

Online Appendix 1: Industries and Brands

We present the distribution of brands across the industries in Table A1.1 and list the top 10 brands in terms of average number of followers from each industry in Table A1.2

Table A1.1 Brand Distribution across Industries

Industry	All Brands			Brands Participating in the BLM Blackout Tuesday Event		
	Freq.	Percent	Cum.	Freq.	Percent	Cum.
Auto/Motorcycle	20	4.6	4.6	3	3.13	3.13
Clothing	223	51.26	55.86	62	64.58	67.71
Food	29	6.67	62.53	5	5.21	72.92
Jewelry & Watches	50	11.49	74.02	10	10.42	83.33
Reseller	83	18.08	93.1	11	11.46	94.79
Sporting	13	2.99	96.09	2	2.08	96.87
Tech	17	3.91	100	3	3.13	100
Total	435	100		96	100	

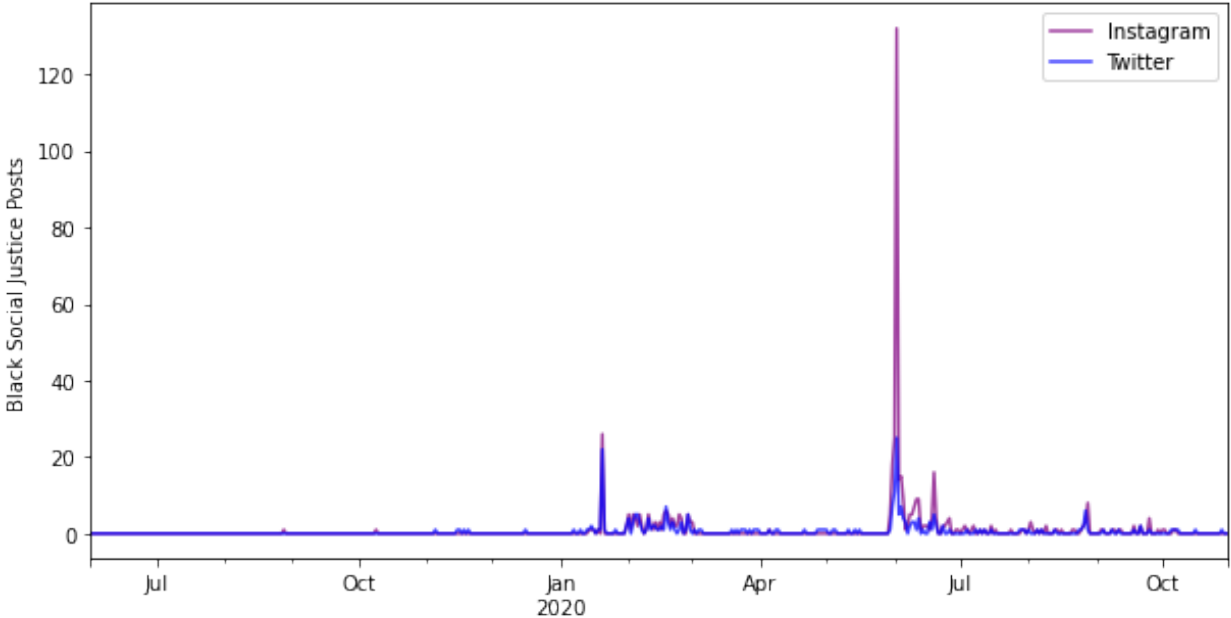
Table A1.2 Examples of Major Brands from Each Industry

Brand	Industry	Brand	Industry
MERCEDES BENZ	Auto/Motorcycle	STARBUCKS	Food
BMW	Auto/Motorcycle	POPEYES	Food
VOLKSWAGEN	Auto/Motorcycle	DAIRY QUEEN	Food
TESLA	Auto/Motorcycle	APPLEBEES	Food
JEEP	Auto/Motorcycle	MCDONALDS	Food
NISSAN	Auto/Motorcycle	DUNKIN	Food
HARLEY DAVIDSON	Auto/Motorcycle	PIZZAHUT	Food
FORD	Auto/Motorcycle	PAPAJOHNS	Food
HONDA	Auto/Motorcycle	TACOBELL	Food
CHEVROLET	Auto/Motorcycle	CHIPOTLE	Food
VICTORIA'S SECRET	Clothing	TIFFANY	Jewelry & Watches
CHANEL	Clothing	CARTIER	Jewelry & Watches
GUCCI	Clothing	BULGARI	Jewelry & Watches
H&M	Clothing	PANDORA	Jewelry & Watches
ZARA	Clothing	SWAROVSKI	Jewelry & Watches
DIOR	Clothing	TAGHEUER	Jewelry & Watches
DOLCE & GABBANA	Clothing	CHOPARD	Jewelry & Watches
VERSACE	Clothing	VANCLEEFARPELS	Jewelry & Watches
BURBERRY	Clothing	MONTBLANC	Jewelry & Watches
PRADA	Clothing	FOSSIL	Jewelry & Watches
FOOT LOCKER	Reseller	FACEBOOK	Tech
NORDSTROM	Reseller	GOOGLE	Tech
GAP	Reseller	MICROSOFT	Tech
PACSUN	Reseller	IBM	Tech

STEVEMADDEN	Reseller	HP	Tech
MARSHALLS	Reseller	APPLE	Tech
NORDSTROMRACK	Reseller	INTEL	Tech
CLAIRE'S STORES	Reseller	DELL	Tech
FOOT ACTION	Reseller	LENOVO	Tech
SHOEPALACE	Reseller	SONY	Tech
NIKE	Sporting		
ADIDAS	Sporting		
NEWBALANCE	Sporting		
REEBOK	Sporting		
BILLABONG	Sporting		
HURLEY	Sporting		
MOUNTAIN HARDWEAR	Sporting		
COLUMBIA	Sporting		
LLBEAN	Sporting		
GANDER RV	Sporting		

Online Appendix 2: Illustration of the Data Collection Process

Below figure presents the distribution of a total of 503 BLM support posting events (=368 on Instagram + 135 on Twitter) from June 1, 2019 to October 31, 2020. The biggest spike is the Blackout Tuesday event.



Online Appendix 3: Technical Details for the Machine Learning Methods

Guided LDA: Since it is impractical to identify brands' past posting topics by hand labeling every post, we take a machine learning approach to identify the topics covered by firms' Instagram and Twitter posts. Importantly, rather than counting only topic keywords whose selection is restricted to researchers' priors, we take a seeded LDA approach (e.g., Jagarlamudi et al. 2012, Toubia et al. 2019) to take advantage of researchers' informative priors while expanding on them based on the empirical distribution of words across and within brands' social media posts.

The standard LDA model (e.g., Pritchard et al. 2000, Blei et al. 2003) attempts to assign words in a document to topics by specifying a distribution of weights over a vocabulary for each topic and a distribution over topics for each document. Specifically, LDA assigns these weights over a set of documents, \mathcal{D} , consisting of $|\mathcal{D}| = M$ documents each of length N_i . Each word position j in document i is a topic draw $z_{ij} \sim \text{Multinomial}(\theta_i)$ where $\theta \sim \text{Dir}(\alpha)$, a Dirichlet distribution with symmetric parameter α . The word in position j of document i is then a draw from the word distribution of topic z_{ij} , i.e. $w_{ij} \sim \text{Multinomial}(\varphi_{z_{ij}})$ where $\varphi \sim \text{Dir}(\beta)$. Note α is a K –dimensional vector where K is a pre-specified number of topics and β is a V –dimensional vector where V is the total vocabulary size.

A simple way of incorporating a researcher's priors into the standard LDA model is to replace the symmetric prior β with a seeded, topic-specific, asymmetric prior, η_i , that can have different weights for each word in each topic. By imposing these priors, we bias the inference of topic-word weights to lean towards those that are important for our research purposes. Specifically, we seed our topic-word priors with the keywords and themes that were uncovered during the manual coding (See Deep Learning Appendix) of a sample of Tweets and Instagram posts in the year before and after the Blackout Tuesday event (See Table A1 for list of topic seeds). However, since the list of topic themes from manual coding are likely not exhaustive, we allow our model to have additional nuisance topics¹. Additionally, given the potential differences in topic composition for different industries, we run the topic models separately for different industries industry groups: fashion-related industries (clothing, jewelry and watches, fashion resellers), food, auto, and technology.

