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Examining the Existence of Double Jeopardy and Negative Double Jeopardy within Twitter

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Purpose
The theory of Double Jeopardy (DJ) is shown to hold across broad ranging geographies and physical product categories. However, there is very little research appertaining to the subject within an online environment. In particular, studies that investigate the presence of DJ and the contrasting view point to DJ, namely that of Negative Double Jeopardy (NDJ), are lacking. This study contributes to this identified research gap, and examines the presence of DJ and NDJ within a product category, utilising data from Twitter.

Design/methodology/approach
354,676 tweets are scraped from Twitter and their sentiment analysed and allocated into positive, negative and no-opinion clusters using fuzzy c-means clustering. The sentiment is then compared to the market share of brands within the beer product category to establish whether a DJ or NDJ effect is present.

Findings
The data reveals an NDJ effect with regards to original tweets (i.e. tweets which have not been retweeted). That is, when analysing tweets relating to brands within a defined beer category, we find that larger brands suffer by having an increased negativity amongst the larger proportion of tweets associated with them.

Research limitations/implications
The clustering approach to analyse sentiment in Twitter data brings a new direction to analysis of such sentiment. Future consideration of different numbers of clusters may further the insights this form of analysis can bring to the DJ/NDJ phenomenon. Managerial implications discuss the uncovered practitioner's paradox of NDJ and strategies for dealing with DJ and NDJ effects.

Originality/value
This study is the first to explore the presence of DJ and NDJ through the utilisation of sentiment analysis derived data and fuzzy clustering. DJ and NDJ are under-explored constructs in the online environment. Typically, past research examines DJ and NDJ in separate and detached fashions. Thus, the study is of theoretical value because it outlines boundaries to the DJ and NDJ conditions. Second, this research is the first study to analyse the sentiment of consumer-authored tweets to explore DJ and NDJ effects. This study also highlights the need to separate original tweets from retweets because our data shows that jeopardy dynamics differ in these different domains. Finally, the current study offers valuable insight into the DJ and NDJ effects for practicing marketing managers.

Keywords: *Clustering; Double jeopardy; Fuzzy c-means; Online environment; Negative double jeopardy; Ranking; Sentiment analysis; Twitter*

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Introduction

Online microblogging sites have transformed the way in which consumers discuss multiple facets of their lives, including brands and products. Understandably, this transformation has been the subject of interest across many areas of research in marketing (see Kaplan and Haenlein, 2010). The purpose of this study is to contribute to the theoretical and practical understanding of Double Jeopardy (DJ) and Negative Double Jeopardy (NDJ) within an online microblogging environment.

The well-established theory of DJ states smaller market share brands suffer twice, less buyers and less loyalty amongst the smaller set of buyers. That is, smaller brands endure fewer customers, lower levels of market penetration and lower rates of brand loyalty, than do larger brands. The presence of DJ has been shown across multiple offline product categories (e.g. Ehrenberg et al., 1990; Colombo and Morrison, 1989; Wright and Sharp, 2001; Ehrenberg and Goodhardt, 2002), and is largely accepted within the marketing discipline as a "law-like" phenomenon (Ehrenberg et al., 1990, p. 90). However, research into the dynamics of online DJ is limited and such studies predominantly focus on NDJ (Kucuk, 2008; Kucuk 2010). NDJ theory states that, in opposite terms to DJ, larger brands suffer more than do smaller brands online, because they attract more attention than do smaller brands and a higher proportion of this attention is negative compared with that experienced by smaller brands (Kucuk, 2008). Research on the NDJ effect is of increasing importance given the continuing development of the Web2.0 and associated social media platforms, where anyone with internet access can continuously co-create contents relating to the brands of an organisation (Kaplan and Haenlein, 2010).

