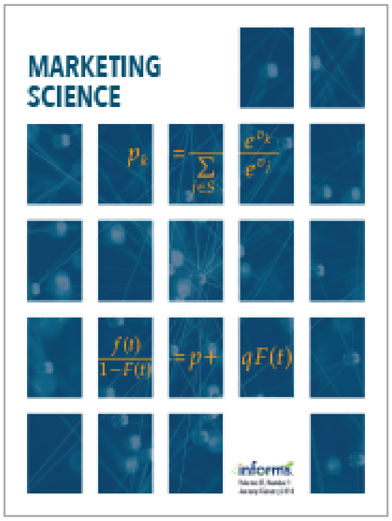

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Frontiers: How Support for Black Lives Matter Impacts Consumer Responses on Social Media

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Abstract. We scrutinize the direct and moderated impact of brands' support for Black Lives Matter (BLM) on consumer responses. Our empirical strategy exploits Blackout Tuesday as a natural experiment in which BLM support occurred on Instagram (treated platform) but not on Twitter (control platform) to perform a within-brand crossplatform difference-in-differences (DID) analysis. We also combine econometric models with machine learning techniques to analyze the unstructured data of the social media content. Based on a unique multiindustry, multiyear, and multiplatform data set of 435 major brands and 396,988 social media posts, we find a negative impact of BLM support on consumer responses, such as followers and likes. Furthermore, our analyses uncover a multifaceted set of heterogeneous DID effects across brands. (1) Although lone-wolf BLM support leads to negligible effects, large-scale BLM support from many brands can lead to strong negative effects (i.e., the bandwagon effect). (2) Posting self-promotional content exacerbates the negative effects of BLM support. (3) Historical prosocial posting on social media attenuates the negative effects. (4) Brands with socially oriented missions suffer less from the negative effects. (5) Customers' political affiliation also matters; the negative effects of BLM support are amplified/attenuated for brands with mostly Republican/Democratic customers. Additionally, (6) slacktivism (showing BLM support in words but without financial donations) can mitigate the negative effects for brands with mostly Republican consumers but amplify the negative effects for brands with mostly Democratic consumers.

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Keywords: Black Lives Matter (BLM) • social media • brand management • causal inference • machine learning

Introduction

Racial justice issues have been at the center of American history since its founding, and Black Lives Matter (BLM) is the latest incarnation of that theme (Auxier 2020). BLM is the most prevalent and impactful racial justice movement that harnessed social media as a mass mobilization channel for hundreds of millions of people, and it garnered a record of 8.8 million social media posts on a single day following the police killing of George Floyd in May 2020 (Anderson et al. 2020). Brands seeking to align their identity with the zeitgeist of racial justice have also turned to social media en masse to articulate and disseminate their support for BLM (Hsu 2020). In 2018, Nike partnered with BLM activist and former National Football League quarterback Colin Kaepernick to launch an ad campaign that became a political flashpoint on social media (Avery and Pauwels 2018). Nike's campaign led to a high level of consumer responses, such as 117,000 new followers on Instagram and a record number of likes (Thomas 2018). Following the success of Nike's racial justice allyship, an increasing number of brands have also taken to social media to express their support for racial justice issues (Hsu 2020, Livingston 2020). Further, brands leveraged social media to coordinate and participate in widespread allyship events to support BLM. Major brands, including 31% of the Fortune 100 (Young 2020), participated in Blackout Tuesday, an event on June 2, 2020 in which brands showed support of BLM by posting black squares to their Instagram accounts to silence commercial content (Coscarelli 2020). This increasingly widespread adoption of brand support for racial justice movements creates a strategic dilemma for brands because of the uncertain consequences. On the one hand, because brands are increasingly expected by many consumers to support racial justice issues, showing public support for a prevalent social movement like BLM may help attract and engage these consumers with positive effects on the brands. On the other hand, such racial justice support may be viewed as more performative and less authentic because of potential bandwagon concerns; consumers may perceive brands as seeking to capitalize by jumping on the bandwagon of allying with salient racial justice movements, thus likely leading to negative effects. Hence, it is an important endeavor to investigate the impact of BLM support on consumer responses and related boundary conditions. However, whether—and how—brands' BLM support impacts their consumer responses on social media have been largely neglected in the extant literature.

To bridge this knowledge gap, we address three key research questions. (1) Does brands' BLM support have a positive or negative impact on consumer responses on social media? (2) Is this impact amplified or attenuated by brands' social media posting behaviors, mission statement, and financial donation? (3) How does customers' political affiliation moderate their responses to brands' BLM support on social media?

We perform four sets of empirical analyses. First, we investigate the associations between BLM support and brands' follower growth based on a multievent analysis of 503 BLM posts by over 430 brands from June 1, 2019 to October 31, 2020. We uncover some preliminary evidence for a negative association between BLM support and follower growth. Interestingly, the negative associations are stronger when more brands concurrently posted messages supporting BLM. These results suggest that "lone-wolf" BLM support on social media generates negligible consumer responses but that large-scale allyship events in support of BLM are associated with significantly negative effects (i.e., the "bandwagon effect").

Second, to pin down the causal impact, we exploit Blackout Tuesday as a natural experiment in which large-scale BLM support occurred on Instagram (treated platform) but not on Twitter (control platform) to perform a within-brand crossplatform difference-in-differences (DID) analysis. Based on a unique data set of 435 major brands from multiple industries and their 396,988 social media posts on Instagram and Twitter, we find consistent evidence that BLM support has a negative causal impact on consumer responses. We further demonstrate that these results are robust to alternate causal inference designs, including within-brand-platform year-over-year (YoY) DID and inverse probability treatment weighting (IPTW) DID, as well as alternative measures of consumer responses.

Third, we perform exploratory analyses on heterogeneous DID effects across brands. Specifically, we analyze the unstructured data of social media content (i.e., historical post topics and concurrent self-promotion while supporting BLM), leveraging machine learning-enabled natural language processing (NLP) tools. Further, we examine BLM-related financial donations during the Blackout Tuesday event and brands' prosocial strategy as reflected by whether their mission statements contain a prosocial component. We find that the negative effects of BLM support are significantly moderated; posting self-promotional content exacerbates the negative effects of BLM support, historical prosocial posts on social media mitigate the negative effects, and brands with prosocial missions suffer less from the negative effects. These heterogeneous effects across brands are consistent with the authenticity explanation of BLM support on social media.

Fourth, given the politically divisive nature of BLM, we examine how customers' political affiliation moderates their responses to brands' BLM support. We show that the negative effects of BLM support are amplified for brands with mostly Republican customers whose political ideology is largely incongruently aligned with the BLM movement (Horowitz 2021) but attenuated for brands with mostly Democratic customers. However, Republican majority brands can mitigate the negative effects by engaging in slacktivism (i.e., voicing BLM support without accompanying financial donations). By contrast, the same slacktivism amplifies the negative effects for brands with mostly Democratic customers.

These findings make three key contributions. First, this study is among the first to investigate consumer responses to brands' racial justice movement on social media, a timely and important topic. Our investigation is based on a robust identification strategy, which combines a natural experiment and machine learning methods and leverages a multiindustry, multiyear, and multiplatform sample of major brands. Second, we not only reveal the main effects of brands' BLM support but also, uncover a multifaceted set of heterogeneous DID effects across brands. Third, our findings offer actionable managerial implications. For example, brands seeking to capitalize by jumping on the bandwagon of allying with salient racial justice movements should heed caution. Firms should not be too quick to resume business as usual with their product promotions when supporting BLM. Furthermore, brands that do not want to sit on the sidelines when major racial justice issues arise should consider making prosociality a core tenet of its social media strategy and brand mission. Moreover, brands should be cognizant of their customers' political ideology. Brands with mostly Republican (versus Democratic) customers may alleviate the negative effects if they do not make financial donations.