Table A3.1 LDA Topic Seeds

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
george floyd	lgbtq	inequality	diversity	trump	globalwarming	healthcare	child	poverty	deal
georgefloyd	lesbian	inner city	poc	biden	environment	diet	baby	hunger	bogo
Black lives	gay		woc	obama	global warming	exercise	babies	shelter	sale
blackouttuesday			inclusion	vote	climatechange	insurance	children	food bank	sales
black lives matter			inclusive	democrat	climate change	nurse			promotion
blacklivesmatter				republican		doctor			discount
systemic racism				legislation					
racism				government					
blm				senate					
				congress					

¹ We experiment with one to 500 additional nuisance topics, and the resulting seeded topics are consistently represented by similar keywords.

each word in the text where the focal input word is in the middle of the frame with two outcome words on either side of focal word. For the focal word “we,” the sliding window includes “stand” and “with.” As a result, we formulate two observations for the training data: (we, stand) and (we, with). Similarly, the window for “black” yields the training input-output pairs of (black, with), (black, the), and (black, community). In essence, skipgram creates a prediction task from unlabeled text data where each focal word is used to predict the nearby context words.

W2V solves the skipgram-generated context prediction task by converting each of V tokens, i.e. words, to a point in a lower L -dimensional space (where $L = 100 < V$)² by finding the a vector of weights for each of the V words in the vocabulary, $v_i \forall i \in \{1, \dots, V\}$, that maximizes the joint probability of observing the training data, $\frac{1}{V} \sum_{i=1}^V \sum_{j \in \mathcal{C}_i} \log p(w_j | w_i)$. The probability that a word w_j belongs in the context of w_i is

$$p(w_j | w_i) = \frac{\exp(v_{w_i} \cdot v_{w_j}^T)}{\sum_{c_i} \exp(v_{w_i} \cdot v_{w_j}^T)},$$

where \mathcal{C}_i is the set of words that belong in the set of all empirically observed words in any context window of w_i . The W2V representation is simply the matrix $\mathbf{V}_{V \times L}$ where each row $i \in \{1, \dots, V\}$ maps the word w_i to the weights $v_i = (\omega_{i1}, \dots, \omega_{iL})$.

To demonstrate the face validity of the W2V model’s representation of semantic meaning, we illustrate the set of most similar words to some of our key BLM words based on their locations the W2V embedding space in Figure A2. For instance, the words and phrases closest to the phrase “black lives matter” include “black community” and “inequality.” Likewise, tokens closest to the “#blackouttuesday” hashtag are also related hashtags such as “#amplifymelanatedvoices” and “#theshowmustbepaused.”

Figure A3.2 Word2Vec Similarity Queries

Black lives matter		#blackouttuesday	
black community	0.776327	👤 (dark skin tone)	0.805478
black lives	0.775162	#amplifymelanatedvoices	0.781415
inclusion	0.771279	#blacklivesmatter	0.778003
inequality	0.769289	👤👤 (dark skintone)	0.777717
dignity	0.757877	-mlk	0.772391
asian community	0.756653	👤 (Default skin tone)	0.759539
violence	0.74871	#equalityforall	0.756689
solidarity	0.74718	lgbt	0.739202
long term	0.746536	#theshowmustbepaused	0.73908
an organization	0.745364	👤 (white skintone)	0.733599

Notes: Each column of the figure illustrates tokens that are most similar to the focal words appearing in the top row. The numbers correspond to the similarity metric (1 is most similar, 0 is least similar). The phrase “black lives

² Note that the choice of L is generally not important and more of a practical trade-off between the richness of semantic meanings that can be captured (larger L) and the amount of data and computational resources available to distinguish between meanings on a large L .

matter” is associated with other phrases related to racial (in)equality. The hashtag “#blackouttuesday” is related to other BLM and prosocial issues related tags and emojis.

Using the sequence of W2V representations of social media posts as inputs, we formulate a deep learning model to predict category labels. Specifically, our model architecture consists of a W2V embedding layer feeding into a bi-directional LSTM (BiLSTM) (e.g., Hochreiter and Schmidhuber 1997, Schuster and Paliwal 1997) and then an attention layer (e.g., Bahdanau et al. 2014, Wang et al. 2016). The BiLSTM layer accounts for the information contained in the forward and backward *sequences* of W2V embeddings that represent each post. Specifically, the bi-directionality improves upon the ability of unidirectional LSTM layers to capture contextual information as both preceding and succeeding words inform the output of each focal LSTM cell.

Each post X is comprised of T W2V representations of tokens, x_t for $t \in \{1, \dots, T\}$, where T is larger than the number of words contained in the majority of posts. Posts shorter than T tokens, are pre-padded with a special null token that takes on the W2V representation of $\mathbf{0}$. In practice, we set $T = 300$, which is greater than 99% of our labeled posts. Recall that each x_t is a 100-dimensional vector in the W2V embedding space. This vector x_t enters as an input to each LSTM cell. Each cell performs three fundamental gating operations. The first is an input gate, i_t , that determines the new information to store in the cell state. The second is a forget gate, f_t , which determines the information to throw away from the cell state. The third is an output gate, o_t , which determines the information output at step t . Each of these operations consists of a Sigmoid activation, σ , that is determined by information output by the prior cell, h_{t-1} , and the inputs at position t , x_t , a set of weights corresponding to each gate, and a set of biases corresponding to each gate (See the Equation 1).

$$\begin{aligned}
 i_t &= \sigma(w_i[h_{t-1}, x_t] + b_i) \\
 f_t &= \sigma(w_f[h_{t-1}, x_t] + b_f) \\
 o_t &= \sigma(w_o[h_{t-1}, x_t] + b_o)
 \end{aligned} \tag{1}$$

$$\text{where } \sigma(\mu) = \frac{1}{1 + e^{-\mu}}$$

These three gates are applied to the cell memory and output to determine the final saved cell state and output. To fully specify the LSTM cell, we must first compute the candidate state at step t , \tilde{c}_t . The candidate memory state is a tanh activated weighting of the prior step output h_{t-1} and the current input x_t . Information from \tilde{c}_t is then selected by the input gate i_t and added to the prior cell memory after applying the forget gate $f_t * c_{t-1}$ to construct the current cell state, c_t . c_t is then passed through a tanh activation function whose output is filtered through the output gate o_t . The gates combined with the cell state and output operations together specify how prior information is incorporated into the network architecture through persistent cell memory (see the Equation 2). BiLSTM also includes the same architecture in the reverse direction. As a result, the BiLSTM generates two output sequences: h_1^F, \dots, h_T^F and h_1^B, \dots, h_T^B where F denotes the forward LSTM and B denotes the backwards LSTM. These two outputs are concatenated into a single sequence of vectors $\mathbf{H} = \{h_1, \dots, h_T\}$ where $h_t = [h_t^F, h_t^B]$. This sequence roughly represents the aspect, i.e. information contained at each token position, that can inform the prediction task given the sentence context in a $2 \times C$ dimensional space where $C = 32$ is the size of each LSTM cell.

$$\begin{aligned}
\tilde{c}_t &= \tanh(w_c[h_{t-1}, x_t] + b_c) \\
c_t &= f_t * c_{t-1} + i_t * \tilde{c}_t \\
h_t &= o_t * \tanh(c_t) \\
\text{where } \tanh(\mu) &= \frac{e^{2\mu} - 1}{e^{2\mu} + 1} \\
\text{and } * &\text{ denotes element-wise products.}
\end{aligned} \tag{2}$$

While we could directly predict the output using \mathbf{H} , Wang et al. (2016) has shown that an attention mechanism can significantly improve the performance of LSTM-based classifiers by selecting the components of a sequence that are most relevant. Intuitively, this is achieved by specifying a nonlinear weighted aggregation of \mathbf{H} specified in Equation 3. Here u_t is a nonlinear transformation of h_t and v is a set of weights that, together with a softmax (logit) activation, transforms u_t into the weight vector α_t in the C dimensional simplex. Given these weights, the most important component of each position is selected by the product $\alpha_t h_t$ and aggregated by summing across $t = 1, \dots, T$.

$$\begin{aligned}
u_t &= \tanh(w_u h_t + b_u) \\
\alpha_t &= \text{softmax}(v' u_t) \\
s &= \sum_{t=1}^T \alpha_t h_t \\
\text{where } \text{softmax}(\mathbf{\mu}_{D \times 1}) &= \frac{e^{\mu_i}}{\sum_{j=1}^D e^{\mu_j}}
\end{aligned} \tag{3}$$

The output of the attention layer is thus the summary vector, $s_{C \times 1}$. This vector is then passed through one more dense layer and Sigmoid activation to map on to the binary label Y as specified in Equation 4. Note that we model the labels as a binary classification problem rather than a multi-class prediction problem since each post can be labeled with multiple topics. The average out of sample performance of our model across our three key binary classification tasks is 0.88 on accuracy, and .83 on precision, .89 on recall (See Table A4.2 for details).