Consumers demonstrate their embracement of the ability to co-create in an ever-increasing number of blogs and tweets. Consumers post messages online to share their consumption experiences (good and bad), the content of which is outside of brand managers' control (Christodoulides, 2009). A popular online platform for capturing consumer viewpoints is Twitter. Through Twitter, users can post opinions of up to 140 characters in length, known as "tweets" (Fox et al., 2009; Jansen et al., 2009). Twitter's popularity and membership has soared, seeing the number of active monthly members growing from 30 million in Q1 2010 to 317 million in Q3 2016 (Statista, 2016), with users posting on average

500M tweets per day (Twitter, 2015). A large proportion of Twitter users (82%) are active on mobile devices (Twitter, 2015), hence tweets are more likely to be spontaneous and are able to capture positive and negative opinions in the moment. Given the character limit, tweets benefit from carrying a focussed message (Zhu et al., 2011).

This study utilises Twitter to assess whether the DJ/NDJ effect is present online. Sentiment analysis of tweets is undertaken, relating to brands within the beer product category. The tweets' sentiments are partitioned into "positive", "negative" and "no-opinion" clusters using fuzzy c-means clustering (Bezdek, 1980; 1981). Using the established clusters, the number of tweets and market share of the studied brands of beer are analysed to assess whether a statistically significant relationship informing DJ/NDJ effect(s) are present. The analysis is conducted, first, for all captured tweets, and second, the mutually exclusive and collectively exhaustive sub-groups of original tweets and retweeted tweets are analysed.

This study contributes to marketing knowledge from a theoretical, methodological and practical standpoint. Theoretically, the study contributes by testing the theory underpinning the DJ/NDJ effect within an online environment. Only one study currently considers DJ online (Donthu and Hershberger 2001), and studies which consider NDJ are currently restricted to assessing the number of hate-sites which are associated with larger brands (Kucuk, 2008; Krishnamurthy and Kucuk, 2009; Kucuk, 2010). It is of note, these studies research only whether, either DJ is present *or* separately whether NDJ is present (i.e. a one-directional approach). This study develops beyond self-imposed DJ and NDJ silos and provides a more holistic analysis of the DJ/NDJ effect by *simultaneously* testing the presence of DJ or NDJ (i.e. a bi-directional approach). This study is also the first of its kind to research whether a DJ/NDJ effect is present within the Twitter environment.

Methodologically, this study is the first of its kind to utilise consumer authored blog sentiment analysis to investigate the DJ/NDJ effect. Further, this study utilises fuzzy c-means clustering to establish clusters of tweets based on their sentiment, this form of analysis acknowledges the ambiguity potentially present in the sentiment of tweets (see McDermott et al., 2013). Additionally, the application of forced-rank parallel coordinates plots to a marketing dataset is a unique addition to this field of study, elucidating the similarity/variation in rank order of beer brands in terms of market share and number/sentiment of tweets.

From a practitioner's perspective, the study findings contribute to knowledge by demonstrating the presence of the NDJ effect within an online environment. The results also show that, in light of the uncovered DJ and NDJ effects, marketing managers cannot treat

brands of differing market shares the same. Finally, suggestions are made as to how a practitioner may utilise DJ and NDJ theory to better manage their brands in the online environment.

Literature Review

Double Jeopardy (DJ)

The DJ effect, within a marketing context, was first identified by William McPhee in 1963, when he observed that comic strips read by fewer people were also liked less by those fewer people (McPhee, 1963). Having identified the same pattern amongst radio presenters, he noted that smaller share brands suffered in two ways, less people buying them and less loyalty amongst that smaller number of buyers.

