WHEN CORPORATE SILENCE IS COSTLY: NEGATIVE CONSUMER RESPONSES TO CORPORATE SILENCE ON SOCIAL ISSUES

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ABSTRACT

The growth of corporate activism on contentious social issues creates a puzzle as to why companies would risk engaging on divisive topics. Indeed, a mixed body of evidence identifies that such activism often reduces stakeholder support. We shed light on this puzzle by reversing attention to the costs of *not* engaging in corporate activism. Grounded in the cognitive model of stakeholder behavior, we theorize whether and when consumers will negatively respond to corporate silence on a social issue based on the visibility of silence. Our theory also suggests that peer activism and market niche are pivotal contingencies that exacerbate or mitigate such negative responses. Using a rigorous within-company cross-platform difference-in-differences econometric model, we find support for our theory and uncover substantial costs of corporate inaction.

MANAGERIAL SUMMARY

We study stakeholder responses to corporate silence on social issues, using the empirical context of fashion firms and the Blackout Tuesday event in support of the Black Lives Matter movement, which occurred on Instagram but not Twitter. We find that there are sizeable risks to staying silent on a highly salient social issue. For firms that do not participate in the event, follower growth slows 33% and likes on their posts drop 12% in the following month on Instagram as compared to Twitter. In addition to issue salience, managers should closely attend to peer activism, which exacerbates these negative reactions. They should also consider their market niche, as a narrow niche offers protection while firms with a wider market experience larger declines in stakeholder support.

INTRODUCTION

> "We've come to understand that to be silent about the violence and threats to the lives and well-being of Black people is to be complicit in that violence and those threats." – Ben & Jerry's, 2016[1]

[1] https://www.benjerry.com/whats-new/2016/why-black-lives-matter

> "If you say something, it's about what you say. But equally you are at risk if you say nothing, because silence is a statement, so silence is controversial, as well." – Temin and Company, a crisis consultancy[2]

Companies and their CEOs increasingly speak out on divisive social issues that are peripheral to their core business activities (Gelles & Sorkin, 2021; Sonnenfeld, 2021). These include public statements advocating for or against polarizing issues like transgender rights, religious freedom, voting restrictions, and racial justice. The growing public engagement of companies in these debates stands out as a departure from traditional preferences for quiet influence strategies and against engagement on contentious issues that can reduce stakeholder support, summed up as the "Michael Jordan dictum that Republicans buy sneakers too" (Chatterji & Toffel, 2018). Indeed, there are many reasons why companies would refrain from such activism: besides alienating misaligned stakeholders (Burbano, 2021; Hou & Poliquin, 2023), divisive social issues are unlikely to be closely related to corporate priorities or competencies (Bundy, Shropshire, & Buchholtz, 2013; Kaul & Luo, 2018), and activism exposes companies to allegations of hypocrisy to the extent that their actions are inconsistent with their stance (Carlos & Lewis, 2018; Melloni, Patacconi, & Vikander, 2023; Vredenburg et al., 2020; Wang et al., 2022).

A growing literature seeks to understand the surprising rise of corporate activism and its implications for performance (Hambrick & Wowak, 2021; Mohliver, Crilly, & Kaul, 2023; Melloni et al., 2023). The evidence so far is mixed: studies find a positive response from aligned stakeholders (Chatterji & Toffel, 2019; Mkrtchyan, Sandvik, & Zhu, 2023; Wowak, Busenbark, & Hambrick, 2022), an asymmetric negative response from misaligned stakeholders that

[2] https://www.bloomberg.com/news/articles/2023-10-19/israel-hamas-war-puts-pressure-on-ceos-and-companies-to-speak-up

surpasses any support from aligned stakeholders (Bedendo & Siming, 2021; Bondi, Burbano, & Dell'Acqua, 2024; Burbano, 2021; Hou & Poliquin, 2023; Hydock, Paharia, & Blair, 2020; Mukherjee & Althuizen, 2020; Wang et al., 2022), or no response at all (Chatterji & Toffel, 2019). Given these inconsistent responses and the relative lack of experience with the practice, corporate activism remains a fundamentally risky endeavor.

In this study, we shed light on the enduring puzzle of why corporate leaders are exposing themselves to this risk by reversing the direction of inquiry to consider stakeholder responses to *corporate silence* on contentious social issues. As theorists note, companies have two possible responses to these issues: “speaking up versus staying silent” (Hambrick & Wowak, 2021, p. 38). For executives hoping to avoid the spotlight, silence is intended to convey neutrality: a company that stays silent on a contentious issue is not expressing support for or against an issue, and so there should be no change in stakeholder responses (Melloni et al., 2023; Mohliver et al., 2023). However, in a societal context of increasing polarization and expectations of corporate activism (Barber & Blake, 2023; Benton, Cobb, & Werner, 2022; Edelman, 2018; Hurst, 2023; Iyengar & Westwood, 2015), silence also risks being viewed as picking a side on an issue (see the opening quotes). In this scenario, silent companies will again be exposed to negative evaluations from misaligned stakeholders, disappointed expectations, and apparent hypocrisy if companies are benefitting from the support of stakeholders that favored corporate activism. As neutrality disappears, the costs of corporate silence may increase, and activism may become a less costly and risky option than inaction (McDonnell, 2016; Odziemkowska & McDonnell, 2023).

Grounded in the cognitive model of stakeholder behavior (Barnett, 2012; Lange, Bundy, & Park, 2022; Vogel, 2005), we theorize whether and when stakeholders such as consumers will negatively respond to corporate silence on a social issue based on the visibility of silence. The emerging literature on stakeholder responses to corporate activism emphasizes stakeholder alignment (Burbano, 2021; Chatterji & Toffel, 2019; Hambrick & Wowak, 2021; Hou & Poliquin, 2023; Melloni et al., 2023; Mohliver et al., 2023; Wang et al., 2022; Wowak et al., 2022), which affects stakeholder evaluations depending on whether they are for or against a company's position. In contrast, we argue that the visibility of silence is central to stakeholder responses because it drives the ability of stakeholders to observe, interpret, and ultimately react to corporate silence (Barnett, 2012). If stakeholders do not notice what a company did or did not do, then they cannot reward or punish the company for this behavior (Barnett, 2012; Hawn & Ioannou, 2016; Marquis, Toffel, & Zhou, 2016). For highly salient issues, stakeholders will pay more attention to corporate behavior on the issue, take more time to assess the meaning of this behavior (Barnett, 2012; Durand, Hawn, & Ioannou, 2019; Mohliver et al., 2023), and are also more likely to expect activism from companies (Hambrick & Wowak, 2021; Wowak et al., 2023). As a result, key stakeholders such as consumers will be more disappointed by corporate inaction on highly salient issues, triggering negative consumer responses to corporate silence.

Furthermore, we theorize peer activism and market niche as pivotal contingencies that respectively elevate and diminish the visibility of silence. Peer activism increases negative reactions to corporate silence by making it easier to notice silence, to assess it as a deliberate choice, and for those who favored activism, to punish the silent firm as an isolated bad actor (Barnett, 2012; Briscoe & Safford, 2008; Reid & Toffel, 2009; Soule, Swaminathan, & Tihanyi, 2014). In contrast, a narrow market niche mitigates negative reactions to corporate silence by decreasing the visibility of firm behavior compared with mass market firms, and by reducing accountability for silence as a deliberate choice (Barnett, 2012; Bartley & Child, 2014; Carroll & Swaminathan, 2000; Graf-Vlachy et al., 2020; King & McDonnell, 2015).

One reason that extant research focuses on corporate activism over silence is the greater feasibility of studying actions rather than inactions. It is difficult to find suitable research designs to identify the effects of silence. We take advantage of a propitious natural experiment provided by the Blackout Tuesday event organized by supporters of the Black Lives Matter (BLM) movement. As part of this event, companies expressed their support for the highly salient social movement of racial justice by replacing their social media content on Instagram with a black square on June 2, 2020. At the same time, this event did not take place on Twitter, which allows us to construct a *within-company* cross-platform difference-in-differences test of how corporate silence (i.e., not participating in Blackout Tuesday) affected stakeholder responses in terms of social media engagement, which can be considered a proxy for customer support (cf. Hou & Poliquin, 2023; Kim & Youm, 2017; Wang et al., 2022). The results from this analysis provide causal evidence in support of our theory. We find that on average, the silent firms' follower growth slowed by around 33% and they received approximately 12% fewer likes due to corporate inaction on a highly salient social issue. Our results also show that while peer activism exacerbates the negative stakeholder reactions to corporate silence, a niche market mitigates such dark side effects of inaction. These effects are substantial and imply that the classic notion that firms can be protected by staying silent on sociopolitical issues may no longer hold in today's world (Maake, 2023).

This paper contributes primarily to the growing literature on corporate activism by complementing prior research on the consequences of expressing a position on a contentious social issue. Previous studies have commented on the risks of silence (Chatterji & Toffel, 2018; Hambrick & Wowak, 2021; Wowak et al., 2022), but few if any papers have focused on stakeholder responses to silence. Our theoretical framework on the distinct drivers of stakeholder response to silence, based on visibility rather than stakeholder alignment, substantiates the importance of studying silence as its own phenomenon. Regardless of stakeholder alignment, silence will only be consequential if its visibility is elevated by peer activism and by the focal firm occupying a broad market niche. These findings are also counterintuitive from the literature on corporate activism where, for example, peer activism is expected to reduce the value of a focal company's activism due to perceived inauthenticity and bandwagon behavior. Further, by demonstrating that silence can be costly too, we help to resolve the puzzle of why an increasing number of companies are taking the risk to speak out on contentious issues. Although activism by mass market firms risks angering misaligned stakeholders, we demonstrate that these firms are also exposed to heightened risks from silence. These results can enhance the way scholars think theoretically about stakeholder alignment, cheap talk, and the costs and benefits of counter-positioning on social issues (Hambrick & Wowak, 2021; Melloni et al., 2023; Mohliver et al., 2023). Secondarily, we contribute to research on stakeholder strategy by elaborating the cognitive model of stakeholder response to corporate behavior (Barnett, 2012; Lange, Bundy, & Park, 2022). We substantiate this model and extend it to consider how stakeholders react to corporate acts of omission as well as commission. In addition, we utilize cutting-edge deep learning methods like GAN-BERT to construct variables from corporate social media posts, extending the application of machine learning to strategy research (Choudhury et al., 2019).

THEORIZING STAKEHOLDER RESPONSES TO CORPORATE SILENCE

According to the cognitive view of stakeholder behavior, many acts of corporate misconduct go unpunished, just as many acts of corporate virtue go unrewarded (Vogel, 2005), in large part because of limits on the abilities of stakeholders to notice, assess, and react to corporate behavior

(Barnett, 2012). Given the boundless number of corporate actions and inactions to notice, the difficulties in assessing their meaning, and the costs to punish or reward companies, most of the time stakeholders will fail to respond to corporate behavior, regardless of stakeholder alignment with this behavior. Consequently, most potential events where stakeholders might challenge corporate behavior pass without recognition (Hoffman & Ocasio, 2001; McAdam & Boudet, 2012).

Further, such stakeholder passivity should be especially likely when the corporate behavior involves the absence of action. First, it is more difficult to notice something that did not happen. Second, the meaning of inaction is more ambiguous since there is typically no statement explaining the company's decision not to act. Third, the costs of rewarding or penalizing an inaction are higher because there is no clear locus of activity to direct a response towards. In what follows, we reverse the focus in Barnett (2012) of explaining why stakeholders do not react to corporate behavior, to theorize factors that enhance the visibility of corporate silence on a social issue, triggering stakeholder reactions.

To begin, corporate silence on a highly salient social issue will be much more visible to stakeholders than silence on an inconspicuous social issue (Hambrick & Wowak, 2021). Following Mohliver et al. (2023, p. 1202), "the salience of a social issue captures both its pervasiveness and its valence," which refers to the number of stakeholders who care about the issue and the intensity of their concern. Stakeholders care deeply about some subset of a nearly infinite number of potential social issues (Best & Loseke, 2003; Durand et al., 2019; McAdam & Boudet, 2012). Since stakeholders have cognitive and resource limits, they can only attend to a sliver of the plausibly important issues (Barnett, 2012). Given these capacity constraints, potential issues and their advocates compete for salience (Hilgartner & Bosk, 1988).

Social movements play a key role in shaping the competition for issue salience. Activists use dramatic tactics to gain media coverage and direct stakeholder attention to an issue (Amenta et al., 2009; Gamson & Modigliani, 1989; Lipsky, 1968). By framing an issue as urgent and its supporters as worthy, unified, numerous, and committed, they also drive further support for their cause (Bailey et al., 2023; Snow et al., 1986). As a result, social movements are especially effective in elevating issue salience and agenda setting (Best, 2012; Soule & King, 2006). For example, expressions of anger by BLM activists at protests attract attention, mobilize supporters, and compel responses from authorities (Kudesia, 2021). In the long run, by innovating and propagating new ideas, social movements are also able to shift attitudes and values, as is evident in the increase in support for civil rights in the U.S. in the 20th century (Rochon, 1998). At the same time, successful movements often trigger opposition and countermobilization from stakeholders with opposing interests and values (Meyer & Staggenborg, 1996). The resulting battle between conflicting movements further elevates attention to an issue (Rohlinger, 2006), as also occurred in the emergence of an "All Lives Matter" opposition to the BLM movement (Paul, 2019). In sum, a vigorous social movement will engage more stakeholders on an issue, both for and against, and intensify how much they care about the issue, increasing issue salience.

Issue salience in turn shapes stakeholder responses to corporate silence. For highly salient issues (such as BLM for racial justice), stakeholders will pay more attention to corporate behavior on the issue, take more time to assess the meaning of this behavior, and invest more effort in rewarding or punishing it (Barnett, 2012; Durand et al., 2019; Mohliver et al., 2023). Stakeholders are also more likely to expect activism from companies on a highly salient issue (Hambrick & Wowak, 2021; Wowak et al., 2023). As a result, key stakeholders such as consumers will be more disappointed by inaction. When a social issue such as BLM for racial justice is highly salient to the public, the possibility for neutrality disappears, and stakeholders will increasingly interpret silence as picking the other side, thus triggering negative reactions.

Conceptually, this dynamic applies across the ideological spectrum of liberal-conservative (cf., Hambrick & Wowak, 2021). Liberals will be angry that a silent company did not vocally endorse a liberal position on an issue or reject a conservative position. Likewise, conservatives will be angry that the company did not vocally endorse a conservative position or reject a liberal one. Issue salience will lead both liberals and conservatives to pay more attention to corporate behavior, interpret its alignment with their stances, and take the effort to reward or punish it accordingly. As issue salience increases, each side becomes more likely to expect corporate action that directly aligns with their preferences, and hence more likely to negatively respond to inaction. Table 1 provides a synopsis of how our theoretical framework applies across stakeholder issue alignment.

INSERT TABLE 1 HERE

At the same time, if corporate action in alignment with one side is becoming the norm, then the “losing side” may be satisfied with neutrality as a partial win (i.e., at least the company did not speak out against that stakeholder’s position). However, there are often asymmetric responses due to violated expectations and greater emotional intensity, leading misaligned stakeholders to punish a firm more than aligned stakeholders reward it (Bondi et al., 2024; Burbano, 2021; Hou & Poliquin, 2023; Hydock, et al., 2020; Mukherjee & Althuizen, 2020; Wang et al., 2022). Our cognitive perspective also argues for stronger responses from misaligned stakeholders because behavior that violates expectations is much more visible than behavior that conforms to expectations, and it triggers greater efforts to interpret and respond to the behavior (Barnett, 2012). These asymmetric cognitive processes should be especially strong for nonactions, which are more difficult to notice, assess, and reward or punish. So even if one side prefers silence, it is likely to be outweighed by the stronger negative response from the opposing side. Moreover, when corporate actions align with one side on an issue, it suggests that there is greater stakeholder support for this side (Hambrick & Wowak, 2021; McKean & King, 2024), fueling the asymmetrically negative reactions to silence.

Following these arguments, we hypothesize:

H1: Stakeholders (i.e., consumers) will punish firms for staying silent on a highly salient social issue (such as BLM for racial justice).

An important component of this hypothesis is a highly salient social issue. If the movement-countermovement dynamics discussed above did not elevate the saliency of an issue, then there should be more room for neutrality, and we would not expect corporate silence to trigger a negative stakeholder response.

Contingency of Peer Activism

Next, we consider contingencies that can shift the visibility of silence and exacerbate or mitigate negative stakeholder responses to corporate silence. First, we argue that silence is more visible with peer engagement on an issue. Stakeholders evaluate a firm in comparison with its peers (Pollock et al., 2019; Sharkey & Bromley, 2015). If a company's peers stay silent, then there is a "safety in numbers" effect that normalizes a silent firm's behavior (Ahmadjian & Robinson, 2001). Stakeholders may attribute silence to larger industry conditions, rather than to a willful choice by a focal firm (Liu, Wang, & Li, 2022). Against a background of shared silence, it also becomes more difficult for a stakeholder to notice an individual firm's inaction, assess its meaning, and punish it (Barnett, 2012). Since the objectionable behavior is common across a group of firms, efforts to punish any one firm will seem more futile to a stakeholder who expected engagement on the issue (Barnett, 2012).

However, if peers take a stand on an issue and engage in corporate activism, then silence becomes much more visible (Hambrick & Wowak, 2021). The sharp contrast with vocal firms makes it much easier for stakeholders to notice and assess the meaning of silence as a deliberate choice (Barnett, 2012). It will also appear more rewarding to punish a silent firm when a stakeholder can focus their response on that firm alone (Barnett, 2012). Altogether, peer activism makes it more likely that stakeholders will notice, assess, and react to corporate behavior that they oppose (Barnett, 2012). In related findings on activism targeting companies, the acceptance of activist demands by peer firms creates tremendous pressure on bystander firms to also concede (Briscoe & Safford, 2008; Reid & Toffel, 2009; Soule, Swaminathan, & Tihanyi, 2014). Companies may also turn to activism to escape these pressures (McDonnell, 2016; Odziemkowska & McDonnell, 2023).

We also argue that the amplification effect of peer activism applies to stakeholders across liberal and conservative ideologies. For each camp, silent firms will become more noticeable for not declaring their allegiances. As peer activism ramps up the expectations for corporate engagement on an issue, stakeholders on either side will be more likely to notice silence, interpret it as picking the other side, and make the effort to punish it. In cases where peer activism concentrates on one side of an issue, it is possible that stakeholders aligned with the other side will react favorably to silence by a focal firm. However, the large number of activist companies also creates a “safety in numbers” effect (Ahmadjian & Robinson, 2001), making it harder for misaligned stakeholders to focus their scorn on a particular activist company. These stakeholders on the “losing side” will then put greater pressure on each holdout to declare their opposition to the "winning side" and disconfirm suspicions that they are aligned with the prevailing position (cf., Hurst, 2023). Moreover, asymmetric processing by stakeholders that favored activism (Bondi et al., 2024; Burbano, 2021; Hou & Poliquin, 2023; Hydock et al., 2020; Mukherjee & Althuizen, 2020; Wang et al., 2022) will likely outweigh any support for silence. Such asymmetric responses will also intensify as peer firms engage on an issue, heightening the contrast with silent firms, thus triggering more negative stakeholder responses to corporate inaction. This reasoning leads to our next hypothesis:

H2: Peer corporate activism will intensify the negative stakeholder response to corporate silence as outlined in H1.

Contingency of Market Niche

We also argue that silence is less visible for companies that occupy a narrow market niche but more visible for mass market firms. Questionable behavior by companies with a narrow market niche attracts less attention, enabling these companies to escape stakeholder oversight (Bartley & Child, 2014; Graf-Vlachy et al., 2020; King & McDonnell, 2015). The intention behind inaction by a niche firm is also opaque, as it is plausibly attributed to a lack of resources and capabilities to respond to a social issue. Niche firms should also benefit from stronger stakeholder attachment (Carroll & Swaminathan, 2000; Hannan, Pólos, & Carroll, 2007; Verhaal, Hoskins, & Lundmark, 2017). Stakeholders who presume greater alignment with a company may also be more willing to believe that the firm did not need to take action on an issue since its position is already perceived to be clear. These factors decrease the visibility of niche firms and the probability that their behavior is noticed, assessed, and penalized or rewarded (Barnett, 2012).

