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Evidence from the British Museum

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Measuring the Impact of Social Media Boycotts on Tourist Arrivals: Evidence from The British Museum

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ABSTRACT

The main objective of this study is to investigate whether social media boycotts have a negative impact on tourist arrivals. We analyzed 17,905 negatively valenced tweets pertaining to the British Museum from 2014 to 2019, which were linked to two separate boycotting campaigns. Employing the local projection method, we assessed the influence of these Twitter boycotts on the British Museum's tourist arrival numbers. Our results suggest that social media boycotts have a modest impact on declining tourist figures, with varying effects observed across campaigns with different themes. Notably, the “Drop BP” boycott demonstrated a statistically significant, albeit mild, correlation between tweet volume and tourist arrivals. This research enhances the understanding of tourism boycotts by providing empirical evidence of social media boycotts’ effects on tourist numbers. We also offer insights for attraction managers on managing and mitigating boycotts.

Keywords: Tourism boycott; Social media; The British Museum; Sentiment analysis; Topic modelling; Local projection

INTRODUCTION

Despite the growing attention from theorists and practitioners to social media boycotts, limited studies examined social media boycotts in the tourism context (Yu, McManus, Yen and Li 2020). Empirical evidence on the impact of social media boycotts on tourism attractions is even more scarce (Su, Jia and Huang 2022). To address this void in the literature, this study examined the impact of boycotting campaigns as depicted on Twitter on tourist arrivals to the British Museum. This study contributes to the boycott literature (Liaukonytė, Tuchman and Zhu 2022) by adding empirical evidence to the impact of boycotts on tourism arrivals. We show that social media users fail to translate their boycotting intentions into real actions, which may be due to the cost of boycotting activities (Klein, Smith and John 2004), or high switching costs (Lasarov, Hoffmann and Orth 2021). The findings of this study underscore the importance of detecting the heterogeneity of boycott themes while measuring the impact of social media boycotting events.

This paper begins with a concise review of relevant literature to establish the theoretical foundation for the subsequent empirical analysis. We then detail the data collection strategies, data processing framework, and empirical models in the methodology section. Next, we present the findings of our research. Finally, we discuss the implications and limitations of our study and suggest directions for future research.

THEORETICAL BACKGROUND

Previous studies suggest that political consumerism (Liaukonytė, Tuchman and Zhu 2022) and ethical consumerism (Koku 2022) are two main factors that motivate consumers' participation in boycotts. According to Stolle and Micheletti (2013), consumers choose to either proactively avoid consumption (boycott) or seek consumption (buycott) for political or ethical reasons. The wide adoption of the internet and social media has made boycotts easier to organize and promote (Yu, McManus, Yen and Li 2020). Although social media sites were not created with activism in mind, they became the most common channel for online activism (Harlow 2012). For example, recently, there have been increasing calls for action on social media to boycott a politically engaged brand (Liaukonytė, Tuchman and Zhu 2022). For example, on 9th Jul 2020, the CEO of Goya praised President Donald Trump following their meeting in the White House. Immediately, the hashtags “#Goyaway” and “#BoycottGoya” went viral on Twitter.

Boycotting activities are believed to have devastating effects on trade (Heilmann 2016), sales (Liaukonytė, Tuchman and Zhu 2022), and firm value (Bhagwat, Warren, Beck and Watson IV 2020). Analyzing US consumers' participation in the boycott of French wine due to the French opposition to the war in Iraq, Chavis and Leslie (2009) found that the movement resulted in a 13% drop in sales over the next six months and a 26% drop in weekly sales at its peak. In contrast, Liaukonytė, Tuchman and Zhu (2022) have shown that following the Twitter boycott, Goya sales temporarily increased by 22%.