Subsequent research has shown the presence of this DJ effect across many geographies and categories, including media ratings, newspapers, automobiles, oil companies and various consumer packaged goods (see for example, Ehrenberg et al., 1990; Colombo and Morrison, 1989; Wright and Sharp, 2001; Ehrenberg and Goodhardt, 2002). The generalised theory of DJ asserts that small share brands are disadvantaged versus larger share brands as they have fewer buyers and are also purchased less by the smaller set of buyers. That is, smaller brands are punished twice for being small because they not only have fewer buyers in comparison to big brands, but their customers are less loyal and make fewer purchases of the brand in comparison to larger brands (Ehrenberg and Goodhardt, 2002). The DJ effect is regarded as a "lawlike" generalisation, which is a rarity within the marketing discipline (Ehrenberg et al., 1990, p. 90; Fader and Schmittlein, 1993). Specifically, the DJ effect is a statistical phenomenon, the mechanisms of which are explained by Dirichlet theorem (Goodhardt et al., 1984). The DJ effect highlights the importance of market penetration. Namely that repeat patronage and customer loyalty should be fostered to increase market penetration

The DJ effect has also been noted in attitudinal responses, where larger share brands attract more positivity in attitude based scores compared to smaller share brands. This effect is prevalent whenever brands are deemed to be competitors which differ in market share size (Ehrenberg et al., 1990; Chaudhuri, 1995). So strong is the notion of the DJ effect that Ehrenberg and Goodhardt (2002, p. 2) state that "*marketing people not knowing about this natural constraint on customer loyalty is like rocket scientists not knowing that the earth is round*".

Despite the importance of the DJ effect, the literature predominantly explores offline behaviour. Research within an online environment is limited to the study by Donthu and Hershberger (2001), who found that larger search engines and larger music websites were more likely to be re-used than smaller ones (i.e. smaller sites were suffering by having fewer users and less loyalty amongst them, which is the DJ effect).

Negative Double Jeopardy (NDJ)

The internet is proving an important vehicle in the development and evolution of DJ theory, namely the existence of Negative Double Jeopardy (NDJ) (Kucuk, 2008). That is, in the era of active, empowered and often largely anonymised customer participation on the internet, large brands endure a disadvantage over smaller brands because larger brands are shown to suffer more negative attention online than do smaller, less visible brands (Hsiao and Tsai, 2014). Kucuk (2008, p. 209) describes the NDJ effect as "*the most valuable brands attract more anti-brand sites while less valuable brands do not have such hate attraction on the Internet*". The global reach of such anti-brand (or hate-sites) is harmful to brand reputation (Kucuk, 2008; Krishnamurthy and Kucuk, 2009). Thus, in online environments, large firms with well-known brands may experience the DJ effect but in the reverse direction. This NDJ effect implies that compared to smaller brands, larger brands suffer by attracting more online attention and more negative attitudes from this increased attention. Thus, definitionally, DJ and NDJ differ in orientation. In contrast to traditional offline environments, the internet and associated social media platforms empowers consumers with a non-hierarchical platform, wherein they can achieve speech equality with many individuals and entities (Kucuk, 2008). To date, research that examines NDJ are restricted to the online environment and the study of hate-sites (Kucuk, 2008; Krishnamurthy and Kucuk, 2009; Kucuk, 2010).

In methodological terms, Kucuk (2008) determines the NDJ effect online through counting the unique number of hate-sites associated with larger brands and concludes that larger brands have a higher prevalence of hate-sites than do smaller brands (hence NDJ). Building on this work, and accounting for the rise of blog posts, Kucuk (2010) also includes data derived from blogs. However, given the nature of the study, only blogs of an anti-brand nature are included. This approach infers that any positive DJ effect which may arise from the brands' presence online is not accounted for. Hsiao and Tsai (2014) also investigate NDJ and focus on the context of co-branding, utilising questionnaire data on fictitious products from hate-sites. However, while this study adds insight, the authors seek only to establish if a NDJ effect is present or not, rather than if a DJ *or* NDJ effect is present. In order to assess

whether there is *either* a DJ *or* NDJ effect present within the same dataset, a suitable variable would need to be established which could lend itself to be positive or negative in orientation. A method to capture this positive or negative sentiment is discussed next.

