate these brand revenues at the county-decile level to build a quarterly panel data for impact evaluation at each decile. For a brand that has products in multiple product categories, we analyze the brand's revenues in the product category(ies) that account(s) for more than 75% of its purchases in the Nielsen Retail Scanner data.

3.3.5.2 Number of Households and Average Spending ($) from Kilts HomeScan Panel Data

The Kilts consumer panel data tracks the purchases of ~80,000 households across the US who volunteer to report all CPG purchases they make from offline and online retail stores along with their demographic information, time of purchase, trip details and purchase details such as price and quantities of products purchased. This helps us further break down the sources of the brand revenue changes in the Retail Scanner data, if any, into the number of households that purchase the brand, and the average household purchase values. Each of these households is assigned a unique consumer code in the Kilts Nielsen HomeScan data. The count of active consumers for a brand in any given quarter was, therefore, calculated as the number of unique consumer codes that purchased at least one SKU from the brand in its primary product category(ies) during that quarter. This was then summed up for each of the ten county deciles in each quarter of the 10-year panel data used in the impact evaluation analysis.

Following a similar procedure to the retail scanner dataset, consumer panel dollar and SKU-quantity purchases for each brand were aggregated at the level of product category, followed by the quarter and finally at the level of the county decile to which the consumer belongs. Furthermore, we divided the total consumer purchases ($) of the brand by the total number of active consumers of the brand to compute the average spending ($) per household for the brand in a given county-decile and quarter. We divided the total consumer purchases ($) of the brand by the quantity of its SKUs purchased in the same geography and time period to compute the average prices ($) at which these purchases were made.

3.3.6 Impact Evaluation

3.3.6.1 Augmented Synthetic Controls Method (ASCM) for computing Average Treatment Effect (ATE)

Since we want to make causal statements about the impact of CSA events on marketplace outcomes, it becomes critical to measure the Average Treatment Effect (ATE) accurately and reliably. As mentioned before, the Nielsen data extends over the period of 2006 to 2020 currently, so it provides a sufficiently long panel data for pre-treatment and post-treatment periods especially at our unit of analysis (which is at the quarter level for each county-decile). It also has a large sample size of retailers and consumers participating in the data collection process, so the inferences drawn from the analysis should reflect the behavior of the typical American consumer. However, there are a few challenges. One issue is that it is limited to CPG brands which makes the CSA events extremely rare – especially because we are interested in brand actions that are important enough to be reported in national newspapers and listed on the LexisNexis database. Second, the Nielsen data, despite its claims of representativeness, is not the cleanest source of data. It may be subject to sampling biases – for instance, a larger proportion of the participating stores come from urban areas. The measures are also subject to a few measurement errors, especially for the self-reported data from consumers being surveyed. Measurement errors could crop up in the retail scanner data too because of changes in the sample of participating stores either through store closures or because of the periodic and random shuffling that Nielsen carries out over time for various reasons. The same shuffling happens with the panel of consumers as well.

A quasi-experimental setup helps eliminate several of these issues – i.e., by treating each CSA event as a natural experiment where the “treated” brand is the one which participates in the activism campaign and the “control” brand is an identical brand that doesn’t. The intent of the quasi-experimental identification strategy (Angrist and Pischke 2008; Chemmanur et al. 2010) would be to capture the effect of the CSA event by comparing the marketplace outcomes in the aftermath of the event with the same brand before the event (i.e., a within-brand effect) and with firms that never participated in activism throughout the observation period (i.e., a between-brand effect). Not only does it reliably predict the ATE attributable to the specific event but it also makes sure the sample-bias and measurement errors (presumably randomized across our sample of focal and control brands) are eliminated by this analysis methodology. The challenge lies in identifying the “identical” control brand that matches the activist brand in several observable features as well as satisfies the parallel trend assumption critical to the success of the quasi-experimental differences-in-differences strategy.

While multiple quasi-experimental methodologies have been successfully used over time (the Diff-in-Diff for instance), the rare-event issue makes it difficult to adequately match the “treated” brand to one or more “control” brands in the sample. The selection of comparison units is a step of crucial importance in comparative case studies and the findings may be extremely sensitive to such choices. Using inappropriate comparisons may lead to erroneous conclusions because any difference in outcomes between these two sets of units may merely reflect disparities in their characteristics. We use the synthetic controls approach (Abadie et al. 2010) as a robust identification mechanism that helps us get around this issue. The synthetic control method (SCM) estimates the impact of a treatment on a single unit in panel data settings with a modest number of control units and with many pretreatment periods (Abadie and Gardeazabal 2003; Abadie et al. 2010, 2015). It provides a systematic way to choose comparison units in small-sample comparative case studies. The idea is to construct a weighted average of control units – i.e., a synthetic control unit that matches the treated unit's pretreatment outcomes in addition to other predictor observables. The estimated impact is then the difference in posttreatment outcomes between the treated unit and the synthetically created control unit. SCM has been widely applied — and has been called "arguably the most important innovation in the policy evaluation literature in the last 15 years" (Athey and Imbens 2017) as it is able to generate the most reliable counterfactual by identically reproducing the pre-treatment outcomes and effectively forcing the parallel trends assumptions to be valid.

Advances in the SCM procedure include the augmented synthetic control method (ASCM) which circumvents a critical limitation of the SCM by reliably predicting ATEs even when the fit on pretreatment outcomes is less than ideal (Ben-Michael et al. 2021). The ASCM extends SCM to settings where such pretreatment fit is infeasible by incorporating bias-corrections for inexact matching. In its basic form, it applies a ridge regression as the outcome model, directly controlling pretreatment fit while minimizing extrapolation. It also allows negative weights on some "control" units in order to precisely mimic the pre-trends prior to the event. We apply this process to build synthetic controls for each CSA event in our sample and use the post-event brand revenues and consumer panel metrics of this synthetic control unit as counterfactual outcomes for the activist brand to compute the ATE attributable to the brand's action. The following sub-section delineates this process for Budweiser's 2017Q1 pro-immigration SuperBowl commercial as a prototypical example for the ATE computation in our analysis.

3.3.6.2 Case Study – ATE for Budweiser Pro-Immigration SuperBowl Commercial

Budweiser advocated for, and developed a campaign in support of liberal political ideology in 2017 Quarter-1 as it launched a pro-immigration Super-Bowl commercial. It drew boycott appeals from conservative-leaning social media users as it appeared to oppose newly elected President

Donald Trump's stance on immigration. This provided an opportunity to compute the abnormal changes in Budweiser's revenues in the aftermath of this CSA campaign across multiple county-deciles.

To start off, we looked at the Nielsen product groups that accounted for the largest share of Budweiser's revenues. In the case of Budweiser, we analyzed its revenues for the 'Beer' product category as it accounts for nearly 95% of its revenues annually on Nielsen. Figure 3-2 Panel A charts the revenues of Budweiser across the different county-deciles for the entirety of the 2006-2020 time period available in the Nielsen data.

Next, we constructed a similar panel of brand revenues for all other brands in the 'Beer' Product group that have not directly or indirectly participated in any activism pertaining to the immigration political issue. These brands were used for the construction of the synthetic control for Budweiser. The list of potential control brands for 'synthetic' Budweiser in our sample includes Heineken, Miller, Corona among others. Figure 3-2 Panel-B charts the revenues of other 'beer' brands in our sample across the different county-deciles for the entirety of the 2006-2020 time period available in the Nielsen data.

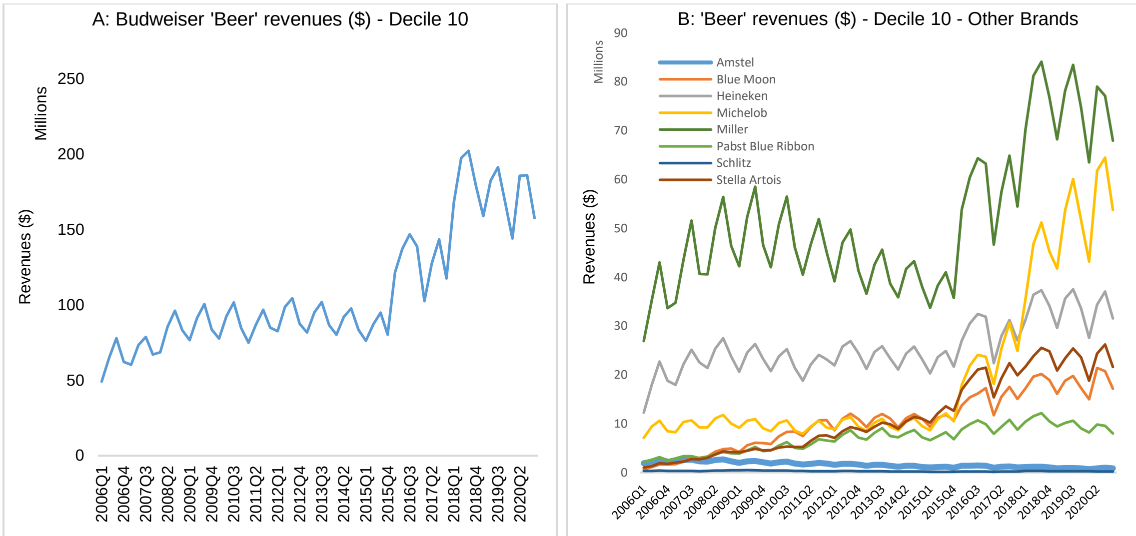


Figure 3-2: Revenues of Budweiser and other 'Beer' brands in County Decile-10 by Quarter

In addition to the revenue data, we also used Y&R BAV measures as predictor variables for the outcomes in our analysis. These include the four pillars - Energized Differentiation, Knowledge, Relevance and Esteem – components of a brand's total asset value computation. We then went ahead and matched the brand 'Budweiser' as closely as possible with the synthetically created control brand using the ASCM procedure described below.

We ran the ASCM for revenues in each county decile separately to compute the ATE for Budweiser – i.e., the abnormal change in revenues of Budweiser over and on top of those of the synthetically created control group. As Table 3-3 points out, the synthetic control brand for Budweiser for this event in the Decile-10 (most democratic or liberal) counties is composed of different weightages of other brands in the 'Beer' category. While 'Miller-Coors' is assigned the highest weightage in 'Synthetic Budweiser', 'Amstel' and 'Schlitz' receives negative weights and 'Michelob' has nearly zero contribution towards the revenues of the synthetic brand in Decile-10 counties. Table 3-3 also provides the values of Y&R BAV pillars (in the year of the CSA event) that were used for matching Budweiser with other products in the category. The same procedure was repeated to help identically match the control brand's pre-event brand revenues and BAV measures with that of Budweiser in the other county deciles.

Table 3-3: Synthetic Budweiser composition in Decile-10 counties and their BAV measures

'Synthetic Budweiser' Brands	'Synthetic Budweiser' Weights	Energized Differentiation	Esteem	Knowledge	Relevance
Heineken	-0.27810160	0.63713	2.10668	0.41717	3.44291
Miller	2.06711603	0.41541	2.11192	0.35883	3.23640
Amstel	-0.97169290	0.46689	1.79717	0.24716	2.01971
Blue Moon	-0.56631182	0.61607	2.42375	0.32689	2.55021
Michelob	-0.07647278	0.47100	2.12377	0.29011	2.73172
Pabst Blue Ribbon	0.76341051	0.41910	1.66598	0.21372	2.83795
Schlitz	-0.90503580	0.39740	1.72622	0.22713	2.10255
Stella Artois	0.96708836	0.63737	2.20745	0.39351	1.97797
Budweiser	NA	0.48566	2.28095	0.50073	3.98056

Figure 3-3 Panel A shows the matching of pre-event trends between Budweiser and its synthetic counterpart and also allows us to compute the pre-event baseline of quarterly revenues of the brand. Figure 3-3 Panel B is the 'Gap Plot' that plots the difference between the 'treatment' brand Budweiser and the synthetic control brand over time along with confidence intervals based on multiple placebo tests with the other brands and other time periods. As expected, the 'gap' between the former and the latter stays at zero throughout the pre-event period because of the synthetic control matching procedure and then increases significantly starting from the quarter of the SuperBowl commercial (2017Q1). This 'gap' in the outcome variable (Brand Revenues) starting the quarter of the CSA event helps us quantify the abnormal change experienced by the brand in these counties. We capture this abnormal change in revenues as the Average Treatment Effect (ATE) of the SuperBowl commercial for Decile-1 counties and attribute it to the CSA event. We further compute this abnormal increase as a percentage of the pre-event baseline revenues to compute the ATE (%).

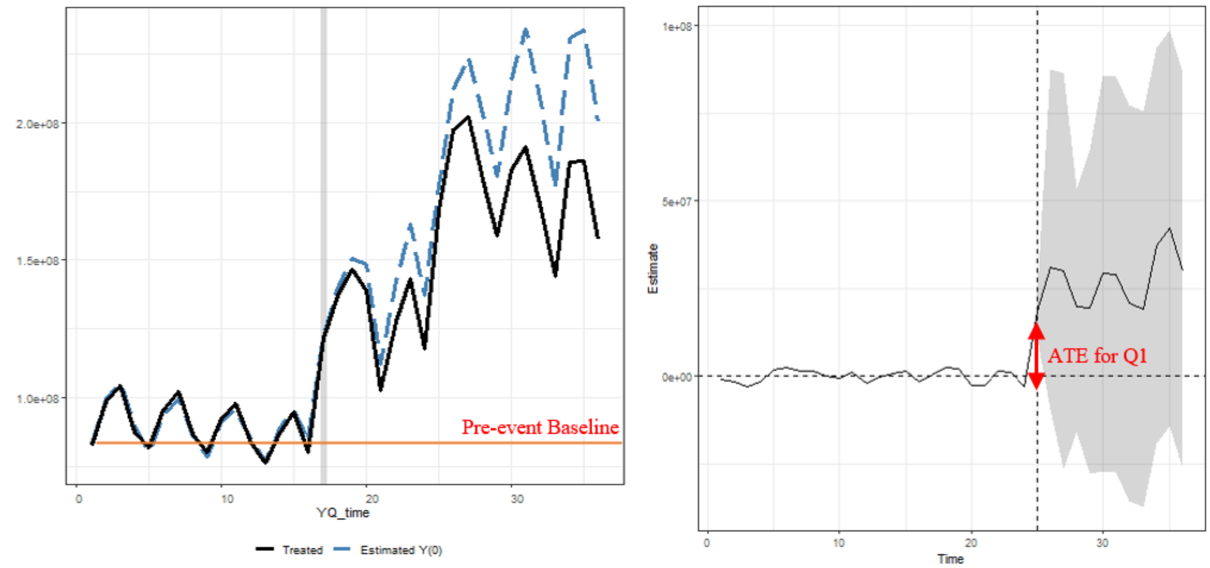


Figure 3-3: Revenues of Budweiser vs ‘Synthetic Budweiser’ (Left) and ‘Gap Plot’ (Right)

We repeat the above process for computing the ATE (%) for each activism event and every county-decile. Figure 3-4 further juxtaposes the revenue gap plots for the 2017Q1 Budweiser activism event in Decile-1 (most conservative) counties versus the corresponding gap plots for Decile-10 (most liberal) counties. The compare-and-contrast reveals that as hypothesized, there is a significant abnormal decrease in revenues of Budweiser in the former set of counties which are misaligned in their political ideologies to the pro-liberal messaging in the SuperBowl commercial. On the other hand, the liberal counties undergo a significant increase in abnormal revenues as compared to the counterfactual. In addition, a similar analysis of the overall revenues of the brand across all counties experiences an abnormal decline in the aftermath of the activism event (Figure 3-5). We find similar results for Doritos’ pro-LGBTQ campaign in 2015Q3 (Figure 3-6). Figures 3-7 and 3-8 present results of replication of this procedure for pro-conservative activism campaigns. Figure 3-7 presents the analysis of Barilla CEO’s anti-LGBTQ comments in 2013Q4 in the aftermath of which the brand sees an abnormal increase in the revenues of Decile-1 (conservative) counties and the overall revenues across all counties – in the case of Barilla, we do not find a significant drop in abnormal revenues in Decile-10 (liberal) counties (although directionally it is consistent with our hypotheses). We also present the analysis of Goya brand's CEO's pro-Donald Trump comments in the midst of the COVID pandemic in 2020, where we see a short-run increase in Goya's revenues overall across all counties, thus replicating Liaukonytė et al. (2022)'s findings (Figure 3-8). Table 3-4 provides the sample of all brands used for each of the product categories analyzed in our sample. Please see Appendix A.2.1 for a more detailed breakdown of number of retailers, households and purchase amounts ($) used for the ASCM procedure.

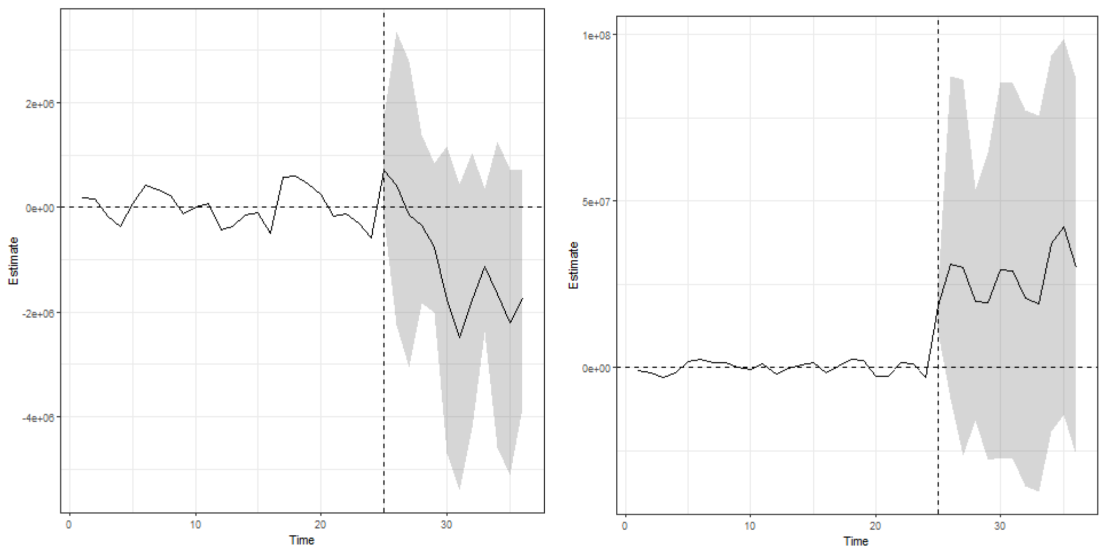


Figure 3-4: Budweiser revenues dropped in conservative Decile-1 counties (left) and increased in liberal Decile-10 counties (right) since 2017.