In contrast, mass market companies have more stakeholders watching them and greater expectations for leadership on social issues (Bartley & Child, 2014; Graf-Vlachy et al., 2020;

King & McDonnell, 2015). As a result, questionable behavior is much more likely to be noticed and interpreted as a deliberate choice. Mass market companies also encounter difficulties in maintaining support from a diverse set of stakeholders (Carroll & Swaminathan, 2000; Hannan et al., 2007; Verhaal et al., 2017), making stakeholders less likely to assume alignment with these companies. Consequently, there is greater visibility for mass market firms and a higher probability that their behavior is noticed, assessed, and penalized or rewarded (Barnett, 2012).[3]

We also argue that the mitigation effect of a narrow market niche applies to stakeholders across liberal and conservative ideologies. In each camp, a niche firm has fewer stakeholders monitoring it and lower expectations for issue engagement, making it more likely that questionable behavior will go unnoticed. Stakeholders of either ideology will also be less likely to negatively assess the intent of inaction by a niche firm as compared to by a mass market firm. Liberal stakeholders who support an issue will be more likely to presume that a silent niche firm also has a liberal stance, while conservatices will be more likely to presume that the firm also has a conservative stance (Burbano, 2021; Hambrick & Wowak, 2021; Mohliver et al., 2023; Wang et al., 2022). In this way, niche firms are more likely to receive the benefit of the doubt than mass market firms. As a result, although a niche firm that is closely aligned with one ideology is less likely to stay silent (McKean & King, 2024), it would have fewer negative reactions to silence than a comparably aligned mass market firm that stays silent. This is because stakeholders would be less likely to notice and negatively interpret the silence by the niche firm. These arguments lead to our last hypothesis:

H3: A narrow market niche will mitigate the negative stakeholder response to corporate silence as depicted in H1.

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[3] For collective action outcomes, more stakeholders could also inhibit a response by increasing free riding behavior, but our theory is about how stakeholders respond as individuals.

DATA AND MODEL

Empirical Context and Data

To empirically test these hypotheses, we leverage a natural experiment in the context of the event of Blackout Tuesday in the BLM movement for racial justice. This movement and social issue are appropriate to investigate because they became highly salient due to numerous protests and counter-protests (e.g., All Lives Matter and Blue Lives Matter), especially following the police killing of George Floyd in May 2020 (Anderson et al., 2020; Wang et al., 2022). In our analysis of Crowd Counting Consortium records, there are about 2.24 million participants at 4825 in-person protest events related to racism from January 1, 2017 up to the Blackout Tuesday event on June 2, 2020.[4] The overlap of this event with the early COVID-19 period, when there was higher engagement with social media and news, also increases the issue salience in our context.[5] In these respects, the BLM movement for racial justice can be considered an extreme case in which "the process of interest is 'transparently observable'" (Eisenhardt, 1989, p. 537). At the same time, reflecting an era of contentious and polarizing politics, there are five other issues with more protest participants during this period: women's rights (7.51 million), LGBTQIA (6.01 million), presidency (i.e., President Trump; 3.8 million), guns (3.36 million), and democracy (2.52 million). Another important aspect about this context is that Blackout Tuesday is an event to support BLM, which suggests that BLM opponents may favor corporate silence. While we

[4] Data sourced from https://github.com/nonviolent-action-lab/crowd-counting-consortium/tree/master, accessed on 5/14/24. We filtered to events with "racism" listed under the "issue" field and summed "size_mean" to count participants.

[5] We thank the Editor for this astute observation and for suggesting the applicability of Crowd Counting Consortium data.

argue that stakeholders on either side of an issue will react negatively to silence, we also address the issue of stakeholder alignment empirically in our robustness checks.

Our data samples major national firms from fashion-related sectors, including the clothing, jewelry and watches, reseller, and sporting industries, for four main reasons. First, a large number of firms in the fashion industry are active in the BLM movement (Livingston, 2020; Williams, Mezey, & Singh, 2021). Second, fashion firms rely heavily on social media platforms, particularly Instagram, to engage with their customers, thus making the observable consumer engagement metrics on these platforms more consequential. Third, fashion-related industries are less concentrated and exhibit fast changes in consumer tastes and industry trends, so the competition among fashion firms is cut-throat (Bain, 2021). Therefore, peer activism may constitute an important differentiation strategy that is germane to the focal firms. Fourth, the large set of competing firms in the fashion industry allows us to have higher generalizability in the results. In our sample, we have a total of 312 firms from the clothing, jewelry and watches, reseller, and sporting industries, and these are major national firms accounting for an over $150 billion market in the U.S. economy (see Online Appendix 1 for a list of the companies in our sample).

We collect data for the 312 major national firms surrounding the natural experiment of BLM's Blackout Tuesday event. This event originated on June 1, 2020, under the hashtag #TheShowMustBePaused. Word of the event quickly went viral, taking on its own identity under the #BlackoutTuesday hashtag on Instagram. On June 2, 2020, BLM supporters, including many firms from the fashion industry, posted black squares on their Instagram feeds to crowd out other content to highlight the issues of racial justice and police brutality (Coscarelli, 2020). Our data come from two main sources, as shown in Figure 1. We collect social media posting level data from Instagram and Twitter, two major social media platforms. For each post, we collect the text content, time stamp, and total like counts. From a third-party tracking website, *Socialblade.com*, we also collect each firm's daily total follower counts for each platform. We identified 312 firms that have social media accounts on both Instagram and Twitter. Among these firms, 124 participated in Blackout Tuesday (e.g., competitor firms that supported BLM on Instagram). We further exclude 2 other firms that posted BLM related contents on Twitter and 8 firms that supported BLM on their website during the event date. This leaves us with 178 firms that stayed silent on all three channels during this natural experiment event.[6] Figure 2 visualizes our data selection process.

We define four weeks before and four weeks after Blackout Tuesday (from May 4, 2020, to June 30, 2020) as our study window, from which we collect 16,017 posts and 17,394 daily follower counts from silent firms on both social media platforms. Furthermore, we collect 202,069 posts from all 312 firms during the pre-study window from January 1, 2020, to May 3, 2020, which we then use to extract social media content topics (e.g., social and promotion topics) before the event.

INSERT FIGURES 1 and 2 HERE

Identification Strategy and DID Model

Identification Strategy for Causal Effects. Identifying the causal effect of staying silent on social issues poses several challenges. To begin with, firms strategically decide whether to publicly support a social movement, thus creating a self-selection issue. However, even with random assignment, we might still face complications as issue salience may itself be affected by the number of firms assigned to support the issue. Ideally, instead of comparing the consumer

[6] The labeling of firms' support for BLM on Blackout Tuesday on different channels (Instagram, Twitter and Firm Website) can also be found in Appendix 1.

responses for firms that speak up and for those who remain silent, one would like to compare the outcome of a firm who stays silent on a salient social issue with one from a counterfactual scenario where, all else being equal, the social issue is not salient.

Our identification strategy of testing H1 relies on leveraging Blackout Tuesday as a natural experiment that occurs on Instagram (where treatment happens) but not on Twitter (control) for the same sets of firms in our analyses. The difference across platforms in the presence of this "precipitating event" (Hambrick & Wowak, 2021) provides within-firm variation in issue salience. The timing of the Blackout Tuesday event is exogenous for the firms because it was initiated only one day earlier than the official date and there is not much lead time for firms to strategize their actions (Wang et al., 2022). Figure 3 visualizes our identification strategy. Since Blackout Tuesday occurred on Instagram, this social issue is more salient on that platform than elsewhere by design. As a result, customer responses to a focal firm, S, who *remained silent* on Instagram during the Blackout Tuesday natural experiment, where the social activism treatment happens, can be regarded as the outcome from the *treatment* group. On the other hand, we rely on Twitter, where Blackout Tuesday did not occur and therefore the issue was less salient, as the *control* platform. We therefore employ a difference-in-differences (DID) design and estimate the causal effect for the silent firms by comparing the change in customer responses before and after the event across the treated (Instagram) and the control (Twitter) platforms. Because we rely on the *same* set of firms on Twitter as the control group, this practice has the advantage of accounting for many firm level confounding factors (e.g., advertising, prices, new products) that vary over time. The DID design is also robust to the average platform-level differences in the outcomes as well as common time trends.[7]

[7] We also consider alternative control groups in the robustness checks.

INSERT FIGURE 3 HERE

DID Models. We specify a DID model to estimate the causal effect of staying silent as follows:

$$Y_{ijt} = \delta * Instagram_j * After_t + \tau_{it} + \gamma_{ij} + \beta * X_{ijt} + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt} corresponds to the consumer responses to the silent firm *i* on platform $j \in \{Instagram, Twitter\}$ during period *t*. $Instagram_j$ is an indicator variable that is 1 for the focal firm *i* on the treatment platform (Instagram) where Blackout Tuesday occurred and 0 otherwise (Twitter), $After_t$ is an indicator variable that is 1 for the period occurring on or after Blackout Tuesday and 0 otherwise. The key coefficient of interest for testing H1 is therefore the interaction between *Instagram* and *After*.

We include a set of firm-time specific fixed effects, specified as τ_{it}. The role of τ_{it} is to capture any additional firm-time specific confounds, i.e., firm activities outside of Instagram and Twitter such as advertising and promotional activities over time, any dynamic changes in firm characteristics such as type of products or firm personality and firms' customer profile composition, and any time-specific characteristics that affect firms such as COVID-19 restrictions, macroeconomic shocks, and seasonality variations. In addition, γ_{ij} is a set of 356 (178*2) firm-platform specific fixed effects. The role of γ_{ij} is to capture any persistent firm-platform specific confounds, such as firms' different social media strategies on Instagram (versus Twitter) and any platform-specific characteristics that affect firms differently due to social media platform differences between Instagram and Twitter (e.g., different activities to attract firms and customers across the platforms). X_{ijt} is a vector of time and platform varying firm covariates, including total postings, social topics postings (e.g., BLM, societal inequality, diversity, climate, LGBTQ, political, poverty, COVID, and other social issues), promotional topics postings, total responses, and total mentions on social media. Including X_{ijt} helps control for the possible changes in firms' posting behavior after the event, which may in turn affect customer engagement. It also helps improve the preciseness of our estimation results. Given this comprehensive list of fixed effects and conditional on the time-platform-firm varying characteristics X_{ijt}, the key parameter of interest, δ, $(Instagram_j * After_t)$ gauges the average treatment impact, i.e., the causal incremental impact of staying silent on a highly salient social issue for the focal firm. This specification enables us to rigorously test H1 by comparing the effects of a firm's silence on the Instagram platform, where the racial justice issue was highly salient, to the same firm's silence on the Twitter platform, where the issue was less salient.

Note that we operationalize two measures of stakeholder response by following the existing literature that emphasizes the importance of social media for shaping firm reputation and exposing firms to stakeholder pressures on social issues (e.g., Etter, Ravasi, & Colleoni, 2019; Kim & Youm, 2017; Heavey et al., 2020; Wang et al., 2022). The first variable, *Follower Growth*, is defined as the weekly change in a focal firm's number of followers. Customers' social media activities have long been acknowledged as being informative of their preferences (Vithayathil, Dadgar, & Osiri, 2020), and more customers are using their following and unfollowing behavior to express their attitudes towards firms (Tang & Chen, 2020).[8] Our second variable, *Consumer Liking*, is defined as the weekly number of likes (log-transformed) received by a firm for its posts. This variable complements our first measure in that it provides a more direct measure of customer attitudes and agreement to a firm's posts.

Moderating Conditions

[8] This variable was 90% winsorized to reduce the effect of possibly spurious outliers. We use the change in the number of followers as our dependent variable, rather than the absolute count, because the parallel trend assumption does not apply to the latter. More information is provided in Appendix 2. In this appendix, we also explore the implications of using absolute follower numbers by applying the 'parallel growth' assumption, as suggested by Mora & Reggio (2012, 2015, 2019). These analyses reveal a coherent picture that aligns with our initial findings.

Our identification strategy can also exploit some natural variations in peer activism in our data to test H2. Specifically, different focal silent firms may experience different degrees of exposure to competitor firms' BLM support. Figure 4 provides a schematic representation of this variation: three close competitors supported BLM in the case of high peer corporate activism (left chart), while only one close competitor firm did so in the case of low peer corporate activism (right chart). Thus, our subsequent DID models can also measure the moderating role of rival BLM intensity to identify how the causal effect varies when peer activism increases.

INSERT FIGURE 4 HERE

To operationalize peer corporate activism, we construct the variable *Rival BLM Intensity*, which captures the proportion of the firm's top 10 closest competitors that posted BLM support on Instagram during the Blackout Tuesday event. A higher *Rival BLM Intensity* score indicates that close competitors of the focal firm supported BLM in the Blackout Tuesday event, thus likely aggravating the negative customer responses for staying silent. We use two approaches to assess the relative closeness of rival firms. First, we analyze Google search results, paying particular attention to the "People Also Search For" section and the relative rankings of firms, to identify the closest competitors for each firm. Second, we employ Doc2Vec (Le & Mikolov, 2014) to vectorize firms' social media posts, enabling us to measure the relative distance between their social media activities and identify the most similar firms. Online Appendix 3 provides further details on these two methods.

Next, we empirically test H2 by adding an additional interaction term between the DID estimator and Rival BLM Intensity to Equation (1). Therefore, δ_2 in Equation (2) captures the heterogeneous treatment effects on focal firms due to their close competitors' participation rates in supporting BLM in Blackout Tuesday:

$$Y_{ijt} = \delta_1 * Instagram_j * After_t + \delta_2 * Instagram_j * After_t * Rival\ BLM\ Intensity_{ij} + \tau_{it} + \gamma_{ij} + X_{ijt}\beta + \varepsilon_{ijt} \quad (2)$$

To test H3, we construct two variables to operationalize market niche. First, we measure the overlap of a firm's followers with those of other firms. Niche market firms, by definition, appeal to a narrower audience with little overlap with customers of firms practicing mass market strategies (Carroll & Swaminathan, 2000). To capture this, we define *Firm Follower Overlap* as the average of the Jaccard similarity indexes between the focal firm's follower set and the follower sets of other firms. A smaller value of Firm Follower Overlap suggests a narrower market niche.

Our second measure focuses on a firm's number of followers, which reflects its positioning strategy. Niche market firms tend to appeal to a smaller customer segment (Hannan et al., 2007), resulting in fewer followers, while a larger follower base suggests a mass market strategy aimed at a broader customer base (Verhaal et al., 2017). We define *Firm Follower Count* as the logged follower count on Instagram as of January 1, 2020, [10] and argue that a smaller follower count indicates a niche market strategy.

Control Variables

In all DID models, we control for firms' posting behavior as it may also affect customer responses. Firms post different types of messages on social media platforms. While most of the messages are intended for a general audience, firms may also respond to a particular customer by including the term "@" at the beginning of their posts. They can further mention some account users by including the same term "@" at the later part of their posts. On both Instagram and

[10] Using the follower counts on Twitter does not change our results qualitatively. Changing the dates of follower counts also gives similar results.

Twitter, all three types of posts are public and can be seen by customers. For each firm, we count daily the number of posts of all three kinds and aggregate them to the weekly average before imposing log transformations, creating three control variables: *Total Regular Posts*, *Total Responses*, and *Total Mentions*.

We further rely on machine learning tools to extract the topics of the social media posts and create two variables that capture the probability that a post is related to social issues (e.g., racism, societal inequality, diversity, climate, LGBTQ, political, poverty, COVID) or promotional topics (e.g., promotion, sales, % off). It is challenging to analyze the topic distributions of social media content because there are no systematic labels for posting content, and human labeling is costly to scale for training text classification machine learning algorithms. We overcome this challenge using GAN-BERT, which is a state-of-the-art semi-supervised deep learning text classification method (Croce, Castellucci, & Basili, 2020). GAN-BERT augments labeled data using a generative neural network to create additional synthesized labeled data, thus increasing classifier training efficiency and accuracy (see Online Appendix 4). We calculate the daily number of social issue posts by summing up the postings weighted by their probability of being related to a social issue topic and construct the variable, *Social Issue Postings*, by aggregating the daily number to the weekly average. The variable, *Promotional Postings,* is defined in a similar manner.

Our unit of analysis is the firm-platform-week. For each of the 178 silent focal firms that did not participate in Blackout Tuesday, we have eight observations in time (four weeks before and four weeks after Blackout Tuesday) across the two social media platforms (Instagram and Twitter).[12] This creates a panel dataset of 2,848 (=178*8*2) observations in the main DID

[12] Our main results are robust to alternative time windows such as 3 and 5 weeks before and after the event. Details of the estimation can be found in Online Appendix 5.

models. Table 2 presents the summary statistics. Variables defined on the post and platform-week levels are reported in Panels A and B, respectively. Note that if a firm does not have any new posts in a week, then *Consumer Liking* for that week is not available. As a result, we have fewer observations for that variable. We also have fewer observations for *Firm Follower Overlap*, as well as *Rival BLM Intensity* based on Google search data, because the relevant information is not available for all firms.

INSERT TABLE 2 HERE

A key assumption in the DID model is a parallel trend before the event. In Figure 5, we provide evidence supporting this assumption and report the evolution of consumer responses in the treated group (Instagram, dashed green line) and the control group (Twitter, solid blue line) around the event for the same silent focal firms. The X-axis corresponds to the time period, with a negative (positive) value representing the number of weeks before (after) the event. The dependent variables for the left and right panels are *Follower Growth* and *Consumer Liking*, respectively. For both variables, the trends between the treatment and control groups are largely parallel before the event (represented by the red dotted line), thus providing direct evidence for the satisfied parallel trend assumptions. Furthermore, in Online Appendix 6, we conduct additional analyses to test the plausibility of our parallel trend assumption, including regression, event-study plot, and the sensitivity analysis as suggested by Rambachan and Roth (2023). We find consistent evidence for the parallel trend before the event.

INSERT FIGURE 5 HERE

RESULTS

Results for H1

Table 3 presents the DID estimation results. The dependent variables for Columns 1-5 and Columns 6-10 are follower growth and consumer liking, respectively. We report the results from our main specification in Columns 1 and 6. For both dependent variables, the average treatment effect, δ, is unfavorable, suggesting that consumers had a negative reaction to focal firms who remained silent during Blackout Tuesday. Specifically, the DID coefficient for the first column is negative and significant, with a value of -249.29 (p=0.001). This implies that firms gain around 250 fewer followers weekly and therefore 1000 fewer followers monthly due to remaining silent on Blackout Tuesday. Considering that an average brand gains about 3000 followers monthly on Instagram, this effect corresponds to a one-third reduction in follower gain. Regarding *Consumer Liking*, firms received approximately 12% fewer likes due to corporate inaction according to the DID coefficient from Column 6 ($\delta = -0.12$, p=0.057). The effects are economically large, given that, as the market for social media platforms becomes increasingly saturated, more firms are using follower growth and social media sentiment as important metrics for firm performance (e.g., Barnhart, 2022; Klipfolio, 2022). This result further indicates that the classic notion that firms can be protected by staying silent on sociopolitical issues may no longer hold in today's world (Maake, 2023). Thus, our data provide strong support for **H1**: Stakeholders (i.e., consumers) will punish firms for staying silent on a highly salient social issue (such as BLM for racial justice).