Sentiment of Opinions

Sentiment analysis is of value to practitioners and researchers because it seeks to flesh out the opinion that underpins a piece of text and in doing so highlights the polarity of expressed experiences and views (Pang and Lee, 2004). Indeed, the analysis of Twitter feed sentiment has been shown to represent a fast and effective means by which to determine public opinion and feedback on numerous marketing activities (Mehta et al., 2012). Further, public opinion and perceptions of brands are demonstrated to impact brand performance (e.g. Aurier and Séré de Lanauze, 2012). Thus, sentiment analysis enables the researcher to gauge the positive or negative judgements that consumers express towards a topic of interest (e.g. Bollen et al., 2011; Tumasjan et al., 2010; Zhang et al., 2011). This technique is especially pertinent to the current study which seeks to determine whether there is a positive (i.e. DJ) effect or negative (i.e. NDJ) effect prevalent within the data set. Accordingly, our study goes beyond the hate site NDJ work undertaken by Kucuk (2008; 2010), in which only a one directional viewpoint was investigated.

Focusing on studies which employ sentiment analysis, Tumasjan et al. (2010) apply sentiment analysis of circa 100,000 tweets to classify the evaluated sentiment into positive or negative opinion concerning political parties leading up to the 2009 German election. The authors use Twitter as the data source given the focused messages derived from the character limitation. Bollen et al. (2011) and Zhang et al. (2011) also utilise sentiment analysis to classify tweets into positive and negative opinion and use this approach to predict the US stock market movement. Alternatively, Asur and Huberman (2010) predict movie box office receipts using the number of tweets and the sentiment within them. These studies make use of text analysis software to extract both positive and negative sentiment. Yet, each of these studies is based on the assumption that every text has a positive or negative opinion. By contrast, Pearanalytics (2009) suggest 40% of Twitter posts are just "pointless babble", and hence highlight that forcing only a negative or positive partitioning can be misleading.

The Twitter "Retweet" concept as an extension to sentiment

A unique mechanism of Twitter is a "retweet". That is, if a user receives a tweet which they find of particular interest they may share it by forwarding it to their own network of followers

(Zhu et al., 2011). The retweet is the "*the key mechanism for information diffusion in Twitter*" (Suh et al. 2010, p. 178). Retweeting is an important phenomenon because it directly engages a message with a new audience, encouraging individuals into the conversation. It is also seen as a means of validation of the original tweet (Boyd et al., 2010). Causes of a retweet may be to comment on the original tweet or to publically agree with the original tweet's contents (Suh et al., 2010). The implication is the contents of the original tweet, which was intended for the original author's network, is now spread further to the recipient's network and hence it is seen to contain important information, given its message has deliberately been communicated to a wider user network (Suh et al., 2010). Suh et al. (2010) also suggest that the nature of a retweet may differ from that of an original tweet in terms of its content such as the inclusion of hashtags and URLs. Factors which trigger a retweet are diverse, ranging from the content of the tweet, the author's online profile, source of the original tweet, time of posting and number of friends in the network (see Zhunchen et al. (2013) for a more detailed discussion).

Zhu et al. (2011) found that determining the characteristics of a retweet during a natural disaster helped the authorities to maximise information diffusion to try and reach those affected. From a marketing perspective, Nagarajan et al. (2010) argue that the notion of a retweet is very important for diffusion of content through viral marketing, while Zhunchen et al. (2013) state the understanding of who will share posts through retweets is of much interest to media organisations. Indeed, the retweet became so popular, that in 2009, a one-click feature was added into Twitter to facilitate ease of retweeting (Suh et al., 2010).

Research Question Development

Investigating DJ theory within marketing has been predominantly restricted to the offline environment. The concomitant online environment demonstrates the limits of traditional DJ thought and has contributed theoretical development through the NDJ extension (Kucuk, 2008; 2010). This work has provided an interesting twist on the original theory, given the ever increasing power of the consumer since the development of the internet, specifically Web2.0 (Kaplan and Haenlein, 2010). However, existing studies (Kucuk, 2008; Krishnamurthy and Kucuk, 2009; Kucuk, 2010), focus only on the negative aspects this increased power may bring and do not consider any positivity which may be brought to brands.