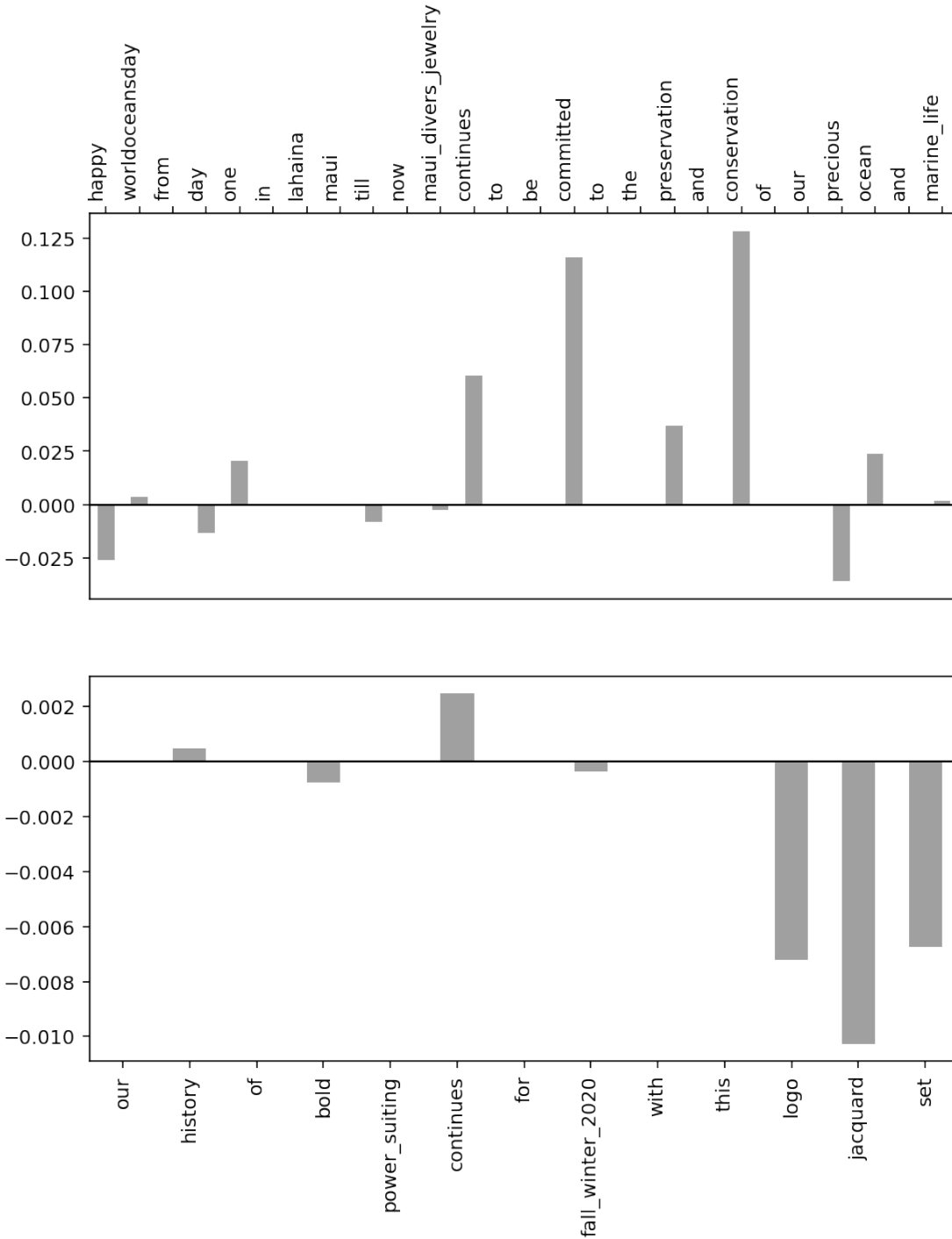
$$Y = \sigma(W_s S + b_s) \tag{4}$$

Table A3.2 BiLSTM Model Performance Metrics

	Training				Testing			
	Loss	Accuracy	Precision	Recall	Loss	Accuracy	Precision	Recall
prosocial issues	0.2073	0.9311	0.8706	0.9338	0.2442	0.9022	0.8221	0.8953
marketing	0.3051	0.8715	0.8830	0.9109	0.3923	0.8628	0.8407	0.8895
blm	0.1953	0.9150	0.7862	0.7000	0.2102	0.9022	0.6282	0.6364

To illustrate the qualitative features of the model, Figure A3 shows the impact of each word on the classification of two different posts, the first is classified as a social issue related post and the second is not. In particular, while "continues" is deemed important for classification of the first Tweet as related to prosocial issues in the top example, it is not important in the bottom example.

Figure A3.3 Examples of Deep Learning Classification



Notes: The above figure represents the marginal contribution of each word (obtained from the attention layer of the BiLSTM neural net architecture) to the classification of each post as an “issues” post. The top post is classified as an issue post with .92 probability while the bottom post is classified as an issue post with only .04 probability. Note the word “continues” is in both posts, but only significantly contributes to the classification as an issue post for the first post.

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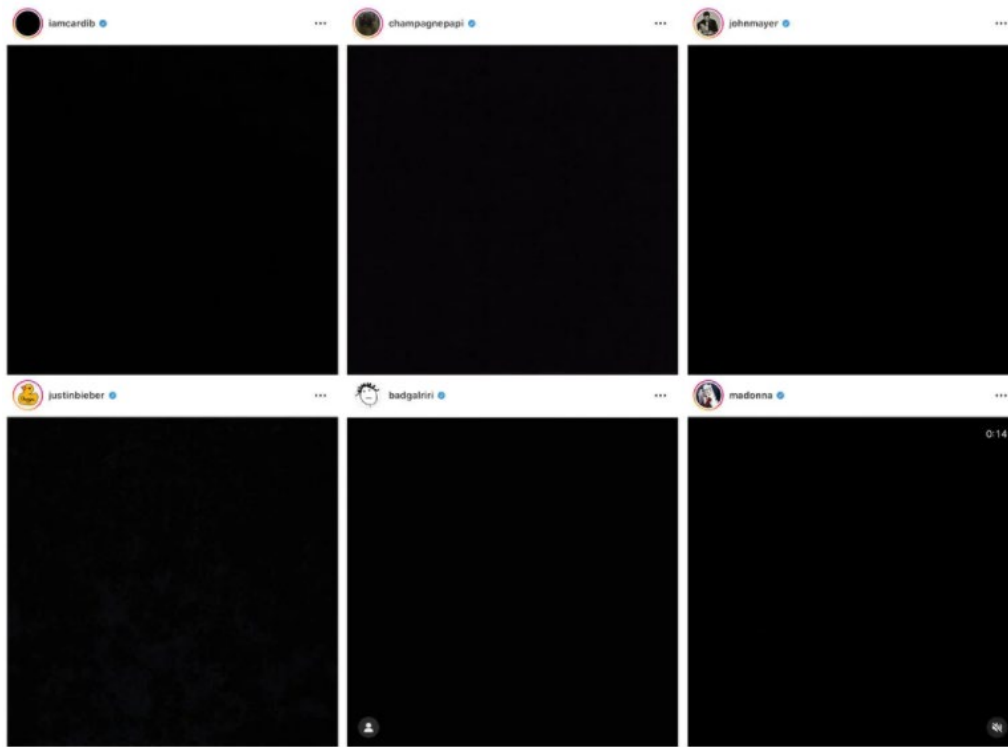
Online Appendix 4: Details on Specific Topic Probabilities