INSERT TABLE 3 HERE

Robustness checks with different control baselines in DID. Next, we test the robustness of our main DID results with alternative sources of controls. First, because Twitter may attract different consumers, and might not be a perfect control of Instagram, we have another DID specification using year-over-year (YOY) comparisons within Instagram to mitigate this concern. Specifically, we use a time window of one year before the event (i.e., May 4, 2019 to June 30, 2020) on Instagram as an alternative control baseline. We focus on consumer responses for the focal firms on Instagram alone and run the following regression:

$$Y_{it} = \delta' * 2020_t * After_t + \tau_{it} + \beta * X_{it} + \varepsilon_{it} \quad (3)$$

where 2020_{it} is an indicator variable that equals 1 for the treatment time window (i.e., May 4, 2020 to June 30, 2020) for a silent focal firm *i* in calendar time *t* and 0 for the control time window one year before (i.e., May 4, 2019 to June 30, 2019). $After_t$ is now defined as an indicator variable that equals 1 if *t* is after Blackout Tuesday in 2020 or is in the second half of the control period (i.e., June 3, 2019 to June 30, 2019) and 0 otherwise. The interaction coefficient (δ') between 2020_{it} and $After_t$ therefore captures the treatment effect using the year before as an alternative control. In addition, because we can rely on both sources of control baselines (i.e., Twitter and the previous year on Instagram) for identification, we further conduct a triple difference in differences (DDD) analysis with the following specification:

$$Y_{ijt} = \delta'' * Instagram_j * 2020_{it} * After_t + \pi_1 * Instagram_j * 2020_{it} + \pi_2 * Instagram_j * After_t + \pi_3 * 2020_{it} * After_t + \tau_{it} + \gamma_{ij} + \beta * X_{ijt} + \varepsilon_{ijt}, \quad (4)$$

where the coefficient of the three-way interaction coefficient (δ'') captures the average treatment effect on the focal firms using both control baselines.

The results for the DID estimations using the one-year-before control group and for the DDD are reported in Columns 4 and 5 of Table 3 for *Follower Growth* and Columns 9 and 10 for *Consumer Liking* , respectively. Across the dependent variables and model specifications, we find that the coefficients for the treatment effects are consistent and mostly significant (with the exception of Column 9, probably due to a smaller number of observations), whether we use a firm's contemporaneous data from Twitter or the firm's prior year data from Instagram as the control group, therefore providing robust empirical support for H1.

Robustness checks excluding inactive firms. One might also wonder if a focal firm's silence on Blackout Tuesday was simply a result of being inactive on the social media platform. Thus, to rule out this alternative explanation, we test the robustness of our findings by excluding the firms that had no social media posts within one week before and after the event. The estimation results consistently support the negative average treatment effect, as reported in Columns 2 ($\delta = -226.87$, p=0.003) and 7 ($\delta = -0.12$, p=0.052) of Table 3.

Robustness checks with a shorter time period. Furthermore, we carry out a robustness check by restricting our data sample to a much shorter time period (two weeks) before and after Blackout Tuesday. This restriction helps pinpoint the causal impact within a short time period that is free from bias due to other concurring events (e.g., a more precise local average treatment effect). The estimation results for follower growth and consumer liking are reported in Columns 3 and 8. The DID coefficients are negative for both dependent variables ($\delta = -310.33$, p=0.001 for Column 3 and $\delta = -0.19$, p=0.08 for Column 8)..

Ruling out Alternative Explanations. Note that our DID model specifications have accounted for many alternative explanations. First, audiences on Instagram and Twitter may overlap; therefore, a focal firm's audience exposure to competitors' Blackout Tuesday content on Instagram may also affect engagement outcomes on Twitter after the event. If such cross-platform spillovers occur, they would bias our causal estimates towards zero and thus make our results more conservative. Consider the extreme case where Twitter and Instagram are identical in every follower who unfollows and every non-follower who does not follow, then both

Instagram and Twitter engagement metrics would change by the same amount, thereby making the difference in differences between the two platforms zero.

In addition, one may be concerned that many concurrent events are happening around the same time as Blackout Tuesday. For instance, ongoing changes in COVID-19 restrictions may have also influenced social media usage, and 2020 was a presidential election year. Moreover, additional BLM protests occurred before and after the event. However, these events are systematic and would affect *both* the treatment and control; thus, our DID model would difference out the effects of such systematic shocks.

Another concern is that some of the control variables might be “bad controls” (Angrist & Pischke, 2009) that could be outcomes of Blackout Tuesday non-participation and consumers’ reactions. These include posts replying or mentioning others, the count of social posts, and promotional posting. In Online Appendix 7, we estimate the DID model without any of these control variables and find the main results are still consistent.

Further, one may be concerned that platform design (such as trending topics or other features that promote buzzworthy content) may lead to non-BLM related content receiving less attention. If platform algorithms highlighted BLM content on Instagram but not Twitter, this could mechanically produce certain results even if consumers are indifferent to silence. We address this concern using two approaches. First, we examine the content and sentiment of consumer comments on brand’s posts and demonstrate that consumers noticed the silence and disliked it. Second, we run an additional regression analysis to rule out this alternative explanation. The details of the discussion and analysis can be found in Online Appendix 8.

Results for H2

The estimated parameters for testing H2 are presented in Table 4. We report the estimation results where *Rival BLM Intensity* is measured using Google Search. The results using Doc2Vec to measure *Rival BLM Intensity* are similar and are provided in Appendix 9. Our findings indicate that the negative impact of remaining silent on customer response varies across different contexts and is influenced by the level of *Rival BLM Intensity*. Specifically, for both dependent variables—*Follower Growth* (from Column 1) and *Consumer Liking* (from Column 3)—the interaction term *DID*Rival BLM Intensity* is negative (δ_2 = -1037.73, p = 0.01 for *Follower Growth*, and δ_2 = -1.20, p = 0.03 for *Consumer Liking*). This indicates that the larger the proportion of a focal firm's close competitors supporting BLM, the more adverse the impact on the silent focal firm.

The moderating effect of Rival BLM Intensity is substantial. Figure 6 illustrates this by showing the estimation results from Columns 1 and 3 of Table 4 (a similar pattern emerges using Doc2Vec measures). The left panel displays the average treatment effect on *Follower Growth*, while the right panel shows the effect on *Consumer Liking*. On the X axis, we see varying levels of *Rival BLM Intensity*, while the Y axis reflects the treatment effect. When other variables are held constant at their main level, the treatment effect for silent focal firms is minimal when *Rival BLM Intensity* is low (approximately 10%, near the 5th percentile). On the other hand, the impact becomes significantly more negative for silent focal firms when *Rival BLM Intensity* is high. For firms with a large proportion of competitors supporting BLM (70%, around the 95th percentile), the negative effect intensifies, leading to 422 fewer net new followers and a 28.9% reduction in consumer likes—nearly double the impact observed at average levels of peer activism. These findings support H2: Peer corporate activism amplifies the negative stakeholder response to corporate silence, as outlined in H1.

INSERT TABLE 4 & FIGURE 6 HERE

Moreover, our results are robust to many additional moderators as alternative explanations. Specifically, in Columns 2 and 4, we include additional moderators such as consumer demographics and political affiliation. We calculate these variables using customer foot traffic data for the firm's physical stores and the demographics of the Census block groups and counties where customers originate (see Online Appendix 10 for details). We find that the coefficients for our key moderator of *DID*Rival Intensity* remain consistently negative (δ_2 = -960.04, p = 0.01 for *Follower Growth*, and δ_2 = -1.20, p = 0.03 for *Consumer Liking*), while those for the additional moderators (*DID*Republican Advantage, DID*Black Population Proportion , DID*Median Income, DID*High Education*) are statistically insignificant in Columns 2 and 4, by and large. These results suggest that the negative treatment effect of staying silent are unlikely driven by consumers with certain demographic characteristics or political affiliation in our data. In other words, worries about potential demographic differences between Instagram and Twitter and differential demographic reactions to confounds (e.g., relaxing COVID-19 restrictions) can be attenuated since controlling for firms with different customer demographic audiences does not affect our DID estimates. These findings are also consistent with our arguments that stakeholders on either side of an issue will react negatively to silence. At the same time, we do not have individual-level data, so it is possible that more precise data would reveal differences by stakeholder alignment.

Another concern is that the negative effect of silence might stem from a deviation in a firm's prior posting behavior rather than from rival activism. For instance, consider two firms that consistently post left-leaning content on social media. These firms likely attract similar customers and are thus close competitors. When Blackout Tuesday happens, one firm participates, which is consistent with its past posting behavior. The other does not and is therefore inconsistent. A change in engagement for the silent firm could be driven by the break with its liberal posting history rather than by comparison with its liberal rival. To empirically test this alternative explanation, we examined the firms' posts on Instagram 6 months before our study period and created a variable named *Social Post Intensity*. This variable is defined as the overall proportion of posts that are related to left-leaning topics (e.g., BLM, LGBTQ, Climate Change, etc.), and is intended to capture the prior posting behavior of a firm related to social topics. We re-ran the DID regression with the three-way interaction between *Instagram*, *After*, and *Social Post Intensity* as an additional term to the specification in Equation (2). If this alternative explanation is the main mechanism, then we would expect *Social Post Intensity* to significantly moderate the effect of corporate silence and, more importantly, to absorb the explaining power of the interaction term, *DID**Rival BLM Intensity*.

Columns 1 and 3 of Table 5 present the estimation results regarding the moderating effect of *Social Post Intensity*. For both dependent variables, the coefficient of *DID**Social Post Intensity* is relatively small and statistically insignificant compared to the coefficient of *DID**Rival BLM Intensity* from Table 4. In contrast, the results in Columns 2 and 4 show that the coefficient of *DID**Rival BLM Intensity* is almost unchanged even after *DID**Social Post Intensity* is included. These findings suggest that the alternative explanation is likely not a major concern in our analysis.

INSERT TABLE 5 HERE

Results for H3

To test H3, we split our sample at the median for each niche market strategy measure and perform DID analyses on the subsamples using Equations (1) and (2). Table 6 shows the results for subsamples based on Firm Follower Overlap (Equation 1), with similar results for Firm Follower Count reported in Appendix 11. Firms are classified as 'niche market' or 'mass market' if their average follower overlap is below or above the sample median (0.002). Columns 1-2 and 3-4 present the results for Follower Growth and Consumer Liking, respectively.

Across all outcome variables, the DID coefficient is negative for the mass market group (δ= -440.68, p = 0.001 for Column 2 and δ = -0.18, p = 0.047 for Column 4), while it is negligible for the niche market group. A difference test confirms that the mass market group's coefficient is significantly more negative than that of the niche market group (p=0.01).[13] Consistent with H3, niche firms, who are less visible, are less likely to be negatively affected by staying silent on a salient social issue. On the other hand, mass-market firms gain around 440 fewer followers weekly and receive around 18% fewer likes, almost doubling the size of DID coefficient in Table 3. These results suggest that the negative impact of staying silent is largely driven by mass-market firms. Therefore, our results strongly support **H3**: A narrow market niche will mitigate the negative stakeholder response to corporate silence as depicted in H1.

INSERT TABLE 6 HERE

An alternative explanation of our finding, however, is that market niche might also be associated with the balance of a customer audience's opinion on particular social issues. For example, niche-market firms might target customers that agree or disagree with the BLM movement. At the same time, the moderating effect of market niche may also depend on whether the niche supports or opposes a given issue.

[13] The statistics were obtained with the bootstrap method with 1000 subsamples.

We rely on two approaches to address this concern. To begin, we create a new variable, *Mass Market*, which is an indicator variable that takes the value of one when the brand belongs to the "Mass Market" group. We interact the variable *Mass Market* with the variables *Instagram* and *After* and use it as an additional regressor to the specification in Equation (1). The estimation results from Columns 1 and 3 from Table 7 suggest a negative moderating role of *Mass Market* (-397.96, p=0.004 for Column 1 and -0.17, p=0.02 for Column 3), which is consistent with the results from Table 6 above. In Columns 2 and 4 from the same table, we include customers' demographic information (i.e., political affiliation, black proportion, median income and high education proportion) as moderators in addition to *Mass Market*. If the alternative explanation is true (that is, the moderating effect of market niche is largely due to customer composition/opinion), then we should expect the moderating effect of *Mass Market* to be absorbed after these additional moderators are included. We do not see such a pattern here, as across the specifications the coefficient of *DID***Mass Market* remains consistent.

INSERT TABLE 7 HERE

We further run a similar analysis on the sub-sample of niche-market firms only. The moderating effect of market niche may also depend on whether "the niche supports or opposes a given issue" according to the alternative explanation. If this is true, then we should expect the treatment effect to vary depending on the extent to which niche market customers agree with the BLM movement. This can be empirically tested by examining the moderating effect of some key demographic variable such as Republican support and proportion of Black population. Columns 5 and 6 of Table 7 report the estimation results. Across dependent variables, none of the moderators significantly affect the treatment effect, suggesting that alternative explanations for market niche are not a major concern.

To further explore the interaction between the key moderators—Peer Corporate Activism and Market Niche—we include the three-way interaction term *Instagram*After*Rival BLM Intensity* in the subsample analysis, with results reported in Table 8. *Rival BLM Intensity* is measured using Google Search, but the results are qualitatively similar when the Doc2Vec approach is applied. The findings are also consistent when *Firm Follower Count* is used to define niche firms. Additional details can be found in Online Appendix 12.

INSERT TABLE 8 HERE

The estimation results in Columns 1 and 2 of Table 8 reveal a significant interaction effect between the two moderators on *Follower Growth*. Mass market firms with a high level of *Rival BLM Intensity* gain 1,620 fewer followers (p=0.01) compared to those with a lower level of *Rival BLM Intensity*, all else being equal. In contrast, for niche market firms, the moderating effect of *Rival BLM Intensity* is minimal and not statistically significant (p=0.28). A similar pattern is observed for Consumer Likes, as shown in Columns 3 and 4 of the same table. This result makes sense because niche firms serve only a small and specific segment of the market, and therefore do not have as many rivals as mass market firms in the first place. As a result, competitors' participation in Blackout Tuesday may not impact niche firms as much as mass market firms.

Figure 7 uses the results from Table 8 to plot the relationship between the DID estimates and Rival BLM Intensity separately for firms with niche market and mass market strategies. For both dependent variables, we observe a clearly divergent pattern for the silent focal firms with different market niche strategies. While the treatment effect becomes more negative as the focal firm's level of Rival BLM Intensity goes up, this pattern is only salient for mass-market firms but not for niche firms. These findings lend more empirical support for our H2 and H3.

INSERT FIGURE 7 HERE

DISCUSSION

This study reverses the focus of extant research on corporate activism to consider the performance implications of staying silent on a contentious social issue. We take advantage of Blackout Tuesday as a “precipitating event” (Hambrick & Wowak, 2021), which occurred on Instagram but not Twitter, to conduct a within-company cross-platform DID analysis and rigorously identify the stakeholder responses to silence. The results support our theory about how visibility triggers negative reactions to silence, enabling us to challenge dominant perspectives in the literature on corporate activism in productive ways (Hambrick & Wowak, 2021; Melloni et al., 2023; Mohliver et al., 2023).

Our primary contributions are to the emerging literature on corporate activism. We offer the first study to focus on stakeholder responses to a company staying silent, as opposed to engaging on a contentious social issue. By identifying the costs of silence, our results help to resolve a puzzle about why so many companies and CEOs are engaging in corporate activism, which often triggers negative stakeholder responses (Bedendo & Siming, 2021; Burbano, 2021; Hou & Poliquin, 2023; Hydock et al., 2020; Mukherjee & Althuizen, 2020; Wang et al., 2022). The prevalence of high-risk activism has been a puzzle in part because much prior work frames the alternative to engagement as staying neutral, which should have no stakeholder consequences. However, in a context of growing polarization and societal expectations for corporate leadership on social issues, neutrality may not be possible; instead, corporate silence may be interpreted as picking a side. Even if a company did not intend to engage in counter-positioning (Mohliver et al., 2023), stakeholders may perceive it as taking an opposing side to vocal firms, especially as peer activism becomes more prevalent and for firms with a wider market niche. Consequently, activism may be the better of two costly and risky options (McDonnell, 2016).

In addition, we provide a theoretical framework to explain when silence will become equated with picking a side, triggering stakeholder reactions. This framework departs from the established focus in the corporate activism literature on stakeholder alignment (Chatterji & Toffel, 2019; Hambrick & Wowak, 2021); instead, we build our arguments around the construct of visibility. Following the cognitive model of stakeholder behavior (Barnett, 2012), visibility is central to stakeholder responses: for a stakeholder to punish or reward a company's behavior, they must overcome barriers to notice, assess, and react to the behavior. We argue that this perspective is especially useful for understanding responses to inactions such as corporate silence, where each step in formulating a stakeholder response is more difficult than it is for corporate actions. However, it also applies to corporate activism, where it can add insight to prior findings. For example, the tendency for asymmetric negative responses can be attributed in part to the greater proclivity of misaligned stakeholders (over aligned stakeholders) to notice, assess, and react to corporate activism that offends a stakeholder's ideology.

Our theoretical framework, centered around visibility rather than stakeholder alignment, also highlights novel contingencies affecting stakeholder responses to corporate behavior on contentious social issues. Peer activism increases negative reactions to corporate silence on these issues because it increases the visibility of silence in several ways: peer activism makes it easier to notice silence, to assess it as a deliberate choice, and for those who favored activism, to punish it as an isolated bad actor. Also, we argue that peer activism plays a different role in shaping stakeholder reactions to corporate silence than it does for corporate activism. Studies of corporate activism find that peer activism dilutes the courage and authenticity of a focal company's activism through a bandwagon effect, reducing stakeholder support (Melloni et al., 2023; Vredenburg et al., 2020; Wang et al., 2022). In contrast, we conclude that peer activism exposes a company's corporate silence to criticism, again worsening stakeholder reactions. While companies that choose activism benefit more from standing alone, lest their voices appear as "cheap talk" (Melloni et al., 2023), companies that choose silence suffer more from the same context, as silence becomes more visible to stakeholders who expect engagement.

Likewise, we develop theory about how market niche affects stakeholder responses to corporate silence. Although less theorized than peer behavior in this literature, prior research suggests that firms with larger market shares should benefit from silence because they have more to lose than to gain from activism (Hydock et al., 2020). This argument makes the recent prevalence of corporate activism among extremely large companies especially puzzling (Chatterji & Toffel, 2018). However, we show that silence can itself become viewed as picking a side when this silence is highly visible. A wide market niche increases the visibility and costs of silence because larger companies receive more stakeholder attention (Bartley & Child, 2014; Graf-Vlachy et al., 2020; King & McDonnell, 2015). Mass market firms also struggle with stakeholder alignment (Carroll & Swaminathan, 2000; Hannan et al., 2007; Verhaal et al., 2017), making them less likely to receive the benefit of the doubt about the meaning of inaction. While activism could still be the costlier of the two options for mass market firms, this research does show that silence can be quite costly for these companies as well.

A second literature we contribute to is stakeholder strategy. We demonstrate the usefulness of applying the cognitive model of stakeholder behavior (Barnett, 2012; Lange et al., 2022) to understand stakeholder responses to corporate inaction on social issues. Although it is difficult for stakeholders to notice, assess, and react to any corporate behavior, and especially so for inaction, we show how this process becomes possible under certain conditions. These findings demonstrate how stakeholder dynamics extend beyond acts of commission to those of omission as well.

This research also offers insights for managers. Although it is tempting to avoid controversial social issues, as an issue gains salience, corporate silence also becomes a risky approach. Managers should closely monitor and anticipate peer behavior, as this is a key condition that controls whether a decision to stay silent will be sheltered in a crowd or made highly visible. In addition, managers should align their choice to engage or stay silent with their market niche: silence is more visible and costly for firms with a wider market, whereas firms with a narrow niche can more easily avoid attention to their silence. Managers who seek to remain neutral on a contentious social issue should also consider explicitly conveying this stance (Bondi et al., 2024), rather than hoping that silence will be interpreted as neutrality.

As with much research on corporate activism, this study has limitations related to the empirical context. We study one movement and precipitating event, as well as one stakeholder group. It would be helpful to consider how other stakeholders respond to corporate silence on other issues. Our context is also defined by a highly salient social issue, which ranks among the most salient issues and movements in history. Importantly, this salience and the platform-specific nature of Blackout Tuesday enable us to better test our theoretical arguments. We would expect similar dynamics of mobilization raising the visibility and costs of corporate silence on other social issues, albeit developing over longer time periods or for a narrower set of companies, making identification of the effects of silence more difficult. The episodic nature of social movements also means that a smaller movement can still create concentrated moments of salience, often clustered around precipitating events, such as a controversial executive action, law, or geopolitical event (cf., Hambrick & Wowak, 2021, p. 48). For example, stakeholders have responded negatively to silence by Uber about immigration,[15] by Disney about LGBTQ issues,[16] and by Nike about the Hamas-Israel conflict.[17] Future work should analyze how variation in salience across issues affects stakeholder responses. It would also be interesting to compare the influence of peer activism across cases where corporations express a greater diversity of views on an issue. Compared to our case, where all vocal companies supported BLM, we might expect peer activism to have a weaker negative effect because stakeholders would focus on vocal misaligned companies. On the other hand, there might be an even stronger negative effect because the conflicting corporate voices make the issue and silence on it more salient, while also elevating stakeholder concerns that a silent company is misaligned. Lastly, our outcomes represent an important form of stakeholder support (Etter et al., 2019; Kim & Youm, 2017), extending a literature that uses diverse measures (e.g., Bedendo & Siming, 2021; Burbano, 2021; Hou & Poliquin, 2023; Wowak et al., 2022), but future studies should examine other types of stakeholder responses to corporate silence. This is especially important because there is evidence that stakeholder responses can differ between social media and consumer purchases, at least in a context of rival boycott-buycott campaigns (Liaukonytė, Tuchman, & Zhu, 2023). In this way, some firms may benefit from negative stakeholder responses if they galvanize a core group of supporters. It is also possible that disaffected stakeholders return to support silent companies over a longer timeframe (cf., Hou & Poliquin, 2023).