In the tourism context, research on social media boycotts is rare. Using seven Chinese tourism boycott movements as case studies, Yu, McManus, Yen and Li (2020) examine the effects of political and non-political animosity-driven tourism boycotts. It has been found that boycotts can lead to significant visitor numbers decline. In addition, the findings suggest that non-political animosity boycotts exert immediate short-term impacts on tourist arrivals, whereas political animosity-driven boycotts tend to have enduring effects. With the exception of Yu et al (2020), however, there is a lack of empirical evidence of boycott movements' impact on tourist arrivals. To add to the literature, this study examines an ethical boycott described as the circumstance that consumers refrain from products or services produced by companies (or countries) that disregard human rights or engage in environmentally unfriendly practices on tourism arrivals.

DATA AND METHODOLOGY

Case Selection, Data Description and Boycotts Identification

We obtained the monthly volume of tourist arrivals to The British Museum (BM thereafter) from 1st Jan 2014 to 31st Dec 2019 from the UK government's website. BM is selected for the case study for the following three reasons: (1) BM is one of the most famous attractions in the world and is ranked the top two free attractions in London (VisitLondon 2022) ; (2) BM has been frequently used as a case study in tourism research (Su and Teng 2018) and especially in tourism demand forecasting research (Kim, Liu, Stienmetz and Chen 2022; Qiu, Lacka and Ansell 2022; Volchek, Liu, Song and Buhalis 2019); (3) BM has been subject to social media boycotts on Twitter (see Table 1). We base the identification of boycott events on narrative records obtained from Twitter. We collected Twitter data for BM via the Twitter API using the query keyword 'British Museum', resulting in a dataset with a total of 582,742 tweets between 1st Jan 2014 and 31st Dec 2019. Since the British Museum is located in London and English

is the most used language by tourists, this study is restricted to search queries and tweets written in English.

The designed analytical framework for boycott identification consists of five steps. In step (1), actions were taken to pre-process tweet texts, including text cleaning, tokenisation, lemmatisation, and stop words removal. In step (2), we adopted the VADER algorithm to determine the valence of each tweet and classify each tweet into one of the following three categories: positive, neutral, and negative. The algorithm generated 264,461 positive tweets, 247,287 neutral tweets, and 70,994 negative tweets. As boycotts will most likely be expressed in tweets with negative valence, hence we focus on negative tweets only. In step (3), we designed a words-matching approach to identify boycott-related tweets. First, we extracted the 50 most frequently used words for negative tweets and all other tweets. Next, we omitted words existing in both negative tweets and non-negative tweets and this process generated 21 words. We then judgmentally categorized these words and determined if any words require further interpretation. Based on our knowledge of BM, we first allocated these words into three groups as follows: C₁: ‘stolen’, ‘elgin’, ‘greece’, and ‘sculpture’; C₂: ‘bp’, ‘protest’, ‘sponsorship’, ‘activist’, ‘oil’, ‘drop’, and ‘sponsored’; and C₃: ‘war’, ‘loan’, ‘lost’, ‘dead’, ‘died’, ‘russia’, ‘attack’, ‘onthisday’, and ‘city’. C₁ and C₂ are about criticism of the British Museum’s “stolen artefacts” and “sponsorship by BP”, respectively. While C₃ consists of words that needed further interpretation. We screened the top 20 most frequently retweeted tweets for each word in C₃ to see if it needs relocation (i.e., 160 tweets in total). The adjusted clustering results are presented in Table 1 below. The existence of C₃ substantiates the drawback of purely valence-based approaches like VADER in specifying discrete and context-dependent consumer emotions. Considering that the research aims to examine the effects of social media boycotts on tourist arrivals, we mainly focused on C₁ and C₂ in the following analysis as they both have a specific boycott theme.

Table 1. Clustering results of negative tweets

Clusters	Words	Amount	Example (text)
C ₁ : Stolen artefacts	‘stolen’, ‘elgin’, ‘greece’, ‘loan’, ‘russia’, and ‘sculpture’	10120	@britishmuseum return what you've stolen! egyptians can open their own museums anywhere in europe. do not justificate theft! :)
C ₂ : Drop BP	‘bp’, ‘protest’, ‘sponsorship’, ‘activist’, ‘oil’, ‘drop’, and ‘sponsored’	7785	We’re outside the BP-sponsored exhibition in the British Museum. We have a simple message. Drop BP.
C ₃ : Other tweets with negative valence	‘war’, ‘lost’, ‘dead’, ‘died’, ‘attack’, ‘onthisday’, and ‘city’	9266	The Troy exhibition at the British Museum has left me a lot to think about. The story of the Trojan War is so *human* and I never felt it as strongly as I did going through this exhibition and seeing modern interpretations of the story alongside ancient pots.