Our work is mainly related to two streams of prior research. First, it complements the literature on brand activism. Cordeiro and Sarkis (1997) found a negative relationship between brands' environmental activism and corporate financial performance. Luo and Bhattacharya (2006) document that corporate activism in terms of societal and stakeholder obligations enhances consumer satisfaction and thus, improves companies' stock performance. Wagner et al. (2009) revealed that inconsistent corporate activism (concerning environmental protection, employee healthcare benefits, and support of the national economy) can induce consumer perceptions of corporate hypocrisy and thus, engender substantial negative consumer reactions. Chatterji and Toffel (2019) showed that CEOs' (chief executive officers) social and political activism can strengthen consumers' purchase intention. Mukherjee and Althuizen (2020) noted that brand activism regarding controversial sociopolitical issues (e.g., illegal immigrants and abortion rights) has a negative impact among consumers who disagree with the stance of the brand involved. Hydock et al. (2020) observed that major brands with a large market share risk losing many loyal customers as a result of their corporate political advocacy (concerning transgender bathroom access and gun control). Similar to other brand activism causes (such as environmental protection, gun control, and abortion), BLM is also a divisive and controversial social movement among consumers (Wagner et al. 2009, Hydock et al. 2020, Mukherjee and Althuizen 2020, Vredenburg et al. 2020). However, BLM is different from other activism in four aspects. (1) Brands are not directly targeted in the case of the BLM movement (versus Walmart in the case of gun control or BP in the case of climate change). (2) Social justice issues like BLM are not necessarily a direct outcome of firm operations, whereas gun manufacturers make guns involved in mass shootings, and oil and gas companies directly produce carbon emissions. (3) Because of the deeply entrenched economic disparity along racial divides and the role of racial injustice as America's "original sin" (Wallis 2016, Gordon-Reed 2018), BLM is further distinct from other social causes, like LGBTQ (lesbian, gay, bisexual, transgender, queer) rights. Additionally, (4) BLM is perhaps the most widespread and influential movement that has mobilized hundreds of millions of people to protest racial inequality. As illustrated in Table 1, our work extends this stream of research by (i) addressing the different but crucial topic of BLM, which represents a racial equity issue and has a real-world bandwagon effect that is difficult to detect in the laboratory; (ii) focusing on different boundary conditions, mechanisms, outcome metrics, data types, and machine learning methods; and (iii) not only documenting robust negative consumer responses to brands' BLM support but also, offering nuanced heterogeneous effects.

Moreover, our study extends the literature on political marketing. As a pioneering study, Gordon and Hartmann (2012) examined the causal effect of advertising in major political events, such as presidential elections. Hutton et al. (2015) suggested that firms with a Republican culture are more likely to face litigation on civil rights, labor, and environmental issues, whereas firms with a Democratic culture are more likely to encounter litigation related to securities fraud and intellectual property rights violations. Fossen et al. (2020) noted that ads that followed a political (versus nonpolitical) ad experience fewer decreases in audience decline and are thus aired to more consumers. Interestingly, Irmak et al. (2020) investigated the role of political ideology and found that conservative consumers are more likely to resist government regulations than liberal ones. Contributing to this stream of research that focuses on the antecedents and outcomes of political ideology, our study explores how customers' political affiliations *moderate* the effects of BLM support on consumer responses. Indeed, little prior marketing research has examined political ideology in the context of racial justice or BLM support. We are among the first to document that conservative (versus liberal) consumers, on average, react more negatively to brands supporting BLM and that slacktivism can mitigate the negative effects for brands with mostly Republican consumers but amplify the negative effects for brands with mostly Democratic consumers.

Data, Natural Experiment, and Results

Data

We programmatically collected data from two major social media platforms: Instagram and Twitter. The data cover multiple industries, including the automotive, clothing, food, high-tech, jewelry and watches, reseller, and sporting sectors (see Online Appendix 1 for industry details and specific brands). Specifically, we started with 435 brands based on the availability of foot traffic data from Safegraph and social media accounts on both Instagram and Twitter.[1] Across all brands, we collected over 396,988 social media posts from June 1, 2019, one full year before Blackout Tuesday, to October 31, 2020.[2] For each post, we gathered information, including posting time stamp, captions, content, and likes. From the social media posts we collected, we identified 96 brands that participated in Blackout Tuesday on Instagram and had social media posts on Twitter. Furthermore, we augmented the social media post data with daily brand-platform–specific followers collected from socialblade.com, igblade.com, and trackalytics.com.

We analyze the textual content of brands' social media posts by leveraging machine learning methods to understand prosocial topics. Although prior work on organizations' interaction with social movements focuses on a comparatively small set of events that

Table 1. Literature Comparison

Article	Activism causes	*X*	*Y*	Mechanisms	Boundary conditions	Data	Sample size	Machine learning
Wagner et al. (2009)	Environment protection (reducing packaging material), employee healthcare benefits, and boycotting outsourcing domestic jobs to foreign countries	Inconsistent corporate social responsibility (CSR) information	Customer attitudes toward the firm and CSR beliefs	Perceived corporate hypocrisy	CSR communication strategies: inoculation/abstractness vs. concrete/proactive vs. reactive	Laboratory	1,484 students and M-Turkers	—
Mukherjee and Althuizen (2020)	Deportation of illegal immigrants and abortion rights	Consumer-brand agreement/disagreement	Customer attitudes toward the brand/consumers' behavioral intentions	The level of consumer-brand identification	The source of a brand's stand/public backlash/a retraction and apology	Laboratory	980 students and M-Turkers	—
Hydock et al. (2020)	Transgender bathroom access and gun control	CPA	Perceived market-level brand choice	Consumer identification with the brand	Perceived CPA authenticity/brand market share	Laboratory	3,779 students and M-Turkers	—
Gordon and Hartmann (2012)	—	Gross rating points	The voting-eligible population	—	—	Observation	1,054,939 market-level individual presidential ads and the county-level vote data	—
Irmak et al. (2020)	—	Political ideology	Consumption perceptions and purchase intention	Perceived threat to freedom	Trait reactance/the source of the regulation	Laboratory/observation	569 M-Turkers	—
Fossen et al. (2020)	—	The number of viewers at the beginning of the ad	Number of viewers at the end of the ad/characteristics of the political ad that precedes the ad	Political advertising spurs negative arousal among viewers	Ad position	Observation	849 national political television ads from the 2016 election	—
This paper	BLM movement	BLM posting in social media platforms	Real-world consumer following and liking on Instagram and Twitter	Large-scale BLM support from many brands may lead to negative consumer responses; isolated support does not. Authenticity explanation and customers' political identity account for the heterogeneous effects	Scale of brand allyship/self-promotion contents/previous prosocial posts/slacktivism/brand mission/customers' political affiliation	Natural experiment	435 brands and 654,648 social media posts	Guided LDA, bi-LSTM (long short-term memory)

Note. CPA, corporate political advocacy.

can be categorized by hand (e.g., Odziemkowska 2020), our context involves labeling tens of thousands of posts, which is prohibitively labor intensive if done by hand. Therefore, we relied on two machine learning approaches: guided LDA and deep learning. Specifically, guided LDA is a machine learning approach that takes advantage of researchers' informative priors for topic analysis (Toubia et al. 2019). For the deep learning approach, we relied on Word2Vec embeddings feeding into a bidirectional LSTM attention-based model (Wang et al. 2016) to discern the functional mapping between latent semantic meanings of our textual data and the labels of posted content (see Online Appendix 3 for details). We first identified prosocial topics from initial manual coding of 4,000 posts (e.g., societal inequality, diversity, climate, LGBTQ, political advocacy, poverty, coronavirus disease 2019 (COVID-19), and other issues). Using the trained models, we then predict the probability of promotional and prosocial topics for each post using both NLP methods (see Online Appendix 4 for details). Table 2 presents the definition and summary statistics of the post-level variables.