In conclusion, one reason for the increasing prevalence of corporate engagement on contentious social issues is that neutrality disappears as an option under certain conditions. With

[15] https://www.nytimes.com/2017/01/31/business/delete-uber.html
[16] https://www.cnn.com/2022/03/11/media/disney-chapek-apology-florida-lgbtq/index.html
[17] https://www.bloomberg.com/news/articles/2023-10-19/israel-hamas-war-puts-pressure-on-ceos-and-companies-to-speak-up

high issue salience, corporate silence is likely the culprit for negative stakeholder responses, especially with more peer activism. Fortunately, companies may avoid such negativity if they have a niche market strategy.

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Table 1: Theoretical Framework by Stakeholder Ideology

Hypotheses	Liberals	Conservatives
H1: Stakeholders react negatively to corporate silence on a highly salient issue.	Expect aligned corporate action on an issue (Hambrick & Wowak, 2021; Mohliver et al., 2023; Wowak et al., 2023), i.e., to endorse a liberal position or reject a conservative one. Interpret silence as misaligned with the liberal position on the issue.	Expect corporate action on an issue (Hambrick & Wowak, 2021; Mohliver et al., 2023; Wowak et al., 2023), i.e., to endorse a conservative position or reject a liberal one. Interpret silence as misaligned with the conservative position on the issue.
H2: Peer activism intensifies the negative reaction in H1.	Have greater expectations of activism (Hambrick & Wowak, 2021). Are more likely to notice silence and interpret it as misaligned with the liberal position on the issue (Barnett, 2012).	Have greater expectations of activism (Hambrick & Wowak, 2021). Are more likely to notice silence and interpret it as misaligned with the conservative position on the issue (Barnett, 2012).
H3: A narrow market niche mitigates the negative reaction in H1.	Are less likely to notice silence and expect issue engagement (Bartley & Child, 2014; Graf-Vlachy et al., 2020; King & McDonnell, 2015). Are less likely to interpret silence as misaligned with the liberal position on the issue (Carroll & Swaminathan, 2000; Hannan, Pólos, & Carroll, 2007; Verhaal, Hoskins, & Lundmark, 2017).	Are less likely to notice silence and expect issue engagement (Bartley & Child, 2014; Graf-Vlachy et al., 2020; King & McDonnell, 2015). Are less likely to interpret silence as misaligned with the conservative position on the issue (Carroll & Swaminathan, 2000; Hannan, Pólos, & Carroll, 2007; Verhaal, Hoskins, & Lundmark, 2017).

Table 2: Summary Statistics

Panel A: Post Level Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Social Issue Posts	10,075	0.09	0.27	0	1.00
Promotional Posts	10,075	0.24	0.41	0	0.99
Consumer Liking	10,075	6172.19	20105.14	0	391,223

Note: Social Issue Posts and Promotional Posts are measures from the GAN-BERT classification model, and represent a continuous likelihood of being classified as one of these categories based on the text.

Panel B: Firm-Platform-Time Level Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Follower Growth	2,848	321.91	1413.03	-748.00	7690.00
Consumer Liking	1,346	2.56	1.08	1.95	7.63
Rival BLM Intensity (Doc2Vec)	2,848	0.39	0.19	0.00	0.90
Rival BLM Intensity (Google Search)	2,000	0.33	0.15	0.00	0.80
Firm Follower Count	2,848	1,896,873	5,756,817	0	39,500,000
Firm Follower Overlap	2,400	0.003	0.003	0.00	0.02
Total Regular Postings	2,848	0.31	0.56	0.00	10.29
Total Responses	2,848	0.26	1.47	0.00	30.14
Total Mentions	2,848	0.13	0.33	0.00	4.71
Social Issue Postings	2,848	0.05	0.16	0.00	2.49
Promotional Postings	2,848	0.11	0.25	0.00	2.13

Table 3: DID Estimates for H1

	(1) Follower Growth	(2) Follower Growth	(3) Follower Growth	(4) Follower Growth	(5) Follower Growth	(6) Liking	(7) Liking	(8) Liking	(9) Liking	(10) Liking
DID (Instagram*After)	-249.29	-226.87	-310.33		-65.19	-0.12	-0.12	-0.19		0.01
(DID with Twitter as control)	[66.21]	[75.92]	[95.43]		[50.43]	[0.06]	[0.06]	[0.11]		[0.03]
2020 *After				-156.51	12.21				-0.06	0.02
(DID with Prior Year as control)				[90.80]	[31.19]				[0.05]	[0.03]
DDD Instagram*After*2020					-185.88					-0.13
(Twitter and Prior Year as controls)					[84.80]					[0.05]
Instagram ∗2020					-664.82					-0.06
					[155.07]					[0.05]
Constant	-505.01	-516.25	-784.07	7073.21	848.90	-0.12	-0.13	-1.10	2.06	-0.03
	[41.51]	[50.95]	[47.65]	[170.46]	[59.48]	[0.04]	[0.04]	[0.18]	[0.10]	[0.03]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm- Period of Year Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	2848	2160	1424	2848	5696	1346	1228	632	1555	2936
R^2	0.853	0.837	0.895	0.921	0.855	0.965	0.966	0.975	0.971	0.963

Note: Columns 1 and 6 present the main models for Follower Growth and Consumer Liking respectively. Columns 2 and 7 exclude the inactive firms that had no social media posts within one week before and after the event. Columns 3 and 8 restrict the sample to two weeks before and after the event. Columns 4-5 and 9-10 use alternative DID control groups. Standard errors clustered by firm are in brackets.

Table 4: Results for H2

	(1) Follower Growth	(2) Follower Growth	(3) Consumer Liking	(4) Consumer Liking
DID (Instagram*After)	96.98	2806.48	0.26	-1.77
	[119.21]	[4796.79]	[0.15]	[3.70]
DID*Rival BLM Intensity	-1037.73	-960.04	-1.20	-1.20
	[415.41]	[394.32]	[0.54]	[0.54]
DID*Republican Advantage		-429.22		-0.24
		[370.97]		[0.40]
DID*Black Population Proportion		83.18		-0.87
		[471.31]		[0.34]
DID*Median Income		-226.81		0.20
		[433.99]		[0.34]
DID*High Education		-1044.05		-0.49
		[1002.11]		[0.80]
Constant	-502.03	-509.65	-0.14	-0.13
	[42.01]	[47.61]	[0.05]	[0.05]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2000	2000	1031	1031
R^2	0.868	0.869	0.963	0.963

Note: standard errors clustered by firm are in brackets.

Table 5: Ruling out the Alternative Explanation for H2

	(1) Follower Growth	(2) Follower Growth	(3) Consumer Liking	(4) Consumer Liking
DID (Instagram*After)	-314.21	57.65	0.13	0.34
	[241.69]	[328.99]	[0.19]	[0.28]
DID * Social Post Intensity	136.24	84.01	-0.53	-0.20
	[498.12]	[643.34]	[0.42]	[0.58]
DID*Rival BLM Intensity		-1039.17		-1.18
		[361.78]		[0.31]
Constant	-503.31	-501.01	-0.13	-0.14
	[263.27]	[268.54]	[0.14]	[0.15]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2848	2000	1346	1031
R^2	0.853	0.868	0.966	0.963

Note: standard errors clustered by firm are in brackets.

Table 6: Results for H3

	(1) Niche Market	(2) Mass Market	(3) Niche Market	(4) Mass Market
	Follower Growth	Follower Growth	Consumer Liking	Consumer Liking
DID (Instagram*After)	-33.43	-440.68	-0.00	-0.18
	[27.63]	[132.15]	[0.01]	[0.09]
Constant	-86.64	-390.55	-0.37	-0.07
	[23.35]	[79.25]	[0.04]	[0.05]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	1200	1200	520	721
R^2	0.901	0.838	0.949	0.965

Note: standard errors clustered by firm are in brackets

Table 7: Ruling out Alternative Explanations for H3

	Full Sample				Niche Firms Only	
	(1) Follower Growth	(2) Follower Growth	(3) Liking	(4) Liking	(5) Follower Growth	(6) Follower Growth
DID (Instagram*After)	-44.71	3858.01	-0.01	0.20	314.72	0.40
	[29.46]	[3656.39]	[0.06]	[2.08]	[1524.99]	[0.53]
DID * Mass Market	-397.96	-364.59	-0.17	-0.15		
	[136.60]	[126.46]	[0.07]	[0.08]		
DID*Republican Advantage		-355.62		-0.03	-162.55	0.03
		[277.30]		[0.19]	[120.32]	[0.04]
DID*Black Population Proportion		-369.57		-0.72	-177.51	0.16
		[696.90]		[0.48]	[286.41]	[0.37]
DID*Median Income		-338.23		-0.02	-39.31	-0.04
		[328.47]		[0.19]	[143.49]	[0.05]
DID*High Education		-555.30		0.35	580.41	0.15
		[762.58]		[0.71]	[518.46]	[0.19]
Constant	-449.54	-463.21	-0.09	-0.09	-62.51	-0.32
	[57.11]	[55.70]	[0.13]	[0.13]	[31.31]	[0.03]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2400	2400	1241	1241	1200	520
R^2	0.846	0.846	0.965	0.965	0.902	0.949

Note: standard errors clustered by firm are in brackets

Table 8: Interaction between H2 and H3

	(1) Niche Market	(2) Mass Market	(3) Niche Market	(4) Mass Market
	Follower Growth	Follower Growth	Consumer Liking	Consumer Liking
DID (Instagram*After)	22.76	174.64	0.02	0.35
	[71.42]	[265.52]	[0.04]	[0.25]
DID*Rival BLM Intensity	-294.40	-1620.22	-0.06	-1.62
	[266.67]	[840.75]	[0.13]	[0.83]
Constant	-72.85	-436.14	-0.38	-0.09
	[24.93]	[74.78]	[0.05]	[0.06]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	704	1008	359	605
R^2	0.916	0.854	0.960	0.960

Note: standard errors clustered by firm are in brackets.

Figure 1: Data Collection

	Posting	Followers
Data Source	Instagram Twitter	Socialblade.com
Description	Content Timestamp Liking counts	Follower counts
Observations	16,017 posts from 178 silent firms during the study window (05/04/2020-06/30/2020) 202,069 posts from 312 firms during the pre-study window (01/01/2020-05/03/2020)	17,394 observations from the 178 firms during the study window (05/04/2020-06/30/2020)

Figure 2: Sample Selection

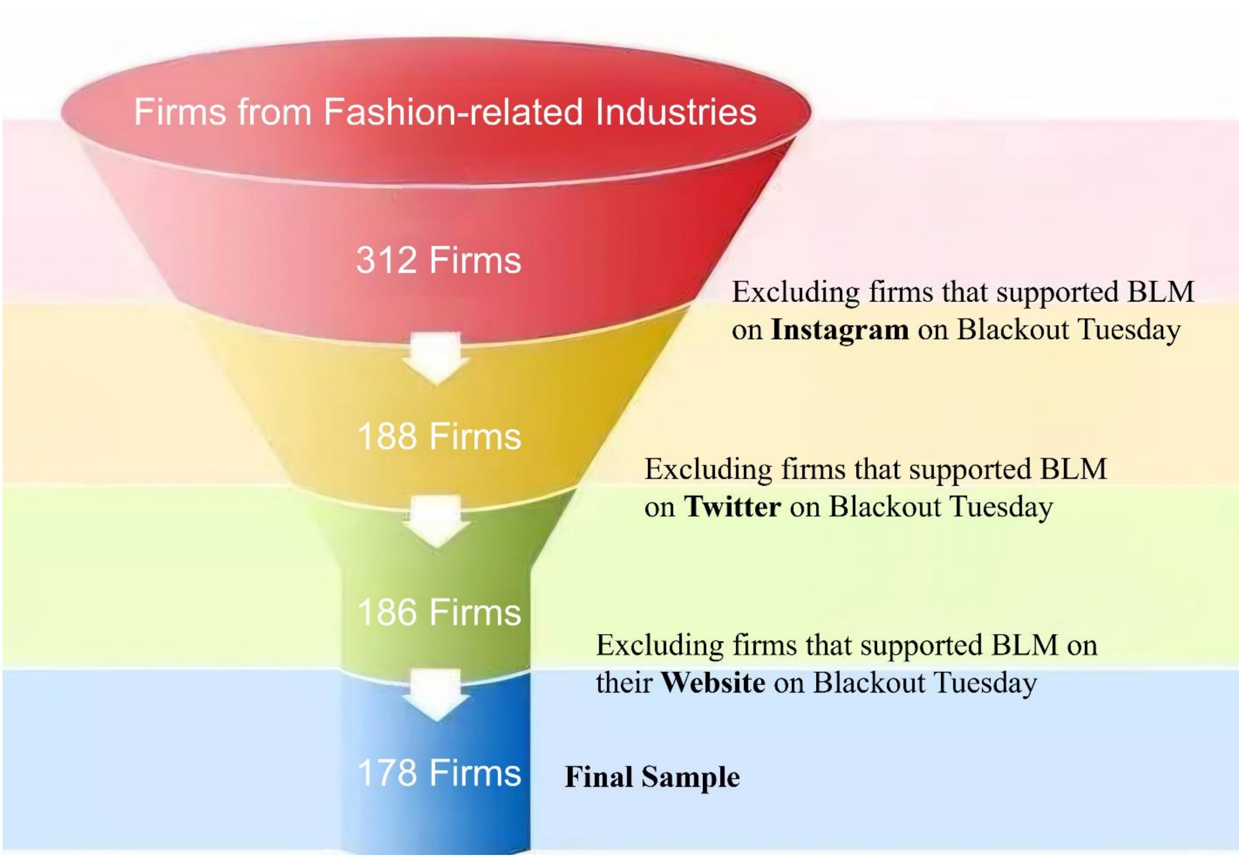


Figure 3: Identification Strategy for Measuring Causal Effects of Corporate Silence