Table note: The clustering results are based on the adjusted classification of 21 frequently used words in negative tweets. Tweets not containing these words are not included in the clustering procedure. All words are converted to lowercase.

Finally, we applied the two-stage topic modelling approach proposed by Ridhwan and Hargreaves (2021) to cross-validate the clustering results in step 5. We first identified the upper bound of the optimal topic numbers for each cluster using the Latent Dirichlet Allocation (LDA) model. Based on the obtained upper-bound topic numbers, we then identified the optimal topic numbers and distributions using the Gibbs Sampling Dirichlet Multinomial Mixture (GSDMM) model. For all LDA models, we set alpha to 0.1, beta to 0.1, chunk size to 10000, and passes to 20. For all GSDMM models, we set alpha to 0.1, beta to 0.4, and iteration numbers to 10. Details of the model tuning process can be provided on request. The results show no significant outlying topics for each cluster and further indicate that the judgmental approach captured topics of negative tweets well (see Table 2). Based on the cross-validated clustering results, we generated two series describing the fluctuation of the number of tweets belonging to C_1 and C_2 , respectively.

Table 2. Topic distribution for each cluster

Cluster	Coherence score	Topic number	Most relevant words (Top 10)	Prevalence
C ₁ : Stolen artefacts	0.78	1	stolen, artefact, return, back, country, people, good, treasure, give, world	37.2%
		2	marble, elgin, loan, greece, russia, greek, sculpture, disputed, outraged, angering	23.5%
		3	stolengood, world, largest, receiver, qc, artefact, benin, loan, nigeria	10.3%
		4	marble, greece, parthenon, elgin, sculpture, stolen, legal, greek, drop, 249, action	22.3%
		5	stolen, bp, object, sponsored, climatechange, indigenous, performance, money, dirty, film	6.8%
C ₂ : Drop BP	0.66	1	bp, protest, exhibition, sponsorship, oil, criminal, corporate, new, sponsored, activist	26.8%
		2	bp, stolen, sponsored, object, climatechange, marble, greece, drop, parthenon, legal	16.7%
		3	oil, drop, dropbp, deal, future, flood, record, high, arctic, melting	12.8%
		4	bp, flash, viking, oil, protester, anti, horde, june, mob, join	14.4%
		5	bp, protest, sponsorship, activist, greenpeace, drop, scale, mark, calling, close	29.3%
C ₃ : Other tweets with negative valence	0.54	1	war, lost, city, dead, exhibition, world, egypt, sunken, ancient, imperial	44.9%
		2	died, war, onthisday, dead, go, lost, artist, skeleton, display, return	34.1%
		3	attack, terror, dead, girl, plotting, lost, grenade, old, female, plotted	21.0%

Table note: All words are converted to lowercase.

Boycott Effects Estimation: The Local Projection Approach

We use the local projection (Jordà 2005) approach to estimate the impulse response of tourist arrivals to BM to two groups of Twitter boycotting campaigns (see Adämmer (2019) for more details about the R package ‘lpirfs’ we used for model estimation). The advantage of local

projection approach is that it can easily accommodate highly nonlinear and flexible specifications and improved robustness to misspecification (Jordà 2005). The local projection method has recently been adopted in tourism boycott research (Yu, McManus, Yen and Li 2020). We specify the baseline model as follows:

$$TA_t = \alpha + \sum_{k=0}^{12} \beta_i B_{i,t-k} + \varepsilon_t \quad (1)$$

where TA describes the number of seasonally adjusted (via the additive X-12 ARIMA (0 1 1) (0 1 1) model) tourist arrivals to BM at time t ; $B_{i,t-k}$ captures the number of tweets at time t for boycott i ; and ε_t is an error term. Specification (1) can be estimated using a fixed-effects regression. The estimates of β_i provide a local projection of the impact of the shock of boycott i to tourist arrivals to BM from the date of occurrence ($k=0$) to 12 months thereafter ($k=12$). Relative research considers a set of control variables for travel costs such as inflation, consumer price, exchange rate and oil price (Adedoyin, Seetaram, Disegna and Filis 2021; Yu, McManus, Yen and Li 2020). Unfortunately, we do not have access to tourists' demographic data, so cannot use these measures. Instead, we incorporated the change of oil price (measured as the global price of Brent crude oil) as the proportion of overseas tourists to BM is over 60 per cent in the past decade. In addition, the effects of serial correlation in the dependent variable have been addressed by including the lags of tourist arrivals in relevant research (Jordà 2005; Yu, McManus, Yen and Li 2020). Regarding the lag length selection, we followed Jordà (2005) and selected the optimal lag length by fitting a VAR model. Based on the Akaike information criterion (AIC) and the Schwarz Criterion (SC), the lag length was determined to be 2. Therefore, we modified the baseline model by adding Y_t which represents a matrix of control variables (the global price of Brent crude oil in our case) and l lags of the dependent variable in the specification. The adjusted benchmark model is specified as follows:

$$TA_t = \alpha + \sum_{k=0}^{12} \beta_i B_{i,t-k} + \sum_{l=0}^2 \beta_i BX_{t-l} + \theta Y_t + \varepsilon_t \quad (2)$$

ANALYSIS AND RESULTS

To ensure the stability of our model estimation, we first performed the standard augmented Dickey-Fuller (ADF) test with trend and intercept to each variable. The null hypothesis of the ADF test is that a unit root exists in the variable. The test results suggest that all variables are stationary in levels at the 0.01 significance level, and hence no further transformation is needed. Based on the full historical sample and the local projection method described above, we present the main results of our analysis of the overall impact of boycott tweets on Tourist arrivals to BM in Figure 1. The shadowed area in each plot represents the 95% confidence band. It demonstrates that twelve months after a shock in the number of boycott tweets, the volume of tourist arrivals to BM did not get impacted dramatically. In addition, no significant difference was observed in estimates for the impact of boycott tweets on the number of tourist arrivals to BM that has been derived from the benchmark model (specification 2) and baseline model (specification 1), suggesting that the number of boycott tweets was exogenous. The comparison of Panel (a) and Panel (b) further demonstrates that including lags of the dependent variable in the specification did not elicit a smaller confidence band. Figure 2 further decomposes the impact of boycott tweets with different themes on the number of tourist arrivals to BM using the benchmark model. We can observe a significant declining trend in the volume of tourist arrivals since the second month after a shock (i.e., a unit change) in the number of boycott tweets about "Drop BP" in Panel (b), although the magnitudes are small. Differently, Panel (a) does not demonstrate a significant decline in the volume of tourist arrivals to BM.

Figure 1 Impact of Twitter boycotts on tourist arrivals

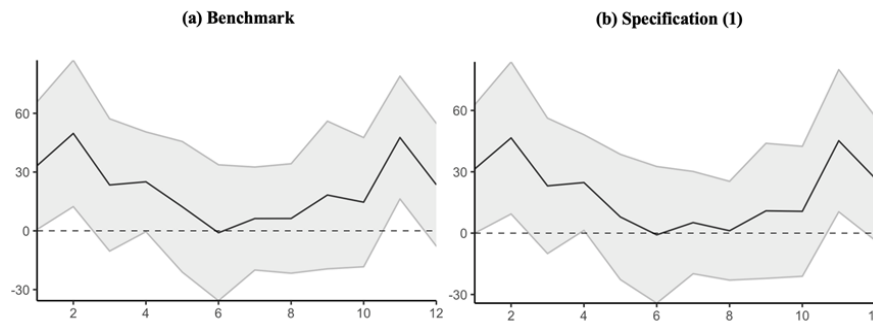


Figure note: Panel (a) presents the benchmark results for the impact of boycott tweets on the number of tourist arrivals to BM. Panel (b) presents the results estimated by specification 1 as the comparison.