Preliminary Evidence for the Effects of BLM Support. To motivate our subsequent main causal inference analysis of a major BLM support event, we first provide some preliminary evidence of the conditions under which BLM support impacts consumer responses. See Figure 1(a) for an overview of the multievent analysis (preliminary evidence) and natural experiment (causal evidence). Specifically, we analyze the daily brand-platform engagement effects of every BLM post from June 1, 2019 to October 31, 2020. There are a total of 503 BLM support posting events (368 on Instagram + 135 on Twitter) (see the distributions of these events in Online Appendix 2) during the 17 months. We operationalize this analysis in a multiple treatment event study pooling social media posts across both Twitter and Instagram as specified in Equation (1):

$$
\begin{aligned}
FollowerGrowth_{ijt} = &\sum_{l=0}^{l=L} \alpha_l BLM_{post\,ijt-l} \\
&+ \sum_{l=0}^{l=L} \beta_l BLM_{post\,ijt-l} Participants_{jt-l} \\
&+ \boldsymbol{X_{ijt}}\delta \\
&+ \epsilon_{ijt}, \qquad (1)
\end{aligned}
$$

$FollowerGrowth_{ijt} = \text{Sign}(Followers_{ijt} - Followers_{ijt-1})\ln(|Followers_{ijt} - \text{Followers}_{ijt-1}|)$ when $|Followers_{ijt} - Followers_{ijt-1}| > 1$, and 0 otherwise,[3]

where $FollowerGrowth_{ijt}$ is the log difference in followers for brand i on platform j for day t,[4] BLM_post_{ijt-l} is an indicator of posting a message of BLM support on day $t - l$ where l is a lag from one through four,[5] and $Participants_{jt-l}$ is the number of sampled brands that concurrently posted BLM support messages on platform j during day $t - l$. Additionally, $\boldsymbol{X_{ijt}}$ represents a matrix of fixed effect controls. We test specifications with both brand + platform × date fixed effects (Spec. A; i.e., $\boldsymbol{X_{ijt}}\delta = \delta_{brand} + \delta_{t,platform}$) and time-specific brand and platform fixed effects plus brand-specific platform fixed effects (Spec. B; i.e., $\boldsymbol{X_{ijt}}\delta = \delta_{brand,t} + \delta_{platform,t} + \delta_{brand,platform}$). Note that Spec. A accounts for the average time-varying differences in follower growth between Instagram and Twitter. This specification compares treated (posted BLM support) brand-platforms with all untreated brand-platforms on the same day and averages those effects across days and platforms. Spec B. adds brand-specific time fixed effects to account for brand-specific time-varying overall social media follower growth trends. Additionally, brand-specific platform fixed effects account for each brand's average differences in follower growth on Instagram versus Twitter. Under Spec B., the analysis approaches causality under the assumption that brand follower growth on Instagram is parallel to that on Twitter, for which we demonstrate evidence in the next section. However, brand-time-platform–specific shocks can still confound our analysis if brands self-select into voicing support for BLM on a particular platform on a particular day.[6] We report parameter estimates in Table 3, where columns (1) and (2) represent parameters estimated under Spec. A, whereas columns (3) and (4) represent those estimated using Spec. B.

Results in column (1) of Table 3 suggest that voicing support for BLM on social media is significantly associated with decreased follower growth ($\alpha_0 = -0.574$, $p < 0.01$), thus providing preliminary evidence that voicing BLM support may backfire. However, once we consider the number of brands that are concurrently supporting BLM in column (2), the main effect of BLM support becomes insignificant, whereas the moderating effect of the number of participants on the same platform is negative and statistically significant ($\beta_0 = -0.008, p < 0.01$). Moreover, it would take at least 25 participating brands to yield the average effect size in column (1). Additionally, we find that the prior day moderating effect of participants can also have a similarly negative effect ($\beta_1 = -0.007, p < 0.01$). Column (3) replicates these results with Spec. B, and column (4) removes Blackout Tuesday and the ensuing four days to show that these results are generalizable. Together, these findings suggest that "lone-wolf" BLM support on social media is not associated with substantial backfiring effects, but large-scale allyship events in support of BLM are associated with strong negative "bandwagon effect." We next carefully investigate the

Table 2. Summary Statistics of Variables: Post Level

Variable	Definition	*N*	Mean	Standard deviation	Min	Max
Probability of Prosocial Posts (LDA)	The probability that a post is related to prosocial topics (e.g., inequality, LGBTQ, COVID-19, poverty …) from LDA	396,988	0.04	0.09	0	0.99
Probability of Self-Promotion (LDA)	The probability that a post is related to promotional topics (e.g., promotion, sales, % off …) for a product or service from LDA	396,988	0.004	0.03	0	0.99
Probability of Prosocial Posts (LSTM)	The probability that a post is related to prosocial topics from LSTM	396,988	0.03	0.05	0	1
Probability of Self-Promotion (LSTM)	The probability that a post is related to promotional topics for a product or service from LSTM	396,988	0.20	0.20	0	0.88
Mention	=1 if the brand mentioned other user(s) in a post	396,988	0.26	0.44	0	1
Likes	The number of likes of the post	396,988	8,234.87	88,030.23	0	5,713,280

causal impact of BLM support when bandwagon effects might be most salient during Blackout Tuesday.

A Natural Experiment

Estimating the causal effect of brands' widespread BLM support is a nontrivial challenge because brands' BLM support behavior is not randomly assigned. Although the analysis in the previous section approaches causality, it can still suffer from endogeneity bias if brands strategically time their platform-specific BLM support posts. Therefore, we require a natural experiment that restricts a brand's ability to endogenously choose their platform when posting BLM support on a specific day.

