OPEN ACCESS

European Journal of Behavioral Sciences
ISSN 2538-807X

Does Cancel Culture Affect the Bottom Line? A Timeseries Analysis of Sentiment and Emotion on the Efficacy of the Call to Cancel Against Abercrombie & Fitch

Paul Reyes-Fournier[1*], Elizabeth Reyes-Fournier[2], David W. Bracken[3]

[1] Department of Business and Accounting, American National University, United States
[2] Department of Undergraduate Psychology, Keiser University, United States
[3] Department of Graduate Psychology, Keiser University, United States

ARTICLE INFO

Keywords:
cancel culture,
theory of emotion,
sentiment analysis,
time series analysis, decision-making in purchasing

ABSTRACT

Social media polemics that call to cancel, boycott, or otherwise disrupt a business have become endemic to the medium. The following case study of Abercrombie & Fitch explores the effectiveness of these "call to cancel" and, by analyzing the sentiment of the tweets, a time-series regression analysis was used to develop a predictive model of correlations to fiscal indicators. Sentiment of Twitter data was collected for each fiscal quarter for 10 years. Results showed a spike in negative sentiment values that corresponded to the call to cancel. The polemic differences were strongly correlated to adjusted sales. Results showed a structural break in sales. The sudden change in sentiment preceded a shock to the fiscal system of the company. Individual emotions were ultimately found to be representing two factors. The implications of this study lend credence to the construct of cancelling while also calling into question the idea of separate emotions.

1. Introduction

There is an assumption that the antecedent of communication will have a causal effect on the recipient. When a group of advocates takes to social media, there is a belief that a call to boycott will, have an effect on the financial stability of the organization. This will force a change in behavior of the company, at which point the boycott will be called off. If the company is deemed irreparable, the boycott will become a call to cancel and will be in effect until the company is bankrupt. If this assumption holds true in a cancel culture environment, then the mechanism for the propagation of ideas that support the call may affect the company's bottom line. In social media, there is a strong emotive component to the propagation of ideas (Zummo, 2017). Companies need to match their responses to both the rational and emotive components of the propagated ideas.

Researchers have used Twitter sentiment to predict market movement with mixed results. Using overall sentiment from Twitter was not a good predictor of Dow Jones stock market

[*] Corresponding author E-mail address: prfournier@an.edu

Cite this article as:
Reyes-Fournier, P., Reyes-Fournier, E., & Bracken, D. W. (2023). Does Cancel Culture Affect the Bottom Line? A Timeseries Analysis of Sentiment and Emotion on the Efficacy of the Call to Cancel Against Abercrombie & Fitch. *European Journal of Behavioral Sciences, 6*(3): 41-56. https://doi.org/10.33422/ejbs.v6i3.1088

movement (Lachanski & Pav, 2017). In this study, besides the methodological criticism, there may be issues with the construct since the study created its own emotion of "calmness". When limited to specific investors, sentiment is predictive of stock return (Padungsaksawasdi, 2020). Likewise, investor sentiment has a predictive relationship with bond yield spread (Nayak, 2010).

According to event systems theory, an important event is a discrete happening that is critical, novel, and disruptive (Baker, 2019). Within organizations, an event may be external to the company but will affect change at one or many levels of the internal hierarchy (Morgeson et al., 2015). In the past, a boycott or strike of a company had a tangible component. In most cases, humans stood in front of a brick-and-mortar building, venting their disagreement. There was little doubt that these pickets were critical, novel, and disruptive to the business, thus making them events. With the rise of social media, it is not a given that a digital call for a boycott will meet those criteria. Social media has generated near continuous streams of big data sets that may or may not constitute an event for a business (Luciano et al., 2017).

Currently, there is limited research that explores the relationship between the affective online behaviors of the general public and the financial impact of targeted boycotts. Cancel culture is a new construct with very little empirical research. This research served to explore the relationship between idea propagation in a cancel culture environment and the financial indicators of success using Abercrombie & Fitch as a case study. Using sentiment analysis, affective communication was explored and related to the fiscal bottom line of the target company. The results will give companies a better understanding of reputational responses in light of their organizational values. Also, advocacy groups will benefit in understanding the efficacy of affective communication when calling for company boycotts.

1.1. Hypotheses

H1: The Altman's *z* score of Abercrombie & Fitch will be correlated to the aggregated quarterly sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H1a: The Altman's *z* score of Abercrombie & Fitch will be positively correlated to the positive aggregated quarterly sentiment of user-generated content of the company's Twitter social media over a ten-year period.

H1b: The Altman's *z* score of Abercrombie & Fitch will be negatively correlated to the negative aggregated quarterly sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H2: The gross sales for each fiscal quarter of Abercrombie & Fitch will be correlated to the sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H2a: The gross sales for each fiscal quarter of Abercrombie & Fitch will be positively correlated to the positive sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H2b: The gross sales for each fiscal quarter of Abercrombie & will be negatively correlated to the negative sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H3: The gross sales of Abercrombie & Fitch will be positively correlated to the mean distance between the positive and negative sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H4: The Altman's *z* score of a U.S. publicly traded business will be positively correlated to the mean distance between the positive and negative sentiment of user-generated content of the company's Twitter social media over a 10-year period.

H5: The type of emotion will have an effect on the gross sales and Altman's z score for Abercrombie & Fitch.