Table A4: Summary Statistics of Topic Probabilities: Post Level

Variable	Instagram (N=183,739)				Twitter (N=213,249)				
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Guided LDA	Prob_BLM	0.004	0.033	0.000	0.988	0.004	0.030	0.000	0.945
	Prob_LGBTQ	0.004	0.032	0.000	0.978	0.004	0.028	0.000	0.858
	Prob_Inequality	0.005	0.033	0.000	0.983	0.006	0.036	0.000	0.948
	Prob_Diversity	0.005	0.035	0.000	0.981	0.005	0.034	0.000	0.950
	Prob_COVID	0.004	0.030	0.000	0.989	0.004	0.029	0.000	0.859
	Prob_Political	0.004	0.032	0.000	0.987	0.004	0.030	0.000	0.953
	Prob_Climate	0.004	0.029	0.000	0.988	0.004	0.028	0.000	0.884
	Prob_Healthcare	0.003	0.028	0.000	0.992	0.003	0.026	0.000	0.840
	Prob_Children	0.004	0.029	0.000	0.982	0.004	0.030	0.000	0.934
	Prob_Poverty	0.005	0.033	0.000	0.980	0.005	0.031	0.000	0.960
	Prob_Promotion	0.004	0.029	0.000	0.992	0.004	0.031	0.000	0.945
Deep Learning	Prob_BLM	0.052	0.122	0.001	0.928	0.061	0.134	0.001	0.928
	Prob_LGBTQ	0.020	0.094	0.001	0.975	0.014	0.076	0.001	0.974
	Prob_Inequality	0.011	0.024	0.001	0.715	0.013	0.033	0.001	0.784
	Prob_Diversity	0.004	0.006	0.002	0.111	0.004	0.006	0.002	0.103
	Prob_COVID	0.001	0.010	0.001	0.832	0.001	0.007	0.001	0.793
	Prob_Political	0.008	0.003	0	0.012	0.007	0.004	0	0.012
	Prob_Climate	0.001	0.007	0.000	0.659	0.001	0.004	0.000	0.693
	Prob_Healthcare	0.011	0.024	0.003	0.266	0.008	0.016	0.003	0.298
	Prob_Children	0.023	0.026	0.006	0.287	0.020	0.024	0.006	0.285
	Prob_Poverty	0.004	0.023	0.001	0.645	0.003	0.022	0.001	0.665
	Prob_Promotion	0.214	0.211	0.001	0.880	0.189	0.199	0.001	0.870

Note: While LDA restricts topics to span a simplex, the deep learning probabilities are independently modeled for each topic, thus each topic deep learning topic weight is bounded by [0,1] while the sum of LDA topics weights must always equal 1.

Online Appendix 5: One Example of Blackout Tuesday Posts (Coscarelli 2020)



Coscarelli J (2020) How Blackout Tuesday Became a Social Media Moment. *nytimes.com*
<https://www.nytimes.com/2020/06/02/arts/music/what-blackout-tuesday.html>.

NEW Online Appendix 6:

Details on Log transformation in follower growth:

Note that we have used the following log transformation to construct our dependent variable, *Follower Growth* (Y):

$$Y_{ijt} = \text{Sign}(Followers_{ijt} - Followers_{ijt-1}) \ln(|Followers_{ijt} - Followers_{ijt-1}|) \text{ when } |Followers_{ijt} - Followers_{ijt-1}| > 1, \text{ and } 0 \text{ otherwise.}$$

Because the $Followers_{ijt}$ is in the **integer** domain (no fractions), $Followers_{ijt} - Followers_{ijt-1}$ between -1 and 1 is set to equal 0 (a flat region), this log transformation is weakly monotone, and a small change in followers is treated equivalently to no change. Approximately 3% of data points fall in this range, and our results are robust to excluding these data points (see below Table Columns 1 and 2).

In addition, we specify an alternative log transformation with:

$$Y_{ijt} = \text{Sign}(Followers_{ijt} - Followers_{ijt-1}) \ln(1 + |Followers_{ijt} - Followers_{ijt-1}|)$$

where we do not need to set $Followers_{ijt} - Followers_{ijt-1}$ between -1 and 1 as equal 0. This alternative log transformation is strongly monotone, symmetric, smooth, and invertible (no flat region), and it leads to almost identical results (see below table Columns 3 and 4)."

	(1)	(2)	(3)	(4)
	Consumer Following (Dropping Zero)	Consumer Following (Dropping Zero)	Consumer Following (Alternative Log Transformation)	Consumer Following (Alternative Log Transformation)
<i>DID</i> (<i>BLM_Treatment</i> × <i>After</i>)	-1.097*** (0.166)	-1.109*** (0.166)	-1.077*** (0.165)	-1.093*** (0.165)
Constant	-4.142*** (0.712)	-4.103*** (0.727)	-2.971*** (0.893)	-3.159*** (0.900)
Social Media Contents (LDA)	Yes	No	Yes	No
Social Media Contents (Deep Learning)	No	Yes	No	Yes
Brand-Time Fixed Effects	Yes	Yes	Yes	Yes
Brand-Platform Fixed Effects	Yes	Yes	Yes	Yes
Covariates:	Yes	Yes	Yes	Yes
R^2	0.784	0.784	0.777	0.778
Observations	2618	2618	2688	2688

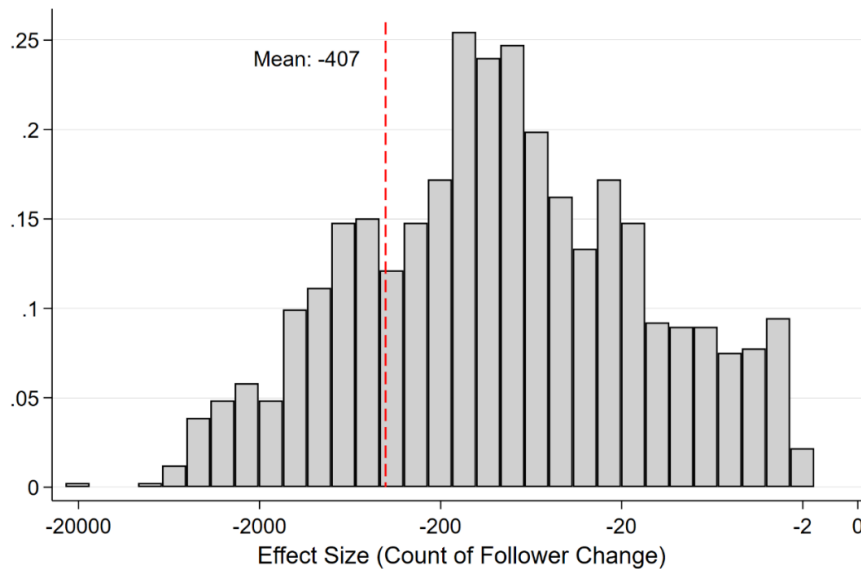
Details on computing DID effect size:

Because we have used log transformation for our dependent variable of *follower growth* (Y) as stated above, to compute the effect size of BLM treatment on **raw** followers changed, we have to do the inverse operations:

Raw followers changed due to BLM treatment

$$= \text{Sign}(Y_t + \text{coeff})\text{EXP}(Y_t + \text{coeff}) - \text{Sign}(Y_t)\text{EXP}(Y_t), \text{ where coeff is about -1 in our DID estimator results.}$$

For example, the effect size of BLM treatment on **raw** followers changed 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** followers changed at the max (11.45) should be calculated as $\exp(11.45-1)- \exp(11.45)= -59,356$ followers. (In terms of percentages, these results correspond to losing about 170% more followers and gaining 61% fewer followers, respectively, both of which suggests substantial negative BLM treatment effects; see more on percentages in below.) Following this computation process, below figure presents the distribution of expected effect sizes measured as number of **raw** follower changes for brands on Instagram. The average effect size of BLM treatment is -407 followers. Therefore, we take this as evidence that our findings have substantially meaningful managerial significance.