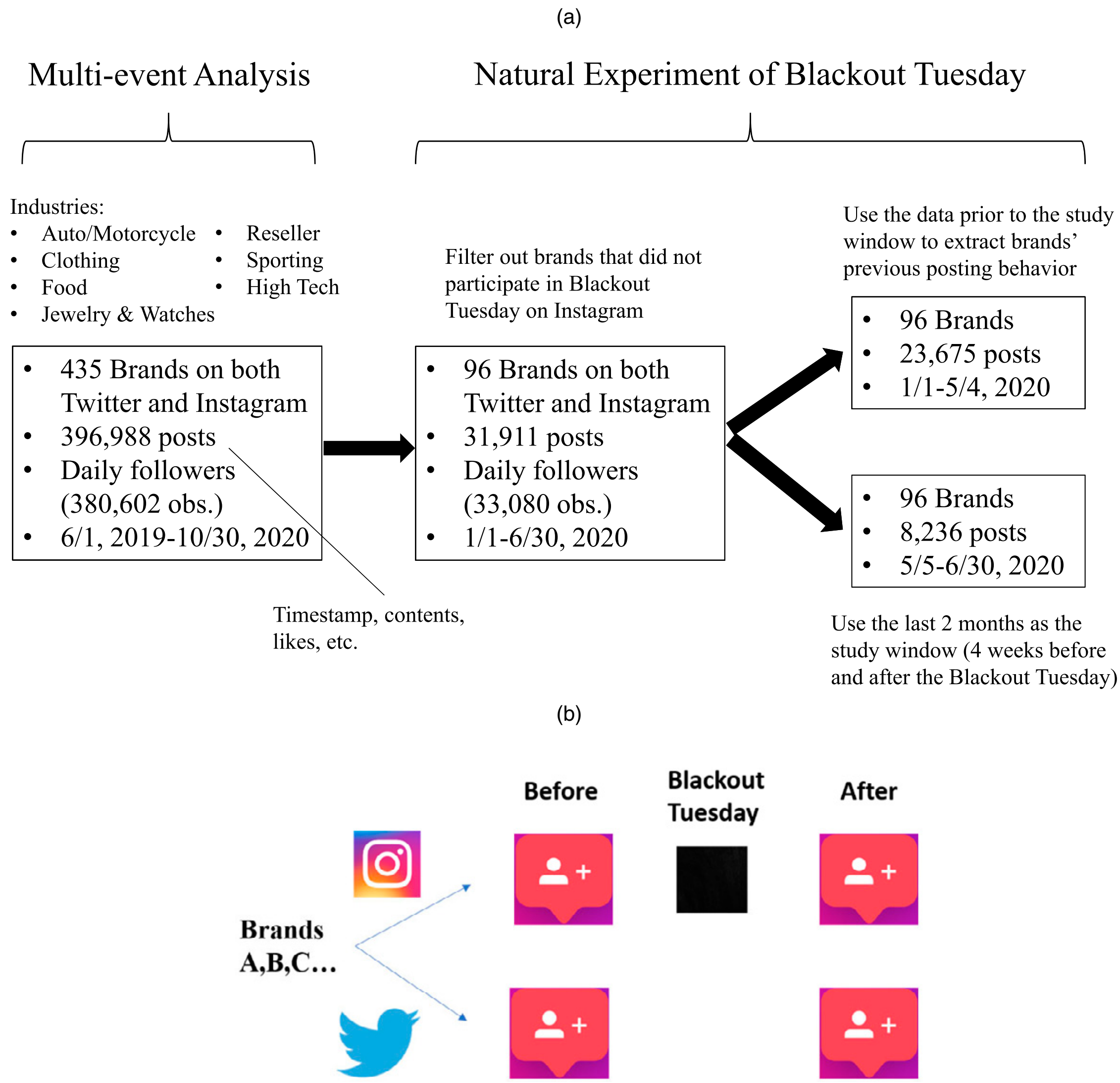
Fortunately, Blackout Tuesday can serve as a natural experiment to overcome the challenge and identify the causal effect. Specifically, this event occurred on June 2, 2020 and was originally proposed by the music industry to protest against systemic racism and police brutality under the hashtag #theshowmustbepaused; it quickly transformed into a global phenomenon on Instagram under the hashtag #BlackoutTuesday (Coscarelli 2020). The viral hashtag reflected brands' method of participation, the posting of a black square image on Instagram to flood the platform with the same message, drawing attention to the BLM movement (see Online Appendix 5 for an illustration). This event can help us pin down the causal effect for two key reasons. First, the timing of the event is likely to be exogenous for brands as it was proposed just one day earlier, so brands had little time to strategize their actions. Second, the Blackout Tuesday event occurred primarily on Instagram but not on other platforms, like Twitter. This is because Instagram is an image-sharing platform, satisfying the black square[7] posting guidelines used to "black out" the platform. The counterfactual for the brands participating in Blackout Tuesday on Instagram (treatment) is the *same* set of brands on Twitter (control). Hence, the within-brand variations across different social media platforms (Instagram versus Twitter) over time (before versus after Blackout Tuesday) constitute a DID strategy to identify the causal effects of BLM support in the Blackout Tuesday event (see Figure 1(b)).[8]

Model-Free Evidence

Using the two-month period before and after the Blackout Tuesday event, we analyze the causal impact of BLM support on follower growth. In our main analyses, we aggregate the observations to four-day windows, where time period 1 begins on Blackout Tuesday, for two reasons. First, the effects of Instagram posts may last several days (Instagram 2021) and depend on the frequency of a brand's posting behavior. In our data set, a median brand posts on average twice a week, suggesting that followers may be in contact with brand content on average every three to four days. Second, the daily-level follower data may be noisy and suffer from missing observations because of inconsistent data collection by third-party follower tracking sites. Nonetheless, we check various time aggregation choices to show that our results remain robust (see Online Appendix 6). Table 4 presents the definition and summary statistics of the variables of interest in our data analyses.

Figure 2 presents the model-free evidence for the effects of BLM support. Specifically, the upper panel illustrates the evolution of the average follower growth (in log follower changes) for brands on Instagram and Twitter before and after Blackout Tuesday, whereas the lower panel plots the difference of follower growth across platforms. The trends across the two platforms before the Blackout Tuesday event

Figure 1. (Color online) (a) Overview of Multievent Analysis (Preliminary Evidence) and Natural Experiment (Causal Evidence) and (b) Illustration of the DID Identification Strategy in the Natural Experiment



appear to be parallel (e.g., zero is included inside the confidence intervals in the lower panel). However, this pattern changed after the event. Compared with Twitter, there was a decrease in follower growth for the same brands on Instagram. This model-free evidence suggests that participating in Blackout Tuesday appears to have had a negative impact on follower growth. Moreover, the parallel pretreatment trends offer evidence consistent with the parallel trends assumption required by our formal DID analysis. Next, we formally test the results from the data using econometric DID models.

DID Models

We estimate a DID model to assess the causal effect of BLM support through Blackout Tuesday on consumer responses as measured by *Follower Growth* by the brands on social media, as specified in Equation (2),

$$\begin{aligned} FollowerGrowth_{ijt} = \alpha_0 &+ \alpha_1 BLM\_Treatment_{ij} \\ &+ \alpha_2 After_t + \alpha_3 BLM\_Treatment_{ij} \\ &\times After_t + \alpha_4 \boldsymbol{X_{ijt}} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

where $FollowerGrowth_{ijt}$ denotes the log change in brands' followers (i.e., follower growth of brand i on platform j at time period t). $BLM\_Treatment_{ij}$ is an indicator variable that equals one for the treated platform, Instagram, and zero for Twitter observations, the control platform. $After_t$ is an indicator variable that equals one for the time periods after Blackout Tuesday and zero otherwise. $\boldsymbol{X_{ijt}}$ represents controls such as brand-time fixed effects and brand-platform fixed effects,[9] as well as some time-varying covariates capturing other characteristics of brand i on platform j at time t,

Table 3. Preliminary Evidence for the Negative Effects of BLM Support

	(1) Follower growth	(2) Follower growth	(3) Follower growth	(4) Follower growth
BLM Post$_t$	−0.574**	−0.372	−0.545	−0.213
	(0.218)	(0.190)	(0.308)	(0.523)
BLM Post$_{t-1}$		0.001	0.006	0.190
		(0.177)	(0.254)	(0.477)
BLM Post$_{t-2}$		0.040	−0.173	0.217
		(0.146)	(0.221)	(0.419)
BLM Post$_{t-3}$		0.034	−0.168	−0.474
		(0.179)	(0.183)	(0.542)
BLM Post$_{t-4}$		0.048	−0.181	−0.277
		(0.186)	(0.231)	(0.311)
BLM Post$_t$ × *Participants*$_t$		−0.008**	−0.009**	−0.146**
		(0.003)	(0.003)	(0.050)
BLM Post$_{t-1}$ × *Participants*$_{t-1}$		−0.007**	−0.008**	−0.208*
		(0.003)	(0.003)	(0.085)
BLM Post$_{t-2}$ × *Participants*$_{t-2}$		−0.001	−0.001	−0.094
		(0.002)	(0.003)	(0.060)
BLM Post$_{t-3}$ × *Participants*$_{t-3}$		−0.003	−0.002	0.061
		(0.003)	(0.003)	(0.045)
BLM Post$_{t-4}$ × *Participants*$_{t-4}$		−0.005	−0.004	−0.008**
		(0.003)	(0.003)	(0.003)
$\delta_{brand} + \delta_{t,platform}$	Yes	Yes	—	—
$\delta_{brand,t} + \delta_{platform,t} + \delta_{brand,platform}$			Yes	Yes
R^2	0.497	0.497	0.828	0.829
Observations	408,810	408,810	408,810	404,810

Note. Standard errors are in parentheses.
*$p < 0.1$; **$p < 0.05$.

including the number of posts, responses, mentions, and prosocial and self-promotional posts derived from either guided LDA or deep learning depending on the specification. ϵ_{ijt} is an idiosyncratic error term. The key coefficient, α_3, is the DID estimator that captures the treatment effect of participating in the Blackout Tuesday allyship event. Importantly, our DID model tested the *within-brand* differences between consumer responses on Instagram and Twitter before and after the brand participated in Blackout Tuesday only on Instagram (i.e., the effect of the treatment on the treated).