2. Literature Review

According to event systems theory, an important event is a discrete happening that is critical, novel, and disruptive (Baker, 2019). Within organizations, an event may be external to the company, but will affect change at one or many levels of the internal hierarchy (Morgeson et al., 2015). In the past, a boycott or strike of a company had a tangible component. In most cases, humans stood in front of a brick-and-mortar building, venting their disagreement. There was little doubt that these pickets were critical, novel, and disruptive to the business, thus making them events. With the rise of social media, it is not a given that a digital call for a boycott will meet those criteria. Social media has generated near-continuous streams of big data sets that may or may not constitute an event for a business (Luciano et al., 2017).

2.1. Cancel Culture

Cancel culture is the attempt to affect change via boycotts against individuals or businesses that have been perceived as offensive (PR Newswire, 2020). In today's society, the primary method for creating a cancel culture boycott is through social media. There is an assumption that behaviors, as they are perceived through a social media lens, need accountability in a cancel culture discourse (Mueller, 2021). The perception of accountability, apology, and morality all become part of idea propagation in a cancel culture environment. There are also political associations to the term cancel culture, with it being linked to politically liberal demographics, though the boycott is used by all parts of the political spectrum (Gleig & Artinger, 2021).

Cancel culture in this context would be online calls for boycotts based on value-oriented disagreements (Mölder & Simm, 2020). During an online call for boycott, the user will need to make an emotional appeal to gain movement in the action. This emotional appeal is called *sentiment*, which is a collective measure of the emotional characteristics of valence and arousal (Prabowo & Thelwall, 2009). Under the cancel culture paradigm, the sentiment of the social media message is designed to minimize the revenue of a company. Here, the definition of a corporation being a person is used (Owie, 2017). Therefore, there is no difference between a cancel culture boycott targeting an individual and one targeting a corporation.

A special form of social control comes under the name cancel culture. To date, there is very little empirical research on this phenomenon, but the limited research in the field shows that cancel culture is real and consistent with the Noelle-Neumann's spiral of silence thesis (Norris, 2021). This theory holds that people holding a minority opinion will be less likely to state that opinion and more likely to conform to the majority. In the case of opinions shared on social media, the greater probability of finding agreement lends itself to polarization instead of conformity (Gaisbauer et al., 2021). The theory dictates that conformity is a function of perceived threat (Dashti et al., 2015). For individuals, this threat may be in the form of shaming or ostracizing. For public personalities and businesses, the threat can come in the form of financial losses.

Cancel culture also has a synopticon aspect which is especially important to businesses as it has an influence on marketing. Synopticon, the concept of many surveilling the few, and panopticon, the concept of many surveilling many, are grounded in the development of the modern prison system, but have become especially important in cancel culture (Mathiesen, 1997). Here, the idea of surveilling a person is any collection of data for the purposes of understanding the intent of the data and effecting a change based on this intent. Within a cancel culture, surveilling allows third-party observers to develop attitudes on antecedent corporate behaviors, even if the behaviors have no direct impact on the observer. Here, social phenomena take hold. In particular, the just-world theory holds that people need to believe that their world is just and that reward and punishment are deserved (De keersmaecker & Roets, 2017). This belief in a just world is a path development mechanism for the creation of attitudes toward both the assumed perpetrator and the victim (Dionysis et al., 2020). Therefore, brand reputation is incumbent on managing cancel culture synopticon attitudes.

2.2. Semantic Communication and Emotion

Linguistically, there is a semantic link between a word and its underlying object. Therefore, the word will have an emotional component that can be assessed on dimensionality, like valence and arousal, or distinct domain, like anger, happiness, fear, disgust, or sadness (Martínez-Huertas et al., 2021). In this context, sentiment is the appraisal of emotional content, as positive, negative, or neutral and the arousal of that content over core emotions.

In 2001, Robert Plutchik proposed a three-dimensional circumplex model of emotions. His model was based on an evolutionary understanding of human emotion and focuses on the premise that emotions are drivers of behavior. He proposed that there are eight primary emotions which are four pairs of opposites. These primary emotions are anger, fear, sadness, disgust, anticipation, joy, trust, and surprise. These primary emotions are often used in the field of semantic analysis (i.e., Ganganwar et al., 2021; Kumar & Manu, 2022; Molina Beltran et al., 2019; Zhang et al., 2018) and figure prominently in the National Research Council of Canada's Emotion Lexicon (NRC Emotion Lexicon) (National Research Council of Canada, 2019).

In the context of social media, the general semantics and sentiment of a Tweet or comment are reliant on the language as well as the order of the words used. Li et al., (2010) explained that sentiment is reliant on the context as well as the orientation of the words. Within the context of this research, the "call to cancel" is an emotional plea as a reaction to the behavior of the company or individual. Ultimately, the call to cancel is an appeal to consumers to decide to condemn and boycott the target or support the target. The "call to cancel" is embedded in a highly valenced sentiment (positive or negative). Then, there is the response from the supporters of the cancel target who respond by providing a positive sentiment of the target, a neutral sentiment (the Tweet will be supportive of the target while condemning the "call to cancel," thus neutralizing the sentiment) or a negative sentiment about the "call to cancel." The choice to respond to this call or not depends on the individual. Research in decision making indicated that positively valenced emotions were better drivers of behaviors (Lerner & Keltner, 2000, 2001) and ethical decision making (Escadas et al., 2020). However, there is evidence that anger and fear can drive decision making and proactive behavior as well (Khan et al., 2021). In a call to cancel, the valence of the sentiment and the underlying emotion would be key in the success of the message. Thus, the inclusion of the basic emotions in this research sought to identify which was most effective at driving the decision-making process and behaviors to affect the company's bottom line.