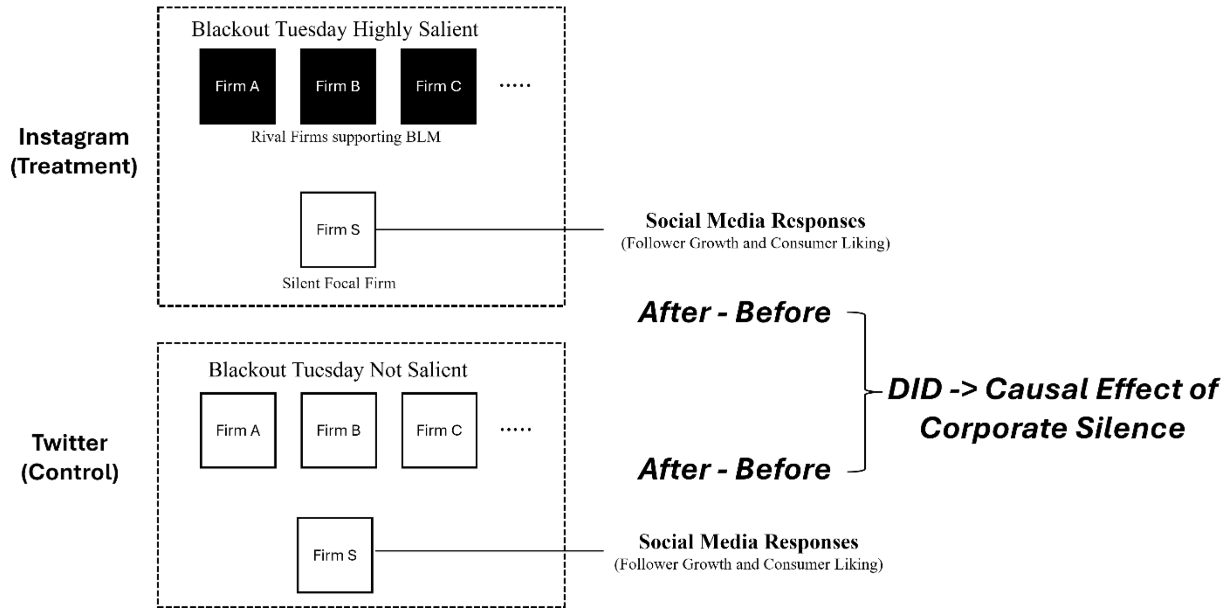


Figure 4: High vs. Low Peer Corporate Activism

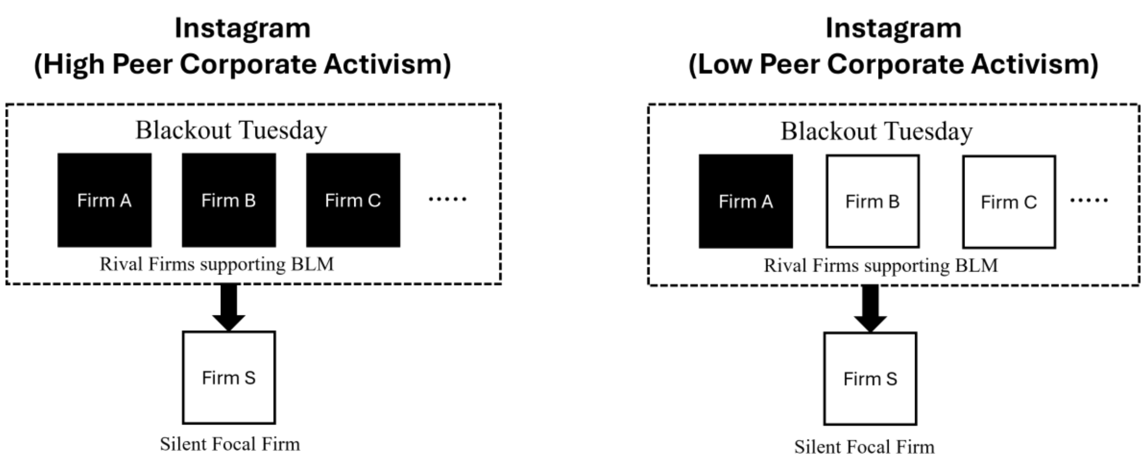
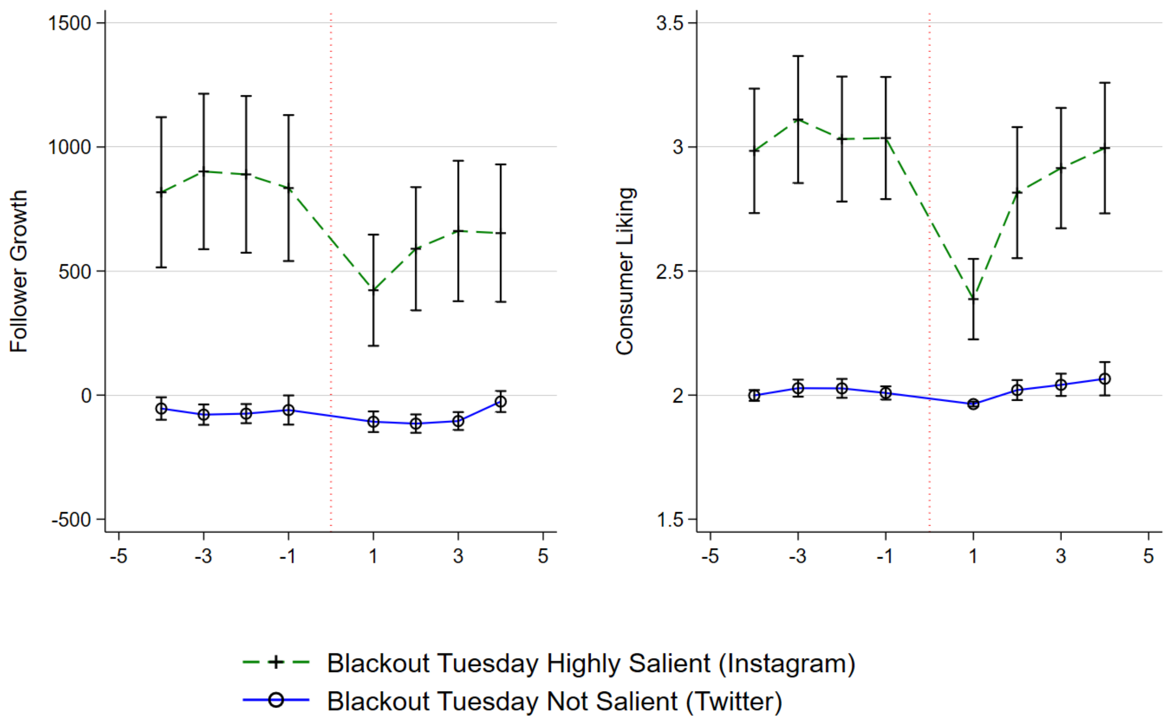
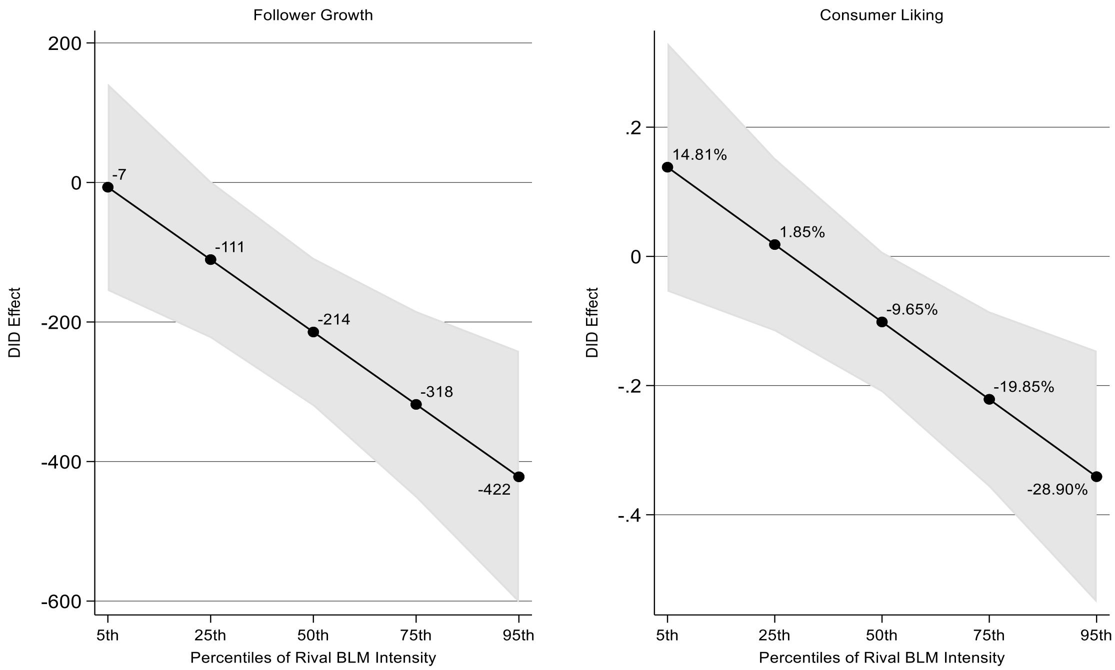


Figure 5: Parallel Trends and Model-Free Evidence



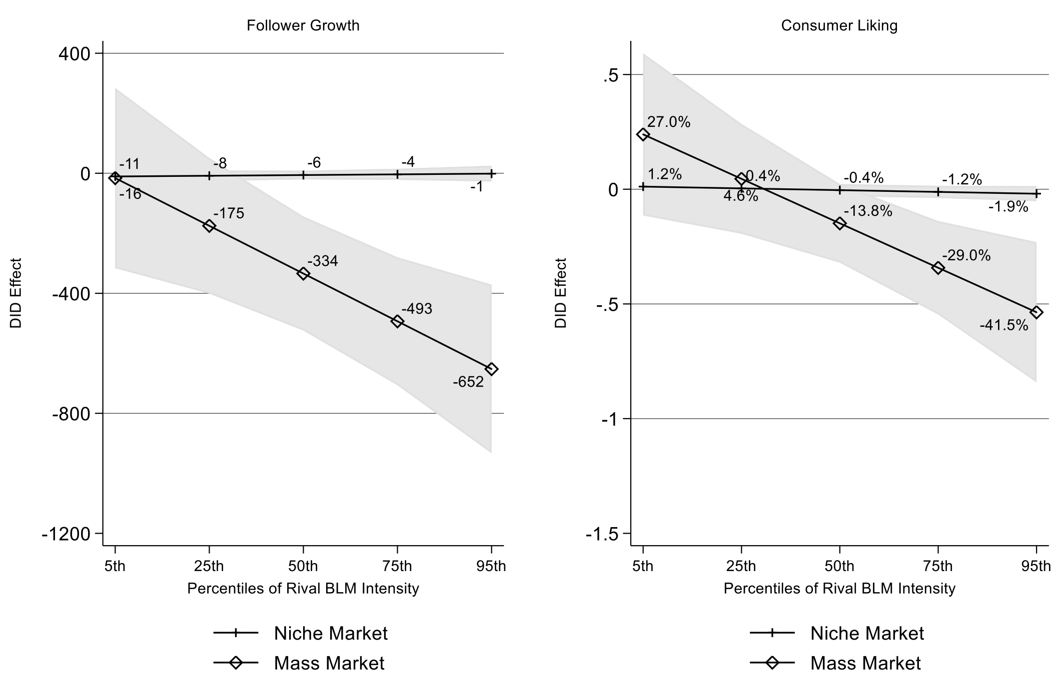
Note: Here, $t = 0$ represents the date of Blackout Tuesday. We have chosen to exclude this date from our data because it is unclear what time of the day the follower count information was collected. If the information was largely collected in the morning (evening), it should be categorized before (after) the event. However, including this date in either category does not change the main results.

Figure 6: Visual Support for H2



Note: 95% confidence intervals included.

Figure 7: Visual Support for H3 and Its Interaction with H2



Note: 95% confidence intervals included.

Web Appendix

WHEN CORPORATE SILENCE IS COSTLY: NEGATIVE CONSUMER RESPONSES TO CORPORATE SILENCE ON SOCIAL ISSUES

APPENDIX 1: A LIST OF THE FOCAL SILENT FIRMS (NO BLM-RELATED CONTENT ON IG, TWITTER, OR WEBSITE) AND RIVAL PARTICIPATING FIRMS (YES IN ANY OF THE THREE SOURCES)

Table A1

			BLM Content		
Firm	**Instagram Account**	**Industry**	**IG**	**Twitter**	**Website**
7 For All Mankind	7FORALLMANKIND	Clothing	Yes	No	No
A Pea in the Pod	APEAINTHEPODMATERNITY	Clothing	No	No	No
Aeropostale	AEROPOSTALE	Clothing	Yes	Yes	No
Abercrombie	ABERCROMBIE	Clothing	Yes	No	No
Adidas	ADIDAS	Sporting	No	No	Yes
Aerie	AERIE	Clothing	Yes	No	No
AG Jeans	AGJEANS	Clothing	Yes	No	No
A'GACI	AGACI_STORE	Clothing	Yes	No	No
Agent Provocateur	AGENTPROVOCATEUR	Clothing	Yes	No	No
Akira	SHOPAKIRA	Clothing	Yes	No	No
ALDO	ALDO_SHOES	Clothing	No	No	No
Alice and Olivia	ALICEANDOLIVIA	Clothing	Yes	No	No
Allbirds	ALLBIRDS	Clothing	No	No	No
AllSaints	ALLSAINTS	Clothing	No	No	No
Al's Formal Wear	ALSFORMALWEAR	Clothing	No	No	No
Altar'd State	ALTARDSTATE	Clothing	Yes	No	No
American Eagle Outlet	AMERICANEAGLE	Clothing	Yes	Yes	No
Ann Taylor	ANNTAYLOR	Clothing	Yes	No	No
Anthropologie	ANTHROPOLOGIE	Clothing	Yes	No	No
Apricot Lane	APRICOTLANEFARMS	Reseller	Yes	No	No
Aritzia	ARITZIA	Clothing	No	No	No
Armani Exchange (A/X)	ARMANIEXCHANGE	Clothing	Yes	No	No
Ashley Stewart	BYASHLEYSTEWART	Clothing	No	No	No
Athleta	ATHLETA	Clothing	Yes	No	No
ATM Anthony Thomas Melillo	ATMCOLLECTION	Jewelry & Watches	No	No	No
Avenue	AVEPLUS	Clothing	No	No	No
Away	AWAY	Reseller	No	No	No
Banana Republic	BANANAREPUBLIC	Clothing	Yes	No	No
Bandier	BANDIER	Clothing	Yes	No	No
Barbour	BARBOUR	Clothing	No	No	No

BCBG	BCBGMAXAZRIA	Clothing	No	No	No
BCBGeneration	BCBGENERATION	Clothing	No	No	No
Ben Bridge Jeweler	BENBRIDGEJWLR	Jewelry & Watches	Yes	No	No
Billabong	BILLABONG	Sporting	Yes	No	No
Blue Nile, Inc	BLUENILEDIAMOND	Jewelry & Watches	No	No	No
Bob's Stores	BOBS_STORES	Clothing	No	No	No
Bonobos	BONOBOS	Clothing	Yes	No	No
BonWorth	BONWORTH	Clothing	No	No	No
Boot Barn	BOOT_BARN_OFFICIAL	Clothing	No	No	No
Brandy Melville	BRANDYMELVILLEUSA	Clothing	No	No	No
Brooks Brothers	BROOKSBROTHERS	Reseller	Yes	No	No
Brown's Shoe Fit Co.	BROWNSSHOEFOCO	Reseller	No	No	No
Brunello Cucinelli	BRUNELLOCUCINELLI	Clothing	No	No	No
Buckle	BUCKLE	Reseller	No	No	No
Bulgari (Bvlgari)	BULGARI	Jewelry & Watches	No	No	No
Burberry	BURBERRY	Clothing	No	No	No
Burkes Outlet	BURKESOUTLET	Reseller	No	No	No
Buy Buy Baby	BUYBUYBABY	Reseller	Yes	No	No
Calvin Klein	CALVINKLEIN	Clothing	No	No	No
Camper	CAMPER	Reseller	No	No	No
Carhartt	CARHARTT	Clothing	Yes	Yes	No
Cartier	CARTIER	Jewelry & Watches	Yes	Yes	No
Casa Raul	CASARAULWESTERNWEAR	Clothing	No	No	No
Catherines	CATHERINESPLUS	Clothing	No	No	No
Cavender's	CAVENDERS	Reseller	No	No	No
Century 21 Department Stores	CENTURY21STORES	Clothing	Yes	No	No
CH by Carolina Herrera	CAROLINAHERRERA	Clothing	No	No	No
Champion	CHAMPION	Clothing	Yes	No	No
Chanel	CHANELOFFICIAL	Clothing	Yes	No	No
Charles Tyrwhitt	CHARLESTYRWHITT	Clothing	Yes	No	No
Chaumet	CHAUMETOFFICIAL	Jewelry & Watches	No	No	No
Cherokee Nation Entertainment	THECHEROKEENATION	Reseller	No	No	No
Chico's	LOVECHICOS	Clothing	Yes	Yes	No
Chopard	CHOPARD	Jewelry & Watches	Yes	No	No
Christopher & Banks	CHRISTOPHERANDBANKS	Clothing	No	No	No
Chrome Hearts	CHROMEHEARTSOFFICIAL	Jewelry & Watches	No	No	No
City Blue	CITYBLUESHOP	Reseller	No	No	No
Claire's	CLAIRESSTORES	Reseller	No	No	No
Clarks	CLARKSSHOES	Clothing	No	No	No
Club Monaco	CLUBMONACO	Clothing	Yes	No	No
Coach	COACH	Clothing	No	No	No
Coldwater Creek	COLDWATERCREEK	Clothing	No	No	No
Cole Haan	COLEHAAN	Reseller	No	No	No
Columbia Sportswear	COLUMBIA1938	Sporting	No	No	No
Cotton On	COTTONON	Reseller	No	No	No

Crazy 8	THECRAZY8SOC	Reseller	No	No	No
Crossroads	CROSSROADSTRADING	Reseller	No	No	No
David's Bridal	DAVIDSBRIDAL	Clothing	No	No	No
DD's Discounts	DDSDISCOUNTS	Reseller	No	No	No
De Beers Jewelry	DEBEERSOFFICIAL	Jewelry & Watches	No	No	No
Desigual	DESIGUAL	Clothing	Yes	No	No
Destination XL	DESTINATIONXL	Clothing	No	No	No
DeVons Jewelers	DEVONSJEWELERS	Jewelry & Watches	No	No	No
DIESEL	DIESEL	Clothing	No	No	No
Dior	DIOR	Clothing	No	No	No
DKNY	DKNY	Clothing	Yes	Yes	No
Dockers	DOCKERSKHAKIS	Clothing	No	No	No
Dolce & Gabbana	DOLCEGABBANA	Clothing	Yes	No	No
Don Roberto Jewelers	DONROBERTOJEWELERS	Jewelry & Watches	No	No	No
Dooney and Bourke	DOONEYANDBOURKE	Reseller	No	No	No
Dr. Martens	DRMARTENSOFFICIAL	Clothing	No	No	No
Dressbarn	DRESSBARN	Clothing	Yes	No	No
Dry Goods	DRYGOODSUSA	Clothing	No	No	No
DSW (Designer Shoe Warehouse)	DSW	Clothing	Yes	Yes	No
DTR/VILLA	DTLRVILLA	Clothing	Yes	Yes	No
Duluth Trading	DULUTHTRADINGCOMPANY	Clothing	No	No	No
DVF (Diane von Furstenberg)	DVF	Clothing	Yes	No	No
Dynamite	DYNAMITECLOTHING	Clothing	Yes	No	No
Eberjey	EBERJEY	Clothing	No	No	No
Eblens	EBLENSFOOTWEAR	Clothing	Yes	No	No
Eddie Bauer	EDDIEBAUER	Clothing	Yes	Yes	No
Eileen Fisher	EILEENFISHERNY	Clothing	Yes	No	No
Elie Tahari	ELIETAHARI	Clothing	No	No	No
Ermenegildo Zenga	ZEGNAOFFICIAL	Clothing	No	No	No
ESCADA	ESCADAOFFICIAL	Clothing	No	No	No
Evereve	EVEREVEOFFICIAL	Clothing	No	No	No
Express	EXPRESS	Clothing	Yes	Yes	No
Expressions Shoes	EXPRESSIONSKIX	Clothing	No	No	No
Fabletics	FABLETICS	Clothing	Yes	Yes	No
Factory Connection	FACTORYCONNECTION	Reseller	No	No	No
Famous Footwear	FAMOUSFOOTWEAR	Reseller	Yes	No	No
Ferragamo	FERRAGAMO	Clothing	Yes	No	No
Fleet Feet Sports	FLEETFEETSPORTS	Sporting	No	No	No
Foot Locker	FOOTLOCKER	Reseller	Yes	Yes	No
Foot Solutions	FOOTSOLUTIONSJB	Clothing	No	No	No
Footaction	FOOTACTION	Reseller	Yes	No	No
Forever 21	FOREVER21	Clothing	No	No	No
Fossil	FOSSIL	Jewelry & Watches	No	No	Yes
Francesca's	FRANCESCAS	Reseller	Yes	No	No
Free People	FREEPEOPLE	Clothing	No	No	No

Frye	THEFRYECOMPANY	Reseller	Yes	No	No
Furla	FURLA	Clothing	No	No	No
G.H. Bass and Co	GHBASS	Clothing	Yes	Yes	No
Gander Outdoors	GANDERRV	Sporting	No	No	No
Gap	GAP	Reseller	Yes	No	No
Geox	GEOX	Clothing	No	No	No
Glik's	GLIKSOFFICIAL	Reseller	Yes	No	No
Goorin Bros.	GOORINBROS	Clothing	No	No	No
Gordon's Jewelers	GORDONJEWELERS	Jewelry & Watches	No	No	No
Gretchen Scott	GRETCHENSCOTTDESIGNS	Clothing	Yes	No	No
Guiseppe Zanotti Design	GIUSEPPEZANOTTI	Clothing	Yes	No	No
H&M (Hennes & Mauritz)	HM	Clothing	No	No	No
Haggar	HAGGARCO	Clothing	No	No	No
Hamrick's	HAMRICK	Reseller	No	No	No
HandPicked	BEHANDPICKED	Reseller	No	No	No
Hanesbrands	HANESBRANDS	Clothing	Yes	Yes	No
Hanna Andersson	HAPPYHANNAS	Clothing	No	No	No
Harry Winston	HARRYWINSTON	Jewelry & Watches	No	No	No
Hat Club	HATCLUB	Clothing	Yes	Yes	No
Helzberg Diamonds	HELZBERGDIAMONDS	Jewelry & Watches	No	No	No
Hollister	HOLLISTERCO	Clothing	Yes	No	No
Hot Topic	HOTTOPIC	Clothing	No	No	No
Hurley	HURLEY	Sporting	Yes	No	No
Icing	ICINGSTORES	Reseller	No	No	No
Indochino	INDOCHINO	Clothing	Yes	No	No
Intermix	INTERMIXONLINE	Clothing	No	No	No
Ivivva	IVIVVA	Clothing	No	No	No
IZOD	IZOD	Clothing	No	No	No
J Mclaughlin	JMCLAUGHLIN	Clothing	Yes	No	No
J.Crew	JCREW	Clothing	Yes	No	No
J.Jill	JJILLSTYLE	Clothing	No	No	No
James Avery Craftsman	JAMESAVERY	Jewelry & Watches	No	No	No
Janie and Jack	JANIEANDJACK	Clothing	Yes	No	No
Jared The Galleria of Jewelry	JAREDTHEGALLERIAOFJEWELRY	Jewelry & Watches	Yes	No	No
Jimmy Choo	JIMMYCHOO	Clothing	Yes	No	No
Jockey	JOCKEY	Clothing	No	No	No
Johnston & Murphy	JOHNSTONMURPHY	Clothing	Yes	No	No
Jos. A. Bank Clothiers	JOSABANK	Clothing	No	No	No
Joyalukkas	JOYALUKKAS	Jewelry & Watches	No	No	No
Jude Connally	JUDECONNALLY	Clothing	No	No	No
Justice	JUSTICE	Clothing	Yes	Yes	No
Kate Spade	KATESPADENY	Clothing	Yes	No	No
Kay Jewelers	KAYJEWELERS	Jewelry & Watches	Yes	No	No
Kendra Scott	KENDRASCOTT	Jewelry & Watches	Yes	No	No
Kids Foot Locker	KIDSFOOTLOCKER	Reseller	Yes	Yes	No