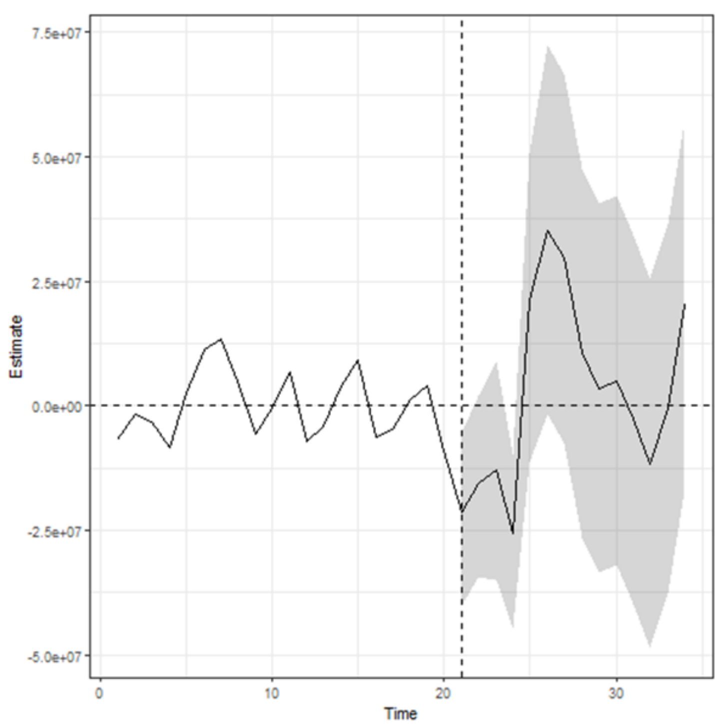


Figure 3-5: Budweiser experienced an abnormal decrease in overall revenues (all counties combined) since 2017.

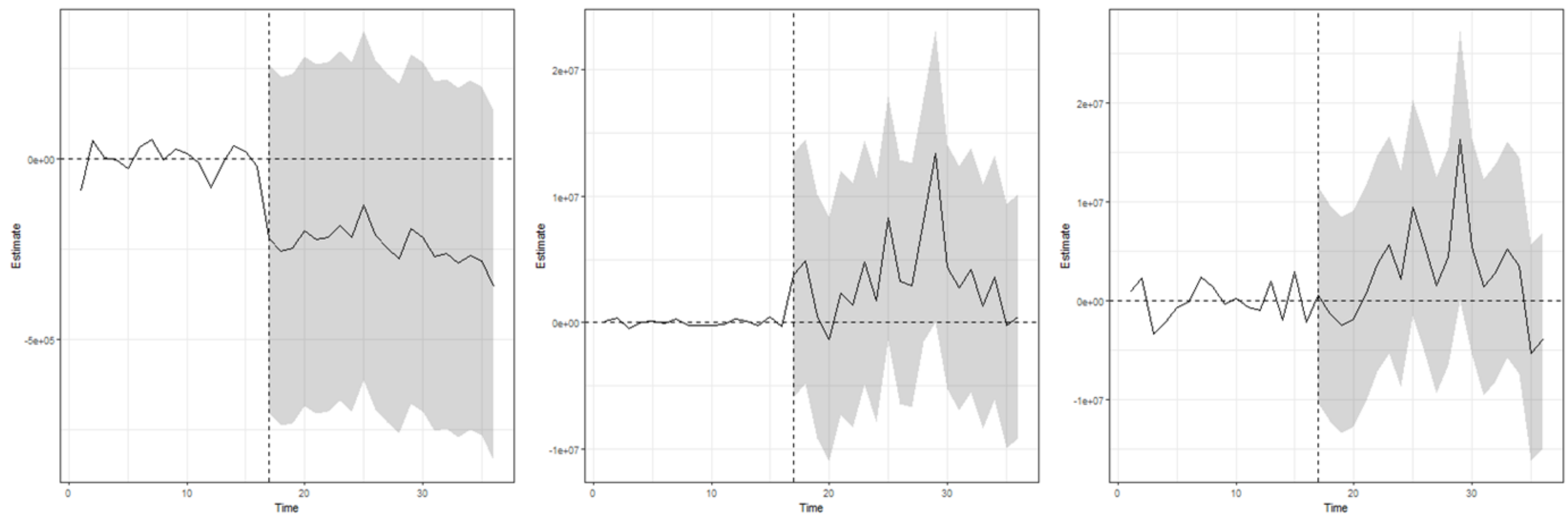


Figure 3-6: Doritos' revenues dropped in conservative counties (left) and increased in liberal counties (middle) since 2015 LGBTQ support. Overall revenues (all counties combined; right) did not undergo significant change

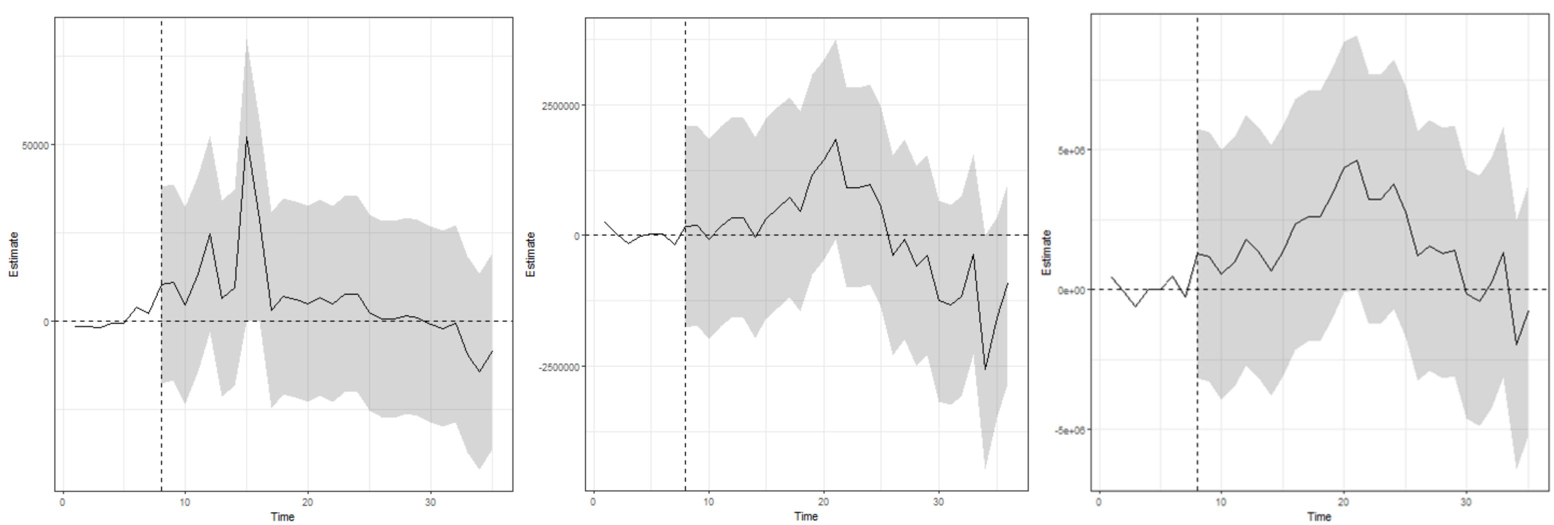


Figure 3-7: Barilla's revenues increased in conservative counties (left), remained unchanged in liberal counties (middle) and increased overall (all counties combined after anti-LGBTQ comments from their CEO

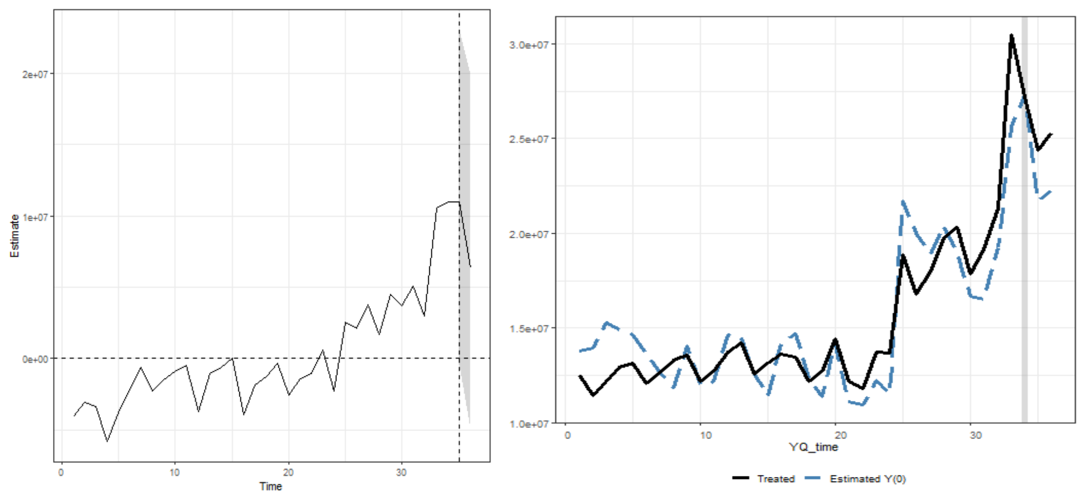


Figure 3-8: Overall revenues for Goya (all counties combined) saw a significant increase replicating Liaukonytė et al. (2022)'s findings

Table 3-4: List of brands analyzed across product categories

Beer	Carbonated Beverages	Canned Vegetables	Coffee	Deo/ Shaving	Candy	Ice Cream	Haircare	Snacks	Condiments
Budweiser	Coca-Cola	Del Monte	Starbucks	Dove	Cadbury	Ben &_Jerrys	Dove	Doritos	Barilla
Heineken	Dr Pepper	Goya	Dunkin Donuts	Gillette	Goya	Dole	Pantene	Goya	Del Monte
Miller	Goya	Green Giant	Illy	Aveeno	nestle	Dove	Aveeno	Planters	Goya
Amstel	Pepsi	Heinz	Maxwell House	Nivea	Skittles	nestle	Burts Bees	Quaker	Heinz
Blue Moon	Red Bull	Chef Boyardee	Old El Paso		Starbucks	Eggo	Loreal	Bumble Bee	Tabasco
Michelob	V8	Grey Poupon	Folgers		Board Head		Suave	Cheetos	A-1
Pabst Blue Ribbon	A & W	Tostitos	Tasters Choice		Ghiradelli			Chi-Chi's	Beechnut
Schlitz	Canada Dry				Hershey			Fritos	Chef Boyardee
Stella Artois	Fanta				Reeses			Johnsonville	Chi-Chi's
	Seagrams				Twix			Kashi	Dawn
	Sierra Mist							Orville R	Grey Poupon
								Pringles	Jack Daniels
								Ruffles	Johnsonville
								Shadybrook Farms	Peeps
								Spam	Shadybrook Farms
								Tostitos	Toblerone
								Wheaties	Tostitos

3.3.7 Hypothesis Testing

Once the ATE (%) is calculated for all CSA events, we ran the linear regression (1) in order to test our hypotheses. β_0 indicates the overall positivity or negativity bias of brand activism events on percentage changes in brand revenues after participating in a CSA event. β_1 indicates the overall impact of alignment of brand activism ideology and county ideology on percentage changes in brand revenues for the base-group of activism type – thus providing a statistical test for Hypothesis H1, and β_3 indicates how this impact changes across different activism types as compared to the base-group chosen for the analysis – thus providing a statistical test for Hypothesis H2. β_2 indicates the positivity or negativity bias of different activism types on percentage changes in brand revenues as compared to the base-group of activism type.

$$\begin{aligned} ATE(\%)_{decile,CSA} \\ &= \beta_0 + \beta_1 Democratic\_vote\_share_{decile} + \beta_2 Activism\_type_{CSA} \\ &+ \beta_3 Activism\_type_{CSA} * Democratic\_vote\_share_{decile} + \beta_{controls} Controls \qquad (1) \end{aligned}$$

Where:

$ATE(\%)_{decile,activism}$:	Impact of CSA on revenues of the brand in county-decile as a percentage of baseline revenues (measured from 1st stage ASCM)
$Activism\_type_{CSA}$:	Categorical variable that takes four values based on activism partisanship and direction of ideology – i.e., Liberal-Low Partisanship, Liberal-High Partisanship, Conservative-Low Partisanship and Conservative-High Partisanship
$Democratic\_vote\_share_{decile}$:	Average Democratic Vote Share of All Counties in a county-decile
$Controls$:	Includes Brand BAV measures - Energized Differentiation, Esteem, Knowledge, Relevance etc.

3.4 FINDINGS

3.4.1 Model-free Evidence

As expected, we see the highest impact of these politically biased brand actions on the counties at the ideological extremes. When we plot the first-quarter-after-the-event revenue ATE (%) for individual brand events by decile (Figure 3-9), we find a linear relationship between them. Figure 3-9 Panels A and B present these plots for two events in our sample – Budweiser's 2017Q1 pro-immigration SuperBowl campaign and Goya CEO's pro-Trump comments in 2020Q3. The linear regression coefficients on the '[Decile]' co-ordinates on Figure 3-9 suggest that there is indeed a significant effect of (mis)alignment of county political ideologies with the brand's activist position on the issue. The positive (negative) significant coefficient of the Constant term in Panel A (B) in the figure suggests that republican counties react more to activism events in terms of percentage change in revenues than democratic counties. These effects are replicated across our entire sample of CSA events (Figure 3-9 Panels C and D). Furthermore, Figure 3-10 suggests that impact of brand activism on polarization of consumer purchases is significantly higher for high-partisanship issues as compared to low-partisanship issues which affect the brand's purchases across counties only marginally. Finally, we find that the net impact of CSA on overall brand revenues across all counties is likelier to be positive for conservative brand activism positions and less likely for liberal brand activism positions (Figure 3-10) because the conservative counties react more to brand activism events than liberal counties.

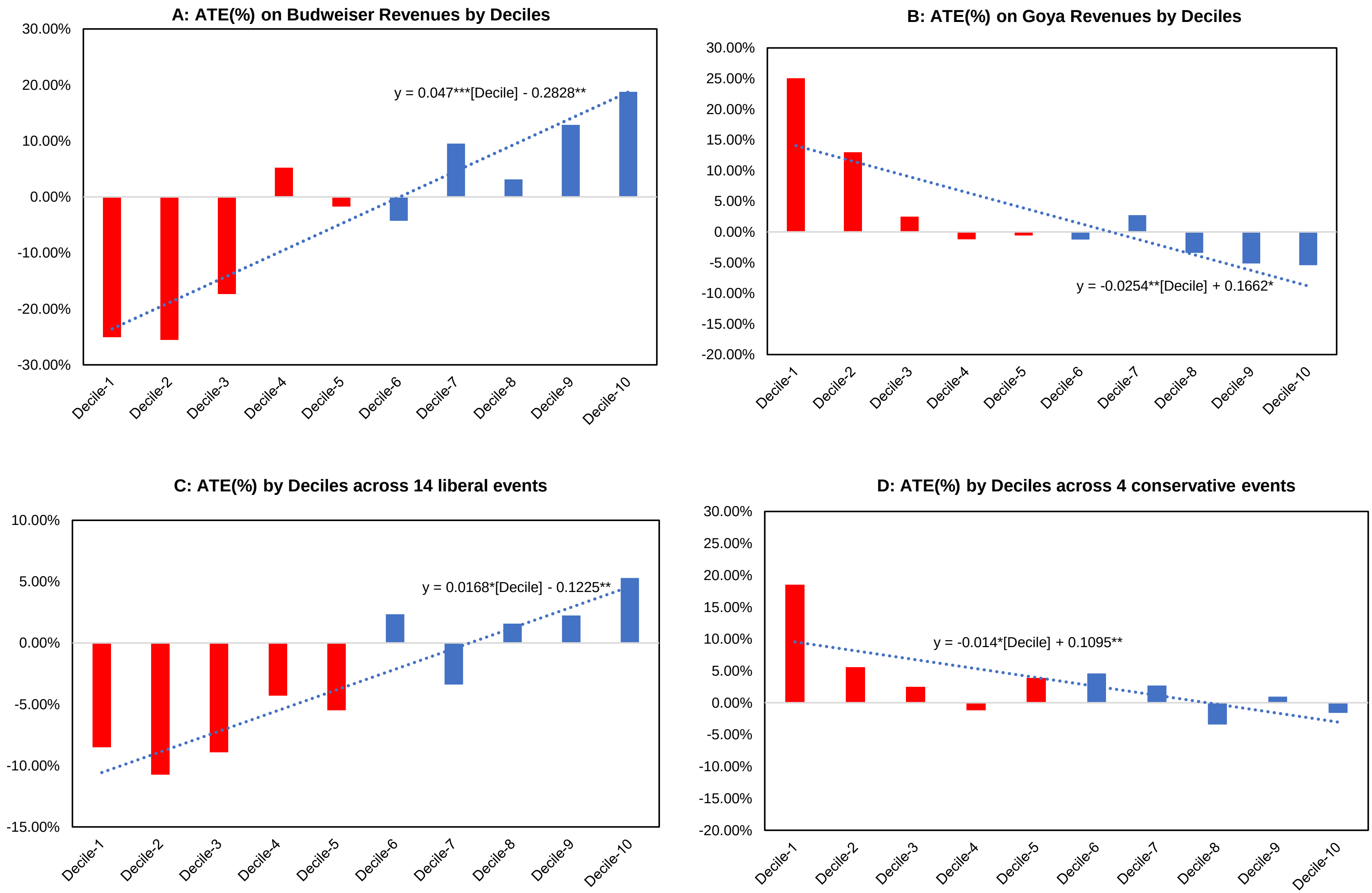


Figure 3-9: Impact of revenues correlates with the political leaning of counties – conservative leaning counties react more

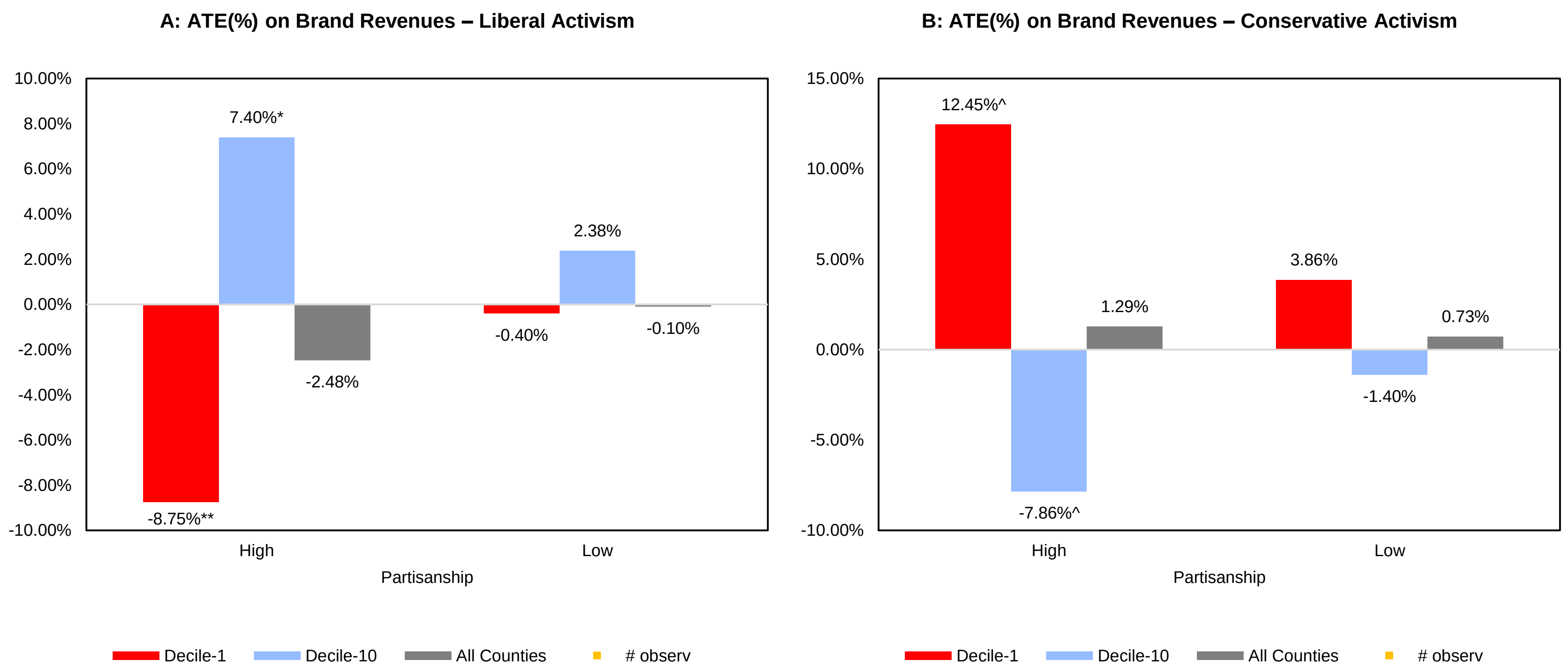


Figure 3-10: There is heterogeneity in consumer responses to different categories of brand activism

3.4.2 Hypothesis Tests

The coefficients β_0, β_1, β_2 and β_3 in Regression Equation (1) uphold these model-free findings and support hypotheses H1-H4. The results of the regression are tabulated in Table 3-5. It is important to note that the post-event window used for the brand revenues ATE (%) in Table 3-5 is the first quarter in the aftermath of the event. The results for Q2, Q3 and Q4 ATEs (%) are tabulated in Table 3-6. We also want to note that the high-partisanship conservative activism is the base category of activism events used in these analyses. The results substantively remain the same when using other categories of brand activism as the base category.