Furthermore, we report the **rate** (percentages) for the effect size of BLM treatment as the ratio of the raw treatment effect on followers changed and then divide by the baseline followers changed:

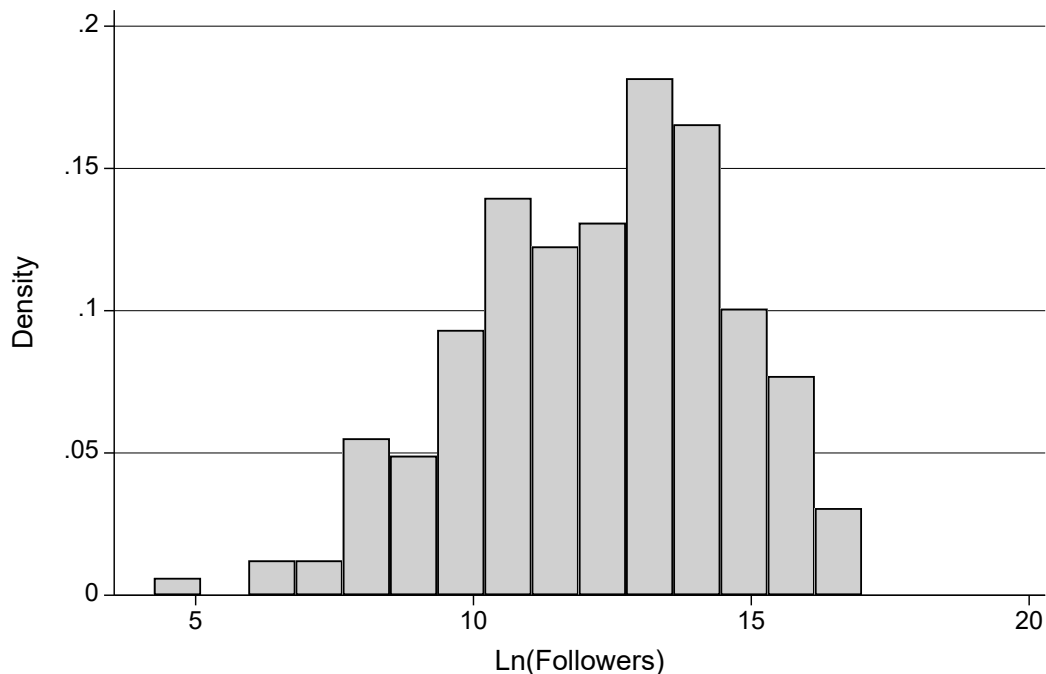
% in raw followers changed due to BLM treatment

$$= \text{Sign}(Y_t + \text{coeff})\text{EXP}(Y_t + \text{coeff}) / \text{Sign}(Y_t)\text{EXP}(Y_t) * 100\%$$

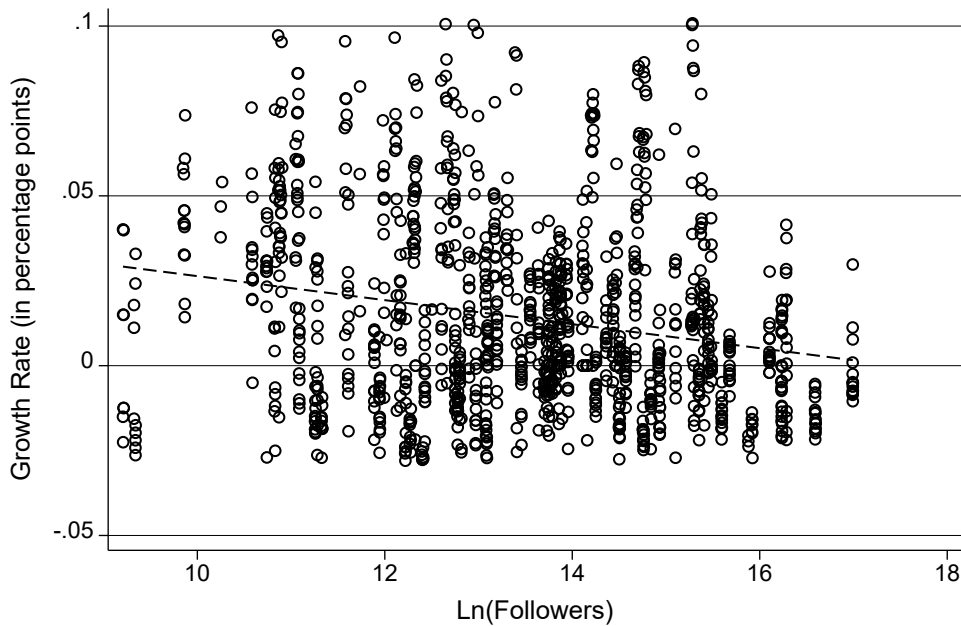
Note that one should be careful when interpreting this rate. Specifically, for the interpretation, when the raw follower change goes from positive to negative, “gain X% fewer followers” should be interpreted as “losing X% of followers that would have been gained in the absence of BLM treatment” for $X > 100$. This would be the case for small numbers of baseline follower increase, i.e. $0 < Y_t < -\text{coeff}$. In our application where $\text{coeff} \sim -1$, this more specific interpretation applies for $0 < Y_t < 1$, or $1 < \text{Follower}_t - \text{Follower}_{t-1} < 3$. Note, however, that this is not an issue with the transformation but an issue with having both negative and positive values of follower changes; any monotonic transformation could yield similar syntactical wording issues (i.e., anytime when you have both negative and positive values of follower changes in data). Relatedly, at small baseline changes (say 1 follower a day), the percent change may be large. However, because the average change is 407 lost followers in our data, this is not a serious issue here.

Nevertheless, when interpreting effect size, we use **both** raw followers changed due to BLM treatment and % in followers changed due to BLM treatment. For example, we now state: “Relative to their Twitter accounts, brands that supported the Blackout Tuesday event on Instagram gained 65.5% fewer followers for a median brand on Instagram in terms of the average daily follower changes in our data; across all brands, the average treatment effect size is 407 followers lost (see more details in online appendix 6)” in the main body.

Moreover, we report some descriptive statistics and histogram to reveal the scale of the follower data across the various brands in our data. Specifically, the mean of raw followers is 198,789, and the max brand’s raw followers are about 24 million (thus large national brands are evaluated in our data). Below is a histogram of the distribution of raw followers across brands.



Finally, we also considered another specification (difference in logs) to measure follower growth, and decided to not use it but adopted our main specification (log the differences) for the following theoretical and empirical reasons. Theoretically, we believe the underlying assumption of the alternative specification $\ln(F(t)) - \ln(F(t-1)) = \ln\left(\frac{F(t)}{F(t-1)}\right) = \ln\left(1 + \frac{F(t) - F(t-1)}{F(t-1)}\right) \approx \frac{F(t) - F(t-1)}{F(t-1)}$ ³ is that BLM treatment has a constant impact on brands' *growth rates* in followers (i.e. raw treatment effect is proportional to total followers). In other words, all participating brands on Instagram would experience the same reduction in their follower growth rates, despite the difference in their growth stages. This assumption may be less likely to hold in our setting because larger (vs. smaller) brands in our data are well-established brands that naturally have smaller (vs. larger) growth rates due to saturation. A constant change in growth rates would imply a big deviation from normal daily changes for brands with saturated growth. Empirically, in our data, below figure presents a scatter plot between brands' follower growth rate (measured in percentage points and excluding the extreme values above the 95th percentile and below the 5th percentile) and their follower base (log transformed) on Instagram. This figure clearly shows that on average, there is a negative correlation between the two variables, which confirms that larger brands tend to have smaller growth rates, while smaller brands have larger growth rates. The alternative specification implies that the BLM treatment effect for larger brands would be substantially larger relative to its typical growth rate. In contrast, our main specification has a greater flexibility in terms of the functional form in addressing effects of BLM for widely different scales of brands.



³ The growth rate $(F(t)-F(t-1))/F(t-1)$ in our data is small in absolute value, ranging from 0 to 0.041, with the mean of 0.0004.

Below we report our DID regression results with different aggregation choices (3-, 5- and 7-day) using the specifications 1 and 2 from Table 3. Results do not change qualitatively.