Results for the DID Effects of BLM Support

Table 5 presents the DID results. Column (1) reflects the specification where posting contents are gauged by LDA, whereas column (2) reflects the same measures gauged by deep learning. Across all specifications, the coefficients of the DID estimator are all negative and significant ($p < 0.01$), suggesting that BLM support in terms of participating in Blackout Tuesday backfired and had a significantly negative and nontrivial impact on follower growth. Relative to their Twitter accounts, brands that supported the Blackout Tuesday event on Instagram gained 65.5% fewer followers.[10] Thus, we find causal evidence that supporting BLM during widespread allyship events engenders negative consumer responses.

In addition to the main DID analyses, we conduct several robustness checks. First, one might be concerned that Twitter is not a perfect control platform because of different characteristics in followers on Instagram relative to Twitter (despite the confirmed parallel pretrend). To alleviate this concern, we collected additional data from the same time period one year before the event (i.e., May 5 to June 30, 2019) to conduct a YoY DID, where 2019 Instagram serves as the control group.[11] The 2019 same platform DID design controls for the systemic temporal evolution of follower growth without the potential confounding posttreatment control group change, which might be a concern when using Twitter as the control. We report these results in column (3) of Table 5. The results from this YoY DID analysis are quantitatively consistent (–1.219, $p < 0.01$) and thus, further bolster the finding that brands' BLM support has a negative impact on their consumer responses on social media.

Second, we explored brands that did not participate in the Blackout Tuesday event on Instagram as an additional control. Using nonparticipants as the control group helped to account for the platform-time–specific effect that may have influenced customer responses and gauged the average treatment effects beyond the treatment on treated effects reported. To account for potential confounding selection into participating, we use IPTW to construct a sample that ensures that the observed covariates (e.g., brands' log number of followers at the beginning of 2020, average race, education level, income, and political affiliation of brands' customers) are similar between the nonparticipating control and the participating brands. The result reported in column (4) shows that relative to brands not participating in Blackout Tuesday, brands doing so have a consistently negative effect (–0.620, $p < 0.01$). Additionally, we show that this negative effect of BLM support remains quantitatively similar (–0.793, $p < 0.01$) in a triple-difference specification with both nonparticipants and Twitter as controls (see Online Appendix 7 for additional details), hence providing more evidence of the negative effects of BLM support.

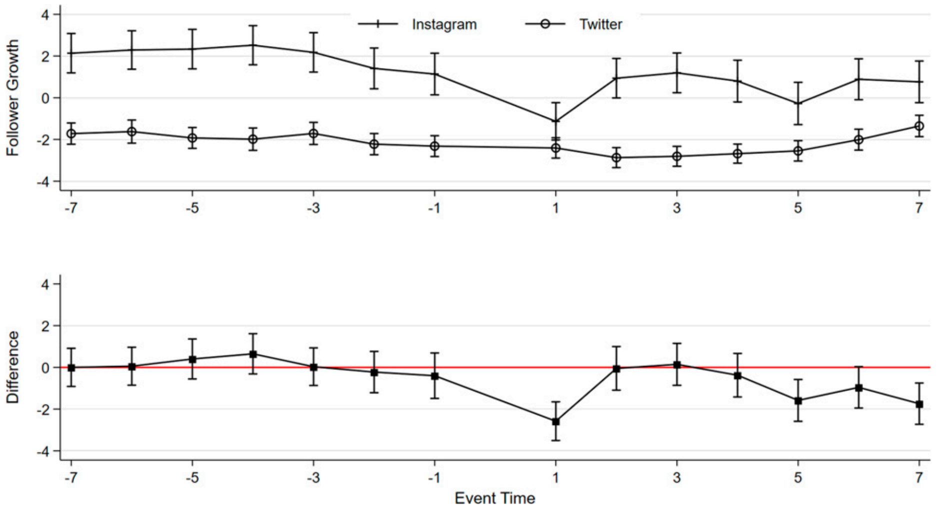
Third, we tested the robustness of our results using social media likes as an alternative measure of consumer responses. The number of likes of a brand's social media content is another important metric of social media engagement, but it suffers from posting selection because only posting brands can receive likes; thus, this presents a more severe missing data problem. Nonetheless, we estimate Equation (2) using the average number of likes per post as an alternate

Table 4. Summary Statistics of Variables: Brand-Platform-Time Level

Variable	Definition	Observations	Mean	SD	Min	Max
Follower Growth	Average daily change in a brand's number of followers (log transformed)	2,688	−0.464	4.180	−8.386	11.460
Consumer Liking	Average daily number of likes of a brand for its posts (log transformed)	1,517	0.941	1.108	0	5.688
Previous Social Posts (Mean) from LDA	Mean of the probabilities that a post by a brand is related to prosocial topics (e.g., inequality, LGBTQ, poverty, COVID-19 …) in the prestudy window from LDA	2,688	0.04	0.014	0.016	0.12
Previous Social Posts (SD) from LDA	SD of the probabilities that a post by a brand is related to prosocial topics in the prestudy window from LDA	2,688	0.089	0.028	0.011	0.176
Probability of Self-Promotion (LDA)	Mean of the probabilities that a post by a brand is related to promotional topics (e.g., promotion, sales, % off) for a product or service from LDA	2,688	0.005	0.009	0	0.051
Previous Social Posts (Mean) from LSTM	Mean of the probabilities that a post by a brand is related to prosocial topics in the prestudy window from LSTM	2,688	0.095	0.077	0.038	0.788
Previous Social Posts (SD) from LSTM	SD of the probabilities that a post by a brand is related to prosocial topics in the prestudy window from LSTM	2,688	0.086	0.030	0.018	0.205
Probability of Self-Promotion (LSTM)	The probabilities that a post by a brand is related to promotional topics for a product or service from LSTM	2,688	0.120	0.108	0.001	0.114
Prosocial Mission	=1 if a brand has prosocial responsibilities in its brand mission	2,688	0.167	0.375	0	1.000
Slacktivism	=1 if a brand fails to accompany the BLM statement with costly actions (i.e., donations)	2,688	0.740	0.439	0	1.000
Republican Advantage	The difference between the percentage of customers voting for Republican and Democratic candidates in the 2016 presidential election (in %)	2,436	−0.037	0.174	−0.507	0.211

Note. SD, standard deviation.

Figure 2. (Color online) Model-Free Evidence for the Effect of Allyship Event Participation



measure of consumer responses and report the results in column (5) of Table 5. We show that, on average, brands participating Blackout Tuesday lost an average of 14.5% of likes per post in the two months following the event, thus consistently suggesting that BLM support yields negative effects with this alterative measure of consumer responses.