3.4.2.1 Effect of county-ideology on Consumer Purchase of Activist Brands (H1)

The negative significant coefficient of β_0 in Table 3-5 provides evidence for a significant negative effect of democratic vote-shares in counties on the activist brand's revenues when the brand chooses a pro-conservative position for the activism. This coefficient becomes positive for brands choosing a pro-liberal position as is indicated by the coefficient β_3 corresponding to the other categories of brand activism in this study. Specifically, we find that the correlation is significantly positive (+0.4%) for high-partisanship pro-liberal activism and marginally negative (-0.1%) for low-partisanship activism events. Taken together, it means that a high-partisanship conservative and liberal activism event could impact revenues in counties by nearly 1% for every 1% change in vote-shares of counties.

3.4.2.2 Effect of Brand Activism Partisanship on Consumer Purchase of Activist Brands (H2)

We provide evidence for H2 through the β_3 coefficients in Table 3-5. The positive significant coefficient of β_3 across the three other categories of brand activism in this study suggests that as brand activism goes from one end of the spectrum – high-partisanship, to the other end of the spectrum – high-partisanship liberal, there is a significant tempering of the negative coefficient β_1. It becomes marginally positive for low-partisanship conservative and liberal activism and then becomes significantly positive for high-partisanship liberal activism, thus showing that high-partisanship activism events cause counties to react a lot more (un)favorably to (mis)aligned activism than low-partisanship activism events.

3.4.2.3 Differential impacts of Brand Activism on Liberal vs Conservative Counties (H3)

In order to provide evidence for hypotheses H3, we ran regression equation (1) separately for deciles 1through 5 (proxy for conservative counties) and deciles 6 through 10 (proxy for liberal counties). We found the results from Table 3-5 being replicated directionally but with higher absolute values of the coefficients β_1 and β_3 in the case of conservative counties and lower absolute values of coefficients in the case of liberal counties. For instance, we find a coefficient of +1.62 for β_1 in the case of conservative counties and +1.28 in the case of liberal counties, which indicates that the former react more strongly in the aftermath of high-partisan conservative CSA events.

3.4.2.4 Positivity or Negativity Bias of Brand Revenues for Conservative and Liberal Activism (H4)

Since conservative counties react more to brand activism events than liberal counties, we find evidence that the net impact of CSA on brand revenues across all counties is significantly positive for conservative brand activism positions and negative for liberal brand activism events. This is indicated by the significant positive coefficient of β_0 in Table 3-5 suggesting a strong positivity bias in the abnormal brand revenue changes (ATE %) in the aftermath of the base category of activism events in the analysis – i.e., high-partisanship pro-conservative activism. The significant negative coefficients of β_2 for all other categories of activism events suggests that this positivity diminishes gradually as we brands move away from conservative activism to liberal activism. The bias becomes significantly negative (-0.2) for high-partisanship liberal activism.

3.4.2.5 Drivers of revenue changes (H5-H6)

In order to investigate the drivers of the ATE (%) on brand revenues, we analyzed household purchases of the two highest impact events in our sample in terms of divergence of abnormal revenue changes (ATEs %) of the brand between conservative and liberal county-deciles. We performed an ASCM procedure on the five measures computed from the HomeScan panel data. We found that the change in brand revenues in both these cases is driven by a change in the number of consumers (Figures 3-11 to 3-14) – indicating the presence of new consumers in politically aligned counties and fewer consumers buying in misaligned counties – thus supporting hypothesis H5. However, we do not find support for hypothesis H6 – i.e., we did not find any significant changes in the average dollar spending levels among consumers across counties. So, while we find evidence of some percentage of consumers boycotting and buycotting brands as a result of activism events, they do not seem to purchasing the brands in larger (or smaller) quantities as compared to the brand's existing consumers in those counties.

3.4.2.6 Additional comments: Long-run impacts

As an additional analysis, we checked if the impacts of activism on brands' revenues last for longer than the first quarter after the CSA event (Table 3-6). Contrary to Liaukonyte et al. (2022)'s findings, we find that the results are replicated over quarters 2,3 and 4 after the activism event. While the magnitude of all coefficients of note decreases, they still remain significant over the period of one year after the event, which suggests there are long-run implications of CSA events for brands.

3.4.2.7 Additional comments: Impact of BAV measures

Interestingly, we find a significant negative coefficient of Esteem on ATE (%) when we add it as a control to the analysis. This may suggest that brands that are high on esteem – i.e., older brands with larger market shares – suffer from CSA events. This would be in line with Hydock et al. (2021)'s findings which suggest higher negativity biases for high market share brands. On the other hand, we find a significant positive coefficient of Energized Differentiation and Relevance. This may indicate that brands that are high on Energized Differentiation (generally smaller brands with growth potential) and Relevance (generally brands with a strong purpose) tend to benefit from such actions.

Table 3-7 provides a summary of the hypotheses that were tested and the results we obtained from the tests.

Table 3-5: Coefficients from Regression Equation (1) for Quarter-1 Post-Event ATE (%)

VARIABLES	ATE (%) QUARTER-1 POST-EVENT>>						
Constant (β_0)	0.963***	0.964***	0.706***	0.530*	0.219	-1.954	-1.954
	(0.116)	(0.117)	(0.135)	(0.277)	(0.528)	(2.014)	(1.514)
Dem Vote Share (%) (β_1)	-1.414***	-1.414***	-1.370***	-1.441***	-1.330***	-1.372***	-1.372***
	(0.312)	(0.313)	(0.302)	(0.300)	(0.289)	(0.276)	(0.286)
β_2 relative to High Partisan Conservative >>							
High_ Liberal	-1.143***	-1.141***	-1.168***	-1.017***	-0.734***	-1.013**	-1.013***
	(0.145)	(0.150)	(0.146)	(0.161)	(0.190)	(0.424)	(0.303)
Low_ Conservative	-0.987***	-0.987***	-0.846***	-0.764***	-0.703***	-0.945***	-0.945***
	(0.250)	(0.251)	(0.245)	(0.247)	(0.248)	(0.345)	(0.270)
High_ Conservative	-0.918***	-0.917***	-0.866***	-0.773***	-0.642***	-1.051*	-1.051***
	(0.147)	(0.151)	(0.149)	(0.167)	(0.202)	(0.551)	(0.298)
β_3 relative to High Partisan Conservative (Moderation effect on Democratic Vote Share %)>>							
High_ Liberal	1.811***	1.813***	1.775***	1.840***	1.737***	1.759***	1.759**
	(0.391)	(0.394)	(0.379)	(0.376)	(0.362)	(0.346)	(0.804)
Low_ Conservative	1.440**	1.440**	1.396**	1.467**	1.356**	1.399**	1.399
	(0.702)	(0.704)	(0.680)	(0.672)	(0.645)	(0.613)	(0.798)
High_ Conservative	1.319***	1.318***	1.262***	1.335***	1.259***	1.273***	1.273
	(0.392)	(0.393)	(0.380)	(0.377)	(0.365)	(0.347)	(0.800)
Controls>>							
Brand Asset		-0.000332					
		(0.00658)					
Brand Stature			-0.0732***				
			(0.0259)				
Brand Strength			0.231***				
			(0.0618)				
Energized Differentiation				0.494**	1.271***	1.623***	1.623***
				(0.214)	(0.288)	(0.543)	(0.0869)
Relevance				0.275***	0.771***	1.310**	1.310***
				(0.0708)	(0.212)	(0.614)	(0.00703)
Esteem				-0.529**	-0.862***	-1.700***	-1.700***
				(0.216)	(0.274)	(0.492)	(0.0427)
Knowledge				-0.116	-0.518***	0.192	0.192**
				(0.0720)	(0.148)	(0.473)	(0.0704)
Preference Percent					-0.0335***	-0.0618***	-0.0618***
					(0.00949)	(0.0223)	(0.00182)
Regularly Use Percent					0.0438***	0.0298	0.0298***
					(0.0121)	(0.0274)	(0.00661)
Lapsed User Percent					0.0398***	0.0567***	0.0567***
					(0.0103)	(0.0148)	(0.00357)
Year-fixed Effects						✓	✓
Clustered at Brand level							✓
Obs>>	189	189	189	189	189	189	189
R-squared	0.379	0.379	0.425	0.446	0.499	0.564	0.564

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3-6: Coefficients from Regression Equation (1) for Quarters-1-4 Post-Event ATE (%)

VARIABLES	ATE % (QTR-1)	ATE % (QTR-2)	ATE % (QTR-3)	ATE % (QTR-4)
Constant (β_0)	-1.954	-1.419***	26.99***	-25.03***
	(2.014)	(0.0532)	(0.359)	(0.823)
Dem Vote Share (%) (β_1)	-1.372***	-0.409*	-0.138*	-0.568***
	(0.276)	(0.231)	(0.0706)	(0.160)
β_2 relative to High Partisan Conservative >>				
High Liberal	-1.013**	-0.785***	8.873***	-8.623***
	(0.424)	(0.0885)	(0.0772)	(0.190)
Low Conservative	-0.945***	-0.778***	2.661***	-3.680***
	(0.345)	(0.0772)	(0.0203)	(0.0478)
High Conservative	-1.051*	-0.653***	7.951***	-8.232***
	(0.551)	(0.0931)	(0.0979)	(0.253)
β_3 relative to High Partisan Conservative (Moderation effect on Democratic Vote Share %)>>				
High Liberal	1.759***	0.764***	0.431***	1.000***
	(0.346)	(0.245)	(0.130)	(0.197)
Low Conservative	1.399**	0.464*	0.142*	0.534***
	(0.613)	(0.231)	(0.0706)	(0.160)
High Conservative	1.273***	0.345	0.0505	0.626*
	(0.347)	(0.259)	(0.114)	(0.297)
High Liberal	1.623***	0.253***	19.56***	-11.06***
	(0.543)	(0.0204)	(0.193)	(0.443)
Controls>>				
Energized Differentiation	1.623***			
	(0.0869)			
Relevance	1.310**	0.729***	1.804***	1.066***
	(0.614)	(0.00809)	(0.00708)	(0.0168)
Esteem	-1.700***	-0.894***	-10.54***	3.952***
	(0.492)	(0.0124)	(0.0900)	(0.206)
Knowledge	0.192	0.339***	-13.97***	10.73***
	(0.473)	(0.0167)	(0.157)	(0.361)
Preference Percent	-0.0618***	-0.0318***	-0.441***	0.224***
	(0.0223)	(0.000518)	(0.00414)	(0.00954)
Regularly Use Percent	0.0298	-0.00181	1.350***	-0.949***
	(0.0274)	(0.00159)	(0.0145)	(0.0332)
Lapsed User Percent	0.0567***	0.0263***	0.802***	-0.462***
	(0.0148)	(0.000861)	(0.00782)	(0.0179)
Year-fixed Effects	✓	✓	✓	✓
Clustered at Brand level	✓	✓	✓	✓
Observations	189	188	170	170
R-squared	0.564	0.575	0.747	0.827

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

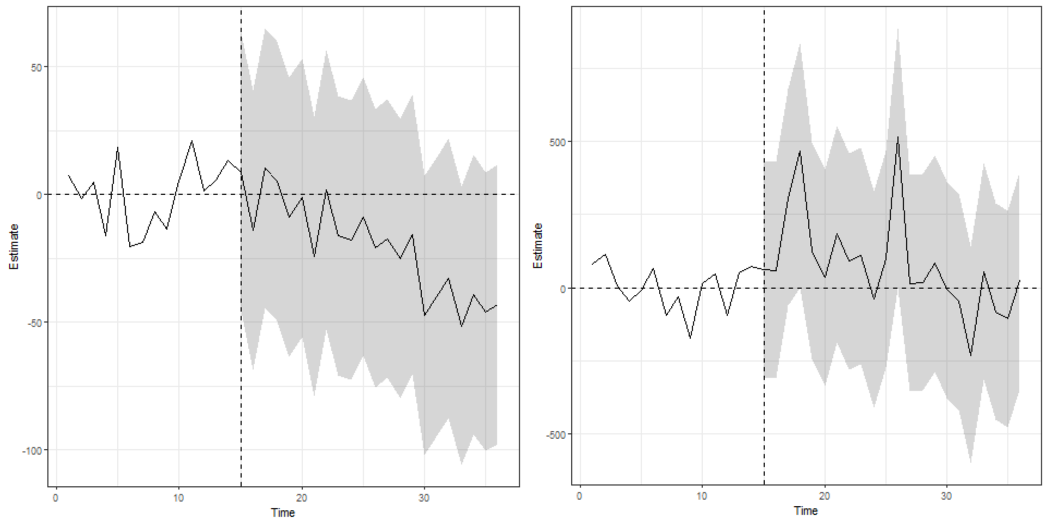


Figure 3-11: Doritos experienced a drop in number of active consumers in conservative Decile-1 counties (left) and an increase in liberal Decile-10 counties (right) since 2015Q3

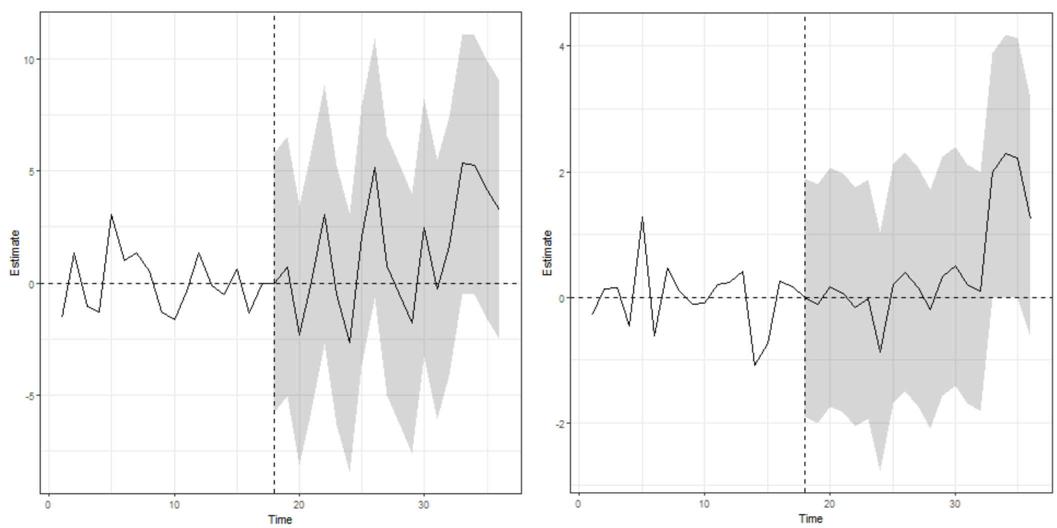


Figure 3-12: Doritos experienced no change in average spending from active consumers in conservative Decile-1 counties (left) or in liberal Decile-10 counties (right) since 2015Q3

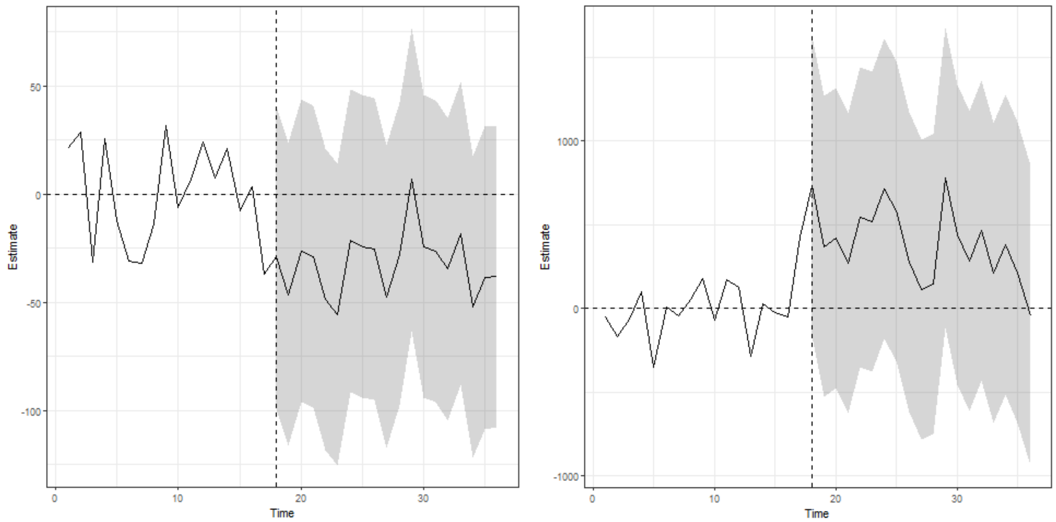


Figure 3-13: Coca-Cola experienced a drop in number of active consumers in conservative Decile-1 counties (left) and an increase in liberal Decile-10 counties (right) since 2016Q2