L.L.Bean	LLBEAN	Sporting	No	No	No
La Senza	LASENZA	Clothing	Yes	No	No
Lacoste	LACOSTE	Clothing	Yes	Yes	No
Lady Foot Locker	FOOTLOCKERWOMEN	Reseller	Yes	Yes	No
Land's End	LANDSEND	Clothing	No	No	No
Lane Bryant	LANEBRYANT	Clothing	No	No	No
Last Call	LASTCALLNM	Clothing	Yes	No	No
LIDS	LIDS	Clothing	No	No	No
Lilly Pulitzer	LILLYPULITZER	Clothing	No	No	No
LOFT Outlet	LOFTOUTLET	Clothing	Yes	No	No
LOLÃ‹	LOLE	Clothing	No	No	No
Lord and Taylor	LORDANDTAYLOR	Clothing	No	No	No
Lorna Jane	LORNAJANEACTIVE	Clothing	Yes	No	No
Louis Vuitton International	LOUISVUITTON_INTERNATIONAL	Clothing	No	No	No
Lucchese Boot	LUCCHESE	Reseller	No	No	No
Lucky Brand	LUCKYBRAND	Clothing	Yes	Yes	No
Madewell	MADEWELL	Clothing	No	No	No
Marine Layer	MARINELAYER	Clothing	Yes	No	No
Marshalls	MARSHALLS	Reseller	Yes	No	No
Massimo Dutti	MASSIMODUTTI	Clothing	Yes	No	No
Maui Divers Jewelry	MAUIDIVERSJEWELRY	Jewelry & Watches	No	No	No
Maurices	MAURICES	Reseller	Yes	No	No
Max Mara	MAXMARA	Clothing	No	No	No
Merle Norman Cosmetics	MERLENORMANINC	Reseller	No	No	No
Merrell	MERRELL	Clothing	Yes	No	No
Michael Kors	MICHAELKORS	Clothing	Yes	Yes	No
Michaels Jewelers	MICHAELSJEWELERS	Jewelry & Watches	No	No	No
Moncler	MONCLER	Clothing	Yes	No	No
Morgan Jewelers	MORGAN.JEWELERS	Jewelry & Watches	No	No	No
Mountain Hardwear	MOUNTAINHARDWEAR	Sporting	Yes	No	No
Muji	MUJIUSA	Reseller	No	No	No
Na Hoku	NAHOKUJEWELERS	Jewelry & Watches	No	No	No
NambÃ©	NAMBE	Reseller	No	No	No
Naturalizer	NATURALIZER	Clothing	Yes	Yes	No
Nautica	NAUTICA	Clothing	Yes	Yes	No
New Balance	NEWBALANCE	Sporting	No	No	Yes
New York & Company	NYANDCOMPANY	Clothing	Yes	Yes	No
Nike	NIKE	Sporting	No	No	Yes
Nordstrom Rack	NORDSTROMRACK	Reseller	Yes	Yes	No
Old Navy	OLDNAVY	Clothing	Yes	No	No
Once Upon a Child	ONCEUPONACHILD	Reseller	No	No	No
PacSun	PACSUN	Reseller	Yes	No	No
Papaya Clothing	PAPAYACLOTHING	Clothing	No	No	No
Patagonia	PATAGONIA	Clothing	No	No	Yes
Perfumania	PERFUMANIA	Reseller	No	No	No

Peter Millar	PETERMILLAR	Clothing	No	No	No
Piercing Pagoda	PIERCINGPAGODA	Jewelry & Watches	No	No	No
Prada	PRADA	Clothing	No	No	No
PUMA	PUMA	Clothing	Yes	No	No
Rag & Bone	RAGANDBONE	Clothing	Yes	No	No
Ragstock	RAGSTOCK	Reseller	No	No	No
Rainbow Shops	RAINBOWSHOPS	Clothing	Yes	No	No
Ralph Lauren	RALPHLAUREN	Clothing	No	No	Yes
Rebecca Taylor	REBECCATAYLORNYC	Clothing	No	No	No
Red Wing Shoes	REDWINGHERITAGE	Clothing	No	No	No
Reebok	REEBOK	Sporting	No	No	Yes
Reeds Jewelers	REEDSJEWELERS	Jewelry & Watches	Yes	No	No
Riddle's Jewelry	RIDDLESJEWELRY	Jewelry & Watches	No	No	No
Robert Wayne Footwear	ROBERTWAYNEFOOTWEAR	Clothing	No	No	No
Rogan's Shoes	ROGANSSHOES	Clothing	No	No	No
Rogers & Hollands	ROGERSANDHOLLANDS	Jewelry & Watches	Yes	No	No
Rogers Jewelry Co.	ROGERSJEWELRYCO	Jewelry & Watches	No	No	No
Rue21	RUE21	Clothing	Yes	Yes	No
Running Room	RUNNINGROOM	Reseller	No	No	No
Saint Laurent	YSL	Clothing	No	Yes	No
Samsonite	MYSAMSONITE	Reseller	No	No	No
SAS San Antonio Shoemakers	SASSHOEMAKERS	Clothing	No	No	No
Scrubs & Beyond	SCRUBSANDBEYOND	Clothing	Yes	No	No
Shane Co	SHANECOMPANY	Jewelry & Watches	Yes	No	No
Sharpe's	SHARPE	Reseller	No	No	No
Shiekh Shoes	SHIEKH	Clothing	Yes	Yes	No
Shoe Carnival	SHOECARNIVAL	Reseller	No	No	No
Shoe Dept Encore	SHOEDEPTENCORE	Reseller	No	No	No
Shoe Sensation	SHOESENSATION	Reseller	No	No	No
Shoe Show Mega	SHOESHOW	Reseller	No	No	No
Shoe Station	SHOESTATION	Reseller	No	No	No
Shoppers World	SHOP_SWB	Reseller	No	No	No
Simon mall	SIMONMALLS	Reseller	No	No	No
Skechers	SKECHERS	Clothing	Yes	Yes	No
Soft Surroundings	SOFT_SURROUNDINGS	Clothing	No	No	No
Soma Intimates	SOMAINTIMATES	Clothing	Yes	Yes	No
Splendid	SPLENDIDLA	Clothing	Yes	No	No
Starr Western Wear	STARRWESTERNWEAR	Reseller	No	No	No
Steve Madden	STEVEMADDEN	Reseller	No	No	No
Stuart Weitzman	STUARTWEITZMAN	Clothing	No	No	No
SuitSupply	SUITSUPPLY	Clothing	Yes	No	No
Super Runners	SUPERRUNNERSNYC	Reseller	No	No	No
Super Shoes	SUPERSHOESSTORES	Reseller	No	No	No
Superdry	SUPERDRY	Clothing	No	No	No
Swatch	SWATCH	Jewelry & Watches	No	No	No

Sweaty Betty	SWEATYBETTY	Clothing	Yes	No	No
Tag Heuer	TAGHEUER	Jewelry & Watches	No	No	No
Talbots	TALBOTSOFFICIAL	Clothing	Yes	Yes	No
Tandy Leather Factory	TANDYLEATHER	Reseller	No	No	No
The Athlete's Foot	THEATHLETESFOOT	Reseller	Yes	No	No
The Children's Place	CHILDRENSPLACE	Clothing	Yes	No	No
The Exchange	EXCHANGESTORES	Reseller	No	No	No
The Jewelry Exchange	THEJEWELRYEXCHANGE	Jewelry & Watches	No	No	No
The Men's Wearhouse	MENSWEARHOUSE	Clothing	No	No	No
The Walking Company	THEWALKINGCO	Reseller	No	Yes	No
Theory	THEORY__	Clothing	No	No	No
Ticknors	TICKNORS	Clothing	No	No	No
Tiffany & Co.	TIFFANYANDCO	Jewelry & Watches	No	No	No
Tilly's	TILLYS	Reseller	Yes	No	No
Timberland	TIMBERLAND	Clothing	Yes	No	No
Timex	TIMEX	Jewelry & Watches	Yes	Yes	No
Title Nine	TITLENINE	Clothing	Yes	Yes	No
Tod's	TODS	Clothing	Yes	No	No
Tommy Bahama	TBAHAMA	Clothing	No	No	No
Topman	TOPMAN	Clothing	No	No	No
Topshop	TOPSHOP	Clothing	No	No	No
Torrid	TORRID	Clothing	No	No	No
Tory Burch	TORYBURCH	Clothing	Yes	Yes	No
Tourneau	TOURNEAU	Jewelry & Watches	No	No	No
True Religion Apparel	TRUERELIGION	Clothing	No	No	No
Tumi	TUMITRAVEL	Reseller	No	No	No
Tuxedo by Sarno	TUXEDOBYSARNO	Clothing	No	No	No
Tuxedo Junction	TUXEDOJUNCTION	Clothing	No	No	No
Tyler's	TYLERSTX	Reseller	Yes	No	No
U.S. Polo Assn.	USPOLOASSN	Clothing	No	No	No
UGG	UGG	Clothing	No	No	No
Under Armour	UNDERARMOUR	Clothing	Yes	Yes	Yes
Uniqlo	UNIQLO	Clothing	No	No	No
Uno de 50	UNODE50	Jewelry & Watches	No	No	No
Untuck It	UNTUCKIT	Clothing	Yes	No	No
Urban Outfitters	URBANOUTFITTERS	Clothing	No	No	No
Urban Zen	URBANZEN	Jewelry & Watches	No	No	No
Valentino	MAISONVALENTINO	Clothing	No	No	No
Van Cleef & Arpels	VANCLEEFARPELS	Jewelry & Watches	No	No	No
Van Heusen	VANHEUSENSTYLE	Clothing	No	No	No
Vans	VANS	Clothing	No	No	Yes
Vera Bradley	VERABRADLEY	Reseller	Yes	No	No
Vera Wang	VERAWANGGANG	Clothing	No	No	No
Versace	VERSACE	Clothing	No	No	No
VF Outlet	VFOUTLET	Reseller	No	No	No

Vince.	VINCE	Clothing	No	No	No
Vineyard vines	VINEYARDVINES	Clothing	No	No	No
Volcom	VOLCOM	Clothing	No	No	No
Western Union	WESTERNUNION	Reseller	No	No	No
White House Black Market	WHBM	Clothing	Yes	No	No
Windsor	WINDSORSTORE	Clothing	Yes	Yes	No
Woolrich	WOOLRICH	Clothing	No	No	No
Work 'N Gear	WORKNGEAR	Clothing	No	No	No
Work World	WORKTHEWORLD	Reseller	No	No	No
YCMC & Shoe City	YCMC	Reseller	Yes	No	No
Zales	ZALESJEWELERS	Jewelry & Watches	Yes	Yes	No
Zara	ZARA	Clothing	No	No	No

APPENDIX 2: CHANGE IN FOLLOWERS VERSUS ABSOLUTE NUMBER OF FOLLOWERS AS THE DEPENDENT VARIABLE

Essentially, with change in followers as the dependent variable, we are trying to measure the impact of corporate silence on the speed with which firms acquire followers on Instagram. Most of the accounts on Instagram continue to gain followers during our study period. While corporate silence on Blackout Tuesday does not necessarily reverse this trend, it may still slow the rate at which firms acquire new followers. We believe that this effect is better captured when we use the change in followers, rather than the absolute number of followers, as the dependent variable.

Empirically, this approach allows us to rely on a weaker parallel trend assumption. While parallel trends in follower counts between the two platforms also imply parallel trends in the change in followers, the reverse does not need to be true. To see this, Figure A1 plots the evolution of follower counts (left panel) and follower changes (right panel) for a hypothetical firm on both Instagram and Twitter. In scenario 1, both follower counts and changes exhibit parallel trends across platforms. Conversely, in scenario 2, parallel trends are observed only in follower changes, not follower counts. The assumption of parallel trend in follower changes allows the two platforms to follow different trends in follower growth.

Figure A1

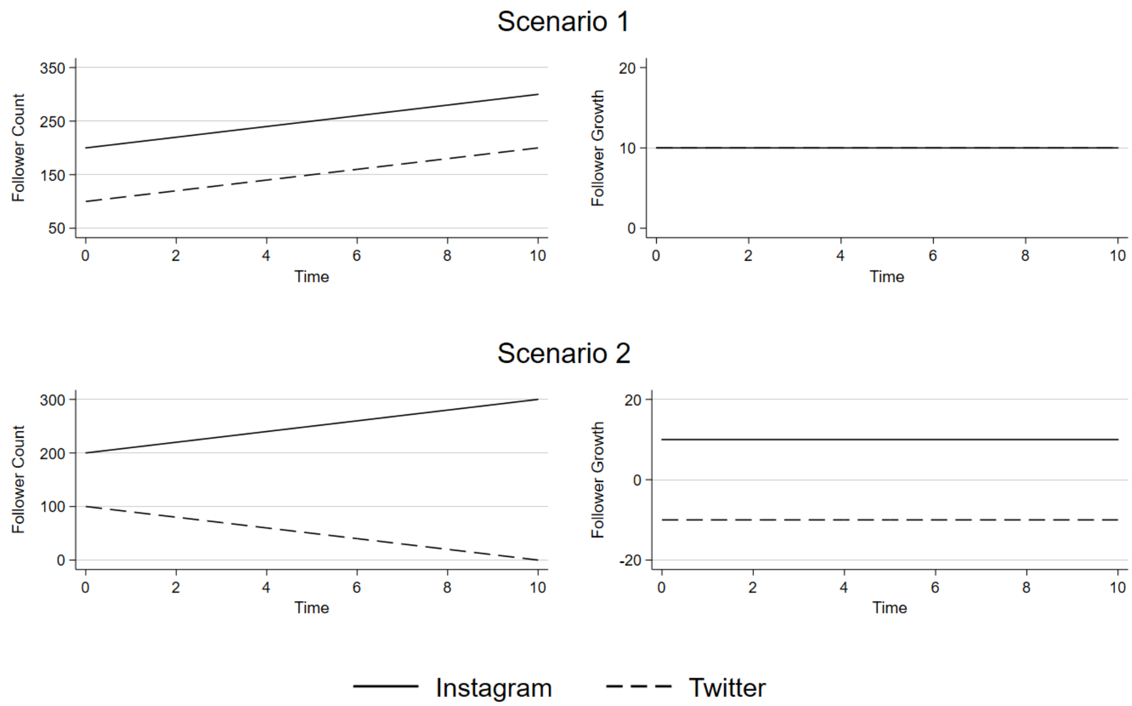
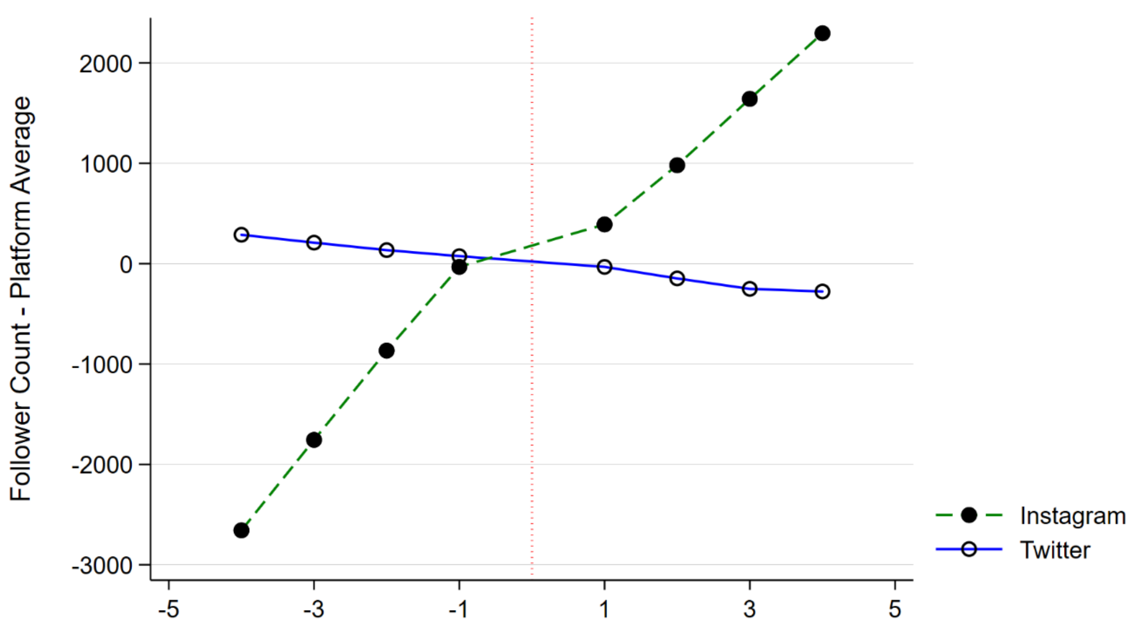


Figure A2 below plots the evolution of raw follower count minus the platform average for the two platforms. The raw follower counts from the two platforms do not follow a parallel trend and therefore may not be used as a dependent variable in our DID analysis.

Figure A2



By using the change in the number of followers as our dependent variable, we measure the additive treatment effect of corporate silence. However, there is still interest in understanding the multiplicative treatment effect even if the parallel trend assumption does not hold for the follower count. To investigate this, we employ a model with alternative parallel assumptions (Mora & Reggio, 2012, 2015, 2019), which allows us to identify the treatment effect in a difference-in-differences framework when the parallel trend assumption is applicable only to the first differences of the dependent variable (i.e., the parallel growth assumption). Specifically, we use the Stata package *didq* to conduct the analysis outlined in Equation (1), treating the absolute number of followers as the dependent variable. The estimation results, presented in Table A2, indicate a treatment effect of -2,695.762 (p=0.044), suggesting that remaining silent on Blackout Tuesday results in an average loss of about 2,700 followers in the month following the event. This finding is largely consistent with our main results presented in Table 3.

Table A2

Conditional Quadratic Trend Model

Output: Follower Count	Number of obs = 2848
Sample Period: -4:4	H0: Common Pre-dynamics = 3.59
Treatment Period: 1:4	p-value for H0 = 0.17

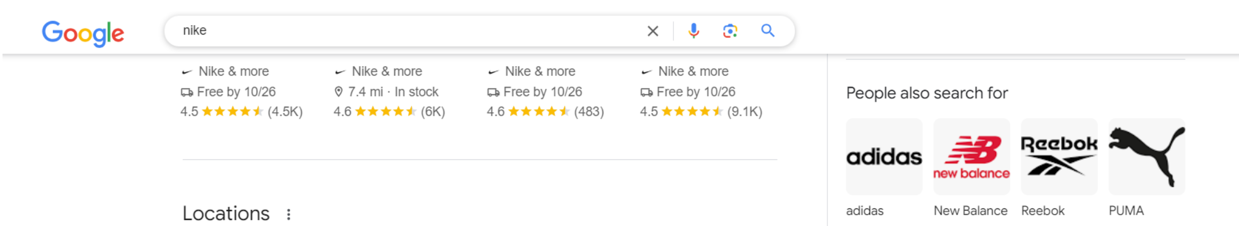
	All s	H0: s =s-1
All q	-2695.76	1.17
	[1300]	[0.76]

Standard errors clustered by firm in brackets
p-values in brackets

APPENDIX 3: IDENTIFYING FIRMS’ CLOSE COMPETITORS

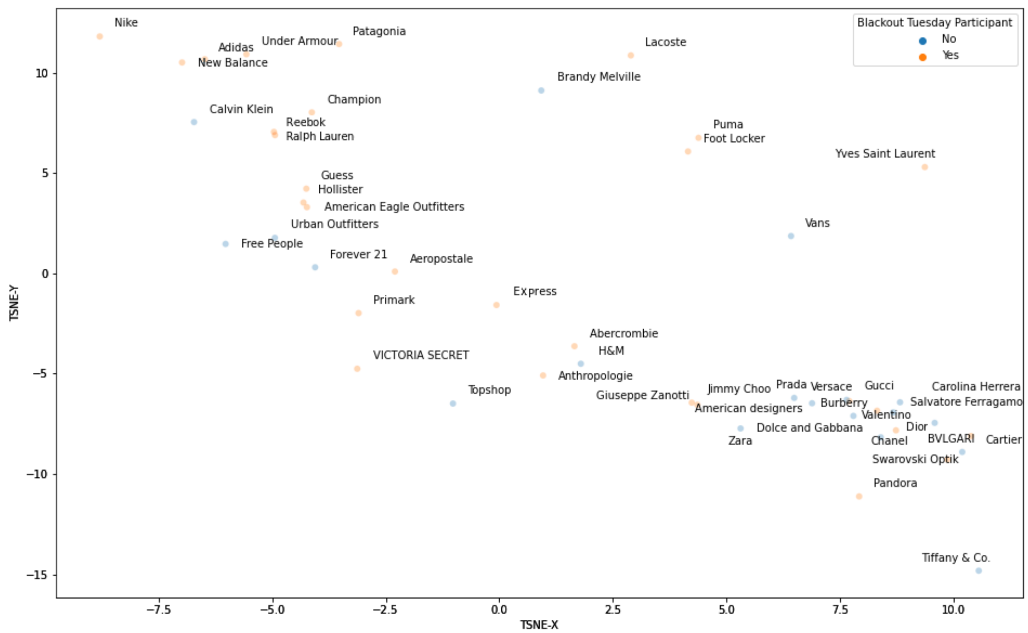
We rely on two approaches to determine the relative closeness among rival firms. Our first approach utilizes Google search results for each firm, focusing specifically on the 'People Also Search For' section to identify closely related competitors. By analyzing the firms that frequently appear alongside the focal firm in these search results, we can ascertain competitive relationships based on consumer search behavior. The relative ranking of these competitors in the search results helps us determine the top closest competitors for each firm. Figure A3 illustrates this process: for example, when we search for Nike, brands like Adidas, New Balance, Reebok, and Puma appear, identifying them as close competitors. During data collection (September 2021), when more than 10 firms were listed, we selected the top 10 as the primary competitors. This method provides a robust framework for identifying rival firms in the marketplace. Among all firms in our dataset, we successfully identified the top competitors of 125 firms from Google search.