Results for Heterogeneous DID Effects Across Brands

Results on the Moderating Role of Brands' Posting Behaviors on Social Media. The effects of brands' BLM support should be considered in the context of brands' historical and concurrent social media topics. For example, brands that post promotional content surrounding the time of their BLM support can pollute the sincerity of that support. To identify promotional topic posts on social media, we relied on guided LDA and deep learning approaches (see Online Appendix 3 for details) to calculate the average probability that a brand's posts were promotion related within seven days before or after Blackout Tuesday.[12] Brands' historical posts supporting prosocial causes can also impact consumer responses by establishing credibility for brands' consistent and authentic activism identity. Using similar NLP methods, we examined each brand's posts prior to the study window and calculated the mean and standard deviation of the probabilities that these posts were related to any prosocial topic. The higher the mean values, the more frequently a brand has leveraged their platform on social media to address prosocial causes. The lower the standard deviation, the more consistently a brand engages in prosocial practices.

We extend our DID specification with triple interactions between the DID term and each moderator. The results are reported in Table 6. Column (1) includes all moderators using the full set of fixed effects using LDA-derived content-based variables (see Online Appendix 9 for consistent LSTM-derived results). Additionally, to obtain a sense of effect sizes, we compute the marginal effects in terms of the total percentage change in follower growth at the 10th, 25th, 50th, 75th, and 90th percentiles of the underlying moderating continuous variable and at both levels of moderating binary variables, as visualized in Figure 4. As reported in column (1), the negative coefficient (–56.67, $p < 0.01$) of *BLM_Treatment* × *After* × *Self-Promotion* suggests that brands engaged in self-promotion around the time of Blackout Tuesday experienced more negative consumer responses, consistent with the idea that concurrent self-promotional content leads consumers to construe the brand's BLM support as less authentic. Moreover, the coefficient of *BLM_Treatment* × *After* × *Mean of Previous Prosocial Post* is positive and significant ($p < 0.01$). At the 75th percentile of historical prosocial posting level, brands experienced a 29% *increase* in follower growth, reversing the negative impact. Further, the coefficient of *BLM_Treatment* × *After* × *SD of Previous Prosocial Post* is negative and significant ($p < 0.01$). Hence, the negative impact of BLM support was amplified for brands that posted prosocial content less consistently prior to Blackout Tuesday. These results together suggest that consistent historical use of social media to support prosocial causes can lend the brand more credibility in BLM support, even potentially yielding positive consumer responses, such as in the case of Nike's Colin Kaepernick campaign.

Table 5. DID Results

	(1) Consumer following	(2) Consumer following	(3) Consumer following	(4) Consumer following	(5) Consumer liking
DID (BLM_Treatment × After)	−1.065***	−1.080***			−0.154***
	(0.164)	(0.163)			(0.043)
2020 × After			−1.219***		
			(0.181)		
BLM Participating Brands × After				−0.620***	
				(0.177)	
Constant	−2.951***	−3.142***	7.013***	−1.055*	−0.102
	(0.884)	(0.891)	(0.744)	(0.617)	(0.123)
Social media contents (LDA)	Yes	No	No	No	No
Social media contents (deep learning)	No	Yes	No	No	No
Brand-time fixed effects	Yes	Yes	No	No	Yes
Brand-platform fixed effects	Yes	Yes	No	No	Yes
Brand-period of year fixed effects	No	No	Yes	No	No
Brand-year fixed effects	No	No	Yes	No	No
Covariates	Yes	Yes	Yes	Yes	Yes
R^2	0.779	0.780	0.791	0.660	0.930
Observations	2,688	2,688	2,352	4,270	1,517

Note. Standard errors are in parentheses.
$^*p < 0.1$; $^{***}p < 0.01$.

Results on the Moderating Role of Brands' Mission Statement and Financial Donation. Brands' overarching mission statement and financial donation may provide additional contexts for consumer responses to BLM support. Specifically, a consistent organization-wide emphasis on prosocial engagements can enhance the perceived authenticity of a brand's BLM support. We created an indicator variable called *Prosocial Mission*, which equals one if the brand included prosocial key words in its brand mission statement (and zero otherwise) (see details in Online Appendix 8). Further, brands that donate to the BLM movement can potentially buck the "slacktivism" label and demonstrate more tangible commitment to BLM support. Thus, we created another indicator variable called *Slacktivism*, which equals one if a brand's BLM post was not accompanied by financial donations. Specifically, we gauge donations by examining posts of each brand on or within seven days after Blackout Tuesday and identified brands that disclosed financial support for BLM. Results in column (1) suggest that the coefficient of *BLM_Treatment × After × Prosocial Mission* is positive and significant across specifications ($p < 0.01$). Compared with brands without a prosocial mission, those with such mission statements experienced *increased* follower growth (Figure 4). The negative impact of BLM support appears to be attenuated for brands that set out to pursue a social mission as a guiding principle, suggesting that brands that conduct business in a socially conscious manner are more likely to be perceived by consumers as participating in Blackout Tuesday in earnest. Although we anticipated that brands that only posted black squares (cheap talk) without accompanying donations are likely to be perceived by consumers as having less genuine BLM support, we surprisingly do not find any significant average moderating effects of slacktivism (we will return to this point subsequently).

Results on the Moderating Role of Consumers' Political Affiliation. Because political affiliation is a fault line in the support of BLM (although 78% of Republicans opposed the BLM movement, 85% of Democrats supported the movement) (Horowitz 2021), brands whose customers are more Republican leaning are likely to have potential social media followers who are less receptive of their BLM support. Thus, we further investigate the moderating role of political affiliation by gauging the Republican advantage of a brand's customer base. We infer brands' customer political affiliation leveraging foot traffic data and presidential election results.[13] First, we used Safegraph foot traffic data to capture the origin of each brand's customers who visit the brand's physical locations in 2019. From customers' origin census block groups, we computed the brands' county-level customer counts. Then, we use brands' county-level foot traffic to infer the brand-level Republican and Democratic proportions based on the 2016 presidential election results. Finally, we compute each brand's "Republican advantage," which is the difference between the percentage of each brand's

Table 6. Heterogeneous DID Effects

	Full sample (1) Follower growth	Republican subsample (2) Follower growth	Democrat subsample (3) Follower growth	Full sample (4) Follower growth	Full sample (5) Follower growth	Full sample (6) Follower growth	Full sample (7) Follower growth
DID (BLM_Treatment × After)	−3.481***	−4.891***	−1.230	−3.434***	−3.461***	−0.747	−1.771
	(0.637)	(0.928)	(1.029)	(0.715)	(0.643)	(1.509)	(1.619)
DID × Previous Social Posts (Mean)	119.527***	116.740***	117.854***	119.311***	117.814***	133.073***	149.206***
	(21.854)	(38.644)	(28.830)	(21.909)	(23.024)	(22.867)	(24.710)
DID × Previous Social Posts (SD)	−33.907***	−28.256*	−37.293**	−34.084***	−33.443***	−37.419***	−41.851***
	(10.818)	(15.037)	(16.093)	(10.889)	(10.997)	(10.953)	(11.370)
DID × Self-Promotion	−56.666***	−76.072***	−6.477	−56.515***	−57.018***	−49.511***	−47.875**
	(18.877)	(19.723)	(42.237)	(18.910)	(18.939)	(19.201)	(19.672)
DID × Social Mission	1.892***	1.770***	1.706***	1.889***	1.906***	1.856***	1.549***
	(0.447)	(0.669)	(0.593)	(0.447)	(0.450)	(0.447)	(0.462)
DID × Slacktivism	0.601	2.052***	−1.471**	0.602	0.601	0.394	0.668
	(0.378)	(0.459)	(0.635)	(0.378)	(0.378)	(0.392)	(0.406)
DID × Republican Advantage	−1.669*			−1.653	−1.623	−1.991*	−2.752**
	(1.012)			(1.019)	(1.031)	(1.024)	(1.086)
DID × House of Brands				−0.051			0.596
				(0.354)			(0.384)
DID × Luxury Brand					0.233		−0.495
					(0.984)		(1.064)
DID × log(*Followers*)						−0.216**	−0.173
						(0.108)	(0.113)
Constant	−3.077***	−1.334	−2.117	−3.072***	−3.077***	−3.132***	−3.220***
	(0.927)	(0.970)	(1.341)	(0.928)	(0.928)	(0.927)	(0.939)
Industry moderators	No	No	No	No	No	No	Yes
Brand-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand-platform fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.778	0.837	0.725	0.778	0.778	0.778	0.780
Observations	2,436	1,148	1,288	2,436	2,436	2,436	2,436