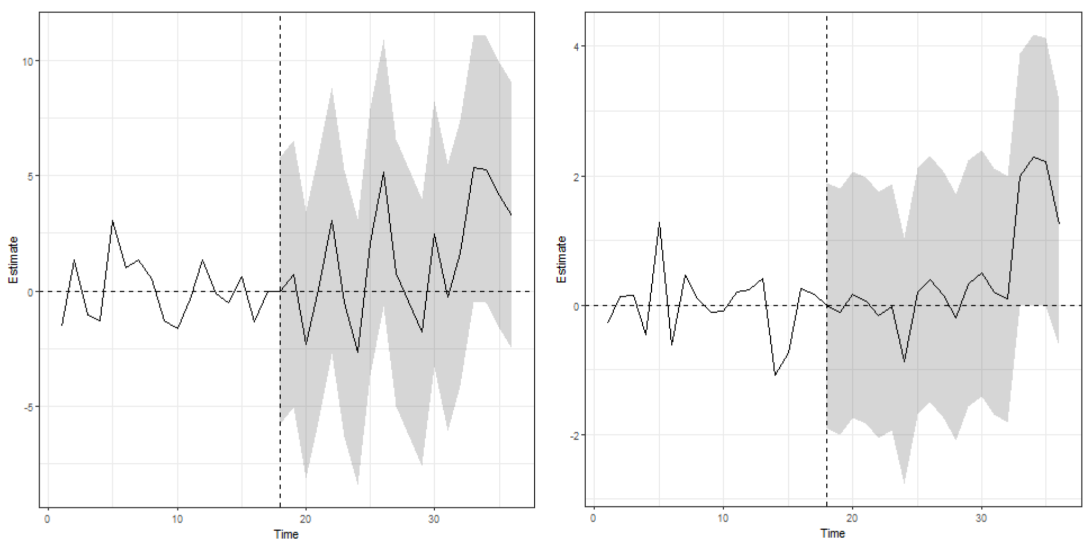


Figure 3-14 Coca-Cola experienced no change in average spending from active consumers in conservative Decile-1 counties (left) or in liberal Decile-10 counties (right) since 2016Q2

Table 3-7: Summary of Hypotheses and Findings

Hypotheses	Findings
H1: Brand revenues should increase (decrease) in markets that are politically aligned (misaligned) to the CSA	Supported
H2: Brand revenues in the aftermath of CSA should be impacted more in high-partisanship political issues as compared to low-partisanship political issues	Supported
H3: Brand revenues in the aftermath of CSA should be impacted more in conservative-leaning markets as compared to liberal-leaning markets	Supported
H4: Brand revenues across all counties should increase (decrease) in the aftermath of CSA in conservative (liberal) leaning CSA	Supported
H5: Change in Brand Revenues in the aftermath of CSA should be driven by increase (decrease) in number of consumers in politically aligned (misaligned) markets	Supported
H6: Change in Brand Revenues in the aftermath of CSA should be driven by increase (decrease) in average spending of consumers in politically aligned (misaligned) markets	Not Supported

3.5 CONCLUDING REMARKS

Despite increasing political polarization in American society and the recent surge in interest around brand activism and political consumerism, we know very little about the effects of socio-political boycott and buycott movements on actual consumption. Liaukonytė et al. (2022) empirically studied the impact of one specific highly publicized event – that involving social media calls for Goya boycotts after its CEO praised President Donald Trump during a particularly tumultuous political environment. In this study, we answer the call for more case studies analyzing similar phenomena in a bid to generalize their findings to a much broader set of brands, product categories and activism characteristics. In order to do so, we analyze multiple major socio-political activism events from CPG brands and their impact on brand revenues using the Nielsen retail scanner and consumer panel datasets. A novel event-study approach using Augmented Synthetic Controls in a quasi-experimental setup provides evidence for: (1) positive (negative) impact of alignment (misalignment) of brands' political stance vis-à-vis ideology of markets on purchase behavior; (2) moderation of partisanship of the brand activism issue; and (3) moderation effect of ideological leaning of the brand activism – i.e., the tendency of conservative (liberal) activism to have an overall positivity (negativity) bias because of CSA events eliciting greater reactions from conservative counties than from liberal counties. These changes in brand revenues tend to be driven by new consumers in markets ideologically aligned to the activism and lapsed consumers from markets that are ideologically opposed to the activism. Finally, we also find these impacts to last for four quarters in the aftermath of the CSA event, thus providing evidence longer-run impacts of such brand actions.

3.5.1 Theoretical Implications

Our research advances marketing strategy literature in the nascent work on corporate socio-political activism (CSA). We build on existing conceptualizations of activism and political consumerism to provide contingencies under which a firm's political engagement impacts its brands positively or negatively in terms of revenues. In the process, we categorize CSA events in our sample on the dimensions of partisanship of the issue and its political leaning; and find significant effects of both characteristics. Drawing on previous literature on political consumption, we explain why brands should expect differences in purchase behaviors from consumers and consequent marketplace outcomes in markets with differing political ideologies. Conservative counties are expected to be more protective of their perceived in-groups while liberal counties are expected to be more open to new ideas and thoughts. This seems to translate into higher acceptance of a brand's counter-narratives in the case of liberal counties while conservative counties react strongly to brands trying to educate society on what is right and what is wrong. As we discover ub the study, this has important effects on the revenues of the brand.

Our research also lays down a framework for ASCM-aided quasi-experimental analyses of long panel data with large pre-event and post-intervention time periods for outcome and predictor variables. The first stage of our analysis incorporates the ASCM procedure for reliably and precisely estimating the average treatment effects of each CSA event across each county-decile. The synthetic control procedure, that has been called "the most important innovation in policy evaluation in the 21^{st} century" enables us to overcome the limitation of having very few cases of CSA events and comparable brands for generating accurate counterfactual outcomes. It also allows us to overcome potential measurement and sampling errors in the Nielsen data by identically matching the synthetic control brand to the activist brand in terms of pre-event outcomes, thus boosting confidence in the ATE estimates generated using this procedure, so that we can causally attribute these abnormal changes solely to the CSA events. The ASCM procedure, especially when applied to our long-panel data, allows us to draw interesting insights about the short-run as well as long-run consequences of the event. For instance, our analysis indicates long-run effects of CSA on brand revenues for a period of one year after the event, thus contradicting Liaukonyte (2022)'s assertions of short-run effects in the case of Goya CEO's pro-Trump statements.

Finally, as mentioned before, our research extends and complements Liaukonyte (2022)'s findings using a larger sample of CSA events, generalizes their findings, and helps us draw boundary conditions under which CSA may or may not work favorably for the brands.

3.5.2 Managerial Implications

This work also has several implications for practitioners. A critical question for managers is whether they should engage in CSA at all. From a managerial implications' standpoint, the measure of revenue elasticities of different markets to various activism campaigns should help firms strategize about which causes they should actively pursue for impact.

Our findings indicate that CSA does indeed have real marketplace outcomes for the brand, which we observe through their effect on abnormal revenue changes. So, the reluctance of CMOs in participating in such actions is warranted. Engaging in CSA is likely to benefit conservative brands more than liberal brands which calls into question the sustainability of liberal brands' political engagement over time, especially given that our findings suggest long-lasting impacts of CSA on brand revenues. CSA is difficult to retract and has lasting financial implications, so managers should be strategic in their decision to publicize it and should only go ahead with it if they have complete conviction in the issue they are supporting or protesting as part of their CSA. We speculate that one of the reasons liberal activism seems to suffer from a negativity bias is the preponderance of progressive and liberal activism from multiple brands over the last few years – which makes liberal activism feel less novel and less effective in differentiating a brand as compared to conservative activism. Instead, some literature suggests that the saturation of the marketplace with progressive brands makes a lot of them look inauthentic and overtly opportunistic, thus again calling into question the sustainability of liberal activism from brands.

Having said that, the silver lining is that brands can expect to engage politically with issues that are low on political partisanship and yet experience minimal impacts on their revenues. In such cases, brands should feel free to express themselves authentically and use it to generate stronger brand associations among its existing and future consumers.

3.5.3 Limitations and Future Research Directions

From a data and methods standpoint, our research suffers from the lack of a large sample size of events, partly because of the general reluctance of CMOs and Top Management teams to engage in CSA events and partly because of the Nielsen data's limitation of being restricted to CPG brands alone. While the ASCM procedure alleviates these issues to a large extent, future studies need to find larger sample sizes to make further generalizations about CSA's impact on brands. Future research should also be dedicated to making strides in overcoming some of the limitations of the quasi-experimental procedures employed in the study and making them capable of generating more precise and meaningful insights out of randomly sampled consumer purchase data (such as Nielsen or IRI)

Our study currently suffers from a few conceptual limitations as well. Our analysis so far does not observe how the relative impact of brand activism is likely to be moderated by activism awareness and publicity, extent of participation of the brand in the activism event, and brand characteristics (such as market penetration, competitive strength and substitutability). For instance, one should expect that higher media coverage of a CSA event on traditional and social media should have larger effects than a similar event with lower media attention. Similarly, product categories and brands with high consumer loyalties or high market concentrations may offer little scope for consumers to switch to other brands or adopt new-to-the-consumer brands because of CSA events. Similarly, dominant brands may behave differently from lower market-share brands as proposed by Hydock et al. (2021). To that point, our additional analysis suggests significant effects of BAV measures on the phenomenon and will also be an interesting next step for researchers in this domain to take up. There is also an opportunity to take a closer look at antecedents of successful activism events (e.g., Nike's Colin Kaepernick campaign) as opposed to failed attempts (e.g., Pepsi's Kendall Jenner BLM commercial). Clearly, the area of CSA is ripe for the discovery of several marketing insights that could forward theoretical and managerial knowledge. Future research should be dedicated to providing answers for some of these aforementioned questions as well as ponder over other remaining theoretical considerations in this evidently complex topic.

4.0 CONCLUSION AND FUTURE RESEARCH

To say that we live in a polarized world is like stating the obvious. We see it in our social media feeds, we see it on national news channels, we even see it in our daily conversations with family and friends. We see it quantified in several examples of research too. Several studies including, but not limited to, Lelkes et al. (2017), Hetherington (2001), Abramowitz and Saunders (2005), Andris et al. (2015), point out how American society has gradually descended into partisan hostility between political parties that has had its ripple effect on the polarization of society too. Investigations of filter-bubbles in politics-related conversations (Garimella and Weber 2017) show that there is a consistent increase in polarization (around 10-20%) over the past decade on Twitter.

As integral parts of this society, brands are increasingly affected by this polarization. On social media, brand fan communities can overnight devolve into hate pages through complaint publicization (Golmohammadi et al. 2021), news of functional and moral transgressions (Herhausen et al. 2019; Hansen et al. 2018) and hostilities towards rival brands (Dhaoui and Webster 2021; Dessart et al. 2020). While the increase in political polarization on social media has mainly been driven by a small group of partisan users who are politically active and hostile towards counter-opinions (Lelkes et al. 2017), their vociferousness forces brands to take note and then themselves express strong support and dissent for controversial issues in the form of corporate socio-political activism. Both these phenomena induce love-hate relationships between brands and consumers.

Of course, brand love and brand hate are not an entirely new phenomenon. Android cellphone users would be quick to dismiss i-Phone lovers as uppity folks with a superiority complex for using an Apple device that retaliates with disdain using the "dreaded green text bubble" emphasizing the differences and creating a manufactured stigma against non-Apple users. Get a group of drunk Boston Red Sox and New York Yankee supporters in a sports bar, and one will quickly conclude that tribalism is just part of human nature. But when banter turns to more serious consequences for brands and their consumers, it calls for a better understanding of such phenomena than extant marketing literature currently provides. Now is as opportune a time as any to contribute to our knowledge about the impacts of extreme brand-hate and brand-love, and this dissertation tries to do that. More importantly, it tries to make substantive contributions by suggesting tactics and strategies to mitigate some of these negative impacts.

The first essay, for instance, demonstrates the process of building 'bridges' between brand-supporters and brand-detractors on social media during online firestorms by implementing carefully curated influencer-seeding strategies. Connecting pro-brand and anti-brand social media users by exposing them to relatively moderate counterviews about the brand seems to have significant improvements on brand filter-bubbles and social media perceptions. The second study finds contingencies when these negative social media perceptions following controversial brand positions on socio-political issues start damaging consumer purchases and brand revenues – thus providing boundary conditions that marketing managers can observe and be wary of.

The findings, however powerful, barely scratch the surface when it comes to such a complex issue facing firms and brands today. I am hopeful that the dissertation essays will fuel future research that delves deeper into these phenomena and helps crystallize these research advancements further. The essays provide quite a few ways in which literature could directly extend their contributions. But there are overarching bigger-picture questions too. For instance, while the studies paint a somewhat bleak picture of the consequences of brand polarization, it is important to understand when polarization can be good. For instance, literature in the political sciences point out that counter to popular belief that polarization turns off voters and depresses turnout, it actually energizes the electorate and stimulates political participation, increasing the popularity levels of political parties (Abramowitz and Saunders 2005). Conventional wisdom would suggest that it should affect brand engagement similarly, and that brands should strive for more engagement rather than less. Since social media takes the good and bad in society and dials it up to an eleven, there is plenty of room to research how one optimizes the positives while keeping the negatives under check. Similarly, brands need to find the right balance between authenticity and activism, and realize that not all brands are probably meant to "have a purpose" – Chaudhari (2022) uses Hellmann's sustainability mission statement to make a larger point about it. On the contrary, some brands may have activism so ingrained in their DNA that they might do well to not spare a second thought about the marketplace outcomes of such actions. Researchers need to do a better job at making a distinction between reactive brand activism and an activism action undertaken from an inherent calling – and communicate it with managers. These issues also raise important questions in the area of brand safety[12] that could have public policy implications too.

At this point, I can only reiterate the privilege I feel in bringing a few of these issues to the fore through this dissertation, and humbly leave it up to more qualified researchers in the future to expand on these areas of inquiry.

[12] https://www.brandsafetyinstitute.com/

Appendix A APPENDICES AND SUPPLEMENTAL CONTENT

Appendix A.1 ESSAY-1 SUPPLEMENTAL CONTENT

Appendix A.1.1 Proposition P1 Stylized Conceptual Development

A corollary to Hypothesis H4 is that it intuitively seems like a reasonable strategy to try and reduce echo-chamberness between pro-brand and anti-brand communities to mitigate the negative long-run and short-run effects of the firestorm. Garimella et al. (2017) demonstrate an algorithmic procedure to reduce echo-chambers by exposing social media users to contrary opinions of commentators across the aisle and hoping that a small number of endorsement edges can be formed. They analytically demonstrate that there are two factors in identifying the edges that would be statistically optimal in this objective – centrality of the nodes being connected by the edge and an acceptance probability of the edge materializing. This translates into a k-edge recommendation problem within a polarized network – say, a graph $G(v, e)$ whose vertices are partitioned into two disjoint sets $X$and Y – such that addition of the set of k edges generates a new graph $G'(v, e')$ where the expected controversy score $E_A[RWC(G', X, Y)]$ is minimized under acceptance model $\mathbb{A}$. The expected change in random walk controversy would then be given by:

$$E_{\mathbb{A}}[\Delta RWC(G \rightarrow G^{'}; X, Y)] = \sum_{i=1}^{i=k} p(u_i \rightarrow v_i) \delta RWC_{u_i \rightarrow v_i} \qquad (1)$$

In the above expression, $\delta RWC_{u_i \rightarrow v_i}$ indicates the change in polarization from forming one of the k edges between the users u_i and v_i, which is directly proportional to the degree-centrality of the nodes being connected – i.e., connecting higher-degree nodes leads to greater decrease in polarization. The other term $p(u_i \rightarrow v_i)$ represents the acceptance probability and is inversely proportional to the difference in polarities between the two nodes being connected. Intuitively, this polarity score R_u of a user u captures how much the user belongs to either side of the controversy – this could be a measure of their attitudes in a particular network (such as brand sentiment), or as Garimella et al. (2017) compute it, a function of their position within the network structure. Finally, they compute the acceptance probabilities as:

$$p(u_i \rightarrow v_i) = \frac{N_{endorsed}(R_u,R_v)}{N_{exposed}(R_u,R_v)} \quad (2)$$

The numerator and denominator in the expression indicate the number of times a user with polarity R_u endorses and is exposed to, respectively, content generated by a user of polarity R_v. The essence of their findings is that extreme recommendations are unlikely to work, and that people 'in the middle' are easier to convince.

Proposition P1 suggests a similar algorithmic approach of connecting optimally selected edges should also be able to improve brand perceptions during a social media firestorm. Firms today have access to several digital tools involving influencer-seeding and online targeting capabilities – so, recommending positive brand-related content from brands' influencers to brand-haters during a crisis could be a potential mitigation tactic for both polarization and brand perception. Below is a stylized theoretical demonstration of how edge-recommendations could influence attitude formation during a crisis, based on De Groot (1974)'s naïve learning model.

We assume that a finite set $S = \{1,2,\dots,N\}$ of social media users interact in a social network. Connections between users are captured through an NxN stochastic nonnegative 'interaction' matrix $\boldsymbol{T}$,where $T_{ij} \geq 0$ indicates the extent to which a user i's brand attitude is influenced by that of user j. We allow the matrix $\boldsymbol{T}$ to be asymmetric, so interactions may be onesided (i.e., a situation where $T_{ij} > 0$ while $T_{ji} = 0$). User i starts off with a brand attitude $A_i^{(0)}$ and updates beliefs iteratively by repeatedly taking weighted averages of their neighbors' beliefs given by the rule $A_i^{(t)} = \sum_{j=1}^{N} T_{ij} A_i^{(t-1)}$. In matrix terms, this can be written as $\boldsymbol{A_i^{(t)}} = \boldsymbol{T^t A_i^{(0)}}$ where $\boldsymbol{A_i^{(j)}}$ is a $Nx1$ vector representing the brand attitudes of N users at the j^{th} iteration. In the case of an aperiodic convergent interaction matrix $\boldsymbol{T}$, the limiting consensus belief is equal to a weighted average of initial beliefs, with user i's weight being s_i, also called the influence weight of user i. s_i represents the ith column element of the row-eigenvector $\boldsymbol{s}$ of interaction matrix $\boldsymbol{T}$, and is given by solving for the set of linear equations $\boldsymbol{sTA_i^{(0)}} = \boldsymbol{sA_i^{(0)}}$ (De Groot 1974 and Golub and Jackson 2010 provide details). It is easy to see that s_i is essentially indicative of the eigenvalue centrality of user i (Golub and Jackson 2010).