2.3. Bankruptcy Prediction Model

The principle of *going concern*, which is a company's ability to fulfill its financial obligations and stay in business, can be threatened by bankruptcy, causing negative financial opinions by auditors and investors (International Federation of Accountants, 2016). By defining the danger of bankruptcy as a threat to going concern, bankruptcy can be used as the standard for cancelation. The Altman *z* score is a well-researched predictor of bankruptcy over multiple industry sectors (Gurbanzada, 2021).

The Altman (1968) *z* score is given by Equation 1:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

where

X_1 = net working capital to total assets ratio
= (current assets–current liabilities) /total assets
X_2 = retained earnings to total asset ratio
= retained earnings /total assets
X_3 = EBIT to total assets ratio
= earnings before interest and taxes/total assets
X_4 = market value of equity to book value of total liabilities ratio
= market value of equity/total liabilities
X_5 = asset turnover ratio
=sales/total assets

A *z* score of 2.99 or greater is an indicator of financial solvency and positive going concern, called the "safe zone." A score of less than 1.81 is called the "distress zone" and is a predictor of bankruptcy (Agarwal & Patni, 2019). Using this scale, advocacy proponents may claim successful cancelation of a company if there is a significant shift from a solvency score to an insolvency score. An analysis of the predictive validity of Altman's *z* score over a wide range of companies and sectors gave a 3-year accuracy of 79.4% for companies that ultimately declared bankruptcy (Salimi, 2015).

2.4. Economic Shock

Economic shock is a sudden, unexpected stressor on an economic system (Abaidoo, 2011). The economic system may be as large as a nation's economy or localized to a business's financial environment. The effects of shock show as a network of interactions and can affect and be affected by the micro-structures of the organization. Granger causality is often used to identify shock effect linkages in a time series (Sebestyén & Iloskics, 2020). Therefore, shock has a causal effect, acting as the stimulus to the company's response. In the context of cancel culture, the shock may be a result of public opinion that drives the economic environment of the company.

2.5. Abercrombie & Fitch Co.

Founded in 1892, Abercrombie & Fitch Co. made its IPO in 1996 (Abercrombie & Fitch, n.d.). Its 2021 net income was $109 million (SEC, 2021a). In 2006, the CEO Mike Jeffries made a statement, comparing the "cool kids" to everyone else and indicating that the Abercrombie & Fitch brand only catered to the "cool kids." It was later observed that the brand did not offer plus-sized apparel (O'Keefe, n.d.). In response to this, the retailer made comments that made it clear that "fat kids" will not be part of the popular crowd, which prompted a boycott led by the National Eating Disorder Association (2013). Hashtags included #BoycottAbercrombie as well as #FitchTheHomeless which featured Abercrombie & Fitch clothing that was donated by an activist to the homeless.

3. Method

3.1. Research Design

This correlational analysis was designed to demonstrate the relationship between the sentiment of a call to action and its effects on indicators of fiscal health. Sentiment analysis was used to ascertain attributes of affective beliefs, including emotional valence of the message, emotional category within eight domains, and strength of the sentiment.

3.2. Data Collection Tools

The raw data for the predictor variables were collected from publicly available Twitter accounts that are associated with the online boycott of Abercrombie & Fitch. The data were drawn in batches of a quarter year, starting on January 1, 2010, and continuing until December 31, 2019. The data were downloaded using the RStudio package rtweet (Kearney, 2019). This package is written in the *r*-programming language and will run in the RStudio environment, Version 1.2.5042.

The raw data for the criterion variables were collected from publicly available financial statements. The quarterly financial statements (Form 10-Q) were downloaded from the SEC (2009) financial reporting database. The dataset was downloaded as a zip file that was exported into Microsoft 365 Excel Version 2201. The ratios were calculated using the Excel formula function. Financial ratios were calculated using International Accounting Standards Board (IASB) guidelines without adjustments to leases or capitalization (de Villiers & Middelberg, 2013).

3.3. Data Analysis

3.3.1. Preprocessing

With OpenRefine (Ham, 2013), the following data cleaning processes took place:

- Contractions were changed to the full form set of words,
- Proper nouns were identified for processing,
- Numbers were converted to their written equivalents,
- Misspellings were changed to their properly spelled words,
- Sentences were identified, and
- Punctuation was removed.

The RStudio package *tm* was used to remove stop words and tokenize the data set (Feinerer et al., 2008).

3.3.2. Processing

The Sentiment.ai RStudio package was used for the semantic analysis. Sentiment.ai is unique in that it is a hybrid system, using first the lexicon then a machine learning model to increase accuracy (Wiseman, 2022). For each fiscal quarter of data, sentiment analysis was run using Sentiment.ai. Using IBM SPSS, cluster analysis was performed. Using unidimensional *k*-means clustering, a three-factor cluster was used such that the final quarterly dataset gave one cluster with a positive sentiment, one with a negative sentiment, and one with a neutral sentiment (Sabo, 2014). Each of the emotions were likewise divided into three clusters, therefore a theoretically positively valenced emotion would still have a positive, negative, and neutral sentiment. This process was repeated for each fiscal quarter.

To give compatibility with measurements, the gross sales were adjusted by using the Ln of sales. Both the Ln of sales and the Altman's *z* score were Fourier detrended using IBM SPSS 28, yielding data for the central trend and one for the periodic trend. An ordinary least squares (OLS) regression analysis was used for the main trends and an autoregressive time-series analysis was used for the periodic trends.