Sentiment analysis helps to establish this underlying opinion, since consumer posts can be regarded as positive, negative or neutral in opinion (no-opinion). However, to date,

sentiment based work has not been employed to investigate DJ/NDJ effects online. Consequently, this study makes pertinent inroads to close this identified gap in the literature and in doing so, assess whether the DJ/NDJ effect is present online through the investigation of consumer authored Twitter posts. Therefore, this study forwards the below research objectives to test the DJ/NDJ effect presence in an online platform.

To summarise, the theory of DJ has two parts, it states that larger brands have more users and more positivity amongst them (e.g. Ehrenberg et al., 1990). Alternatively, NDJ argues that larger brands have more users and more negativity amongst them (e.g. Kucuk, 2008). Both DJ and NDJ effects therefore insist that larger brands attract more attention. Where they differ is in the nature of this attention. The considered first research question (RQ1) addresses the first aspect of DJ/NDJ in that larger brands online attract more attention than smaller brands, defined as the following:

RQ1: Do larger brands attract a larger number of posts within Twitter compared to smaller brands?

If RQ1 is demonstrated then the study can continue to establish the second part of the DJ/NDJ effect. From a DJ effect perspective, this suggests that smaller brands attract less loyalty (e.g. Donthu and Hershberger, 2001). Also based on the offline DJ effect literature, it is expected that smaller brands will have a less positive image compared with larger brands (Ehrenberg et al., 1990; Chaudhuri, 1995). Within this question, specific consideration is given to exploring the differences which may emerge from a DJ/NDJ effect perspective of Twitter posts which have not been retweeted (hereafter referred to as "original tweets") and also those which have been retweeted (hereafter referred to as "retweets"). This separation in tweet source has occurred due to the underlying differences of the two types of tweets as discussed above, i.e. the contents of the tweet communicated more widely (Suh et al., 2010; Zhu et al., 2011), differences in diffusion of content (Nagarajan et al., 2010), and the increased interest shown by media agencies (Zhunchen et al., 2013). The current study seeks to establish whether different conclusions are reached if all tweets are considered in one analysis (i.e. no distinction given to original tweets and retweets) compared to whether the original tweets and retweets are investigated separately.

Should a difference in findings between the two groups be uncovered, interesting conclusions are raised for the marketing practitioner from a theoretical and practical perspective (e.g. Nagarajan et al., 2010; Zhunchen et al., 2013). Consequently, three further sets of research questions are forwarded. The first set considers the tweets with no distinction

between original tweets and retweets (see RQ2a and RQ2b). The second set will explore only the original set of tweets (see RQ3a and RQ3b) and the third set only the retweets (see RQ4a and RQ4b). If different conclusions are drawn from analysing RQ2 vs both RQ3 and RQ4, then this would offer supportive empirical evidence of the importance of segmenting tweets into original tweets and retweets as suggested by the literature (Suh et al., 2010; Wright, 2009; Zhu et al., 2011; Nagarajan et al., 2010; Zhunchen et al., 2013).

Thus, the following research questions are constructed, first relating to all tweets (RQ2a/RQ2b):

RQ2a: Do smaller brands attract less positivity online from the relatively fewer number of posts compared to larger brands?

If RQ1 and RQ2a are demonstrated, this would establish the existence of DJ, i.e. smaller brands are suffering online by attracting a fewer number of tweets (RQ1) and less positivity sentiment from this reduced set of tweets (RQ2a). Conversely, if NDJ is prevalent, extant research in an online context suggests that larger brands attract more negativity online than do smaller brands. This is evidenced in the literature through the increasing number of documented hate-sites (e.g. Kucuk, 2008; 2010). Hence, the following research question (RQ2b) is forwarded:

RQ2b: Do larger brands attract more negatively online from the relatively larger number of tweets compared to smaller brands (NDJ)?

If RQ1 and RQ2b are demonstrated, larger brands are attracting more attention online and more negativity from this increased amount of attention. The two research questions, RQ2a and RQ2b, are subdivided, since only one condition will exist because the two research questions depict opposite, mutually exclusive, conditions. Therefore, RQ2a and RQ2b notation are adopted rather than RQ2 and RQ3 as they are not logically independent statements.