We try and estimate below how the consensus belief might change if a brand tries to manipulate the network polarization score by successfully getting a negative brand commentator neg to retweet or share content posted a positive brand commentator pos (see Figure 2-3). The consensus belief now converges to $\boldsymbol{s_{new}}(\boldsymbol{T} + \boldsymbol{\delta T})\boldsymbol{A_i^{(0)}}$ where $\boldsymbol{s_{new}}$ is the influence vector corresponding to the new interaction matrix $\boldsymbol{T} + \boldsymbol{\delta T}$, and $\boldsymbol{\delta T}$ is given by:

$$\boldsymbol{\delta T} = \begin{pmatrix} 0 & .. & .. & .. & .. & .. & .. & 0 \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & \frac{-\delta}{d_{neg}} & 0 & .. & \frac{-\delta}{d_{neg}} & \delta & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ 0 & .. & .. & .. & .. & .. & .. & 0 \end{pmatrix} \qquad (A.1.1)$$

Here, δ represents pos' influence on neg, and d_{neg} represents neg's degree. The analytical proof of brand perception improvement through the edge-addition procedure outlined in Essay-1 is as follows:

Improvement of sentiment through addition of one extra edge is given by:

$$\boldsymbol{\Delta Sent.} = \boldsymbol{s_{new}A^{(0)} - sA^{(0)} = (s_{new} - s)A^{(0)}} \qquad (A.1.2)$$

Since $\boldsymbol{s_{new}}$ and $\boldsymbol{s}$ are eigenvectors of $(\boldsymbol{T + \delta T})$ and $\boldsymbol{T}$ respectively, we know that:

$$\boldsymbol{sT = s} \qquad (A.1.3)$$

And,

$$\boldsymbol{s_{new}(T + \delta T) = s_{new}} \qquad (A.1.4)$$

Subtracting $(\boldsymbol{A.1.3})$ from $(\boldsymbol{A.1.4})$, we get:

$$\boldsymbol{s_{new} - s = s_{new}(T + \delta T) - sT = (s_{new} - s)T + s_{new}\delta T} \Rightarrow \boldsymbol{(s_{new} - s)(I - T) = s_{new}\delta T}$$

$$\Rightarrow \boldsymbol{(s_{new} - s) = s_{new}\delta T(I - T)^{-1}} \qquad (A.1.5)$$

Substituting $(\boldsymbol{A.1.5})$ in $(\boldsymbol{A.1.2})$, we get that incremental change in sentiment as:

$$\boldsymbol{\Delta Sent. = s_{new}\delta T(I - T)^{-1}A^{(0)}} \qquad (A.1.6)$$

Since $\boldsymbol{\Delta Sent.}$ is a scalar quantity, the right-hand side of $(\boldsymbol{A.5})$ can be equated to the trace of the resultant matrix multiplication. Also, the order of matrices can be changed as long as the matrix dimensions remain consistent, So, $(\boldsymbol{A.5})$ transforms to:

$$\boldsymbol{\Delta Sent. = tr\left(s_{new}\delta T(I - T)^{-1}A^{(0)}\right) = tr\left(s_{new}\delta TA^{(0)}(I - T)^{-1}\right)}$$

$$\Rightarrow \boldsymbol{\Delta Sent. = s_{new}\delta TA^{(0)}tr((I - T)^{-1})} \qquad (A.1.7)$$

Where,

$\boldsymbol{s_{new}\delta T A^{(0)}}$

$$= \begin{pmatrix} s_1 & s_2 & .. & s_i & .. & .. & .. & s_n \end{pmatrix} \begin{pmatrix} 0 & .. & .. & .. & .. & .. & .. & 0 \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & -\delta/d_{neg} & 0 & .. & -\delta/d_{neg} & \delta & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ 0 & .. & .. & .. & .. & .. & .. & 0 \end{pmatrix} \begin{pmatrix} A_1^{(0)} \\ A_2^{(0)} \\ .. \\ A_i^{(0)} \\ .. \\ .. \\ .. \\ A_n^{(0)} \end{pmatrix}$$

$$\Rightarrow \boldsymbol{s_{new}\delta T A^{(0)}} = \delta \left\{ A_{pos}^{(0)} * s_{pos} - \frac{\sum_{j=1}^{j=d_{neg}} \left(A_{neg\ j}^{(0)} * s_{neg\ j} \right)}{d_{neg}} \right\} \qquad (A.1.8)$$

Combining two mathematical results – (1) trace of a matrix is the sum of its eigenvalues, and (2) eigenvalue $\lambda_{(I-T)^{-1}}^{(k)}$ of $\boldsymbol{(I-T)^{-1}}$ is related to eigenvalue $\lambda_T^{(k)}$ of $\boldsymbol{T}$ through $\lambda_{(I-T)^{-1}}^{(k)} = \frac{1}{1-\lambda_T^{(k)}}$, we get:

$$\boldsymbol{tr}((\boldsymbol{I}-\boldsymbol{T})^{-\boldsymbol{1}}) = \sum_{k=1}^{k=n} \lambda_{(I-T)^{-1}}^{(k)} = \sum_{k=1}^{k=n} \frac{1}{1-\lambda_T^{(k)}} = Positive\ constant\ R \qquad (A.1.9)$$

The constant R is positive because of the rule that stochastic matrices (such as T) have all positive eigenvalues $\lambda_T^{(k)}$. Substituting $(\boldsymbol{A.1.8})$ and $(\boldsymbol{A.1.9})$ into $(\boldsymbol{A.1.7})$, we get:

$$\boldsymbol{\Delta Sent.} = \boldsymbol{s_{new}\delta T A^{(0)} tr}((\boldsymbol{I}-\boldsymbol{T})^{-\boldsymbol{1}}) = R\delta \left\{ A_{pos}^{(0)} * s_{pos} - \frac{\sum_{j=1}^{j=d_{neg}} A_{neg\ j}^{(0)} * s_{neg\ j}}{d_{neg}} \right\}$$

$$(A.1.10)$$

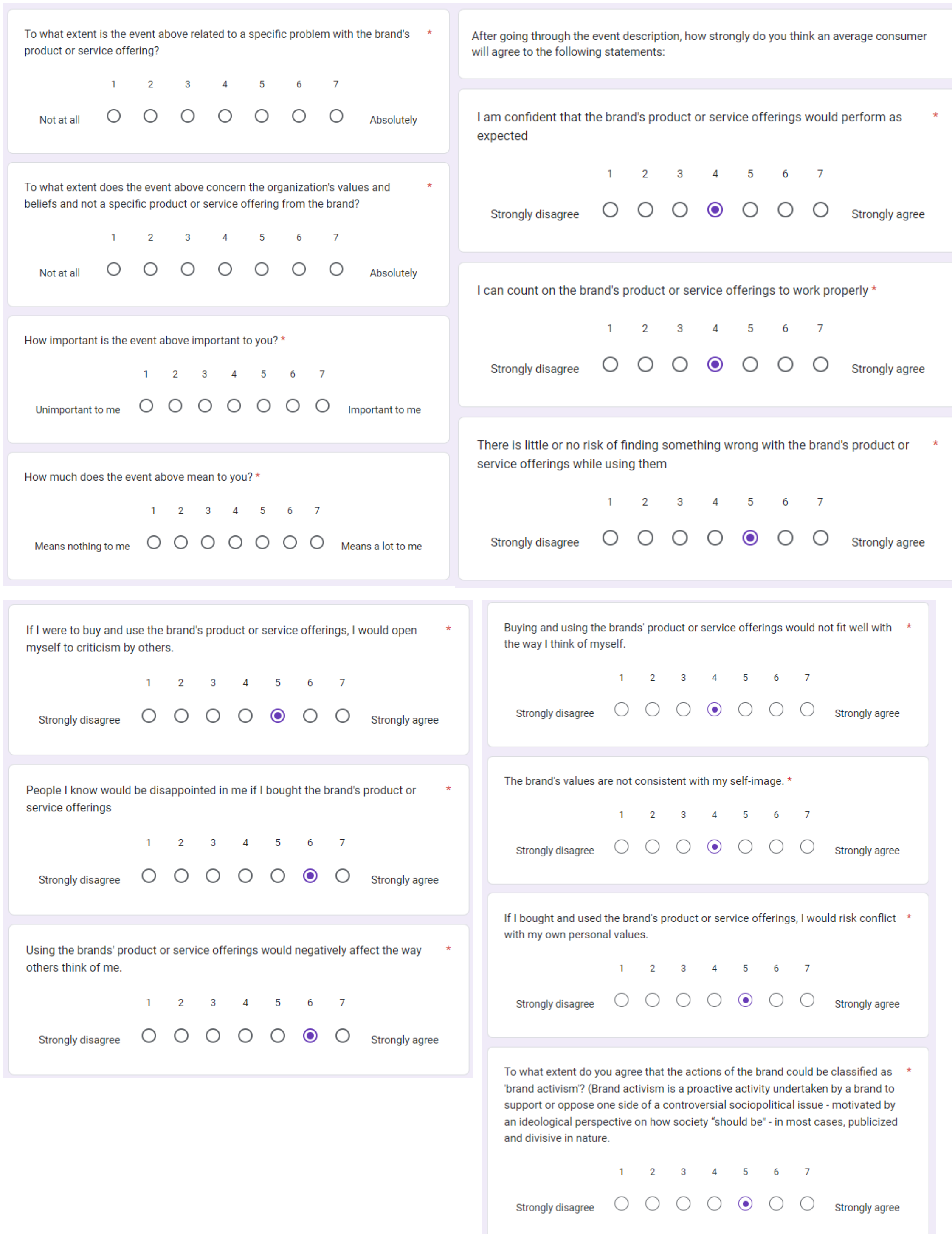
The above analysis suggests that (1) the added edge between the two communities would indeed improve overall brand sentiment and (2) these improvements in brand perception are higher if these connections are being built from nodes that were originally connected to high-degree negative sentiment nodes but are capable of being induced to endorse positive users with high eigenvalue centrality willing to be influenced by positive users with high eigenvalue centrality. As in the case of random walk controversy scores, acceptance likelihoods of these edges would need to be incorporated to be able to calculate the realistically expected brand sentiment improvements. Based on these expectations, we propose Proposition P1 which suggests that optimizing network-level interventions (through influencer-seeding, for instance) should mitigate random walk controversy and negative brand perceptions in the aftermath of social media firestorms.

Appendix A.1.2 Generalized Diff-in-Diff Event Study Analysis

We further generalize the differences-in-differences analysis in Section 2.4.5 by incorporating a temporal dimension in the estimation. We use the event study approach of Autor (2003) and Kline (2012), which leads to a richer understanding of the event by identifying pre-trends and day wise post-event changes due to the event. Visualizing the parallel trends assumption and eliminating the possibility of pre-trends assists us in attributing the changes solely to the online firestorm. We accomplish this by adding event-time dummies for all observations from one month before the event to one month after the event for the brand perception measures. We effectively divide the event time into 61 parts, with these binary event-time variables serving as primary focal predictor variables — they take the value 1 if the firm is in one of those states relative to the event occurrence and 0 otherwise.

We focus on the differences-in-differences coefficients $\alpha_{(did,T)}$ and $\alpha_{(cr,did,T)}$ of the event-time dummies, which indicate whether there is a significant upward or downward change in the dependent variables on the Tth day of the event progression and what the magnitude of that change is relative to the baseline (Day "-1"). We then plot these coefficients in Figure A.1.3 along with their 95% confidence intervals (CIs) on the event timeline following Autor (2003) and Kline (2012).

Appendix A.1.3 Essay-1: Supplemental List of Figures



To what extent is the event above related to a specific problem with the brand's product or service offering? *

1 2 3 4 5 6 7

Not at all ○ ○ ○ ○ ○ ○ ○ Absolutely

To what extent does the event above concern the organization's values and beliefs and not a specific product or service offering from the brand? *

1 2 3 4 5 6 7

Not at all ○ ○ ○ ○ ○ ○ ○ Absolutely

How important is the event above important to you? *

1 2 3 4 5 6 7

Unimportant to me ○ ○ ○ ○ ○ ○ ○ Important to me

How much does the event above mean to you? *

1 2 3 4 5 6 7

Means nothing to me ○ ○ ○ ○ ○ ○ ○ Means a lot to me

After going through the event description, how strongly do you think an average consumer will agree to the following statements:

I am confident that the brand's product or service offerings would perform as expected *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ◉ ○ ○ ○ Strongly agree

I can count on the brand's product or service offerings to work properly *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ◉ ○ ○ ○ Strongly agree

There is little or no risk of finding something wrong with the brand's product or service offerings while using them *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ○ ◉ ○ ○ Strongly agree

If I were to buy and use the brand's product or service offerings, I would open myself to criticism by others. *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ○ ◉ ○ ○ Strongly agree

People I know would be disappointed in me if I bought the brand's product or service offerings *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ○ ○ ◉ ○ Strongly agree

Using the brands' product or service offerings would negatively affect the way others think of me. *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ○ ○ ◉ ○ Strongly agree

Buying and using the brands' product or service offerings would not fit well with the way I think of myself. *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ◉ ○ ○ ○ Strongly agree

The brand's values are not consistent with my self-image. *

1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ◉ ○ ○ ○ Strongly agree

If I bought and used the brand's product or service offerings, I would risk conflict with my own personal values. *

1 2 3 4 5 6 7

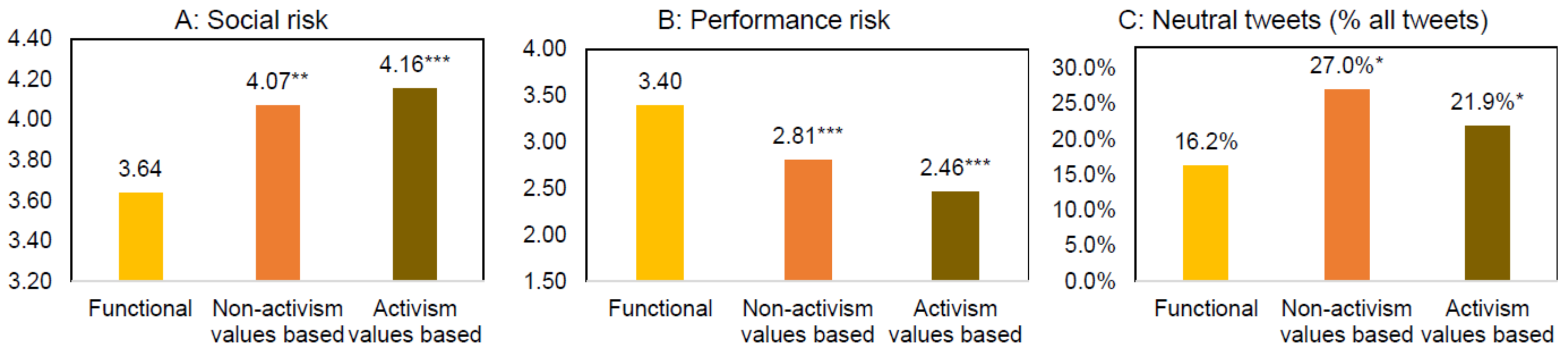
Strongly disagree ○ ○ ○ ○ ◉ ○ ○ Strongly agree

To what extent do you agree that the actions of the brand could be classified as 'brand activism'? (Brand activism is a proactive activity undertaken by a brand to support or oppose one side of a controversial sociopolitical issue - motivated by an ideological perspective on how society "should be" - in most cases, publicized and divisive in nature. *

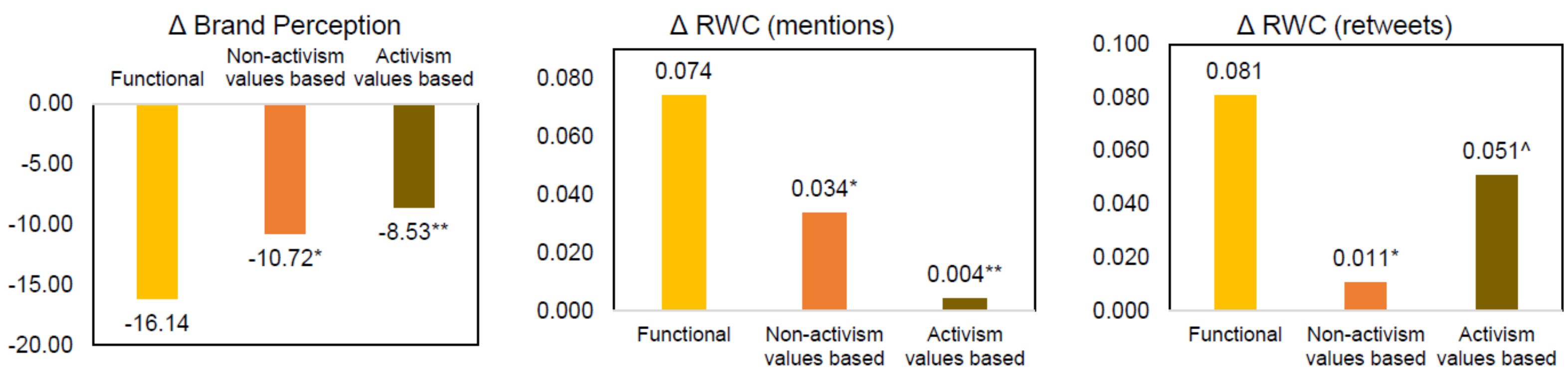
1 2 3 4 5 6 7

Strongly disagree ○ ○ ○ ○ ◉ ○ ○ Strongly agree

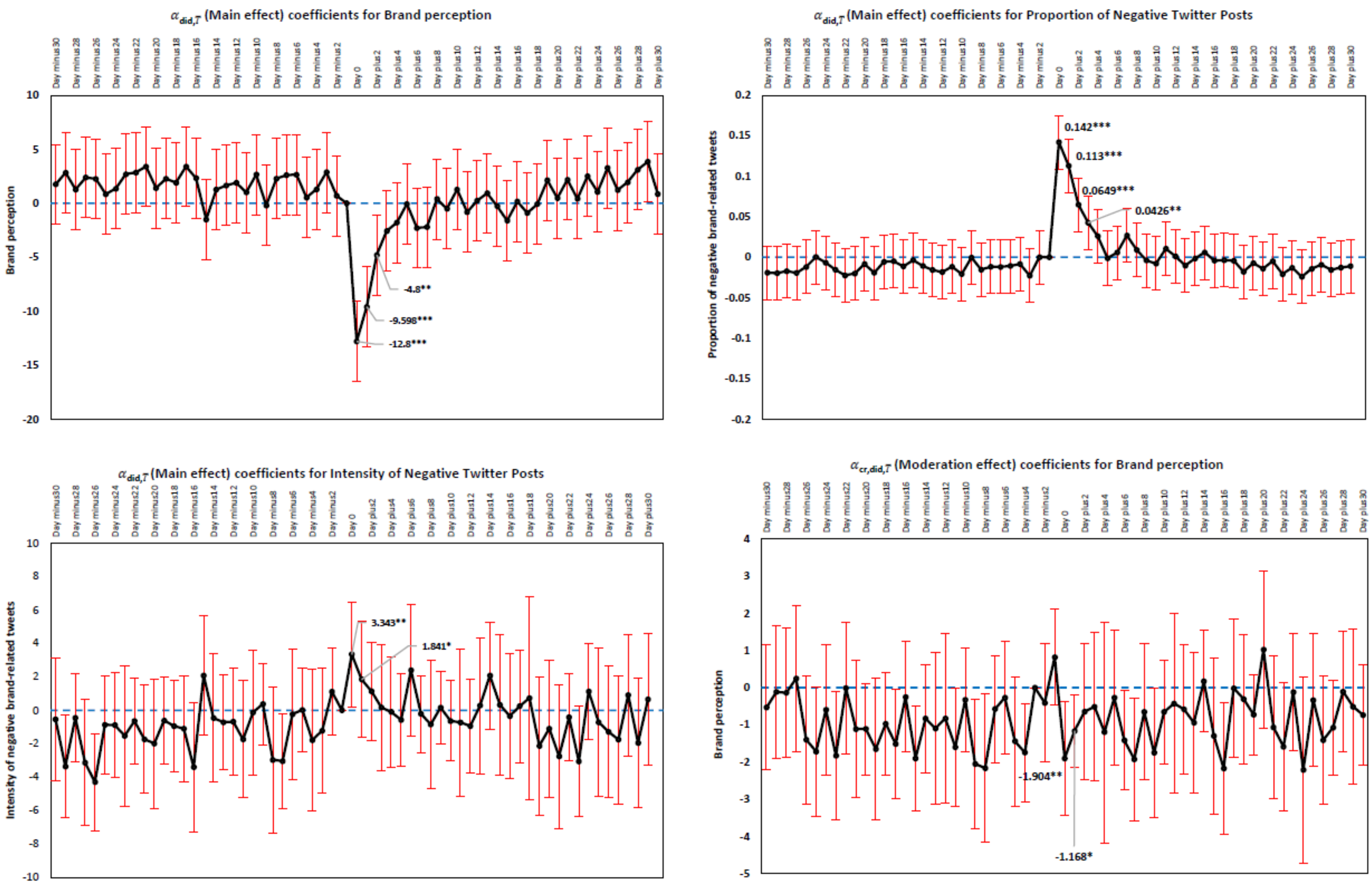
Appendix Figure A.1- 1: Survey Questionnaire for Brand Classification (Based on Dutta and Pullig 2011)