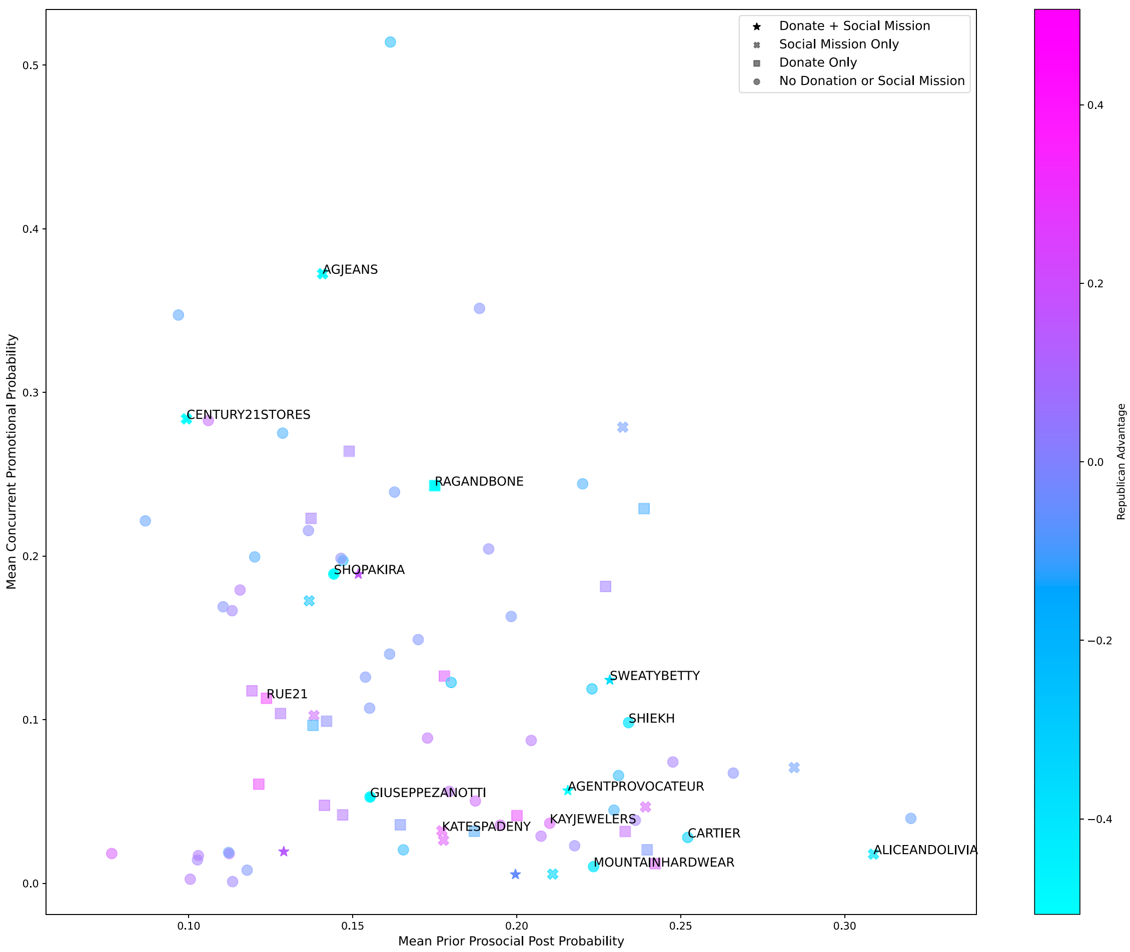
Note. Standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

customers who voted Republican and Democrat in the presidential race. Figure 3 shows that brands with both Republican and Democrat affiliation customer bases appear well represented for every combination of other moderators (e.g., no high correlations among all moderators). Further, our classification of *Republican Advantage* is consistent with the alternate measures proposed by Schoenmueller et al. (2022).[14]

Results in column (1) indicate that there are more negative effects for brands with mostly Republican customers ($p < 0.01$); see Online Appendix 10 for consistent results with subsample analyses. The overall average decrease to follower growth ranges from −36.7% at the 10th percentile of Republican advantage (−29% Republican advantage) to −70.8% at the 90th percentile of Republican advantage (17% Republican advantage). Although these results are intuitive, it is still significant that many companies with Republican majority customers participated in Blackout Tuesday (40 of the 96 participating brands have a Republican majority customer base in our data).

To further investigate how political affiliation may interact with other moderators, we conducted a split-sample analysis. Columns (2) and (3) present the results for brands with more Republican and Democratic customers, respectively. The coefficients for the moderating effects reported are largely consistent between the two subsamples. Interestingly, we observed a sharp contrast in the effect of slacktivism for brands with customers aligned with the two political parties; the coefficient of *BLM_Treatment × After × Slacktivism* is positive and significant ($p < 0.01$) for brands with more Republican customers but negative and significant ($p < 0.05$) for those with more Democratic customers. As portrayed in Figure 5, political affiliation interacts with slacktivism in the negative effects of BLM support, where slacktivism can mitigate the negative effects for brands with mostly Republican consumers but amplify the negative effects

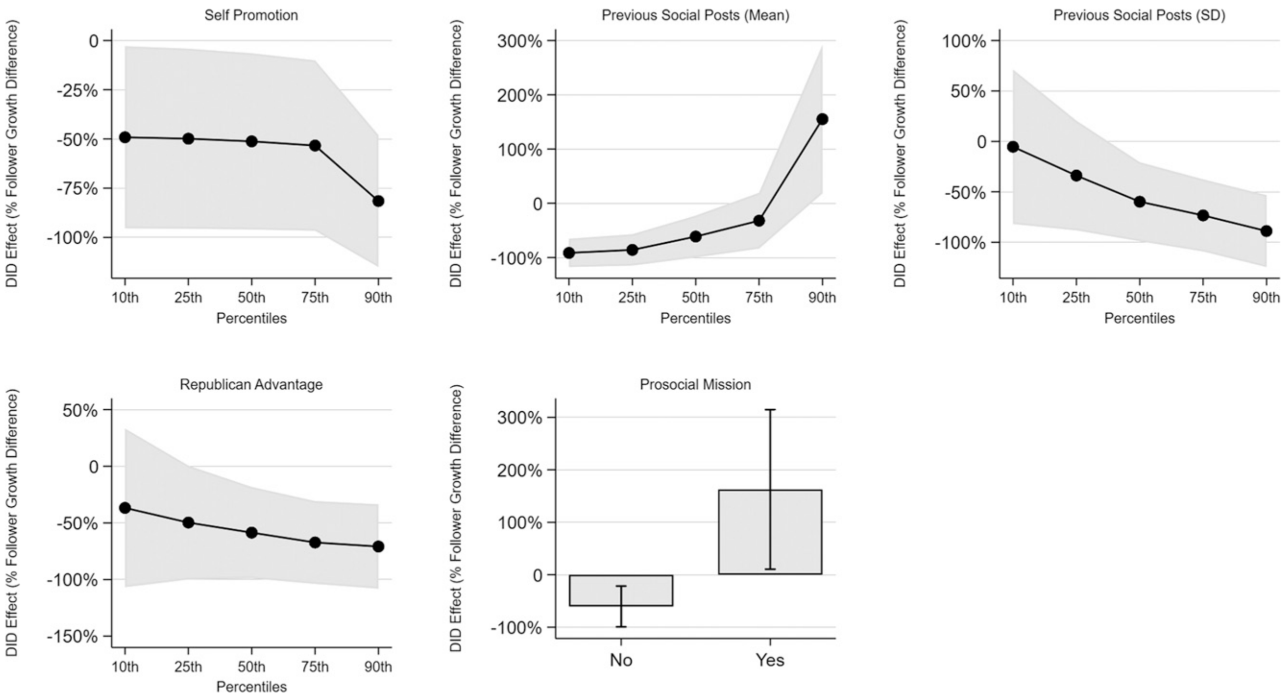
Figure 3. (Color online) Visualization of Moderators



for brands with mostly Democratic consumers. These results make sense because of Republican customers' overall misalignment with the BLM movement.