Figure A3



Next, we employ Doc2Vec (Le & Mikolov, 2014) to vectorize firms’ social media posts, from which we can gauge the relative distance of firms’ social media posting and identify the most similar firms. Specifically, we aggregate the concatenated postings of each firm before the natural experiment into documents and train the Doc2Vec model to represent each document in a 300-dimensional vector. The similarity between any two competing firms can therefore be calculated as the cosine similarity between the two corresponding vectors. Figure A4 visualizes the results for the top 50 firms by follower count in a 2-dimensional mapping from our 300-dimensional Doc2Vec space obtained using T-SNE (Van der Maaten & Hinton, 2008). Doc2Vec does a reasonably good job in the vector representation of the rival firms, as evident in the clustering of high-end firms in the lower-right region, while firms that are more sports related are closer to the upper-left region. The fact that social media postings include both marketing and social contents suggests that our measure captures dimensions beyond typical marketing features when calculating the similarities between firms. In today's world where customers increasingly care about a firm's political stance, this Doc2Vec measure better captures firm rivalry in the eyes of the customers in our data context.

Figure A4



Reference

van der Maaten L, Hinton G. 2008. Visualizing Data using t-SNE. *Journal of Machine Learning Research* **9**(86): 2579–2605.

APPENDIX 4: DETAILS OF THE GAN-BERT MODEL

To tackle the machine learning text classification challenge, we turn to GAN-BERT (Croce, Castellucci, and Basili 2020), a state-of-the-art method that combines two paradigms of machine learning: transfer learning and generative adversarial networks. First, the transfer learning paradigm posits that sophisticated models trained on large data for general tasks can serve as a jumping off point for accomplishing specific tasks through fine tuning (Ng 2016; Stevo and Fulgosi 1976). In GAN-BERT, weights from BERT (Devlin et al. 2018) trained on the English Wikipedia corpus are fine tuned for a classification task on the small set of our custom-labeled texts. However, BERT fine tuning on its own might be insufficient when there are few labeled examples from the downstream classification task. Therefore, the second component of GAN-BERT, the generative adversarial network (GAN), is necessary to improve the efficiency and accuracy of the BERT based classification. While GANs' primary applications involve "creative" tasks such as generating new photo-realistic images, they can also be used in a data augmentation role to artificially increase the number of negative samples for the classification network, thereby improving its efficiency. GANs work through two networks: a discriminator net and a generative net. The discriminator is used to solve a classification problem, in GAN-BERT, this constitutes a pre-trained BERT model with an additional fully connected layer with softmax activation over K+1 classes, where K is the number of category labels and 1 is added to accommodate the 'fake' data generated by the generative network. The objective of this net is to minimize the sum of cross entropy loss for correctly classifying labeled data and the entropy loss for identifying 'fake' data generated from the generative network. In the generative net, Gaussian noise is simulated as an input to a neural network that is trained on the sum of two loss functions. First, the feature-matching loss function penalizes the Euclidean distance of the average generated output from the average output from an intermediate embedding layer of BERT. Second, the unsupervised loss function penalizes the entropy for the discriminator correctly classifying the generated samples.

Specifically, following the original notation in Croce, Castellucci, and Basili (2020), our model consists of a discriminator network, D, and a generator network, G. D is fed by a BERT model that takes in texts from labeled examples as input and outputs the classification head, h_{CLS}. D itself is a multilayer perceptron which outputs K+1 vector of logits. In our application, since our labeled data do not consist of mutually exclusive categories, K is set to equal 2, for either a positive or negative label for each category including BLM, general branding, social issues, and promotions. The additional category for the output of D accommodates the fake data generated by G. G, in turn, is another multilayer perceptron (fully connected feed-forward network) that takes white noise as an input and outputs fake samples of dimensions equal to that of h_{CLS} from BERT. The fake examples are then fed to D which attempts to minimize the sum of two cross entropy (negative log likelihood) losses: one for correctly classifying labeled data and one for correctly identifying fake data. Simultaneously, G is trained to minimize the sum of two losses: the Euclidean distance between the average fake sample and the average real h_{CLS} and the entropy loss induced by D correctly identifying the fake examples generated by G. Figure A5, reproduced from Croce, Castellucci, and Basili (2020) illustrates the overall model architecture.

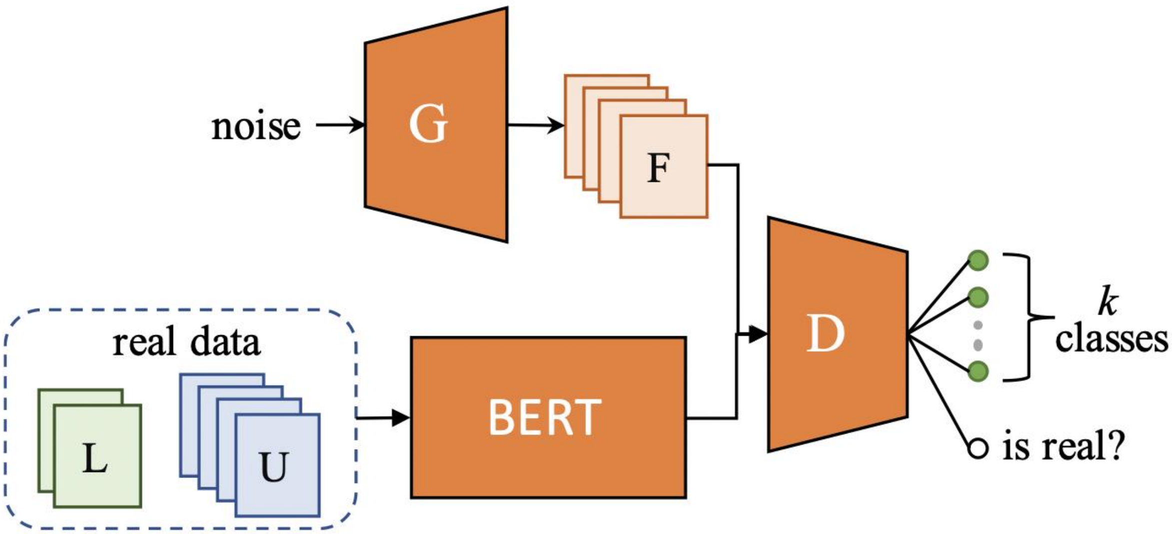


Figure A5 GAN-BERT Architecture Reproduced from Croce, Castellucci, and Basili (2020)

We train the GAN-BERT model on 90% of the labeled data and tabulate the out of sample predictive classification statistics on the remaining 10% of the data. Two research assistants labeled a sample of 4000 posts from the relevant corpus as belonging to various topics including BLM, branding messages, and other social issues, and 300 posts were labeled by both assistants. The resulting inter-rater agreement is α=.846 for the BLM labeling task. Given our objective of using GAN-BERT predictions as measures of proportion of content belonging the BLM category, we focus primarily on the accuracy metrics. Across all labels, and particularly for BLM labeled posts, we see that the out of sample accuracy is greater than 0.95. This gives us confidence to use the metrics in our resulting analyses.

Table A3

	Accuracy	Sensitivity	Specificity	Precision	F1
BLM	0.9571	0.9351	0.9605	0.7826	0.8521
Social Issues	0.9280	0.9686	0.9082	0.8371	0.8981
Promo	0.9108	0.6780	0.9370	0.5479	0.6061

References

Croce, Danilo, Giuseppe Castellucci, and Roberto Basili (2020), "GAN-BERT: Generative Adversarial Learning for Robust Text Classification with a Bunch of Labeled Examples," 2114–19.

Devlin, Jacob, Ming Wei Chang, Kenton Lee, and Kristina Toutanova (2018), "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, 1, 4171–86.

Ng, Andrew (2016), "Nuts and Bolts of Building Applications using Deep Learning," *NeurIPS*, (accessed December 21, 2021), [available at https://nips.cc/Conferences/2016/Schedule?showEvent=6203].

Stevo, Bozinovski and Ante Fulgosi (1976), "The influence of pattern similarity and transfer learning upon the training of a base perceptron B2," *Proceedings of Symposium Informatica*, 3 (121–5).

APPENDIX 5: ALTERNATIVE DID TIME WINDOW LENGTHS

Table A4

	3-Week Window		5-Week Window	
	(1)	(2)	(3)	(4)
	Follower Growth	Consumer Liking	Follower Growth	Consumer Liking
Instagram*After	-273.59	-0.18	-148.36	-0.09
	[75.77]	[0.08]	[49.21]	[0.05]
Constant	-627.73	-0.26	-416.84	-0.17
	[39.70]	[0.04]	[36.13]	[0.04]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2136	998	3560	1718
R^2	0.863	0.968	0.815	0.965

Standard errors clustered by firm in brackets

APPENDIX 6: PARALLEL TREND TEST

In Appendix 6, we conduct additional analyses to test the validity of our parallel trend assumption. Table A5 reports the regression results where we interact Instagram with periods t-2, t-3 and t-4. None of the interactions are significant, thus providing support for our parallel trend assumption.

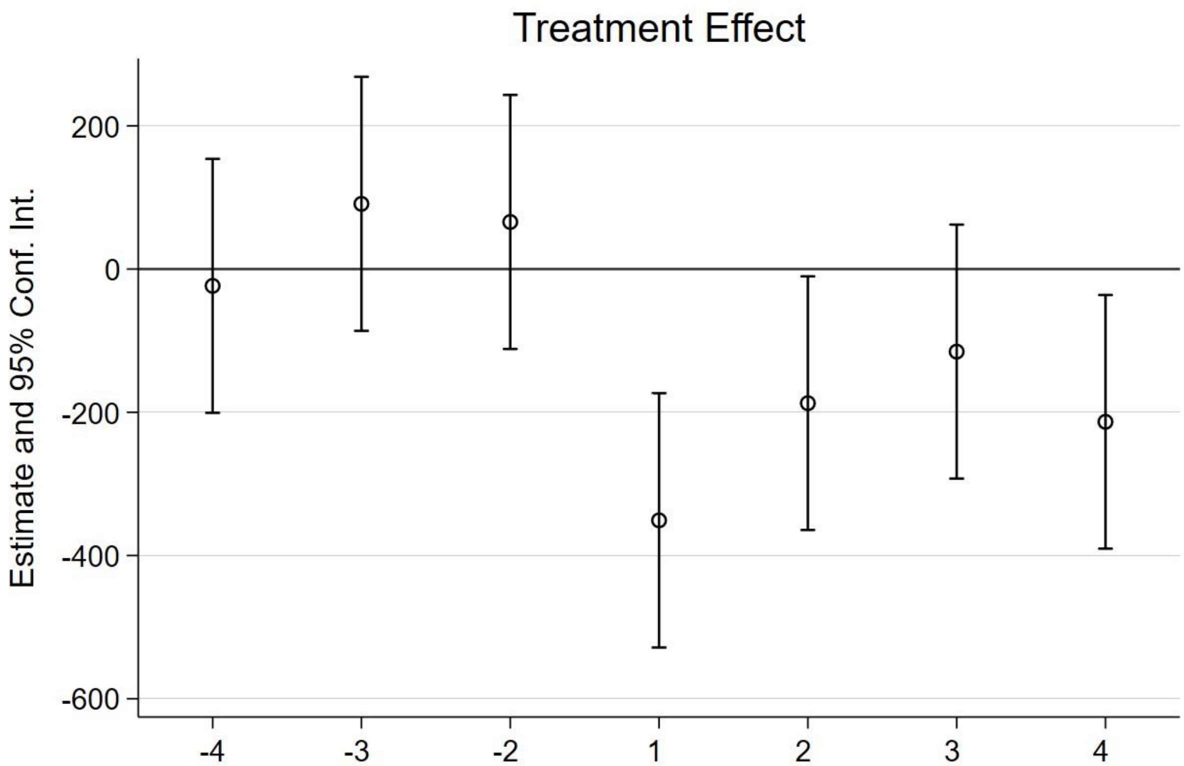
Table A5

	(1) Follower Growth	(2) Follower Growth	(3) Consumer Liking	(4) Consumer Liking
DID (Instagram *After)	-224.11	-225.21	-0.26	-0.10
	[130.12]	[73.29]	[0.11]	[0.05]
Instagram *Period t-4	-22.52	-31.29	-0.07	-0.03
	[139.08]	[92.75]	[0.11]	[0.05]
Instagram *Period t-3	-11.78	72.72	-0.06	0.04
	[139.29]	[92.76]	[0.11]	[0.05]
Instagram *Period t-2	-3.36	67.04	-0.08	0.05
	[139.18]	[92.79]	[0.11]	[0.05]
Instagram	778.83		0.93	
	[110.80]		[0.09]	
After	-9.62		0.05	
	[69.78]		[0.07]	
Constant	-99.29	-210.53	-0.25	-0.12
	[52.46]	[221.92]	[0.06]	[0.14]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	No	Yes	No	Yes
Firm-Time Fixed Effects	No	Yes	No	Yes
Observations	2848	2848	1346	1346
R^2	0.142	0.834	0.413	0.966

Note: We include the interactions between $Instagram_{ij}$ and the time indicator variables for each of the time periods before the date of BLM Blackout Tuesday to test the hypothesis that, before the date of the natural experiment, the trends in consumer responses for the focal firms on the two platforms (or over the two years) are similar. Standard errors clustered by firm in brackets.

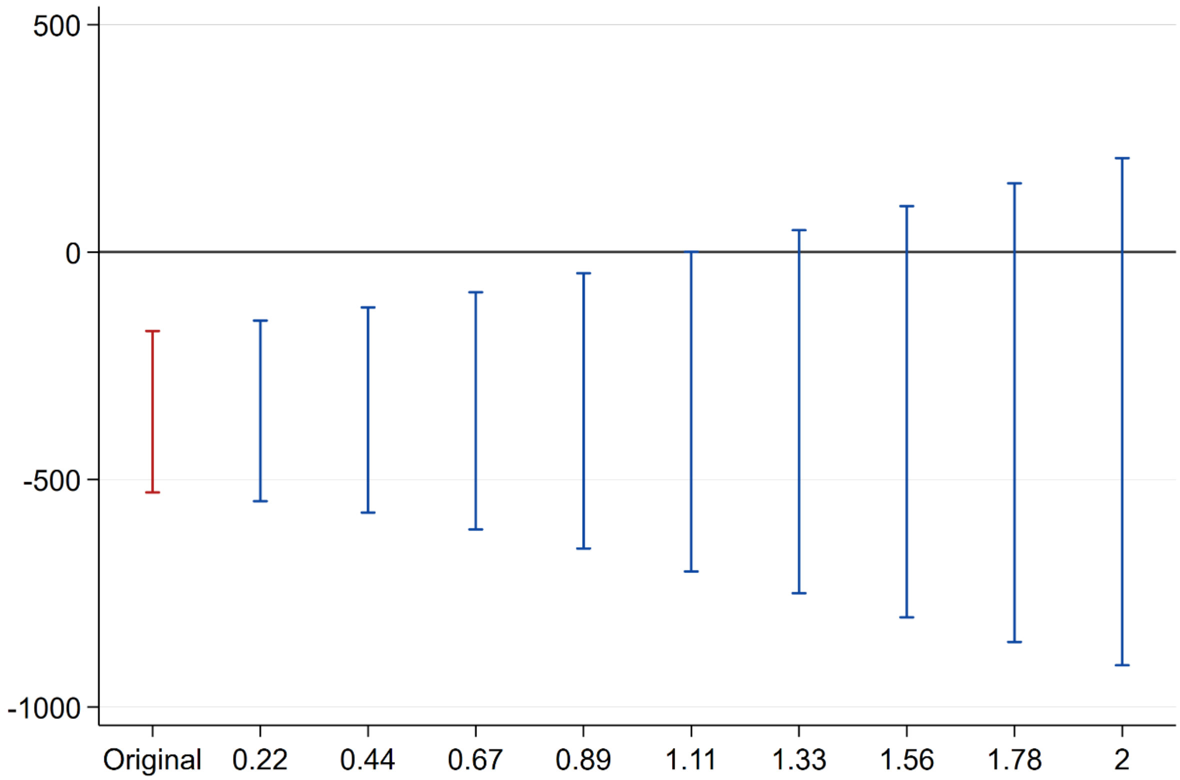
We further created an event study plot (Figure A6) to visualize the treatment effect over time. Again, the results are consistent with the parallel trend assumption.

Figure A6



We further conducted the sensitivity analysis suggested by Rambachan and Roth (2023). This analysis tests the robustness of our results by assessing how sensitive they are to potential violations of the parallel trend assumption post-treatment. Our findings indicate that the results are robust as long as the post-treatment parallel trend violation is no larger than the worst pre-treatment violation of parallel trends. The detailed results of this sensitivity analysis are presented in Figure A7. By demonstrating that our results hold under these conditions, we reinforce the credibility and reliability of our conclusions. This analysis confirms that our findings are not unduly sensitive to reasonable deviations in the parallel trend assumption.

Figure A7



APPENDIX 7: DID REGRESSION WITH ONLY FIXED EFFECTS

Table A6

	(1) Follower Growth	(2) Follower Growth	(3) Follower Growth	(4) Follower Growth	(5) Follower Growth	(6) Liking	(7) Liking	(8) Liking	(9) Liking	(10) Liking
DDD (Instagram*After*2020)					-194.50					-0.14
					[82.56]					[0.05]
Instagram*After	-257.71	-232.05	-312.07		-63.21	-0.11	-0.11	-0.20		0.02
	[68.38]	[75.16]	[97.71]		[49.38]	[0.06]	[0.06]	[0.12]		[0.03]
2020*After				-194.10	0.40				-0.16	0.00
				[79.92]	[26.71]				[0.06]	[0.03]
Instagram*2020					-651.52					-0.05
					[153.40]					[0.05]
Constant	-527.67	-521.43	-760.51	7299.56	932.40	-0.05	-0.04	-1.24	2.93	0.10
	[36.84]	[46.35]	[34.15]	[49.08]	[46.04]	[0.03]	[0.03]	[0.12]	[0.03]	[0.02]
Firm-Platform Fixed Effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
Firm-Period of Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	2848	2160	1424	2848	5696	1346	1228	632	1555	2936
R^2	0.852	0.835	0.894	0.921	0.853	0.958	0.958	0.970	0.960	0.958

Standard errors clustered by firm in brackets.

APPENDIX 8: PLATFORM DESIGN AS AN ALTERNATIVE EXPLANATION

One possible alternative explanation for our main results is related to platform design. Specifically, if platform algorithms highlighted BLM content on Instagram but not Twitter, this could mechanically produce certain results even if consumers are indifferent to silence.

We address this concern using two approaches. First, we collected evidence of customers responding negatively to a firm's silence on Blackout Tuesday. The examples can be found in Figure A8 below. Unfortunately, we are not able to perform a comprehensive analysis because, after 4 years, many firms have deleted their previous posts on Instagram (e.g., apeainthepodmaternity, camper, llbean, etc.) or may have removed some of the comments they received during our study period.

In our second approach, we examine firms' posting behaviors just days before Blackout Tuesday. Specifically, we divide the firms into two groups depending on whether they have posted anything on Instagram up to 3 days before the event. We believe that examining the differences in the treatment effect between the two groups of firms may help alleviate the concerns of this alternative explanation.