	3-Day Aggregation		5-Day Aggregation		7-Day Aggregation	
	(1)	(2)	(3)	(4)	(5)	(6)
	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth
Interaction (Treatment*After)	-1.215***	-1.168***	-1.044***	-1.016***	-1.089***	-1.060***
	(0.158)	(0.158)	(0.186)	(0.185)	(0.222)	(0.220)
Constant	-4.476***	-4.382***	-4.241***	-4.193***	-5.066***	-4.976***
	(0.670)	(0.666)	(0.807)	(0.804)	(0.977)	(0.976)
Social Media Contents (LDA)	Yes	No	Yes	No	Yes	No
Social Media Contents (Deep Learning)	No	Yes	No	Yes	No	Yes
Brand-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Brand-Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates:	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.753	0.756	0.769	0.772	0.801	0.804
Observations	2952	2952	2040	2040	1360	1360

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

Online Appendix 7: Triple DID Regression Results using Twitter and Non-participating Brands as Controls

	(1) Follower Growth	(2) Follower Growth	(3) Follower Growth
Participating Brands	-0.693*** (0.090)	-0.623*** (0.110)	
Treatment (Instagram)	2.817*** (0.127)	2.865*** (0.142)	2.904*** (0.107)
Participating Brands*After	-0.316*** (0.112)	0.135 (0.154)	0.058 (0.152)
Instagram*After	-0.514*** (0.170)	-0.038 (0.201)	-0.103 (0.156)
Participating Brands*Instagram	0.845*** (0.222)	0.800*** (0.230)	0.657*** (0.174)
Participating Brands*Instagram*After	-0.424 (0.309)	-0.900*** (0.325)	-0.793*** (0.265)
Constant	-1.211*** (0.044)	-0.115*** (0.038)	-1.372*** (0.343)
Brand Fixed Effects	No	No	Yes
Period Fixed Effects	No	Yes	Yes
R^2	0.162	0.178	0.494
Observations	8540	8540	8540

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

Online Appendix 8: Labeling Brands' Prosocial Mission Statements

We hired two external labelers to examine the mission statements of the participating brands of the Blackout Tuesday event and to label whether any of the statements are prosocial. That is, whether a brand incorporates social responsibility in its mission statement. The social responsibility can be either on a broad level or related to a specific topic (e.g., human trafficking, empowering women, black community, etc.). The Cronbach's alpha score is reasonably high at 0.91, suggesting high consistency between the coders. Below we present the brands' mission statements as well as their final labels.

Brand	Mission Statement	Prosocial Mission
AEROPOSTALE	We provide customers with a focused selection of high quality fashion and fashion basics at compelling values in an innovative and exciting store environment. Aéropostale maintains control over its proprietary brands by designing, sourcing, marketing and selling all of its own merchandise.	0
AG JEANS	At AG, our mission is to provide quality product while exercising corporate social responsibility on all levels. We strive to be a positive example of business integrity, and that commitment plays a crucial role in guiding the day-to-day practices and long-term strategies of our company.	1
AGACI	Make the A'GACI Way Your Way. When it comes to how you live your life, you've got a choice. You can settle for just okay. Or you can strive for something much more. At A'GACI, we choose more. We give a little extra. And we get a whole lot in return. It's what makes life at work-and at home-more challenging, more exciting, and more rewarding every day. Get on board with the A'GACI Way. And see for yourself why our way is the best way.	0
AGENT PROVOCATEUR	Agent Provocateur is committed to preventing slavery and human trafficking in all its corporate activities, and to ensuring that its supply chains are free from both.	1
AKIRA	AKIRA will always represent Chi-town (ahem, Chicago) in the fashion world. Up until now, fashion in America has primarily focused on the East and West Coast. AKIRA is determined to change this mindset with original thinking and an emphasis on strong designers and curated styles. We are working hard to heighten awareness across the country and put Chicago on the Fashion Map. A CULTURE OF SERVICE It's all about people. When it comes down to it, business is simply "People selling things to other people". So, we want to make sure that our people are the right ones. And so far, they are. With a very rigorous selection process, AKIRA is fanatical about ensuring that customers are styled by experts who eat, sleep, and breathe fashion. We live to make AKIRA customers look good and feel good. Let us do the heavy lifting while you reap the rewards.	0
ALICE AND OLIVIA	Full-time CEO and Creative Director, Bendet is also a wife and mother of three daughters who makes supporting charity endeavors a priority in her personal and professional activities. She is a member of the board of trustees of New York-based GOOD+ Foundation, a foundation that provides essentials for children of families in need, she supports Ronald McDonald House, which offers assistance to the families of children suffering from life-threatening illnesses, and she is also a member of the board of the Jay H. Baker Retailing Center of The Wharton School at the University of Pennsylvania, her alma mater.	1
AMERICAN EAGLE	Our purpose is to show the world that there's REAL power in the optimism of youth.	0
ANN TAYLOR	Ann Taylor mission statement is "to inspire and connect with our clients to put their best selves forward every day." This statement by Ann Taylor reveals how important it is for this company to constantly be ahead of the needs of its customers.	0
ATHLETA	Our mission is to ignite a community of active, healthy, confident women and girls who empower each other to reach their limitless potential. Today, Athleta operates more than 190 stores in the United States.	1
BANANA REPUBLIC	The people that make up Banana Republic share the same qualities as our brand: curious, connected, undaunted by boundaries. Join us for the adventure of what's next.	0

BANDIER	we are fashion and fitness. high style meets high performance. THE ULTIMATE EDIT. MADE FOR SWEATY BREAKTHROUGHS. FIT FOR IDLE BLISS.	0
BEN BRIDGE JWLR	For over 100 years, Ben Bridge has had a singular mission: help customers celebrate special moments.	0
BONOBOS	Make fit happen. For every body. Our team is dynamic, confident and colorful—just like our brand. We value self-awareness, empathy, intellectual honesty, positive energy and judgment, often over experience. We’ve created a culture where hard work, perseverance and communication are paramount, all while making time for humor, fun and the celebration of extraordinary efforts. Check out our awesome jobs at www.bonobos.com/jobs	0
BURGERKING	Burger King's mission statement is to “offer reasonably priced quality food, served quickly, in attractive, clean surroundings.” This mission statement indicates the kind of outputs expectable from the organization.	0
CARHARTT	Carhartt, Inc. As a premium brand, Carhartt is committed to conducting business in a fair and ethical manner. Carhartt's Social Compliance Department's Mission is To serve and protect the hardworking people who make our products.	1
CARTIER	Creativity, freedom, sharing and excellence are all central to its values. This vision enables a creative territory that is shaped around a unique style. From jewelry and fine jewelry to watchmaking and perfumes: Cartier's creations symbolize the fusion of exceptional savoir-faire and timelessness.	0
CENTURY21	C21 CORE VALUESOUR HIGHER PURPOSEDeliver Value to Live BetterOUR VALUESRESPECT: Value, empower and connect with each other, with humilityCOMMUNICATE: share, discuss and listen openly, with empathy.TEAMWORK: Take care of each other and give backHONESTY: Act with IntegrityGROW: Grow, and drive changePOSITIVITY: Be positive, passionate and have funAMAZE: Deliver amazing experiences to each other, our community and our guests	1
CHAMPION	Enhance comfort, beauty, and energy efficiency in millions of homes.	0
CHILDRENS PLACE	Our mission is to expand sales and market share around the world by being mom’s favorite PLACE for value, quality and fun fashion loved by kids; by providing an engaging in-store and online shopping experience; and developing innovative and efficient operational capabilities to drive growth.	0
CHIPOTLE	Chipotle was born of the radical belief that there is a connection between how food is raised and prepared, and how it tastes. Real is better.	0
CHOPARD	As a family-owned luxury watch & jewellery manufacturer with a worldwide presence, we are honoured to interact with our community and nurture the art of excellence and innovation with the highest respect for tradition.	1
CLUB MONACO	Club Monaco was founded in 1985 around the idea of “better basics”—creating classic, effortless pieces that contribute to the lives of our customers and allow them to live with ease.	0
DESIGUAL	Creating positive emotions through original, colourful, quality clothing for everyone, with a mission: to share joy, a love of life and a slightly unconventional spirit. Desigual clothes are an invitation to life, they inspire those who wear them.	0
DKNY	OVERVIEW OF DKNY'S MISSION STATEMENT: A DESIGN DRIVEN COMPANY THAT REPRESENTS THE INTERNATIONAL PULSE OF NEW YORK. THEY BOAST THE HIGHEST STANDARD OF CREATIVITY, INTEGRITY, QUALITY & INNOVATION TO THEIR PRODUCTS. THEIR BRAND IS ALSO INTERNATIONAL, ELECTRIC, FUN & REAL.	0
DOLCE GABBANA	The Group's mission is to design, produce and distribute high-end clothing, leather goods, footwear and accessories under the Dolce&Gabbana brand, as well as manage, through its licensees, the production and distribution of the fragrances, make-up, eyewear, timepieces and jewels lines.	0
DVF	to empower women—through my work by making them sexy and powerful, through mentoring and through philanthropy. And it's all related. Everything I do is about being the woman you want to be.	1
EDDIE BAUER	To be the best global, multichannel, active outdoor lifestyle brand; the outfitter of choice for your life s adventures.	0