4. Results

Using the keyword *Abercrombie*, after cleaning, 2,067,217 user-generated tweets were scraped (n = 2,067,217) with an average word count of 8.53 per tweet (SD = 3.67). A visual inspection of adjusted sales per period (Figure 1) shows that there is a structural break in the linearity of the data, confirmed by the Chow test ($F[2,36] = 6.30$, $p = .005$), at approximately Period 13, which corresponds to the beginning of the boycott campaign. There is no structural break in the Altman's *z* score data.

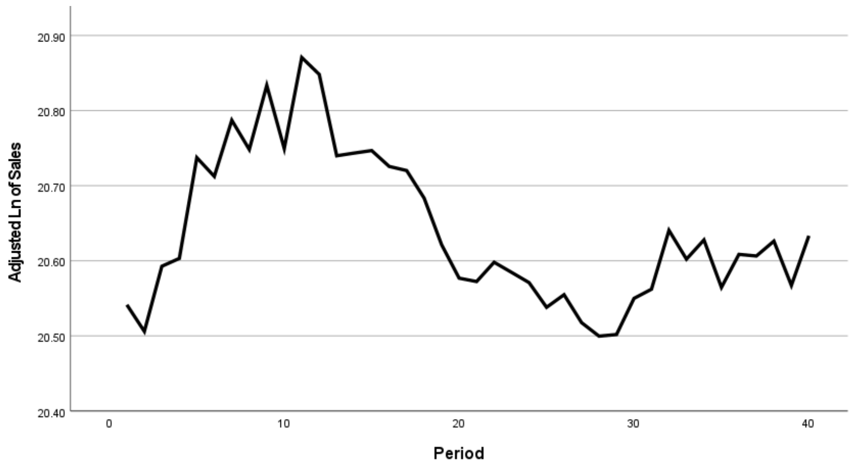

Figure 1. Central Trend of the Ln of Sales by Period

The central trend of the Ln of sales for all the periods and the periods after the structural break showed correlations for the negative sentiments of fear, anger, disgust, sadness, and trust and positive anger, shown in Table 1. Fear, anger, disgust, and sadness have valences that generally align with the perception of the emotion. For example, fear is generally assigned a negative valence. Negative trust would be synonymous with distrust. An example of positive anger would be "abercrombie mad racist laugh loud", in which the emotion is anger but the overall valence is positive in that the behavior of racism is being addressed. The negatively valanced emotions show moderate to large negative correlations with the anger and disgust showing large negative correlations for the periods after the structural break (Cohen, 1988).

Table 1.
Central Trend of Ln of Sales

	All Periods	Periods > 13
Negative Fear	$-.404^{**}$	$-.541^{**}$
Positive Anger	$.477^{**}$	$.511^{**}$
Negative Anger	$-.513^{**}$	$-.640^{**}$
Negative Disgust	$-.479^{**}$	$-.611^{**}$
Negative Sadness	$-.445^{**}$	$-.537^{**}$
Negative Trust	$-.362^{*}$	$-.534^{**}$

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

The Altman's *z* score showed correlations over all the emotions as shown in Table 2. The Altman's *z* score is composed of financial behaviors that may or may not be directly related to the call to cancel. The correlations show small to moderate negative correlations for all but positive anger and positive disgust, which have small positive correlations (Cohen, 1988). The intuition for the positive correlations that the efficacy of the call to cancel may promote a positive valence for anger and disgust.

The polemic distance is an indicator of the magnitude of disagreement, using the Euclidian distance between the positive and negative clusters for each emotion. Table 3 shows the correlations for the polemic distance for each emotion to the central trend of the Ln of Sales and Altman's z score. All six of the core emotions showed positive correlations to sales with anger and disgust having large positive correlations (Cohen, 1988). The Altman's *z* score showed small to moderate positive correlations to the polemic distances for anger, disgust, joy, and surprise. There were no significant correlations to the Altman's *z* score for the polemic distances of fear, anticipation, sadness, or trust.

Table 2.
Central Trend of Altman's z score

Neutral Fear	-.365*
Positive Anger	.330*
Neutral Anger	-.476**
Positive Anticipation	-.370*
Neutral Anticipation	-.512**
Negative Anticipation	-.395*
Positive Disgust	.367*
Neutral Joy	-.330*
Negative Joy	-.428**
Negative Sadness	-.335*
Negative Surprise	-.437**
Neutral Trust	-.450**
Negative Trust	-.354*

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

Table 3.
Correlations of Polemic Distance to Ln of Sales and Altman's z score

	Central Trend for Ln of Sales	Central Trend for Altman z score
Fear	.421**	No Correlation
Anger	.590**	.361*
Anticipation	.446**	No Correlation
Disgust	.652**	.473**
Joy	.394*	.393*
Sadness	.516**	No Correlation
Surprise	.385*	.443**
Trust	.410**	No Correlation

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

The emotions dataset was subjected to principal components analysis (PCA) using SPSS Version 28. The Kaiser-Meyer-Oklin value was .82, exceeding the recommended value of .6 (Kaiser, 1970, 1974) and the Bartlett's Test of Sphericity (Bartlett, 1954) reached statistical significance, supporting the factorability of the correlation matrix. Principal components analysis revealed the presence of two components with eigenvalues exceeding 1, explaining 47.9 percent and 22.3 percent of the variance, respectively. PCA is a dimensional reduction method which statistically reduces large data sets into smaller sets that retain the same characteristics of the large set. Table 4 gives the rotated component matrix which shows that the theoretically negative emotions load on one factor and the positive emotions load on the other. This indicates that the data set only has two relevant factors which are aligned to the valences regardless of the emotion. This indicates that the perceived valence may play a greater role in the call to cancel than the granular emotions.