Appendix Figure A.1- 2: Characteristics of different firestorms



Appendix Figure A.1- 3: Perception and controversy scores of different firestorms



Appendix Figure A.1- 4: Generalized Differences-in-differences event study plots for brand perception and its drivers

Appendix A.1.4 Essay-1: Supplemental List of Tables

Appendix Table A.1- 1: Matching of focal brands and control brands on pre-firestorm characteristics

Variables	Focal all (N=574)	Focal RWCs converged (N=292)	Control (N=292)	p-Value
Normalized BAV	1899.854	2253.994	2196.812	0.703
Energized Differentiation	58.29	62.613	63.559	0.704
Relevance	64.658	63.227	61.349	0.53
Esteem	74.023	73.259	71.834	0.537
Knowledge	82.476	84.607	81.244	0.022**
Brand Stature	80.036	80.793	78.266	0.148ˆ
Brand Strength	65.281	65.581	64.115	0.603
Brand Asset	78.586	79.53	76.938	0.173
Usage Preference	4175.114	4547.378	4576.732	0.906
Total Users pct	37.585	38.824	39.735	0.662
Volume pre event	19131.49	33113.41	41145.97	0.316
Valence pre event	5.795	2.626	4.573	0.051*

Appendix Table A.1- 2: Main and moderating effects of online firestorms and Crisis type (continuous var.) respectively on Brand Perception and Echo-chamberness

Table-1	A: Average Brand Perception (30,1)				B: Mentions network polarization (30,1)				C: Retweet network polarization (30,1)			
	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors
Crisis type (Continuous)		-1.383**	-1.269*	-1.269*		0.0192**	0.0200**	0.0200**		0.0163^	0.0213**	0.0213***
		(0.669)	(0.680)	(0.651)		(0.00782)	(0.00788)	(0.00896)		(0.00995)	(0.00962)	(0.00699)
Pre-Post	-13.29***	-13.94***	-17.34***	-17.34***	0.0431***	0.0957***	0.131***	0.131***	0.0492***	0.0569***	0.243***	0.243***
	(1.127)	(1.164)	(3.470)	(2.401)	(0.0132)	(0.0297)	(0.0402)	(0.0273)	(0.0167)	(0.0173)	(0.0491)	(0.0288)
Observations	296	296	295	295	296	296	295	295	296	296	295	295
R-squared	0.000	0.014	0.194	0.194	0.000	0.060	0.207	0.207	0.000	0.009	0.264	0.264

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix Table A.1- 3: Main and moderating effects on Brand Perception drivers on first day firestorm

Table-2	A: Proportion of negative tweets				B: Intensity of negative tweets				C: Intensity of positive tweets			
	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors	Pre-Post	With Moderator	With controls	Clustered errors
Crisis type (Continuous)		0.00701	0.00548	0.00548		0.0895	0.240	0.240		-0.901	-0.511	-0.511
		(0.00628)	(0.00626)	(0.00568)		(0.539)	(0.542)	(0.494)		(0.747)	(0.746)	(0.904)
Pre-Post	0.152***	0.156***	0.356***	0.356***	2.875***	2.919***	18.39***	18.39***	-5.789***	-6.230***	3.935	3.935
	(0.0105)	(0.0109)	(0.0536)	(0.0246)	(0.896)	(0.935)	(4.638)	(3.030)	(1.246)	(1.297)	(6.383)	(3.338)
Observations	294	294	293	293	294	294	293	293	294	294	293	293
R-squared	0.000	0.004	0.213	0.213	0.000	0.000	0.194	0.194	0.000	0.005	0.209	0.209

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix Table A.1- 4: Main and moderating effects on Brand Perception and Social media polarization over multiple event windows

	A: Avge. Brand Perception with clustered errors				B: Mentions RWC with clustered errors				C: Retweet RWC with clustered errors			
	Event windows>>											
	(30,2)	(30,3)	(30,4)	(30,5)	(30,2)	(30,3)	(30,4)	(30,5)	(30,2)	(30,3)	(30,4)	(30,5)
Crisis type	-0.458	-0.0464	0.0454	0.111	0.0179***	0.0165***	0.0138**	0.0122*	0.0139*	0.0149***	0.0107^	0.0114*
(Continuous)	(0.528)	(0.438)	(0.425)	(0.363)	(0.00629)	(0.00536)	(0.00587)	(0.00670)	(0.00700)	(0.00513)	(0.00623)	(0.00613)
Pre-Post	-30.05***	-23.17***	-17.75***	-14.55***	0.102***	0.131***	0.0660**	0.0726*	0.135***	0.146***	0.0792***	0.0861***
	(1.751)	(1.787)	(1.451)	(1.583)	(0.0213)	(0.0300)	(0.0310)	(0.0363)	(0.0295)	(0.0226)	(0.0277)	(0.0273)
Observations	344	363	369	374	344	363	369	374	344	363	369	374
R-squared	0.180	0.150	0.121	0.124	0.183	0.161	0.159	0.156	0.195	0.189	0.173	0.163

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix Table A.1- 5: 3SLS Path analysis over multiple event windows

3SLS mediation results for event windows (30,2) to (30,4)												
Networks>>	Mentions>>						Retweets>>					
Intervals>>	(30,2)		(30,3)		(30,4)		(30,2)		(30,3)		(30,4)	
Covariates	Δ RWC	Δ Perc	Δ RWC	Δ Perc	Δ RWC	Δ Perc	Δ RWC	Δ Perc	Δ RWC	Δ Perc	Δ RWC	Δ Perc
Crisis type	0.0177***	0.431^	0.0163*	0.486**	0.0137***	0.615	0.0136	-0.0684	0.0148**	0.198	0.0106*	0.177
	(0.00167)	(0.311)	(0.00924)	(0.229)	(0.00317)	(0.679)	(0.0121)	(1.633)	(0.00731)	(0.185)	(0.00640)	(0.374)
Δ RWC		-51.94*		-34.27^		-42.10^		-31.66		-18.67		-13.96***
`		(30.69)		(22.45)		(33.03)		(58.01)		(19.01)		(3.199)
Pre-post	-0.00263	-11.38**	0.0716	-4.868	0.0574	-2.256	0.193***	-6.157	0.135**	-5.150	0.0479	-4.876
	(0.0295)	(4.868)	(0.0615)	(4.195)	(0.0521)	(7.080)	(0.0438)	(16.22)	(0.0628)	(5.397)	(0.0527)	(9.247)
Observations	344	344	363	363	369	369	344	344	363	363	369	369
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.15 Errors clustered at category level												

Appendix Table A.1- 6: Path analysis showing that change in network polarization explains the variance in the primary drivers of the brand perception dips

	A: 3SLS Mediation with ΔRWC (mentions)>>				B: 3SLS Mediation with ΔRWC (retweets)>>			
	Negative intensity (30,1)		Negative tweets proportion (30,1)		Negative intensity (30,1)		Negative tweets proportion (30,1)	
Covariates	Δ RWC	Δ Neg Int.	Δ RWC	Δ Neg Prop.	Δ RWC	Δ Neg Int.	Δ RWC	Δ Neg Prop.
Crisis type	0.0199**	-0.873	0.0200**	0.000972	0.0211^	-0.664	0.0212^	0.00145
	(0.00928)	(1.124)	(0.00977)	(0.00490)	(0.0129)	(1.075)	(0.0130)	(0.00470)
Δ RWC		56.28^		0.226		43.35*		0.193^
`		(43.60)		(0.402)		(22.45)		(0.150)
Pre-Post	0.0862	-7.693	0.0785	0.207**	0.167^	-9.773	0.159^	0.195***
	(0.106)	(9.120)	(0.134)	(0.0893)	(0.106)	(9.071)	(0.117)	(0.0504)
Observations	293	293	293	293	293	293	293	293
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.15 Errors clustered at category level								

Appendix Table A.1- 7: Robustness checks for main and moderating effects

(I)	A: Avge. Brand Perception with clustered errors				B: Mentions RWC with clustered errors				C: Retweet RWC with clustered errors			
Intervals>>	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)
Perf. Risk	-2.473^	-1.452	-1.205^	-1.142^	0.0171	0.00556	0.000315	-0.00127	0.0159	0.00400	0.00691	0.00283
	(1.754)	(1.336)	(0.934)	(0.781)	(0.0150)	(0.0120)	(0.0101)	(0.0135)	(0.0226)	(0.0162)	(0.0145)	(0.0161)
Pre-Post	-29.85***	-25.76***	-20.06***	-14.94***	0.0856*	0.0608^	0.109***	0.0512	0.166***	0.103**	0.109**	0.0582
	(6.325)	(4.547)	(4.152)	(2.744)	(0.0413)	(0.0356)	(0.0380)	(0.0511)	(0.0566)	(0.0424)	(0.0392)	(0.0492)
R-squared	0.192	0.183	0.155	0.126	0.189	0.166	0.145	0.147	0.251	0.188	0.180	0.168

(II)	A: Avge. Brand Perception with clustered errors				B: Mentions RWC with clustered errors				C: Retweet RWC with clustered errors			
Intervals>>	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)
Soc. Risk	1.547	0.684	-0.0667	-0.353	-0.0283^	-0.0317^	-0.0268*	-0.0188^	-0.0183	-0.00904	-0.0138	-0.00133
	(1.384)	(0.812)	(0.867)	(0.837)	(0.0208)	(0.0191)	(0.0154)	(0.0125)	(0.0150)	(0.0153)	(0.0132)	(0.0134)
Pre-Post	-41.55***	-31.92***	-22.85***	-16.48***	0.233**	0.194**	0.211***	0.119*	0.273***	0.147**	0.178***	0.0703^
	(7.323)	(4.231)	(4.374)	(3.925)	(0.0903)	(0.0774)	(0.0699)	(0.0611)	(0.0459)	(0.0528)	(0.0427)	(0.0516)
R-squared	0.187	0.179	0.150	0.121	0.194	0.178	0.155	0.152	0.252	0.189	0.181	0.168
Observations	293	344	363	369	293	344	363	369	293	344	363	369

(III)	A: E/I Index (30,1)			B: GMCK (30,1)			C: Embeddedness controversy (30,1)			C: Betweenness controversy (30,1)		
IVs>>	Moderator	Controls	Robust err	Moderator	Controls	Robust err	Moderator	Controls	Robust err	Moderator	Controls	Robust err
Crisis type	-0.00180	-0.00517	-0.00517	0.00128	0.00144	0.00144	-0.00146	0.00335	0.00335^	0.0441	0.0682^	0.0682
(Continuous)	(0.00668)	(0.00659)	(0.00638)	(0.00143)	(0.00148)	(0.00202)	(0.00330)	(0.00331)	(0.00235)	(0.0490)	(0.0484)	(0.0652)
Pre-Post	-0.0598***	-0.0733^	-0.0733***	0.0152***	0.0196^	0.0196**	0.0522***	0.137***	0.137***	0.777***	1.555***	1.555***
	(0.0116)	(0.0564)	(0.0160)	(0.00248)	(0.0146)	(0.00707)	(0.00573)	(0.0283)	(0.0173)	(0.0856)	(0.428)	(0.185)
Observations	294	293	293	275	274	274	294	293	293	282	281	281
R-squared	0.000	0.223	0.223	0.003	0.154	0.154	0.001	0.198	0.198	0.003	0.219	0.219

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix Table A.1- 8: Robustness checks for mediation effects

3SLS mediation results for alternate brand echo-chamberness measures												
Networks>>	Mentions>>						Retweets>>					
Measures>>	Emb. Cont. (30,1)		GMCK (30,1)		Bet. Cont. (30,1)		E/I Index (30,1)		Emb. Cont. (30,1)		GMCK (30,1)	
Covariates	Δ EC	Δ Perc	Δ GMCK	Δ Perc	Δ BC	Δ Perc	Δ EC	Δ Perc	Δ GMCK	Δ Perc	Δ BC	Δ Perc
Crisis type	-0.00323	-1.883	15.42	-1.032*	0.0357*	-2.614**	0.00061	-1.071	15.46	-1.031^	0.0165	-1.462^
(Continuous)	(0.00352)	(1.885)	(36.59)	(0.592)	(0.0187)	(1.239)	(0.0033)	(1.377)	(48.56)	(0.643)	(0.0332)	(0.917)
Δ RWC		-209.6		-0.0121		-38.88**		-230.2^		-0.0126^		-14.88
`		(308.5)		(0.0100)		(17.85)		(160.9)		(0.0097)		(25.84)
Pre-Post	0.0498	-7.537	1,033^	-4.041	-0.858	18.78	0.0818^	2.117	1,170**	-1.361	-0.124	-15.39
	(0.0645)	(9.360)	(648.2)	(19.28)	(1.010)	(22.32)	(0.0538)	(16.62)	(558.1)	(18.13)	(0.718)	(22.97)
Observations	293	293	293	293	293	293	293	293	293	293	293	293
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, ^ p<0.15 Errors clustered at category level												

Appendix Table A.1- 9: Robustness checks with control group

	A: Avge. Brand Perception with clustered errors				B: Mentions RWC with clustered errors				C: Retweet RWC with clustered errors			
Intervals>>	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)
Crisis type	0.0366***	0.0250***	0.0251***	0.0507***	0.0252***	0.0282***	0.0269**	0.0224**	0.0158^	0.0387**	0.0211^	0.0169^
(Continuous)	(0.0086)	(0.0083)	(0.0058)	(0.0119)	(0.0085)	(0.0059)	(0.0110)	(0.0099)	(0.0101)	(0.0151)	(0.0140)	(0.0123)
Pre-post	0.252***	0.0952**	0.216***	0.428***	0.206***	0.387***	0.0131	0.00218	0.0141	-0.0107	-0.0478	-0.0388
	(0.0865)	(0.0333)	(0.0241)	(0.0571)	(0.0385)	(0.0361)	(0.0559)	(0.0429)	(0.0470)	(0.0626)	(0.0392)	(0.0413)
Observations	217	229	239	217	229	239	868	924	964	868	924	964
R-squared	0.25	0.316	0.293	0.271	0.253	0.295	0.428	0.442	0.444	0.37	0.426	0.441

Appendix Table A.1- 10: Robustness checks: Check for reverese causality

	A: Mentions RWC with clustered errors				B: Retweets RWC with clustered errors			
	(30,1)	(30,2)	(30,3)	(30,4)	(30,1)	(30,2)	(30,3)	(30,4)
Crisis type	0.0187**	0.0190*	0.0198**	0.0195**	0.0202**	0.0206***	0.0208***	0.0203***
(Continuous)	(0.00868)	(0.00934)	(0.00897)	(0.00887)	(0.00730)	(0.00699)	(0.00706)	(0.00667)
Pre-Post	0.0788**	0.0800**	0.0869***	0.102***	0.166**	0.170**	0.165**	0.193**
	(0.0312)	(0.0352)	(0.0257)	(0.0355)	(0.0632)	(0.0684)	(0.0604)	(0.0874)
valence301	-0.00107				-0.000864			
	(0.000992)				(0.00104)			
volume301		1.24e-07^				7.29e-08		
		(7.61e-08)				(1.02e-07)		
neg_prop301			0.0431				0.0822	
			(0.0975)				(0.153)	
neg_int301				0.00218*				0.00389***
				(0.00108)				(0.000840)
Observations	293	293	293	293	293	293	293	293
R-squared	0.212	0.211	0.206	0.223	0.266	0.265	0.265	0.298

Appendix Table A.1- 11: Robustness checks: Polarization's impact on brand perceptions beyond immediate aftermath

	A: Avge. Brand Perception (-90,60)		B: Negative Tweets proportion (%) (-90,60)		C: Negative Intensity (-90,60)	
Δ RWC (Mentions)	-0.449^		0.0928*		1.651*	
	(0.353)		(0.0133)		(0.972)	
Δ RWC (Retweets)		-0.379		0.0133^		1.577**
		(0.882)		(0.0107)		(0.763)
Pre-Post	-2.646**	-2.703**	0.0352**	0.0333**	0.0618	0.0551
	(1.157)	(1.159)	(0.0163)	(0.0163)	(0.224)	(0.223)
Observations	280	280	280	280	294	294
R-Squared	0.154	0.154	0.354	0.357	0.010	0.014

Appendix Table A.1- 12: Robustness checks: Impact of immediate short-run brand perceptions on stock returns (Days 0-4)

	CARs after firestorm>>					CARs with moderator and all controls>>				
	CAR_DAY 0	CAR_DAY 1	CAR_DAY 2	CAR_DAY 3	CAR_DAY 4	CAR_DAY 0	CAR_DAY 1	CAR_DAY 2	CAR_DAY 3	CAR_DAY 4
Δ Brand Perception						0.000457***	0.000365**	0.000390**	0.000466**	0.000362*
						(0.000126)	(0.000158)	(0.000173)	(0.000190)	(0.000200)
Pre-Post	-0.00475**	-0.00889***	-0.0119***	-0.0124***	-0.0129***	0.00701	0.00302	0.00739	0.00640	0.0121
	(0.00196)	(0.00247)	(0.00272)	(0.00305)	(0.00317)	(0.0104)	(0.0130)	(0.0142)	(0.0156)	(0.0164)
Observations	281	281	281	281	281	271	271	271	271	271
R-squared	0.213	0.181	0.175	0.168	0.152	0.364	0.335	0.333	0.325	0.306

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix Table A.1- 13: Robustness checks: Impact of immediate short-run brand perceptions on stock returns (Days 5-9)

	CARs after firestorm>>					CARs with moderator and all controls>>				
	CAR_DAY 5	CAR_DAY 6	CAR_DAY 7	CAR_DAY 8	CAR_DAY 9	CAR_DAY 5	CAR_DAY 6	CAR_DAY 7	CAR_DAY 8	CAR_DAY 9
Δ Brand Perception						0.000406*	0.000519**	0.000565**	0.000478**	0.000538**
						(0.000228)	(0.000241)	(0.000256)	(0.000223)	(0.000257)
Pre-Post	-0.0142***	-0.0160***	-0.0154***	-0.0143***	-0.0134***	0.00201	-0.00324	0.00577	0.0288^	0.00911
	(0.00340)	(0.00369)	(0.00395)	(0.00393)	(0.00403)	(0.0187)	(0.0198)	(0.0210)	(0.0224)	(0.0211)
Observations	281	281	281	281	281	271	271	271	271	271
R-squared	0.000	0.000	0.000	0.000	0.000	0.233	0.259	0.262	0.130	0.289