EXPRESS	Express aims to Create Confidence & Inspire Self-Expression through a design & merchandising view that brings forward The Best of Now for Real Life Versatility.	0
FERRAGAMO	The Foundation's main mission is to offer young people, who focus their activity on fashion, design and the highest forms of Italian craftsmanship, opportunities of professional growth and training in line with values and principles at the root of Made in Italy concept and on which Salvatore Ferragamo based his ...	0
FOOT LOCKER	At Foot Locker, Inc., our purpose is to inspire and empower youth culture through our family of brands by fueling a shared passion for self-expression and creating unrivaled experiences at the heart of the sport and sneaker communities.	0
FOOT LOCKER WOMEN	With approximately 3,000 retail stores in 27 countries across North America, Europe, Asia, Australia and New Zealand, as well as websites and mobile apps, the Company's purpose is to inspire and empower youth culture around the world, by fueling a shared passion for self-expression and creating unrivaled experiences at ...	0
FOOTACTION	At Foot Locker, Inc., our purpose is to inspire and empower youth culture through our family of brands by fueling a shared passion for self-expression and creating unrivaled experiences at the heart of the sport and sneaker communities.	0
FRANCESCAS	Surprise and delight every guest, every time. Our Vision• francesca's® is an inviting boutique serving the guest looking for personalized service, with unique and stylish merchandise at a great value. Our Values• Put People First• Win Together (and Learn Together)• Do What You Say• Be Outstanding• Love What You Do	0
GAP	We're looking for true individuals. People with the courage to take chances. Who understand that making a difference takes passion, patience, and persistence.	0
GHBASS	G.H. Bass & Co.'s mission statement is "To make the best possible shoe for the purpose in which it will be used."	0
GIUSEPPE ZANOTTI	The brand's signature audacious elegance embraces a new urban, modern attitude, which, while responding to the needs of today's consumers, at the same time focuses on its most authentic mission: celebrating individuality with a unique mix of creativity and craftsmanship.	0
HARLEYDAVIDSON	More than building machines, we stand for the timeless pursuit of adventure. Freedom for the soul.	0
HOLLISTER	The quintessential apparel brand of the global teen consumer, Hollister Co. celebrates the liberating spirit of the endless summer inside everyone. Inspired by California's laidback attitude, Hollister's clothes are designed to be lived in and made your own, for wherever life takes you.	0
HURLEY	At Hurley, our vision is to create a healthier future for every child, adult and senior citizen. We will not only treat people when they are sick or injured and then return them to their homes, but we will find ways to help them stay in their homes living vibrant, healthy, active lives.	1
IBM	To lead in the creation, development, and manufacture of the industry's most advanced information technologies, including computer systems, software, networking systems, storage devices, and microelectronics.	0
INTEL	Intel's vision and mission statement includes driving innovation for a safe, productive world and helping customers overcome technical challenges.	0
J CREW	Each season we tell stories, some familiar and some new. Inspired by the places we go, the people we admire and all the unexpected stuff in between, our collections feature modern twists on classic fashion. With everything we do, we hope to make your life a little more special.	0
J MCLAUGHLIN	Our mission is 'To capture the Hearts of Women and Inspire Men Around the World'. To achieve our mission, we thrive on talent and passion.	0
JANIE AND JACK	Quality is our highest priority. It's in everything we do, from our design (always starting with the finest materials) and production (at the world's most renowned factories, where much of the work is done by hand) to our personalized service.	0
JARED THE GALLERIA OF JEWELRY	McLaughlin was founded in 1977 by brothers Jay and Kevin with a mission to create a new American sportswear brand that offers two key components: classic	0

	clothes with current relevance and a retail environment with a neighborhood feel.	
JEEP	The Jeep Brand builds on two core values: freedom and authenticity. Freedom as a state of mind and individual determination to follow one's own instincts with the confidence of being able to enjoy any adventure thanks to benchmark off-road capabilities.	0
JIMMY CHOO	As part of Signet Jewelers, our mission is to enable all people of all means to Celebrate Life and Express Love.	0
JOHNSTON MURPHY	Johnston & Murphy is a pillar of classic workmanship and a beacon of American style. Since 1850, J&M has provided the highest quality products and set the standard for successful, professional men everywhere. In 2008, Johnston & Murphy continued its commitment to style, craftsmanship and innovation by introducing a new line of shoes, leather goods and accessories for women.	0
KATE SPADE	we're stronger together through our on purpose collection, we build suppliers that help transform communities by employing and empowering its primary agents of change: women.	1
KAY JEWELERS	As part of Signet Jewelers, our mission is to enable all people of all means to Celebrate Life and Express Love.	0
KENDRA SCOTT	We care deeply about the communities we call home, and are committed to making a positive impact on the world around us.	1
KIDS FOOTLOCKER	They provide a safe place, caring adult mentors, fun, friendship and high-impact youth development programs on a daily basis during critical non-school hours. Priority programs emphasize academic success, healthy lifestyles, good character and citizenship.	0
LACOSTE	Life is a beautiful sport!	0
LASENZA	La Senza offers women outstanding lingerie from comfortable sleepwear, bras and panties. Their mission is to provide an outstanding lingerie presentation in a world class environment. La Senza provides customers with outstanding personal service, while combining quality, fit and value.	0
LASTCALLNM	"Neiman Marcus Stores will be the premier luxury retailer recognized for merchandise leadership and superior customer service. We will offer the finest fashion and quality products in an exceptional environment."	0
LOFT OUTLET	We believe in offering versatile, accessible and affordable fashion with undeniably feminine appeal, special and unexpected details and a great fit.	0
LORNA JANE ACTIVE	We are on a mission to empower every woman to lead her best life through Active Living. What started as a passion to deliver unique and inspiring designs to fellow gym lovers, Lorna Jane has now given a whole new meaning to staying fit and healthy - it's a lifestyle that transcends the walls of the gym. All for the love of health and wellness, the Lorna Jane sisterhood aspires to be their own personal best by embracing the daily practice of Move Nourish Believe.	1
LUCKY BRAND	Lucky Brand specializes in high quality, comfortable clothing. We've got denim jeans, jackets, tees and accessories for both men and women.	0
MARINE LAYER	Together, we've built a brand around absurdly soft shirts that are perfect for a 7-day weekend kinda lifestyle.	0
MARSHALLS	Our mission is to deliver great value on ever-changing selections of brand name and designer fashions at prices generally 20%-60% below department and specialty store regular retail prices on comparable merchandise.	0
MASSIMO DUTTI	Our mission is to always ensure high quality fabrics that are also practical and comfortable for the independent and cosmopolitan men women and kids of today.	0
MERCEDES BENZ USA	Every task is a chance to grow. Our vision is to become the world's most renowned center for customer service in the automotive sector.	0
MERRELL	Merrell exists to share the simple power of being outside. We believe the trail is for everyone. Our goal is to provide thoughtfully designed, rigorously tested products that over-deliver on performance, versatility, and durability.	0
MICHAEL KORS	Our mission is to provide a sophisticated Jet Set lifestyle to our customers around the world through our trend setting innovative products and exceptional service experience in-store and online.	0
MICROSOFT	Our mission is to empower every person and every organization on the planet to achieve more.	0