The quarterly frequencies of the emotions, given as a percentage of total, were compared to the 40-period data set for the sales and Altman's *z* score. Table 5 compares the frequencies of emotionally charged words to Tweets without those emotions, using an independent samples t-test. It shows that all the core emotions have an effect on the sentiment of the Tweet.

Table 4.
Rotated Component Matrix

	Component	
	1	**2**
Fear	0.832	0.141
Anger	0.853	0.204
Sadness	0.811	0.146
Disgust	0.837	0.136
Joy	0.123	0.883
Anticipation	0.165	0.812
Surprise	0.107	0.761
Trust	0.221	0.782

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 3 iterations.

Table 5.
Effects of Emotion on Sentiment

Variable	**t test**			**Effect size**		
	t value	**df**	**p value**	**Cohen's d**	**CI lower**	**CI upper**
Anger	272.18	2,067,463	<.001	0.474	0.470	0.477
Anticipation	-107.54	2,067,463	<.001	-0.173	-0.176	-0.170
Disgust	292.24	2,067,463	<.001	0.546	0.542	0.549
Fear	272.68	2,067,463	<.001	0.515	0.511	0.519
Joy	-195.63	2,067,463	<.001	-0.318	-0.321	-0.315
Sadness	264.64	2,067,463	<.001	0.486	0.482	0.490
Surprise	-77.66	2,067,463	<.001	-0.158	-0.162	-0.154
Trust	-31.45	2,067,463	<.001	-0.047	-0.050	-0.044

Table 6 shows the correlations of the frequencies of emotions in the Tweets to the Ln of sales and Altman's *z* score, showing that the volume of certain affective words may have an effect on the sales and Altman's *z* score. Note that the emotion of disgust again has the strongest correlation.

Table 6.
Pearson Coefficient of Frequency of Emotion to Financials

Variable	**Ln of sales**	**Altman's *z* score**
Frequency of anger	0.39*	-
Frequency of disgust	0.47**	-
Frequency of joy	0.35*	0.38*

Table 7.
Granger-Causality for Valenced Emotions

	Residuals of Ln of Sales	**Residuals of Altman's *z* score**
Neutral Fear		H_0: Altman's z score does not Granger-cause Neutral Fear $F[1,28] = 5.84, p < .01$
Negative Fear	H_0: Negative Fear does not Granger-cause Ln of Sales $F[1,28] = 4.19, p < .01$	H_0: Altman' z scores does not Granger-cause Negative Fear $F[1,28] = 3.35, p = .02$ H_0: Negative Fear does not Granger-cause Altman's z score $F[1,28] = 3.19, p = .03$
Positive Anger		H_0: Altman's z score does not Granger-cause Positive Anger $F[1,28] = 3.74, p = .02$
Negative Anticipation	H_0: Ln of Sales does not Granger-cause Negative Anticipation $F[1,28] = 3.35, p = .02$	H_0: Negative Anticipation does not Granger-cause Altman's z score $F[1,28] = 7.32, p < .01$
Negative Sadness	H_0: Ln of Sales does not Granger-cause Negative Sadness $F[1,28] = 3.50, p = .02$	H_0: Negative Sadness does not Granger-cause Altman's z score $F[1,28] = 2.93, p = .04$
Neutral Surprise		H_0: Altman's z score does not Granger-cause Neutral Surprise $F[1,28] = 3.95, p = .01$
Negative Surprise	H_0: Ln of Sales does not Granger-cause Negative Surprise $F[1,28] = 2.85, p = .04$	
Neutral Trust	H_0: Neutral Trust does not Granger-cause Ln of Sales $F[1,28] = 3.98, p = .01$	

The Phillips-Perron Unit Root test was used to identify unit roots for the residuals (periodicity) or the Ln of sales and Altman's *z* score as well as each of the emotions (Hamilton, 2020). Each of the variables are stationary, making Granger causality appropriate for analysis (Norrulashikin et al., 2016). Table 7 shows the results for variables in which the Granger null hypothesis was rejected. Granger causality is a statistical measure of prediction that states that if Xn "Granger-causes" Xn+1 then all of the values before Xn will give more predictive information for Xn+1 than Xn alone (Norrulashikin et al., 2016). Since this is a multivariant analysis, Granger causality is a measure of the causality of one variable on the system of the other variables. Since Granger causality uses hypothesis testing, the table gives the null hypothesis that is rejected for each of the variable pairs. The rejected hypothesis indicates that there is a time series causality of the first variable on the second.

5. Discussion

There were correlations between Altman's *z* score and the emotions as well as Granger causality between the negatively valenced emotions and Altman's *z* score. Therefore, the null hypothesis for H1 is rejected in favor of the alternative hypothesis as is the negative emotion hypothesis.

For hypothesis H2, the null hypothesis is not rejected as the sales were not correlated consistently to sentiment in companies with a structural break. Instead, it seems that the structural break created economic shock on the company. The structural break seems to correspond to a dip in sentiment at the time of the call to cancel but the sentiment rebounds within a period.

The polemic distances of the emotions showed a correlation to the Ln of sales for the central trend with disgust having the strongest correlation of this analysis. Therefore, the null hypothesis for H3 is rejected in favor of the alternative hypothesis.

The polemic distances for half of the emotions showed a moderate correlation to the Altman's z score and null hypothesis H4 can be rejected and the alternative hypothesis can be accepted.