The intuition is that the two possible mechanisms have the opposite prediction regarding which group would have a more negative effect. If the negative treatment effect was mainly driven by less attention due to platform design factors, then we should expect the effect to be more negative for those who haven't posted anything 3 days before the event. This is because, compared with the other group, they have even less exposure on the social media platform.

On the other hand, however, if our mechanism is correct, then we should expect the effect to be more negative for those firms who posted just days before the event. This is because the posts make their silence on BLM more salient, which in turn invites more negative responses from customers. Unfollowing most likely occurs as users interact with an account's content when scrolling through their feed. If the firm is not in a customer's feed to begin with, the unfollowing effect should be smaller or negligible.

We conducted another DID analysis with DID*Posting Firms as an additional regressor. Here, Posting Firms is defined as an indicator variable that takes the value of 1 if a firm has posted anything on Instagram up to 3 days before the event. The estimation results are reported in Table A7 below. The coefficient of DID Posting Firms is negative and significant in Column

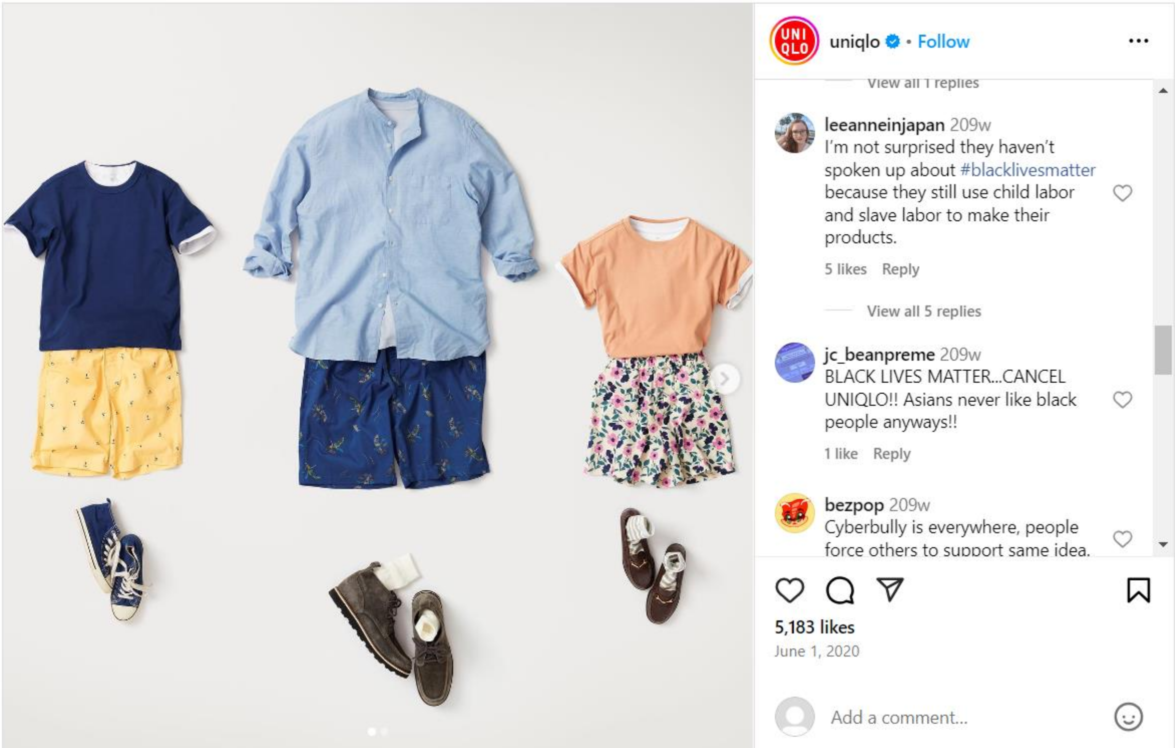
1. These results suggest that firms who posted just before the event suffered more in follower growth and therefore provide more support for our mechanism.

Table A7

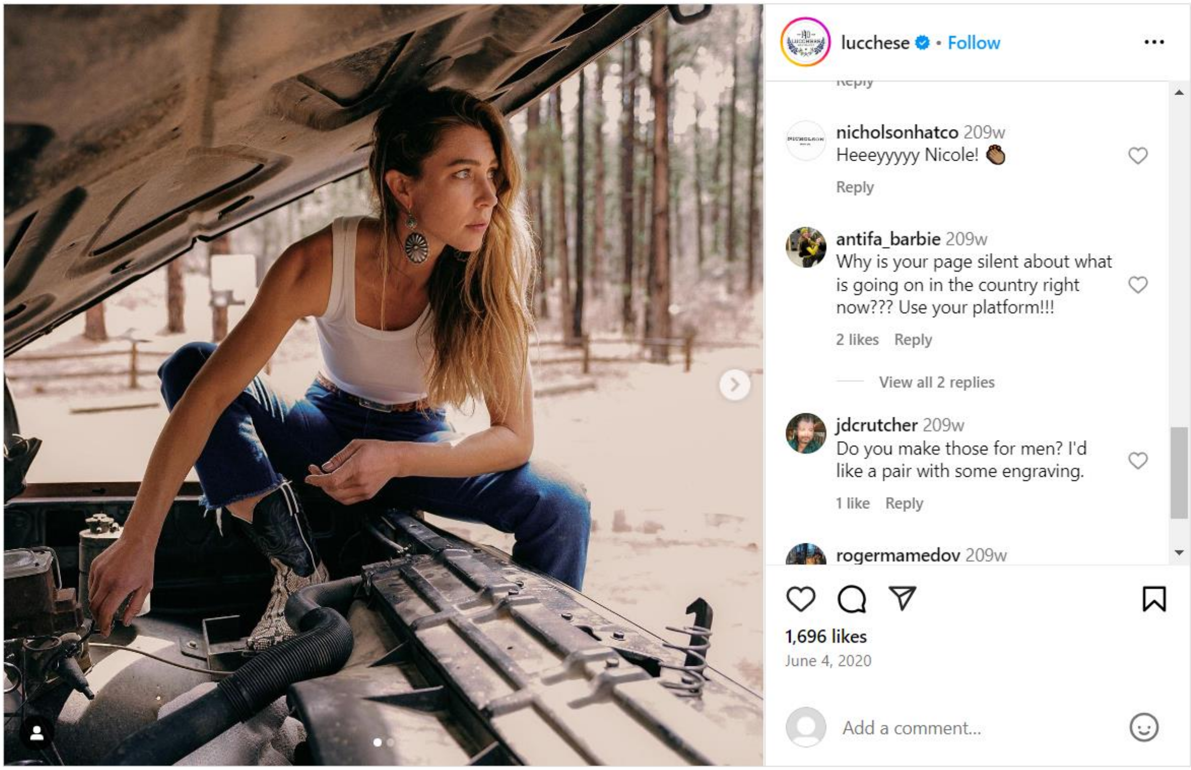
	(1) Follower Growth	(2) Consumer Liking
DID (BLM_Treatment *After)	-131.53	-0.07
	[59.34]	[0.05]
DID* Posting Firms	-280.91	-0.09
	[91.63]	[0.07]
Constant	-467.26	-0.11
	[262.96]	[0.14]
Covariates	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes
Firm-Period of Year Fixed Effects	Yes	Yes
Observations	2848	1346
R^2	0.854	0.966

Standard errors clustered by firm in brackets.

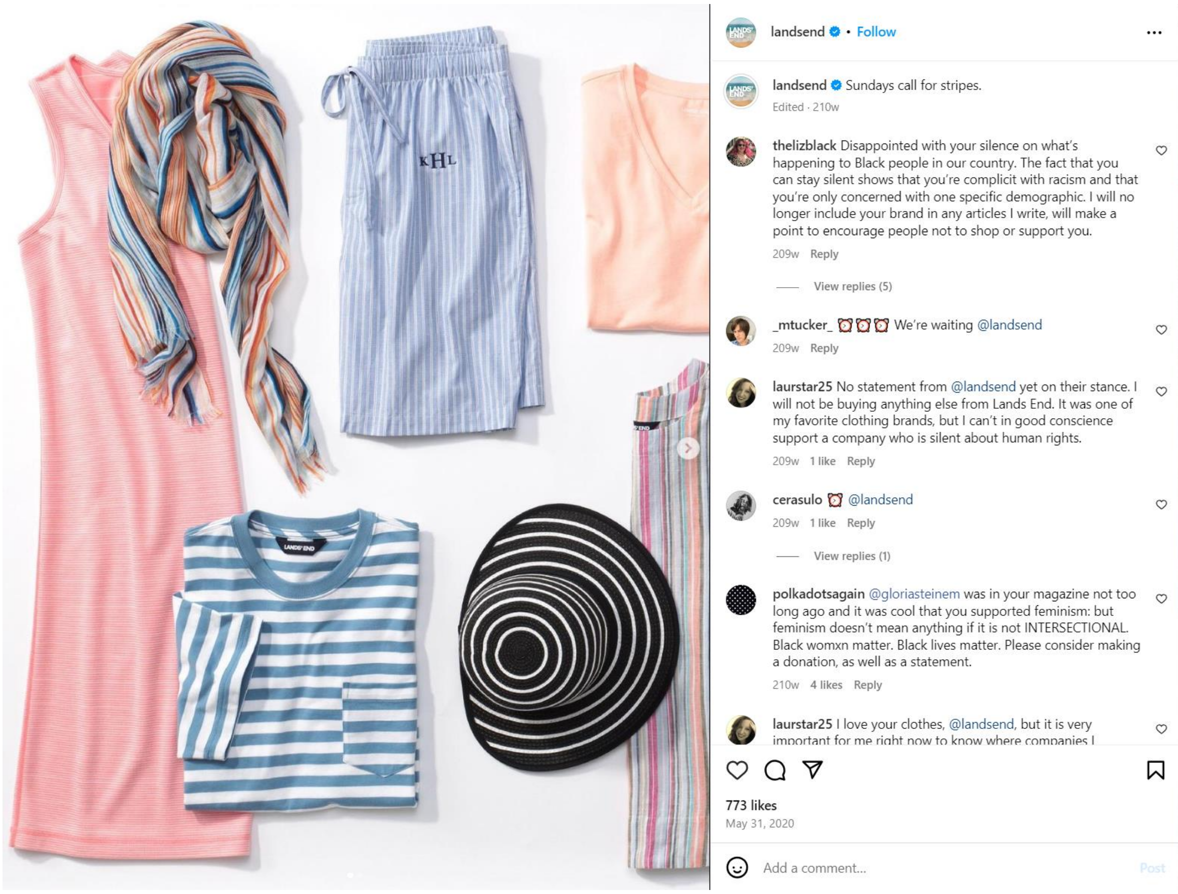
Figure A8


uniqlo • Follow
View all 1 replies
leeanneinjapan 209w
I'm not surprised they haven't spoken up about #blacklivesmatter because they still use child labor and slave labor to make their products.
5 likes Reply
View all 5 replies
jc_beanpreme 209w
BLACK LIVES MATTER...CANCEL UNIQLO!! Asians never like black people anyways!!
1 like Reply
bezpop 209w
Cyberbully is everywhere, people force others to support same idea.
5,183 likes
June 1, 2020
Add a comment...


buckle • Follow
A DAY!!!!! "Oh we're not going to post our shitty summer clothes for a DAY, and that will make them happy!" You choosing to stay silent is even worse than saying you support all lives matter cause right now your white privilege is showing hard. You need to check yourself a brand and as a company.
5 likes Reply
View all 1 replies
wickedlittlelooks 210w
Not surprised that y'all decided to stay silent on the issue. Half your management team down in Texas was abruptly racist and or homophobic
Reply
660 likes
June 1, 2020
Comments on this post have been limited.


lucchese • Follow
nicholsonhatco 209w
Heeeyyyyy Nicole!
Reply
antifa_barbie 209w
Why is your page silent about what is going on in the country right now??? Use your platform!!!
2 likes Reply
View all 2 replies
jdcrutcher 209w
Do you make those for men? I'd like a pair with some engraving.
1 like Reply
rogermamedov 209w
1,696 likes
June 4, 2020
Add a comment...


davidsbridal • Follow
209w 4 likes Reply
View replies (1)
victoriouslyfierce Disappointed
209w Reply
heavenlymassage Beautiful
209w Reply
victorygardens @davidsbridal you represent and dress Black brides, so why not put out a statement that says #BlackLivesMatter?
209w 2 likes Reply
kaylahurstphoto @davidsbridal stop using the lame ass copy paste response. This doesn't make any statement except that by posting a model of color you think you are. NEVER, EVER will I send brides to you ever, ever, ever.
209w 6 likes Reply
scecil37 hi @davidsbridal, we as brides want to know exactly what you're doing to address systemic racism in this country by supporting Black Lives Matter and amplifying black voices. we don't just want to see you post black models and canned responses to important comments. the clock is ticking.
209w 5 likes Reply
ajabelmanphoto How dare you use a black model's image but refuse to stand up for her life. You are happy to profit off of black bodies in our industry, but stay silent now? Please take a good hard look at your ability to reach people (400k+ of them) and make a better choice moving forward. Stand with the BIPOC who line your pockets. It's literally the least you could do, other than this.
209w 6 likes Reply
3,548 likes
June 4, 2020
Add a comment...
Post


KHL
landsend • Follow
landsend Sundays call for stripes.
Edited · 210w
thelizblack Disappointed with your silence on what's happening to Black people in our country. The fact that you can stay silent shows that you're complicit with racism and that you're only concerned with one specific demographic. I will no longer include your brand in any articles I write, will make a point to encourage people not to shop or support you.
209w Reply
View replies (5)
mtucker ⏰⏰⏰ We're waiting @landsend
209w Reply
laurstar25 No statement from @landsend yet on their stance. I will not be buying anything else from Lands End. It was one of my favorite clothing brands, but I can't in good conscience support a company who is silent about human rights.
209w 1 like Reply
cerasulo ⏰ @landsend
209w 1 like Reply
View replies (1)
polkadotsagain @gloriasteinem was in your magazine not too long ago and it was cool that you supported feminism: but feminism doesn't mean anything if it is not INTERSECTIONAL. Black womxn matter. Black lives matter. Please consider making a donation, as well as a statement.
210w 4 likes Reply
laurstar25 I love your clothes, @landsend, but it is very important for me right now to know where companies I
773 likes
May 31, 2020
Add a comment...
Post


bvlgari • Follow
immoqueen_no.1 209w
Reply
jhbk430 209w
Reply
claudiacoll1 209w
Reply
ravneetmk 209w
Are you also #unapologetic about your silence towards the murders occurring?
2 likes Reply
ravneetmk 209w
32,824 likes
June 4, 2020
Add a comment...

APPENDIX 9: TESTING H2 USING THE ALTERNATIVE MEASURE OF RIVAL BLM INTENSITY BASED ON DOC2VEC

Table A8

	(1) Follower Growth	(2) Follower Growth	(3) Consumer Liking	(4) Consumer Liking
DID (Instagram*After)	144.24	3081.26	0.33	-1.09
	[119.55]	[2861.64]	[0.17]	[2.43]
DID*Rival BLM Intensity	-817.89	-753.12	-0.90	-0.91
	[265.74]	[278.15]	[0.36]	[0.36]
DID*Republican Advantage		-220.70		-0.03
		[245.52]		[0.25]
DID*Black Population Proportion		-193.93		-0.66
		[461.39]		[0.29]
DID*Median Income		-249.92		0.15
		[257.66]		[0.24]
DID*High Education		-804.08		-0.72
		[586.37]		[0.97]
Constant	-461.18	-468.72	-0.06	-0.05
	[46.45]	[46.62]	[0.05]	[0.05]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2848	2848	1346	1346
R^2	0.854	0.854	0.966	0.967

Note: standard errors clustered by firm are in brackets.

APPENDIX 10: MEASURING CUSTOMER DEMOGRAPHICS AND POLITICAL AFFILIATIONS OF THE SILENT FOCAL FIRMS

We leverage census demographic data and consumer foot traffic data to infer the characteristics of a firm’s customers. Specifically, we create three variables, Black Proportion (the proportion of black customers), Median Income (the median customer income) and High Education (the proportion of customers with bachelor’s degree and above), to capture the demographic information of the customers. These three variables are constructed in two steps. First, we use Safegraph foot traffic data to capture the origin of each firm’s customers who visit the firm’s physical stores. From customers’ origin census block groups, we then approximate the firms’ aggregate customer demographics using the matched census data. Additionally, to capture customers’ political affiliation, we create another variable, Republican Advantage, which is defined as the difference between the proportions of customers who voted for Republican and

Democratic candidates in the 2016 presidential election. To measure Republican Advantage, after the two steps mentioned above, we further aggregate the census block group customer counts to the county level to match the presidential election results (so that we could calculate the proportion of each firm's Republican and Democratic supporters in 2016). Table A9 presents the definition and summary statistics of the variables. Around 11% of the customers of these firms are black. The median income of the customers for an average firm is about 72,000 dollars annually. 20% of the customers have bachelor's degree and above. In terms of political affiliation, Democratic customers seem to have a slight advantage (3%) for the firms studied.

Table A9

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Black Proportion	Proportion of black customers	178	0.11	0.11	0.00	0.97
Median Income	Median customer income (log transformed)	178	11.17	0.22	10.36	12.23
High Education	Proportion of customers with bachelor's degree or above	178	0.20	0.08	0.00	0.47
Republican Advantage	% Republican customers - % of Democratic customers	178	-0.03	0.22	-0.67	0.50

APPENDIX 11: TESTING H3 USING THE ALTERNATIVE MEASURE OF NICHE FIRMS BASED ON FIRM FOLLOWER COUNT

Table A10

	(1) Niche Market	(2) Mass Market	(3) Niche Market	(4) Mass Market
	Follower Growth	Follower Growth	Consumer Liking	Consumer Liking
DID (Instagram*After)	-7.55	-490.42	-0.01	-0.20
	[8.48]	[125.32]	[0.01]	[0.10]
Constant	7.57	-380.12	-0.06	-0.09
	[5.62]	[69.72]	[0.04]	[0.06]
Covariates	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	1424	1424	563	783
R^2	0.735	0.850	0.846	0.961

Note: Cutoff-value of Firm Follower Count for defining niche firms is 136,049. Standard errors clustered by firm are in brackets

APPENDIX 12: TESTING THE INTERACTION BETWEEN H2 AND H3 USING THE MEASURE OF RIVAL BLM INTENSITY BASED ON DOCUMENT TO VEC

Table A11

BLM Intensity Measure	Doc2Vec								Google Search			
Market Niche Measure	Firm Follower Count				Firm Follower Overlap				Firm Follower Count			
	(1) Niche Market	(2) Mass Market	(5) Niche Market	(5) Niche Market	(5) Niche Market	(5) Niche Market	(7) Niche Market	(8) Mass Market	(5) Niche Market	(5) Niche Market	(7) Niche Market	(8) Mass Market
	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Consumer Liking	Consumer Liking	Follower Growth	Follower Growth	Consu mer Liking	Consu mer Liking
DID (Instagram*After)	11.17	-10.57	92.46	92.46	92.46	92.46	0.01	0.44	-12.87	143.22	0.02	0.43
	[14.79]	[315.59]	[63.35]	[63.35]	[63.35]	[63.35]	[0.03]	[0.26]	[19.17]	[233.93]	[0.04]	[0.25]
DID*Rival BLM Intensity	-43.43	-902.52	-276.55	-276.55	-276.55	-276.55	-0.03	-1.19	23.25	-1590.99	-0.08	-1.94
	[44.64]	[533.19]	[181.78]	[181.78]	[181.78]	[181.78]	[0.05]	[0.54]	[60.75]	[711.47]	[0.09]	[0.82]
Constant	6.18	-342.06	-72.38	-72.38	-72.38	-72.38	-0.36	0.01	4.92	-427.25	-0.12	-0.11
	[4.97]	[72.10]	[27.09]	[27.09]	[27.09]	[27.09]	[0.04]	[0.06]	[4.94]	[63.12]	[0.04]	[0.06]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1424	1424	1200	1200	1200	1200	520	721	816	1184	365	666
R^2	0.736	0.850	0.902	0.902	0.902	0.902	0.949	0.966	0.895	0.865	0.917	0.958

Note: standard errors clustered by firm are in brackets.