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1, ^ p<0.2

Appendix A.2 ESSAY-2 SUPPLEMENTAL CONTENT

Appendix A.2.1 Essay-2: Supplemental List of Tables

Appendix Table A.2- 1: Number of retail stores in our sample by decile and year

	Year>>								
Deciles	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Decile 1	511	518	527	518	523`	516	681	674	652
Decile 2	1362	1388	1382	1358	1349	1263	2133	2111	2061
Decile 3	1997	2014	1994	1945	1921	1861	2904	2849	2742
Decile 4	1577	1590	1568	1541	1539	1467	2282	2232	2138
Decile 5	2474	2545	2517	2478	2423	2351	3496	3422	3307
Decile 6	2506	2519	2523	2462	2460	2362	3618	3549	3439
Decile 7	3545	3555	3539	3486	3423	3376	5203	5139	4992
Decile 8	4910	4883	4799	4772	4665	4496	6892	6767	6598
Decile 9	5804	5868	5835	5725	5696	5452	7986	7863	7677
Decile 10	11315	11441	11349	11225	11199	10990	14496	14292	13920
Grand Total	**36001**	**36321**	**36033**	**35510**	**35198**	**34134**	**49691**	**48898**	**47526**

Appendix Table A.2- 2: Number of household trips in our sample by product category, county-decile and year

	Year>>									
	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
BEER										
Decile 1	1887	1774	1806	1599	1010	842	781	912	1250	11861
Decile 2	3765	3615	3769	3529	1861	1678	1403	1508	1636	22764
Decile 3	3610	3558	3758	3811	2393	2460	2367	2364	2829	27150
Decile 4	4011	3777	4233	4130	3963	4319	4397	4426	3704	36960
Decile 5	5643	5928	6390	5901	4421	4147	4138	4138	5247	45953
Decile 6	7718	7894	7680	6959	6309	5666	5582	5207	6725	59740
Decile 7	10441	10649	10719	9750	7301	6837	6673	7243	7885	77498
Decile 8	14371	13740	14183	13453	13570	12858	11639	12600	15638	122052
Decile 9	24097	23383	23696	21425	22067	19938	18309	18456	24266	195637
Decile 10	28293	28996	28740	28006	41075	38057	36112	34786	34279	298344
CANDY										
Decile 1	15219	15319	15943	14759	7866	7220	8184	8530	8640	101680
Decile 2	26411	25827	27562	27015	15298	15142	15081	16374	19554	188264
Decile 3	31958	32203	34703	32237	23132	22516	23460	23993	24035	248237
Decile 4	40837	41162	43283	42266	35753	36446	35652	37330	33153	345882
Decile 5	48573	49818	53050	50913	40556	38682	39492	40678	46194	407956
Decile 6	71905	70599	74544	70330	56672	56187	56704	56655	56345	569941
Decile 7	72161	73927	75697	70902	62521	61614	60835	63905	71546	613108
Decile 8	104079	105990	110444	101908	105086	100103	100292	104979	115549	948430
Decile 9	180246	182290	179619	168940	161832	157768	157740	159660	169494	1517589
Decile 10	213078	217972	218053	202332	296730	288780	284048	284678	271663	2277334
CARBONATED BEVERAGES										
Decile 1	14872	14596	15082	13999	8341	8304	7861	8521	10004	101580
Decile 2	30678	30045	29014	29360	16508	15390	15276	16101	20160	202532
Decile 3	36654	35329	36650	35361	25132	24863	24198	24600	24425	267212
Decile 4	43652	41832	42639	40275	36418	34304	32694	33271	31099	336184
Decile 5	54448	54935	56304	52964	41373	37753	37086	36380	43418	414661
Decile 6	70394	68650	69167	64959	52043	48952	48339	48189	52522	523215
Decile 7	78789	76599	76643	74189	61628	58141	57657	57746	68291	609683
Decile 8	107081	104154	105511	99708	101845	93041	90189	90520	109482	901531
Decile 9	184664	181463	173986	165342	153984	142742	140757	140026	161873	1444837
Decile 10	221701	215635	202400	189522	278999	256999	246968	245217	256355	2113796
COFFEE										
Decile 1	3356	3520	3488	3471	2286	1879	1988	2021	1961	23970
Decile 2	6398	6658	6689	6743	4044	3640	3539	3429	4309	45449

Decile 3	7640	8077	8303	8024	5766	4981	4853	5113	4754	57511
Decile 4	9941	10332	10675	10497	8647	8001	7744	7956	6990	80783
Decile 5	12026	12999	12790	12588	10353	9157	9382	9509	10587	99391
Decile 6	17299	18455	18467	17626	14349	12793	12894	12412	13467	137762
Decile 7	18025	19471	20249	19935	16420	14438	14174	14281	16416	153409
Decile 8	27460	28430	28599	27710	28469	25971	25328	24679	27749	244395
Decile 9	45789	49572	47886	47146	44580	40692	40129	38182	43226	397202
Decile 10	56523	59472	58441	55646	81017	74622	71264	70625	71628	599238
CONDIMENTS, GRAVIES, AND SAUCES										
Decile 1	3849	3741	3885	3699	2272	2091	2026	1903	2026	25492
Decile 2	7687	7513	7577	7297	3968	3929	3523	3562	4308	49364
Decile 3	8874	8865	8994	8654	5946	6088	5552	5168	5654	63795
Decile 4	12157	11711	11703	11462	9939	9653	9065	8470	8087	92247
Decile 5	14356	13865	14503	13924	11262	10928	10109	9418	11995	110360
Decile 6	21308	21230	20247	19565	15687	15396	14543	13393	14818	156187
Decile 7	22261	22182	21568	20626	19270	18785	17464	16498	21021	179675
Decile 8	33007	32594	31173	30130	31246	30755	27997	26959	34139	278000
Decile 9	56451	56293	52855	50981	50132	48990	45157	42596	50885	454340
Decile 10	68788	67477	63619	60087	89709	88313	80637	75676	82090	676396
DEODORANT										
Decile 1	930	910	1040	881	579	553	499	579	611	6582
Decile 2	1826	1676	1580	1623	950	918	876	973	1056	11478
Decile 3	2030	1868	1924	2007	1524	1571	1415	1425	1474	15238
Decile 4	2509	2459	2354	2322	2137	2136	2181	2206	1712	20016
Decile 5	2991	3125	3255	2969	2396	2366	2226	2331	2770	24429
Decile 6	4121	4216	4025	3748	3365	3206	3160	3225	3227	32293
Decile 7	4713	4649	4742	4543	3891	3996	3708	3755	3988	37985
Decile 8	6786	6440	6235	6107	6669	6688	6231	6515	6746	58417
Decile 9	11775	11605	11065	10599	11149	10617	9945	10108	10400	97263
Decile 10	14435	14546	14226	13431	21097	20897	19533	19261	16982	154408
HAIR CARE										
Decile 1	2782	2668	2961	2721	1566	1437	1337	1327	1262	18061
Decile 2	4872	4736	4689	4438	2406	2366	2450	2348	2341	30646
Decile 3	5532	5494	5953	5570	3587	3881	3504	3352	3235	40108
Decile 4	7367	6910	7684	6820	6350	5898	5774	5456	4140	56399
Decile 5	8570	8871	9601	8538	6641	6761	6709	6166	6513	68370
Decile 6	12511	12341	12927	11553	9048	8616	8411	7743	7644	90794
Decile 7	12962	12948	13353	12836	10540	10305	9041	8811	9298	100094
Decile 8	18029	17291	18208	16663	17804	16538	15784	15228	15504	151049

Decile 9	32488	32418	32660	30431	29646	27132	25786	24053	24421	259035
Decile 10	36041	35491	35669	32851	51017	47587	44464	42042	36836	361998
ICE CREAM, NOVELTIES										
Decile 1	1089	1117	1058	1056	483	468	541	369	494	6675
Decile 2	2075	2138	2298	2500	1165	1092	996	1068	1329	14661
Decile 3	2344	2524	2439	2589	1431	1323	1573	1431	1392	17046
Decile 4	3550	3644	3718	3804	2827	2578	2767	2706	2234	27828
Decile 5	4560	4741	4611	4795	3154	3090	2844	2895	3401	34091
Decile 6	6888	7820	7433	7387	4919	4539	4472	4100	4697	52255
Decile 7	8228	9216	8684	8648	6001	5645	5228	5172	6784	63606
Decile 8	12148	13281	12230	11332	11286	9898	9954	9504	12291	101924
Decile 9	24329	25227	23299	23114	20859	19736	18801	17350	21661	194376
Decile 10	32512	33247	31802	29868	43858	39406	38760	35637	38448	323538
PASTA										
Decile 1	1261	1304	1284	1402	586	547	528	501	576	7989
Decile 2	2213	2091	2126	2313	1153	1133	901	870	1136	13936
Decile 3	2661	2600	2767	2681	1916	1898	1683	1565	1679	19450
Decile 4	3857	3909	4112	3722	3248	3208	2461	2613	2457	29587
Decile 5	4603	4586	4896	4758	3754	3451	3135	2950	4041	36174
Decile 6	7657	8031	7898	7317	5348	5224	4640	4424	4697	55236
Decile 7	8123	8123	8478	7732	6685	6392	5617	5555	6562	63267
Decile 8	12336	12551	12829	11938	12100	11947	10562	10220	12184	106667
Decile 9	28823	28224	27464	24239	22333	22068	18978	18751	21311	212191
Decile 10	35162	35618	34551	29747	45351	45763	38552	37493	38134	340371
SHAVING NEEDS										
Decile 1	975	857	798	675	406	313	284	283	285	4876
Decile 2	1640	1826	1408	1277	679	605	598	526	543	9102
Decile 3	2054	1994	1718	1402	992	1003	797	748	753	11461
Decile 4	2449	2390	1798	1627	1666	1533	1389	1212	930	14994
Decile 5	3102	3113	2825	2242	1634	1499	1427	1195	1362	18399
Decile 6	4064	4298	3489	2963	2608	2322	1860	1786	1708	25098
Decile 7	4472	4621	3939	3391	2928	2614	2160	1930	2207	28262
Decile 8	5993	5925	5057	4308	5002	4357	4014	3672	3701	42029
Decile 9	11518	11262	8993	8052	8367	7466	6627	5740	6249	74274
Decile 10	12803	13030	10936	9443	15145	13495	12014	10778	9918	107562
SNACKS										
Decile 1	12188	11945	12415	13081	7468	7115	7290	7476	7202	86180
Decile 2	21925	21732	22093	21877	12751	12572	12453	12951	14377	152731
Decile 3	25645	26110	27506	26963	19332	17894	17926	16981	17414	195771
Decile 4	30126	30603	31251	31045	28794	27546	27148	27307	24199	258019

Decile 5	36377	37560	39297	39495	31854	29349	28518	29147	35183	306780
Decile 6	49366	49085	49306	48066	41619	39868	40653	39590	40814	398367
Decile 7	54272	53877	55441	54736	45954	43605	43347	43625	50437	445294
Decile 8	75859	74419	75648	73458	78878	74940	75341	75257	84616	688416
Decile 9	125459	124964	122744	122237	120350	114750	112219	113294	131327	1087344
Decile 10	146085	144749	141754	136792	220758	209049	206987	208632	205492	1620298
SPICES, SEASONING, EXTRACTS										
Decile 1	79	113	105	65	37	34	33	26	42	534
Decile 2	114	157	165	160	82	70	74	51	66	939
Decile 3	116	166	159	168	108	99	111	100	89	1116
Decile 4	133	257	271	260	166	159	157	168	144	1715
Decile 5	202	320	280	266	275	244	227	192	204	2210
Decile 6	332	555	462	435	277	234	327	248	273	3143
Decile 7	380	609	592	609	442	479	499	389	467	4466
Decile 8	616	939	845	838	787	704	848	744	911	7232
Decile 9	1319	1981	1605	1760	1772	1599	1655	1462	1694	14847
Decile 10	2594	3151	3030	2987	3733	3539	3641	3441	3957	30073
VEGETABLES - CANNED										
Decile 1	3926	3600	3771	3468	1755	1568	1393	1375	1486	22342
Decile 2	8231	7448	8255	8037	3745	3214	2794	2480	2676	46880
Decile 3	9014	8548	8700	8978	6028	5633	4787	4156	4052	59896
Decile 4	10601	9551	10264	9576	8851	8546	7140	6482	6215	77226
Decile 5	12424	11481	12761	12406	9119	9076	7845	7322	8367	90801
Decile 6	18345	16950	17442	16637	12501	11241	10341	8985	9404	121846
Decile 7	20055	18586	19421	18649	14822	13243	11973	10695	13485	140929
Decile 8	26942	24319	26238	23715	26321	24467	21960	20006	23738	217706
Decile 9	47446	44193	45858	43228	40595	37645	33750	29740	34961	357416
Decile 10	57162	54418	56046	50784	72511	68997	62453	55944	56934	535249

Appendix Table A.2- 3: Revenues of UPCs in our sample by Product Category, County-Decile and Year

	Year>>									
	2012	2013	2014	2015	2016	2017	2018	2019	2020	Grand Total
BEER										
Decile 1	$28,205,007	$26,646,748	$29,513,469	$34,269,643	$12,464,617	$14,678,928	$24,637,171	$24,728,498	$27,529,391	$222,673,471
Decile 2	$58,763,884	$54,166,818	$57,878,886	$61,667,833	$27,819,425	$31,185,817	$44,035,631	$44,096,909	$51,694,390	$431,309,593
Decile 3	$75,597,152	$78,640,534	$80,048,494	$91,476,565	$39,961,167	$37,331,113	$64,347,863	$65,142,430	$69,390,354	$601,935,672
Decile 4	$98,455,114	$96,785,606	$99,216,340	$102,320,412	$75,949,883	$66,269,881	$117,629,524	$116,759,948	$103,925,470	$877,312,179
Decile 5	$168,221,970	$161,567,178	$165,583,425	$167,930,690	$93,748,261	$90,652,910	$130,189,929	$128,702,028	$164,568,546	$1,271,164,937
Decile 6	$152,124,929	$148,198,104	$149,615,716	$150,731,443	$132,134,634	$120,686,078	$198,470,958	$197,877,856	$229,757,613	$1,479,597,332
Decile 7	$255,098,670	$250,955,587	$263,643,200	$268,205,728	$171,573,308	$153,423,822	$247,666,041	$245,589,415	$323,417,422	$2,179,573,193
Decile 8	$340,924,106	$334,054,954	$331,159,369	$332,508,628	$291,883,636	$251,248,726	$440,663,678	$436,578,501	$548,503,896	$3,307,525,494
Decile 9	$676,734,559	$655,983,347	$647,697,017	$642,889,150	$591,642,597	$543,301,688	$833,755,672	$810,447,570	$1,060,610,421	$6,463,062,021
Decile 10	$803,719,037	$791,694,463	$784,592,475	$763,849,552	$1,210,421,555	$1,123,116,215	$1,625,736,248	$1,579,227,975	$1,534,860,910	$10,217,218,431
CANDY										
Decile 1	$31,188,317	$32,135,709	$34,216,216	$35,313,923	$11,967,804	$12,261,583	$14,475,332	$14,341,374	$14,821,243	$200,721,502
Decile 2	$48,873,763	$49,585,239	$51,984,959	$52,114,482	$25,090,891	$25,714,875	$28,217,282	$28,044,727	$30,809,111	$340,435,329
Decile 3	$63,236,776	$65,219,207	$67,144,937	$69,155,347	$33,732,572	$32,873,184	$39,529,419	$39,707,799	$41,957,936	$452,557,177
Decile 4	$87,787,242	$90,287,894	$92,968,072	$93,781,836	$62,784,510	$59,406,195	$72,254,253	$72,256,738	$59,945,267	$691,472,008
Decile 5	$124,094,223	$127,606,877	$131,635,153	$132,082,368	$78,449,552	$77,016,372	$91,044,655	$90,977,729	$103,870,887	$956,777,816
Decile 6	$167,238,063	$170,707,497	$173,638,064	$171,618,219	$114,515,425	$109,567,926	$135,912,368	$136,070,126	$143,312,057	$1,322,579,746
Decile 7	$191,800,327	$198,263,421	$205,497,167	$206,512,524	$141,641,638	$136,811,218	$169,766,243	$170,364,692	$214,340,706	$1,634,997,935
Decile 8	$286,140,443	$295,861,850	$299,352,209	$296,433,521	$260,212,091	$247,999,487	$311,873,376	$314,529,005	$379,126,463	$2,691,528,445
Decile 9	$604,792,417	$623,168,067	$625,367,343	$626,350,019	$519,605,774	$506,092,616	$610,751,503	$613,532,410	$729,844,394	$5,459,504,543
Decile 10	$840,439,952	$867,769,063	$875,501,004	$872,810,539	$1,273,978,320	$1,250,160,355	$1,447,195,081	$1,437,170,813	$1,357,645,942	$10,222,671,069
CARBONATED BEVERAGES										
Decile 1	$67,772,923	$65,372,750	$68,765,592	$77,422,196	$31,278,358	$32,251,235	$45,201,384	$47,243,513	$51,321,614	$486,629,563
Decile 2	$131,191,756	$122,670,496	$127,878,541	$132,800,767	$74,256,495	$79,224,963	$94,263,862	$99,122,007	$115,503,736	$976,912,624
Decile 3	$169,896,840	$165,939,348	$167,193,093	$181,801,513	$89,293,252	$86,621,912	$121,546,628	$127,491,357	$147,804,059	$1,257,588,003
Decile 4	$217,932,751	$213,346,900	$212,989,852	$217,628,214	$153,599,053	$138,092,472	$202,832,418	$210,823,763	$201,759,893	$1,769,005,316
Decile 5	$312,622,892	$304,638,719	$308,691,944	$314,505,940	$192,737,403	$187,645,831	$247,037,661	$255,176,882	$305,360,232	$2,428,417,503
Decile 6	$358,739,959	$349,015,643	$347,515,360	$344,936,062	$265,046,120	$248,626,615	$351,519,238	$366,417,917	$423,217,974	$3,055,034,889
Decile 7	$438,645,229	$434,914,430	$445,217,235	$449,631,516	$306,162,313	$292,341,224	$405,015,025	$422,399,284	$576,789,086	$3,771,115,342
Decile 8	$594,701,982	$585,920,576	$579,169,070	$580,871,067	$536,227,734	$484,734,899	$727,455,962	$757,202,891	$973,773,761	$5,820,057,941
Decile 9	$1,223,635,946	$1,193,241,817	$1,165,283,058	$1,171,069,000	$982,283,991	$930,402,627	$1,313,901,084	$1,357,847,665	$1,801,042,016	$11,138,707,204
Decile 10	$1,612,933,881	$1,573,184,312	$1,545,511,396	$1,545,914,909	$2,336,693,884	$2,218,450,931	$2,958,313,359	$3,047,647,516	$3,133,855,502	$19,972,505,689
COFFEE										
Decile 1	$19,455,378	$18,185,959	$19,638,965	$22,557,979	$8,435,970	$8,328,490	$10,273,794	$10,103,966	$10,896,639	$127,877,140
Decile 2	$38,110,656	$35,578,106	$37,556,292	$40,362,542	$21,144,215	$22,254,391	$22,784,584	$22,305,142	$26,393,593	$266,489,520
Decile 3	$50,458,272	$49,837,475	$51,014,248	$56,802,406	$25,698,351	$24,113,614	$30,018,088	$29,604,108	$36,033,168	$353,579,732
Decile 4	$69,888,229	$69,722,504	$70,778,117	$76,182,576	$49,136,563	$43,017,338	$54,547,816	$53,415,354	$55,707,322	$542,395,818
Decile 5	$101,867,286	$101,457,515	$104,195,083	$111,247,712	$64,704,045	$61,768,200	$73,944,825	$72,805,535	$91,243,302	$783,233,502