There seems to be a distinct difference in effects between positive and negative emotions. The factor analysis loads on only two factors, positive emotions and negative emotions. The emotion of disgust showed the highest correlational values throughout the analysis. Therefore, H5 is inconclusive.

The correlations and Granger causality seem to indicate a causal direction with a decrease in sales or Altman's z score causing a change in the negative valenced emotional arousal.

6. Conclusions

This research uses sales and the Altman's *z* score as a measure of effectiveness of a call to cancel. Where a boycott will affect the sales, a call to cancel should negatively affect the Altman's score. The results showed that the affective component of a boycott, measured as sentiments within core emotional categories, did correspond to a change in sales in an effective boycott and had an effect on the Altman's *z* score. As a whole, the past values of the sentiment, sales, and Altman's *z* score had an effect on the current values, lagging between two and six periods.

The positive emotions had a smaller effect size than the negative emotions and, by extension, a smaller effect on the Altman's *z* score. The frequencies of emotion words were analyzed with the frequency of disgust words having a medium-to-strong positive correlation with Ln of sales. As this is a polemic dialogue, the target of disgust may not be the company. Since the frequency of disgust words is positively correlated to sales, the target of disgust may be the holders of the opposing view.

Corporate decision-making is largely affect-infused (Zolotoy et al., 2020). Senior management will often attempt to make decisions based on rational analysis, but in the absence of good data, the process will take on more and more emotional content. A call to cancel can shift the sentiment, creating a fiscal shock to the company. As evidenced by the IRF analysis, shock on the system creates an increase in error which decreases the validity of the predictive analysis. This, in turn, makes corporate decisions, and their associated behaviors, riskier and more infused with more emotional content.

The type and frequency of emotion words seem to be a strong driver of the sentiment with disgust words holding the greatest impact on the system. From an evolutionary perspective, disgust is a driver of avoidance behaviors (Rottman, 2014). It kept primitive humans from absorbing dangerous pathogens. Under the theory of meta-emotions, disgust would be a primary emotion, with the other negative emotions taking a secondary position (Bartsch et al., 2008). Yet it seems that it is the valence of the emotion that is being measured in this research. Instead of a distinct emotion, disgust may be a measure of the intensity of arousal associated with the perceived violation of values and the secondary emotions are simply arousals with lower intensity. Rather, the intensity of the communication was shown to be a better predictor of Abercrombie & Fitch's bottom line.

In separating the modality of past boycott behavior from the new paradigm of cancel culture and calls to cancel, this research shows that there is a new opportunity to create fiscal shock in a company using social media. The value-based propagation of ideas between the company and its consumers may serve as a framework for mitigating this shock. It seems that the core values of the company may influence the level of shock that a company needs to manage. Therefore, this research links to concepts of value alignment and agility. If properly aligned, the organization can "lean in" to the values, creating a solid brand message, and solidifying consumer loyalty. Cancel culture can then be defined as a value-driven environment that is characterized by the strength of the polemic.

7. Limitations and Recommendations for Future Research

Fiscal data are only given in quarterly periods on SEC reports. This forced the use of aggregate sentiments for parity. By using a mean sentiment, the results lost some granularity. Likewise, vector autoregressive analysis has some mathematical limitations in balancing the number of lags and the number of variables with the size of the data set. Using 40 periods limited the number of lags to a maximum of six and the number of variables in a model to a maximum of four. If a daily financial indicator was used, this big dataset would allow more variables and significantly more lags to be used.

It is possible that a syntactic analysis will show new variables to be included in a regression model. The current analysis only focused on the sentiment of the tweets and not on the syntax of the tweets. The word usage and grammatical structure may have an effect on the sentiment and the rate of idea propagation. This research only identified the call to cancel as a structural break in the sales and did not address the company's response to the call. A sentiment and a syntactic analysis of the company's response may offer insight into the path of idea propagation and the effect on financial indicators.

References

Abaidoo, R. (2011). U.S. job creation growth rate and sub-sector vulnerability to economic shock. *The Journal of Applied Business and Economics, 12*(5), 66–79. http://m.www.na-businesspress.com/JABE/AbaidooR_Web12_5_.pdf

Abercrombie & Fitch. (n.d.). *Company history*. Retrieved January 31, 2022, from https://corporate.abercrombie.com/our-company/about-us/company-history

Agarwal, A., & Patni, I. (2019). Applicability of Altman *z*-score in bankruptcy prediction of BSE PSUs. *Journal of Commerce and Accounting Research, 8*(2), 93–103. http://publishingindia.com/jcar/

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589–609. https://doi.org/10.2307/2978933

Baker, J. E. (2019). Et tu, Brute? Surprising actions and their market reaction. *American Journal of Management, 19*(4), 10–26. https://doi.org/10.33423/ajm.v19i4.2384

Bartlett, M. S. (1954). A note on the multiplying factors for various chi square approximations. *Journal of the Royal Statistical Society, 16* (Series B), 296–298. https://doi.org/10.1111/j.2517-6161.1954.tb00174.x

Bartsch, A., Vorderer, P., Mangold, R., & Viehoff, R. (2008). Appraisal of emotions in media use: Toward a process model of meta-emotion and emotion regulation. *Media Psychology*, *11*(1), 7–27. https://doi.org/10.1080/15213260701813447

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Dashti, A. A., Al-Abdullah, H., & Johar, H. A. (2015). Social media and the spiral of silence: The case of Kuwaiti female students' political discourse on Twitter. *Journal of International Women's Studies, 16*(3), 42–53. https://vc.bridgew.edu/jiws/vol16/iss3/4/