Additional Results on Brand Characteristics. Furthermore, we explore several widely adopted brand characteristics that may also lead to heterogeneous DID effects: (1) a house of brands vis-à-vis branded house, (2) luxury brands or not, and (3) brand size.[15] Specifically, a branded house is the practice of housing different products under the same brand; for example, Chanel is a branded house brand because it sells a variety of products under the same brand, such as accessories, apparel, cosmetics, and fragrances (Yu 2020). In contrast, Gap is a house of brands because it houses many products under different brand names, such as Banana Republic, Gap, and Athleta, with separate social media accounts. We identify luxury brands, such as Yves Saint Laurent and Dior, by matching our list of brands to those listed by Brand Finance in their "Brandirectory" ranking of luxury brands.[16] Additionally, brand size is measured by the number of followers on social media (Instagram) at the beginning of the study window. Results in columns (4)–(7) indicate insignificant coefficients of *BLM_Treatment* × *After* × *House of Brands* and *BLM_Treatment* × *After* × *Luxury Brand*. Thus, there is no strong empirical evidence that a house of brands and luxury brands explain the heterogeneous DID effects in our data. However, in column (6), the coefficient of *BLM_Treatment* × *After* × log(*Followers*) is negative and statistically significant, suggesting some evidence that larger brands may experience more negative effects of showing BLM support. This finding is not only consistent with the arguments of Hydock et al. (2020) that large brands may have less to gain but more to lose by advocating for controversial social causes, but also, it extends their contexts from transgender bathroom

Figure 4. Visualization of Heterogeneous DID Effects



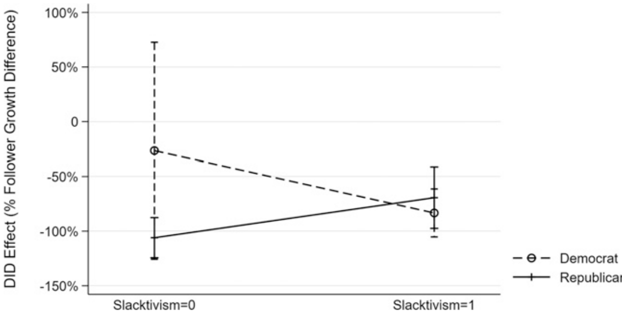
access and gun control concerns to racial justice movements, like BLM. Importantly, even after controlling for these nuanced brand characteristics, our main results on the negative effects of BLM support and heterogeneous DID results reported are robust and consistent.

Conclusion

This study examines consumer responses to brands' support of BLM on social media and the heterogeneous effects across brands using a natural experiment and machine learning tools. We reveal that BLM support engenders largely negative consumer responses on average. Our exploration of the boundary conditions suggests that to enable their BLM support to resonate with consumers, brands should avoid the posting of concurrent self-promotional content, but rather, they should foster a corporate mission of prosociality and establish a track record of frequent and consistent social media solidarity in prosocial practices. Moreover, firms should consider their customers' political affiliation when advocating racial justice issues. Brands with Republican supporters experienced more backfiring effects of BLM support, but this can be partially mitigated through slacktivism. In stark contrast, brands with more Democratic supporters experienced even worse consumer responses when practicing slacktivism in BLM support on social media.

Our work has several limitations, which serve as avenues for future research. First, our data on consumer responses are limited to social media engagement metrics. Thus, future work may link BLM support to firms' financial performance if causal effects are identifiable. Second, although we examined a battery of moderators, such as the Republican versus Democratic division, other relevant variables may be examined to shed light on the full range heterogeneous effects. For example, can brand target segmentation (e.g., young people brands like Nike) and environmentally friendly brands like REI generate positive effects of BLM support? These are open and fertile questions for future research. Finally, we call for future work to evaluate consumer responses to brand activism in other important social issues, such as Stop Asian Hate, gun control, abortion, and LGBTQ rights.

Figure 5. Consumer Political Affiliation Interacts with Slacktivism for DID Effects



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Endnotes

[1] We use Safegraph foot traffic data to compute the political affiliation of brands' customers.

[2] We have excluded brands' direct responses to their customers, as those posts are less relevant for our study.

[3] Our results are robust to the strongly monotone log transformation as reported in the Online Appendix 6.

[4] Because this analysis requires the use of daily-level aggregation in order not to double count the dependent variable, we had to perform linear interpolation to fill in missing data (6.9% of observations used in analysis).

[5] We choose a maximum four-day lag to allow for effects for multiday effects because the median brand posts around two posts per week.

[6] We address this by studying Blackout Tuesday, where platform and date choice are exogenously restricted.

[7] Instagram uses a default square aspect ratio, the premise upon which posting black squares is built.

[8] Note that the source of the identifying variation (within brand-date, between platform) is the same as in our analysis of all posts. However, Blackout Tuesday imposes the exogenous restriction that brands wishing to participate in the event can only do so on Instagram. Indeed, the vast majority of Blackout Tuesday participating brands did not post anything on Twitter during the event, and our data analyses involve 96 such major brands.

[9] Note that α_1 and α_2 terms will be subsumed because of the brand-platform and brand-time fixed effects in the DID model.

[10] Because we have used log transformation for our dependent variable of *follower growth*, to compute the effect size of BLM treatment on raw follower changes, we have to do the inverse operations: *Raw followers changed due to BLM treatment* $= Sign(Y_t + coeff)EXP(Y_t + coeff) - Sign(Y_t)\mathrm{EXP}(Y_t)$, where coeff is about −1 in our DID estimator results. For example, the effect size of BLM treatment on raw follower changes at the min (−8.36) of our dependent variable should be calculated as $[-\exp(|-8.36-1|) - (-\exp(|-8.36|)] = -7{,}342$ followers. Similarly, the effect size of BLM treatment on raw follower changes at the max (11.45) should be calculated as $\exp(|11.45-1|) - \exp(|11.45|) = -59{,}356$ followers. Following this computation process, the average effect size of BLM treatment is −407 raw follower changes in our data. See a distribution of expected effect sizes measured as number of raw follower changes in the Online Appendix 6.

[11] We acknowledge one anonymous reviewer for this insight.

[12] There are two main reasons why we also include the postings *before* the event. First, the George Floyd protests began as early as May 25, 2020. Therefore, posting promotional messages during early protests but participating in the event later may be viewed as hypocritical. Besides, Instagram arranges postings of an account in chronological order. As a result, when customers visit the main page of a brand, it is easy to spot the promotional postings shortly before its Blackout Tuesday postings, making the contrast more salient.

[13] We remove technology and auto/motorcycle firms from this exercise because of the underrepresentativeness of their retail store foot traffic of their overall customer base.

[14] The measures are available on www.social-listening.org/CompareBrands.html.

[15] We acknowledge one anonymous reviewer, the associate editor, and the senior editor for this insight.

[16] The source is https://brandirectory.com/rankings/luxury-and-premium/table.

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