Decile 6	$126,194,686	$125,401,582	$126,214,099	$133,923,149	$91,154,091	$83,223,731	$106,799,111	$105,313,025	$138,797,304	$1,037,020,778
Decile 7	$148,600,889	$150,520,623	$155,851,224	$167,036,881	$113,391,108	$107,683,922	$136,248,189	$135,991,117	$208,559,903	$1,323,883,855
Decile 8	$217,191,730	$219,293,298	$220,031,957	$234,044,208	$213,507,016	$193,026,385	$255,472,822	$252,782,729	$375,449,110	$2,180,799,254
Decile 9	$477,680,171	$482,564,995	$479,159,502	$520,849,265	$432,488,719	$409,416,866	$522,156,824	$515,258,237	$782,355,079	$4,621,929,658
Decile 10	$631,723,660	$637,027,547	$637,997,686	$679,611,275	$1,042,141,078	$996,349,332	$1,236,090,447	$1,218,371,192	$1,533,055,364	$8,612,367,580
CONDIMENTS, GRAVIES, AND SAUCES										
Decile 1	$5,989,022	$5,560,770	$5,920,153	$6,994,995	$2,452,048	$2,431,451	$3,255,760	$3,268,857	$3,715,200	$39,588,257
Decile 2	$12,185,628	$11,300,538	$11,733,828	$12,373,680	$6,691,067	$7,296,304	$7,473,688	$7,416,584	$9,405,931	$85,877,249
Decile 3	$16,032,339	$15,748,908	$16,048,204	$17,803,596	$7,845,932	$7,462,091	$9,743,847	$9,876,761	$12,957,941	$113,519,620
Decile 4	$26,042,586	$25,642,402	$25,570,716	$26,912,740	$16,158,486	$13,675,969	$17,675,593	$17,585,171	$18,776,917	$188,040,580
Decile 5	$34,573,537	$33,967,807	$34,360,874	$36,336,624	$21,176,906	$20,166,306	$25,614,442	$25,213,069	$30,455,558	$261,865,123
Decile 6	$45,085,676	$44,503,268	$44,074,551	$45,225,551	$31,295,120	$28,891,170	$39,466,616	$39,346,281	$49,664,559	$367,552,793
Decile 7	$49,692,828	$49,944,362	$51,065,316	$52,927,117	$39,755,557	$37,547,311	$49,931,100	$50,295,816	$73,289,341	$454,448,747
Decile 8	$76,471,674	$76,956,259	$75,713,966	$77,637,542	$69,873,239	$62,092,653	$86,613,379	$86,771,090	$125,512,591	$737,642,393
Decile 9	$179,040,411	$179,391,625	$175,606,967	$180,541,307	$146,195,153	$139,629,109	$187,708,402	$185,777,942	$251,362,233	$1,625,253,149
Decile 10	$232,444,886	$231,210,597	$226,070,295	$228,824,611	$350,531,200	$335,082,758	$435,763,786	$432,017,804	$509,823,023	$2,981,768,961
DEODORANT										
Decile 1	$2,301,845	$2,424,137	$2,762,709	$3,013,206	$804,064	$835,390	$862,993	$881,357	$912,620	$14,798,321
Decile 2	$3,990,294	$4,034,316	$4,418,732	$4,629,100	$1,820,880	$1,901,043	$1,951,207	$2,045,001	$2,078,302	$26,868,875
Decile 3	$5,011,126	$5,173,548	$5,556,162	$6,006,141	$2,732,080	$2,792,675	$3,084,917	$3,297,201	$3,255,463	$36,909,313
Decile 4	$7,406,826	$7,722,843	$8,254,668	$8,814,663	$5,920,673	$5,844,273	$6,576,828	$6,935,736	$4,862,454	$62,338,964
Decile 5	$11,136,162	$11,527,673	$12,568,202	$13,302,634	$7,303,893	$7,473,977	$8,458,003	$9,034,372	$10,235,603	$91,040,519
Decile 6	$14,970,178	$15,428,149	$16,475,249	$17,228,211	$11,027,494	$10,999,908	$12,987,259	$13,856,227	$14,226,824	$127,199,499
Decile 7	$19,212,693	$20,151,129	$22,116,597	$23,338,219	$14,749,925	$14,796,561	$17,832,586	$18,849,979	$22,396,878	$173,444,567
Decile 8	$30,537,414	$31,680,634	$33,944,185	$35,802,721	$30,134,521	$30,244,128	$35,602,256	$37,686,026	$44,522,393	$310,154,275
Decile 9	$69,371,163	$71,384,289	$75,919,421	$80,890,674	$67,500,118	$69,431,981	$81,982,616	$86,109,045	$102,998,737	$705,588,043
Decile 10	$121,611,814	$124,700,922	$132,684,703	$140,666,096	$212,901,037	$218,001,115	$246,795,239	$256,154,635	$222,592,733	$1,676,108,295
HAIR CARE										
Decile 1	$8,522,945	$8,574,463	$9,333,463	$9,238,716	$2,519,571	$2,487,702	$2,309,108	$2,187,959	$2,300,983	$47,474,911
Decile 2	$14,263,506	$14,110,141	$14,792,342	$14,174,734	$5,559,687	$5,415,170	$5,117,377	$4,950,386	$5,048,888	$83,432,231
Decile 3	$17,533,208	$17,503,516	$18,175,036	$18,004,677	$8,022,314	$7,635,370	$7,744,818	$7,599,286	$7,905,118	$110,123,343
Decile 4	$25,129,500	$25,093,556	$26,084,472	$25,816,150	$17,385,298	$16,066,137	$16,358,399	$15,539,694	$11,654,720	$179,127,927
Decile 5	$37,286,716	$37,535,103	$39,622,546	$38,752,979	$20,882,582	$19,794,751	$20,975,721	$20,171,089	$22,481,291	$257,502,779
Decile 6	$51,786,653	$51,390,158	$52,870,609	$51,511,991	$31,162,398	$28,811,128	$31,534,448	$30,328,796	$32,307,316	$361,703,498
Decile 7	$66,057,542	$66,771,645	$71,107,412	$70,204,533	$41,337,494	$38,422,614	$43,357,447	$41,449,558	$50,395,587	$489,103,833
Decile 8	$101,964,498	$101,999,345	$105,146,525	$102,526,423	$82,009,547	$75,482,506	$82,833,919	$79,593,597	$97,262,635	$828,818,994
Decile 9	$225,708,524	$225,205,416	$229,819,785	$226,274,510	$177,734,519	$166,414,122	$183,156,837	$174,685,154	$216,267,484	$1,825,266,351
Decile 10	$346,195,819	$346,730,848	$351,186,884	$342,472,879	$497,122,104	$466,575,742	$488,943,239	$465,707,068	$424,510,949	$3,729,445,532
ICE CREAM, NOVELTIES										
Decile 1	$3,839,898	$3,648,777	$4,048,856	$5,096,996	$1,277,287	$1,332,990	$1,929,896	$2,019,123	$2,123,892	$25,317,714
Decile 2	$6,248,081	$5,670,121	$6,060,016	$7,369,817	$3,243,750	$3,579,634	$4,156,910	$4,314,930	$5,080,313	$45,723,573
Decile 3	$8,712,525	$8,537,493	$9,008,859	$10,825,810	$4,279,574	$4,155,929	$5,878,128	$6,215,510	$7,250,783	$64,864,611
Decile 4	$14,607,027	$14,160,668	$14,663,682	$16,636,766	$10,367,393	$9,435,926	$12,577,538	$13,043,165	$12,078,022	$117,570,187
Decile 5	$21,677,844	$21,206,320	$22,467,972	$25,932,240	$13,009,282	$12,910,064	$16,314,653	$16,980,604	$21,317,301	$171,816,280
Decile 6	$30,190,514	$29,158,570	$29,970,800	$32,385,756	$20,031,040	$19,005,652	$25,734,722	$27,098,642	$32,289,709	$245,865,404

Decile 7	$39,710,062	$39,530,116	$41,786,283	$46,515,319	$26,794,817	$26,045,170	$35,022,140	$36,654,325	$53,324,259	$345,382,492
Decile 8	$61,486,757	$60,528,754	$61,137,627	$66,062,572	$53,701,398	$50,461,814	$69,048,624	$71,129,902	$101,746,296	$595,303,745
Decile 9	$153,217,971	$150,359,673	$148,431,835	$158,822,293	$127,619,971	$125,819,841	$165,734,023	$169,023,218	$245,568,430	$1,444,597,254
Decile 10	$233,017,423	$228,390,259	$228,623,663	$237,936,691	$364,539,304	$362,999,145	$460,975,069	$464,300,253	$523,031,553	$3,103,813,360
PASTA										
Decile 1	$1,266,485	$1,838,624	$2,028,790	$2,404,326	$557,053	$566,806	$662,278	$691,199	$680,026	$10,695,586
Decile 2	$1,553,347	$2,238,826	$2,429,104	$2,717,507	$1,370,578	$1,636,389	$1,541,073	$1,528,076	$1,832,972	$16,847,873
Decile 3	$2,279,953	$3,588,413	$3,897,901	$4,511,827	$1,629,912	$1,653,496	$1,918,989	$1,924,615	$2,561,140	$23,966,246
Decile 4	$4,442,914	$6,823,109	$7,137,072	$7,436,596	$4,285,108	$3,888,890	$4,479,797	$4,417,514	$4,379,528	$47,290,527
Decile 5	$6,299,965	$9,592,629	$10,330,841	$11,140,997	$5,675,505	$5,628,807	$6,568,041	$6,504,886	$7,973,478	$69,715,149
Decile 6	$9,626,337	$14,099,285	$14,382,834	$14,776,905	$8,449,356	$8,035,033	$10,101,463	$10,179,412	$12,776,524	$102,427,149
Decile 7	$11,431,825	$17,404,291	$18,366,273	$19,673,632	$11,058,841	$10,760,325	$13,007,831	$13,258,260	$20,353,588	$135,314,867
Decile 8	$17,698,143	$26,290,151	$26,387,015	$27,871,335	$22,468,603	$21,137,262	$26,863,763	$27,636,366	$39,740,276	$236,092,915
Decile 9	$52,892,751	$75,669,013	$73,846,198	$77,435,095	$55,269,576	$53,797,658	$67,913,517	$68,974,663	$99,164,734	$624,963,204
Decile 10	$73,042,751	$107,163,094	$103,880,044	$109,092,418	$163,364,145	$157,518,913	$192,912,426	$194,806,695	$222,818,926	$1,324,599,411
SHAVING NEEDS										
Decile 1	$7,154,996	$7,174,269	$7,147,054	$7,212,222	$1,667,323	$1,396,338	$1,320,475	$1,275,636	$1,275,556	$35,623,869
Decile 2	$12,093,533	$11,854,336	$11,388,053	$10,920,586	$3,596,405	$3,109,999	$3,110,317	$3,058,330	$3,005,518	$62,137,077
Decile 3	$14,635,651	$14,452,583	$13,656,412	$13,657,234	$5,509,494	$4,597,462	$4,900,175	$4,743,894	$4,591,774	$80,744,680
Decile 4	$21,863,675	$21,702,985	$20,584,147	$20,335,381	$12,525,229	$10,252,017	$12,092,901	$11,437,723	$6,873,064	$137,667,121
Decile 5	$33,587,862	$33,604,507	$32,391,837	$31,609,417	$14,918,579	$12,759,146	$13,880,664	$13,371,653	$15,763,716	$201,887,379
Decile 6	$45,617,809	$44,963,059	$42,016,364	$40,570,755	$22,819,978	$19,038,755	$22,251,202	$21,016,984	$21,330,343	$279,625,250
Decile 7	$58,633,341	$58,919,207	$56,345,257	$54,850,838	$30,785,027	$25,978,045	$29,989,897	$28,317,890	$33,401,771	$377,221,274
Decile 8	$93,273,602	$92,323,525	$87,204,119	$84,294,274	$64,617,090	$54,388,762	$62,499,268	$58,824,139	$67,374,879	$664,799,658
Decile 9	$209,328,061	$207,810,306	$194,851,244	$189,272,993	$142,909,137	$123,472,412	$136,210,819	$126,931,922	$149,382,792	$1,480,169,686
Decile 10	$335,406,475	$334,019,650	$315,788,022	$304,616,367	$418,119,817	$359,230,298	$383,587,279	$356,434,314	$299,753,600	$3,106,955,821
SNACKS										
Decile 1	$28,909,634	$28,391,788	$29,986,434	$34,720,311	$12,756,300	$13,216,492	$17,897,408	$18,461,995	$19,546,303	$203,886,664
Decile 2	$51,033,450	$49,145,812	$51,064,764	$53,769,048	$28,964,112	$31,199,013	$36,141,795	$37,516,889	$41,970,775	$380,805,657
Decile 3	$66,478,277	$66,669,205	$67,256,738	$74,816,011	$35,601,818	$34,885,373	$47,293,356	$48,810,301	$56,463,516	$498,274,594
Decile 4	$92,542,109	$93,177,196	$93,832,235	$96,377,688	$65,527,081	$59,801,837	$82,648,731	$85,667,094	$77,578,413	$747,152,384
Decile 5	$132,725,930	$132,193,162	$133,380,995	$137,208,782	$81,848,535	$81,141,976	$104,111,158	$107,059,754	$121,881,338	$1,031,551,629
Decile 6	$152,996,469	$152,782,445	$151,768,978	$151,948,631	$115,983,290	$111,538,124	$152,915,709	$157,643,647	$177,845,775	$1,325,423,069
Decile 7	$195,031,402	$198,473,210	$203,746,359	$207,634,117	$134,043,417	$130,317,799	$179,637,895	$186,788,338	$247,790,299	$1,683,462,836
Decile 8	$275,077,551	$277,930,328	$274,938,945	$276,182,185	$247,603,024	$232,591,553	$336,713,589	$351,995,060	$443,550,873	$2,716,583,107
Decile 9	$593,446,469	$592,227,258	$580,876,315	$585,378,941	$491,165,959	$485,160,376	$671,773,892	$700,059,404	$904,469,106	$5,604,557,719
Decile 10	$785,313,203	$786,588,675	$779,470,097	$767,896,681	$1,215,157,902	$1,211,598,862	$1,595,717,489	$1,669,849,823	$1,687,516,925	$10,499,109,656
SPICES, SEASONING, EXTRACTS										
Decile 1	$128,875	$165,609	$195,644	$241,510	$65,194	$58,646	$80,921	$68,421	$53,210	$1,058,029
Decile 2	$286,088	$370,753	$393,914	$420,606	$192,006	$166,100	$201,246	$162,148	$167,319	$2,360,180
Decile 3	$409,239	$543,230	$568,518	$638,547	$206,379	$175,272	$256,406	$217,507	$254,128	$3,269,228
Decile 4	$561,042	$746,483	$745,930	$805,912	$542,509	$440,363	$620,687	$520,925	$440,483	$5,424,333
Decile 5	$1,026,803	$1,354,749	$1,395,389	$1,475,429	$684,149	$586,665	$773,387	$657,429	$755,541	$8,709,542
Decile 6	$1,151,998	$1,540,786	$1,560,265	$1,615,984	$916,955	$774,215	$1,083,648	$967,863	$1,220,334	$10,832,049
Decile 7	$1,604,589	$2,069,403	$2,157,615	$2,264,572	$1,196,540	$898,501	$1,268,822	$1,165,443	$1,794,659	$14,420,144

Decile 8	$2,892,473	$3,499,366	$3,471,487	$3,606,152	$2,537,655	$1,998,425	$2,850,927	$2,607,373	$3,499,207	$26,963,064
Decile 9	$6,691,639	$8,091,520	$7,687,470	$7,859,767	$5,727,156	$5,043,693	$7,145,183	$6,847,879	$9,825,456	$64,919,763
Decile 10	$13,494,022	$15,040,206	$14,369,602	$14,415,957	$19,222,088	$17,347,279	$24,064,408	$24,557,711	$29,385,903	$171,897,176
VEGETABLES - CANNED										
Decile 1	$4,725,934	$3,749,722	$4,042,103	$4,807,038	$1,633,268	$1,529,068	$2,013,379	$1,962,465	$2,092,777	$26,555,754
Decile 2	$9,007,577	$7,152,950	$7,666,914	$7,973,206	$4,200,279	$4,417,856	$4,247,684	$4,216,073	$5,279,736	$54,162,275
Decile 3	$12,288,131	$10,457,137	$10,775,378	$11,838,305	$4,868,143	$4,463,502	$5,872,842	$5,885,555	$7,073,784	$73,522,776
Decile 4	$17,354,854	$14,937,730	$15,280,345	$15,285,855	$10,028,941	$8,401,474	$10,371,080	$9,943,711	$10,029,315	$111,633,305
Decile 5	$24,919,033	$21,503,222	$21,961,430	$22,027,237	$12,512,157	$11,806,044	$13,800,418	$13,330,626	$15,246,147	$157,106,313
Decile 6	$29,014,745	$25,097,392	$24,941,330	$24,203,813	$17,463,888	$15,770,466	$19,823,456	$19,231,723	$23,876,819	$199,423,632
Decile 7	$33,445,390	$30,145,277	$31,096,839	$30,555,551	$20,967,942	$19,929,011	$23,564,177	$23,293,132	$33,229,164	$246,226,484
Decile 8	$46,067,304	$41,487,923	$40,776,245	$40,333,850	$37,353,799	$31,769,962	$42,531,323	$42,268,317	$57,846,724	$380,435,448
Decile 9	$105,752,439	$96,748,293	$93,316,958	$92,539,253	$73,984,842	$68,523,257	$87,626,087	$86,874,768	$119,385,729	$824,751,627
Decile 10	$141,186,473	$129,159,480	$123,461,620	$119,307,596	$181,758,472	$166,871,782	$212,509,887	$213,016,425	$246,566,564	$1,533,838,300
Grand Total	**$18,380,638,799**	**$18,324,664,051**	**$18,318,355,425**	**$18,579,602,121**	**$18,570,736,698**	**$17,628,091,347**	**$23,204,028,046**	**$23,395,862,928**	**$26,927,512,429**	**$183,329,491,843**

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