De keersmaecker, J., & Roets, A. (2017). All victims are equally innocent, but some are more innocent than others: The role of group membership on victim blaming. *Current Psychology*, *39*(1), 254–262. https://doi.org/10.1007/s12144-017-9763-9

de Villiers, R. R., & Middelberg, S. L. (2013). Determining the impact of capitalising long-term operating leases on the financial ratios of the top 40 JSE-listed companies. *The International Business & Economics Research Journal (Online), 12*(6), 655. http://dx.doi.org/10.19030/iber.v12i6.7871

Dionysis, S., Leonidou, C. N., Charalampos, S., & Giuseppe, M. (2020). Pathways to civic engagement with big social issues: An integrated approach. *Journal of Business Ethics, 164*(2), 261–285. https://doi.org/10.1007/s10551-019-04276-8

Escadas, M., Jalali, M. S., & Farhangmehr, M. (2020). What goes around comes around: The integrated role of emotions on consumer ethical decision-making. *Journal of Consumer Behaviour*, *19*(5), 409-422. https://doi.org/10.1002/cb.1847

Feinerer, I., Hornik, K., & Meyer, D. (2008). Text mining infrastructure in *R*. *Journal of Statistical Software, 25*(5), 1–54. https://doi.org/10.18637/jss.v025.i05

Gaisbauer, F., Pournaki, A., Banisch, S., & Olbrich, E. (2021). Ideological differences in engagement in public debate on Twitter. *PLoS One, 16*(3). https://doi.org/10.1371/journal.pone.0249241

Ganganwar, V., Babu, N., Kudale, P., Singh, R., & Tanwar, S. (2021). Sentiment analysis of legal emails using Plutchik's Wheel of Emotions in quantified format. *Turkish Journal of Computer and Mathematics Education, 12*(6), 4979-4987.

Gleig, A., & Artinger, B. G. (2021). The #BuddhistCultureWars: BuddhaBros, alt-right dharma, and snowflake sanghas. *Journal of Global Buddhism, 22*(1), 19–48. https://doi.org/10.5281/zenodo.4727561

Gurbanzada, E. (2021). *Financial performance evaluation and bankruptcy prediction*. Varazdin Development and Entrepreneurship Agency (VADEA).

Ham, K. (2013). OpenRefine (Version 2.5). *Journal of the Medical Library Association, 101*(3), 233–234. https://doi.org/10.3163/1536-5050.101.3.020

Hamilton, J. D. (2020). *Time series analysis*. Princeton University Press. https://doi.org/10.2307/j.ctv14jx6sm

Kaiser, H. (1970). A second generation Little Jiffy. *Psychometrika*, 35, 401–415. https://doi.org/10.1007/BF02291817

Kaiser, H. (1974). An index of factorial simplicity. *Psychometrika*, 39, 31–36. https://doi.org/10.1007/BF02291575

Kearney, M. W. (2019). rtweet: Collecting and analyzing Twitter data. *Journal of Open Source Software, 4*(42), 1829. https://doi.org/10.21105/joss.01829

Khan, A., Khail, S. J., & Shah, F. A. (2021). The mediating analysis of complex pathway between discrete negative emotions, proactive behavior and constructive decision making. *Review of Applied Management and Social Sciences*, *4*(4), 795-809. https://doi.org/10.47067/ramss.v4i4.184

Kumar, P., & Manu, V. (2022). PWEBSA: Twitter sentiment analysis by combining Plutchik wheel of emotion and word embedding. *B V I C A M's International Journal of Information Technology, 14*(1), 69-77. https://doi.org/10.1007/s41870-021-00767-y

Lachanski, M., & Pav, S. (2017). Shy of the character limit: "Twitter mood predicts the stock market" Revisited. *Econ Journal Watch, 14*(3), 302-345.

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. Cognition & Emotion, 14(4), 473–493. https://doi.org/10.1080/026999300402763

Lerner, J. S., & Keltner, D. (2001). Fear, anger and risk. Journal of Personality and Social Psychology, 81(1), 146–159. https://doi.org/10.1037/0022-3514.81.1.146

Li, F., Huang, M., & Zhu, X. (2010). Sentiment analysis with global topics and local dependency. *Proceedings of the AAAI Conference on Artificial Intelligence*, *24*(1), 1371-1376. https://doi.org/10.1609/aaai.v24i1.7523

Luciano, M. M., Mathieu, J. E., Park, S., & Tannenbaum, S. I. (2017). A fitting approach to construct and measurement alignment. *Organizational Research Methods*, *21*(3), 592–632. https://doi.org/10.1177/1094428117728372

Martínez-Huertas, J. Á., Jorge-Botana, G., Luzón, J., M., & Olmos, R. (2021). Redundancy, isomorphism, and propagative mechanisms between emotional and amodal representations of words: A computational study. *Memory & Cognition, 49*(2), 219–234. https://doi.org/10.3758/s13421-020-01086-6

Mathiesen, T. (1997). The viewer society: Michel Foucault's "Panopticon" revisited. *Theoretical Criminology, 1*(2), 215–234. https://doi.org/10.1177/1362480697001002003

Mölder, B., & Simm, K. (2020). Disagreements: An introduction. *Trames: A Journal of the Humanities and Social Sciences, 24*(3), 271–277. https://doi.org/10.3176/tr.2020.3.01