MOUNTAIN HARDWEAR	We create performance apparel and equipment to empower outdoor athletes to live boldly.	0
NATURALIZER	The platform and its launch campaign, “Today We Will,” is not only the statement of the brand's commitment to continuously make better shoes in support of women, but an invitation to women everywhere to be present, engage and declare their intentions to live their best lives and support each other.	1
NORDSTROM RACK	Nordstrom mission statement is “to provide outstanding service every day, one customer at a time. A further focus is provided to Nordstrom employees at all levels with this Nordstrom goal, which is also a management mission.	0
NY AND COMPANY	The Company's vision is to be the premier incubator of lifestyle brands by leveraging the Company's expertise in celebrity, design, customer, eCommerce, operations, real estate, and inventory optimization to identify accretive brand and profit opportunities.	0
OFFICIALPANDAEXPRESS	To deliver exceptional Asian dining experiences by building an organization where people are inspired to better their lives.	0
OLD NAVY	At Old Navy, we're on a mission to ensure the world runs right by creating a better tomorrow for future generations through inclusivity, opportunity and sustainability.	1
PUMA	Becoming the fastest brand in the world isn't just a mission statement, it's the rally cry for a company culture determined to discover and shape what lies beyond. Driven by our FOREVER FASTER positioning, our ambition is to capture the attention of the world through world-records, iconic athletes and that undeniable PUMA touch we bring to sport and culture.	0
RAG AND BONE	Our people define our culture—the company was founded through an entrepreneurial approach and this spirit runs through all that we do. When faced with challenges we work closely to ensure we have common goals and can move forward in unison, with no job too big or small. We love what we do and our passion is evident, through the product we create, the people we work with, through to the way in which we function—always as one team.	0
RAINBOW SHOPS	As the Leading Retailer in the markets we serve, we respect and value people, product, and performance to ensure that the customer is our main focus.	0
REEDS JEWELERS	Bill's motto was “The harder you work, the luckier you become.” To that end, REEDS was one of the first jewelers to provide late-night hours to give customers greater shopping convenience.	0
RUE21	It is our mission to provide the latest trends with an affordable price tag. rue21 is different (i.e. we never stop moving!). We work fast so that we can bring you the newest styles that don't exist anywhere else. We believe that fashion should be fun and accessible to all.	0
SCRUBS AND BEYOND	Create an enjoyable shopping experience by providing value, service, quality, and selection to medical professionals and BEYOND.	0
SHANE COMPANY	the leader in every market we serve. Our customers are customers for life because our people are fun, happy, empowered and committed.	0
SHIEKH	NA	0
SOMA INTIMATES	We embrace beauty, strength and creativity from the inside-out, and empower women to do the same.	1
SPLENDID LA	At Splendid we believe in bringing people together. In good company and great conversation. We believe in taking time to enjoy the little things and more importantly celebrate the big things. We think that people should cherish every moment.	0
SUBWAY	Subway's mission statement is “to be the world's favorite destination for discovering great value and unique selection.” The mission statement underlines the resolve of Subway to go out of its way to create a reputation that keeps bringing its customers back for more.	0
SUIT SUPPLY	Suitsupply's mission is to offer high quality suits at competitive prices. The service to the customer is essential in doing so. Besides creating a standardized message through media communication, Suitsupply must also focus its organizational culture by changing its right to exist, values and identity.	0
SWEATY BETTY	Empowering women through fitness and beyond. ... Named after her determination to make it cool to sweat, Sweaty Betty is a design-driven activewear brand on a mission to empower women through fitness and beyond.	1

TACOBELL	Taco Bell's full mission statement: "We take pride in making the best Mexican style fast food providing fast, friendly, & accurate service. We are the employer of choice offering team members' opportunities for growth, advancement, and rewarding careers in a fun, safe working environment.	0
THE ATHLETES FOOT	Our vision is to create a world where everyone is proud to be themselves, where people wear their identities proudly. On every court and every street, we'll be there alongside the players and the dreamers. We're shaking up the world of street style. We are TAF.	0
THE FRYE COMPANY	Frye's mission, to make iconic leather goods that endure, has remained unchanged throughout its storied history. http://www.TheFryeCompany.com .	0
TILLYS	Tillys is a leading specialty retailer of casual apparel, footwear and accessories for young men, young women, boys and girls with an extensive assortment of iconic global, emerging, and proprietary brands rooted in an active and social lifestyle.	0
TIMBERLAND	Our mission is to equip people to make a difference in the world. We do this by creating outstanding products and by trying to make a difference in the communities in which we live and work.	0
TIMEX	our Mission is to be the "leader" in high-fashion watches. Everyone in our organization lives and breathes the Maisons' DNA, awareness, image, activities etc... and is expected to create extraordinary experiences for our consumers, by designing, developing, producing and marketing a wide range of luxury fashion watches.	0
TODS	The firm's mission is to offer global customers top-quality products that satisfy their functional requirements and aspirations.	0
UNDER ARMOUR	To Make All Athletes Better Through Passion, Design, And The Relentless Pursuit Of Innovation	0
UNTUCKIT	It's the way people are made—but not how traditional shirts are made. We've totally reengineered the casual dress shirt to have the perfect untucked length and that just-right fit, so they can help every guy look his best—always.	0
WHBM	White House Black Market is an omnichannel fashion retailer that began as two small Baltimore, Maryland boutiques—The White House, opened in 1985 and Black Market, opened in 1995. The brand, acquired by Chico's FAS in 2003, is dedicated to making women feel beautiful and confident through stylish and versatile clothing and accessory items, including everyday basics and premium denim, polished casual apparel, relaxed workwear, black and white pieces, and feminine all-occasion dresses—all delivered through coveted, curated collections and personalized customer service.	0
ZALES JEWELERS	As part of Signet Jewelers, our mission is to enable all people of all means to Celebrate Life and Express Love.	0

Online Appendix 9: Heterogeneous DID Effects (Deep Learning)

Here we present the estimation results of heterogeneous DID effects using the covariates calculated from deep learning methods. The specifications are identical to those in Table 5.

	Full Sample	Republican Sub-sample	Democrat Sub-sample	Full Sample	Full Sample	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth	Follower Growth
DID (BLM_Treatment *After)	-1.282*	-2.081**	-0.577	-1.042	-1.099	-0.534	-0.335
	(0.742)	(0.957)	(1.195)	(0.758)	(0.750)	(1.555)	(1.691)
DID*Previous Social Posts (Mean)	13.386**	7.355	19.848**	13.348**	8.729	13.924**	12.382*
	(6.191)	(9.574)	(9.188)	(6.189)	(6.796)	(6.269)	(7.458)
DID*Previous Social Posts (SD)	-15.126***	-11.684	-16.619*	-15.181***	-11.684*	-15.401***	-15.105**
	(5.750)	(8.424)	(8.688)	(5.748)	(6.111)	(5.773)	(6.589)
DID*Self Promotion	-2.158	-2.082	1.809	-2.087	-2.709	-2.160	-1.005
	(1.789)	(3.029)	(2.415)	(1.789)	(1.819)	(1.789)	(1.923)
DID*Social Mission	1.121**	0.334	1.300**	1.097**	1.293***	1.111**	1.116**
	(0.446)	(0.660)	(0.613)	(0.446)	(0.458)	(0.447)	(0.463)
DID*Slacktivism	0.467	2.206***	-1.814***	0.473	0.500	0.401	0.545
	(0.374)	(0.462)	(0.642)	(0.374)	(0.374)	(0.393)	(0.410)
DID*Republican Advantage	-2.872***			-2.671**	-2.791***	-2.918***	-3.110***
	(1.062)			(1.070)	(1.063)	(1.065)	(1.091)
DID*House of Brands				-0.518			-0.065
				(0.339)			(0.367)
DID*Luxury Brand					1.687*		1.221
					(1.017)		(1.101)
DID*Log(Followers)						-0.056	-0.065
						(0.103)	(0.113)
Constant	-3.355***	-1.375	-2.258*	-3.290***	-3.386***	-3.367***	-3.615***
	(0.939)	(0.993)	(1.349)	(0.940)	(0.939)	(0.940)	(0.952)
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	0.774	0.833	0.722	0.774	0.774	0.774	0.776
Observations	2436	1148	1288	2436	2436	2436	2436

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

Online Appendix 10: Main DID Regression with Split-Sample Analysis (Republican vs. Democrat Advantage)

Here we present the results of the split-sample analyses based on consumer political affiliation. We use the same specifications as Columns 1 and 2 of Table 4, but conduct regression on subsamples of brands with more Republican and Democratic customers, respectively.

Table A10: Regression Results

	Guided LDA		Deep Learning	
	Republican	Democrat	Republican	Democrat
	(1)	(2)	(3)	(4)
	Consumer Following	Consumer Following	Consumer Following	Consumer Following
DID (BLM_Treatment *After)	-1.655***	-0.681***	-1.632***	-0.650***
Constant	(0.228)	(0.248)	(0.228)	(0.248)
	-0.818	-2.669**	-0.965	-2.660**
	(0.989)	(1.355)	(0.998)	(1.352)
Brand-Time Fixed Effects	Yes	Yes	Yes	Yes
Brand-Platform Fixed Effects	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
R^2	0.828	0.715	0.828	0.716
Observations	1148	1288	1148	1288

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$