Figure 2 Impact of Twitter boycotts on tourist arrivals case by case

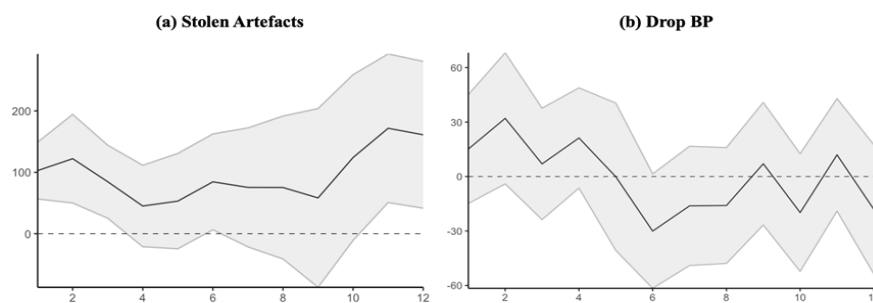


Figure note: Panel (a) presents the benchmark results for the impact of boycott tweets about “Stolen artefacts” on the number of tourist arrivals to BM. Panel (b) presents the benchmark results for the impact of boycott tweets about “Drop BP” on the number of tourist arrivals to BM.

CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

Driven by the lack of empirical evidence on social media tourism boycotts, this study explores the effects of boycott-related tweets on tourist arrivals, using the British Museum as a case study. Despite numerous boycott tweets targeting the British Museum, our local projection approach reveals no discernible influence on tourist arrivals over a 12-month period. Analyzing the heterogeneity of boycott themes, we observe a small negative impact on tourist arrivals from the “Drop BP” theme beginning in the second month. However, despite a larger volume, the “Stolen Artefact” theme does not show a negative effect on tourist arrivals. Two potential factors may contribute to the varying effects of different boycott themes against the British Museum. First, growing concerns about climate change might encourage consumers to avoid products and services supported by “dirty energy” providers like BP (Kennedy 2017). Consequently, the “Drop BP” theme negatively affects tourist arrivals. Second, despite calls to return artefacts to their origin, the law prevents the British Museum from taking action¹. According to Klein, Smith and John (2004), consumers need to believe that boycotts will make a real difference before acting. As a result, Twitter boycotts with the “stolen artefacts” theme are unlikely to elicit a tangible response, aside from drawing public attention

¹ Check https://www.britishmuseum.org/sites/default/files/2019-10/De-accession_Policy_Nov2018.pdf for The British Museum’s policy statement.

This study enriches the tourism boycott literature by providing empirical evidence of the intention-behaviour gap (Liaukonytė, Tuchman and Zhu 2022) in social media tourism boycotts. Restrained by the cost of boycotting activities (Klein, Smith and John 2004), such as high switching costs (Lasarov, Hoffmann and Orth 2021), individuals may struggle to transform their boycotting intentions into concrete actions. Furthermore, our findings highlight the significance of accounting for the heterogeneity of boycott themes when evaluating the impact of social media boycott events (Yu, McManus, Yen and Li 2020). We also propose a five-step analytical framework for identifying boycott events with varying themes using narrative records from Twitter, thereby advancing the methodology for detecting social media boycotts. At first glance, our results may seem promising for attraction managers confronted with social media boycott pressure and disheartening for third parties advocating for boycotts. Despite the heightened attention ethical consumerism receives on social media and the perception that such boycotts could have negative consequences (Koku 2022), the impact on the British Museum was minimal.

While our results may initially seem encouraging for attraction managers facing social media boycott pressure, the study's limitations should be considered. Our findings are based on a single case study, and it is unclear whether the modest impact of social media boycotts is due to the British Museum's distinctiveness. Additionally, the low frequency of our dependent variables poses a limitation. Future research should explore data sampled at higher frequencies and examine the short-term effects of social media boycotts in various contexts.

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