Molina Beltrán, C., Segura Navarrete, A. A., Vidal-Castro, C., Rubio-Manzano, C., & Martínez-Araneda, C. (2019). Improving the affective analysis in texts: Automatic method to detect affective intensity in lexicons based on Plutchik's wheel of emotions. *The Electronic Library, 37*(6), 984-1006. https://doi.org/10.1108/EL-11-2018-0219

Morgeson, F. P., Mitchell, T. R., & Liu, D. (2015). Event system theory: An event-oriented approach to the organizational sciences. *Academy of Management Review*, *40*(4), 515–537. https://doi.org/10.5465/amr.2012.0099

Mueller, T. S. (2021). Blame, then shame? Psychological predictors in cancel culture behavior. *The Social Science Journal*, 1–14. https://doi.org/10.1080/03623319.2021.1949552

National Eating Disorder Association. (2013). *Update: Monday, May 20th Abercrombie and Fitch protest cancelled.* https://www.nationaleatingdisorders.org/blog/update-monday-may-20th-abercrombie-and-fitch-protest-cancelled

National Research Council Canada. (2019, June 3). *Sentiment and emotion lexicons*. https://nrc.canada.ca/en/research-development/products-services/technical-advisory-services/sentiment-emotion-lexicons

Nayak, S. (2010). Investor sentiment and corporate bond yield spreads. *Review of Behavioural Finance*, *2*(2), 59-80. https://doi.org/10.1108/19405979201000004

Norris, P. (2021). Cancel culture: Myth or reality? *Political Studies*. https://doi.org/10.1177/00323217211037023

Norrulashikin, S. M., Yusof, F., & Kane, I. L. (2016). Instantaneous causality approach to meteorological variables bond. *AIP Conference Proceedings*. https://doi.org/10.1063/1.4954615

O'Keefe, B. (n.d.). *Abercrombie & Fitch CEO Mike Jeffries: Stop telling teens they aren't beautiful; make clothes for teens of all sizes!* Change.org Retrieved February 1, 2022, from https://www.change.org/p/abercrombie-fitch-ceo-mike-jeffries-stop-telling-teens-they-aren-t-beautiful-make-clothes-for-teens-of-all-sizes

Owie, E. (2017). The imperative of the corporation and socially conscious leadership. *Journal of Social Change, 9*(1). https://doi.org/10.5590/JOSC.2017.09.1.14

Padungsaksawasdi, C. (2020). On the dynamic relationship between gold investor sentiment index and stock market: A sectoral analysis. *International Journal of Managerial Finance, 16*(3), 372-392. https://doi.org/10.1108/IJMF-11-2018-0334

Plutchik, R. (2001). The nature of emotions. *American Scientist, 89*, 344-350. https://doi.org/10.1511/2001.28.344

PR Newswire. (2020, July 25). *Red Banyan CEO tackles the questions: What is cancel culture? How to handle cancel culture? How to find a cancel culture PR firm?* https://www.prweb.com/releases/red_banyan_ceo_tackles_the_questions_what_is_cancel_culture_how_to_handle_cancel_culture_how_to_find_a_cancel_culture_pr_firm/prweb17283759.htm

Prabowo, R., & Thelwall, M. (2009). Sentiment analysis: A combined approach. *Journal of Informetrics*, *3*(2), 143–157. https://doi.org/10.1016/j.joi.2009.01.003

Rottman, J. (2014). Evolution, development, and the emergence of disgust. *Evolutionary Psychology*, *12*(2). https://doi.org/10.1177/147470491401200209

Sabo, K. (2014). Center-based l1-clustering method. *International Journal of Applied Mathematics and Computer Science, 24*(1), 151–163. http://dx.doi.org/10.2478/amcs-2014-0012

Salimi, A. Y. (2015). Validity of Altman's *z*-score model in predicting bankruptcy in recent years. *Academy of Accounting and Financial Studies Journal, 19*(2), 233–238.

Sebestyén, T., & Iloskics, Z. (2020). Do economic shocks spread randomly? A topological study of the global contagion network. *PLoS One, 15*(9). https://doi.org/10.1371/journal.pone.0238626

U.S. Securities and Exchange Commission. (2009, January 1). *Financial statement data sets*. https://www.sec.gov/dera/data/financial-statement-data-sets.html

U.S. Securities and Exchange Commission. (2021a). *Abercrombie & Fitch Co.: Form 10-K. Item 8: Financial statements and supplementary data*. https://www.sec.gov/ix?doc=/Archives/edgar/data/1018840/000101884021000023/anf-20210130.htm#ieaab4df327cd4aef9e559d322e30f114_70

Wiseman, B. (2022, March 19). *CRAN: Package sentiment.ai*. The Comprehensive R Archive Network. https://cran.r-project.org/package=sentiment.ai

Zhang, L., Dong, W., & Mu, X. (2018). Analysing the features of negative sentiment tweets. *The Electronic Library, 37*(5), 782-799. https://0634sbb10-mp01-y-https-doi-org.prx-keiser.lirn.net/10.1108/EL-05-2017-0120

Zolotoy, L., O'Sullivan, D., Seo, M., & Veeraraghavan, M. (2020). Mood and ethical decision making: Positive affect and corporate philanthropy. *Journal of Business Ethics*, *171*(1), 189–208. https://doi.org/10.1007/s10551-020-04432-5

Zummo, M. L. (2017). A linguistic analysis of the online debate on vaccines and use of Fora as information stations and confirmation Niche. *International Journal of Society, Culture & Language, 5*(1), 44–57.