According research questions are also constructed to investigate the above discussed original and retweets as separate categories. This will facilitate the exploration of any differences in the DJ/NDJ effect. First the original tweets (RQ3a/RQ3b).

RQ3a: Do smaller brands attract less positivity online from the relatively fewer number of original tweets compared to larger brands?

Under the same logic as applied to the set of total tweets, if RQ1 and RQ3a are demonstrated, this would establish the existence of DJ, i.e. smaller brands are suffering online by attracting a fewer number of original tweets (RQ1) and less positivity sentiment amongst them (RQ3a).

The NDJ argument is presented through RQ3b (in the same manner as RQ2b for total tweets)

RQ3b: Do larger brands attract more negatively online from the relatively larger number of original tweets compared to smaller brands (NDJ)?

Again, applying the same logic as per total tweets, empirical support for RQ1 and RQ3b would demonstrate NDJ (larger brands attract more attention from original tweets and more negativity from this increased amount of attention).

The third set of research questions apply the same logic to retweets. RQ4a researches the presence of DJ:

RQ4a: Do smaller brands attract less positivity online from the relatively fewer number of retweets compared to larger brands?

Under the same logic, if RQ1 and RQ4a are demonstrated, the existence of DJ is established (smaller brands suffering online by attracting a fewer number of retweets (RQ1) and less positivity sentiment amongst them (RQ4a). NDJ is questioned through RQ4b (in the same manner as RQ2b and RQ3b)

RQ4b: Do larger brands attract more negatively online from the relatively larger number of retweets compared to smaller brands (NDJ)?

The empirical demonstration of RQ1 and RQ4b would provide evidence of NDJ (larger brands suffer by attracting more retweets and more negativity amongst the retweets).

Methodology

Category Selection

This study considers eight brands of beer. As a product category, beer is widely studied with research focusing on numerous issues including, brand identification and taste (Allison and Uhl, 1964), building of demand models for the category (Frances, 1991), and effects of communities and neighbourhood stores from beer pricing (Harwood et al., 2003).

Additionally, the importance of beer brands themselves in respect to marketing has previously been discussed (e.g. Wood, 1999).

Data Sources

In order to establish whether the DJ/NDJ effect is present within a microblogging environment, data were required which related to the size of the brand in terms of market share and the sentiment towards that brand within a microblog. Data relating to the size of each considered beer brand was captured via Euromonitor's Global Market Information Database (GMID) Euromonitor (2016). Driven by extant literature (e.g. Fox et al., 2009; Jansen et al., 2009; Twitter, 2015; Zhu et al., 2011), microblogging data was sourced from Twitter.

Sampling Frame

Given the global nature of Twitter, assessing the geographic origin of a tweet is almost impossible to code, as the location field is user defined and hence tends to contain erroneous or misleading information (Takhteyev et al., 2012). This was also evident in the data captured in this study, where on inspection, the location field was populated by 90,818 unique names, with some suggesting inter-planetary locations. Therefore, a pseudo-market comprising of English language tweets was established since English is the internet's predominant language (Worldstats, 2016).

In order to match the countries to these English language tweets, sales data were sourced from countries where English is the official language. Sample countries were also selected to ensure they have a wide and relatively unrestricted access to the internet. Based on these criteria, the countries chosen were Australia, Canada, Ireland, New Zealand, South Africa, UK and USA (Worldstats, 2016; Databank, 2016; OpenNet Initiative, 2012; British Council, 2016).

Selecting Brands

Brand sales data within the GMID are well defined and uniquely identifiable. However, gathering information on brands through Twitter is a less trivial exercise and several steps were taken to ensure the reliability and validity of the data set. First, some brands share the same (or very similar) name to other brands (not-relevant to this study), objects, organisations or people's names, etc. To minimise this bias, a number of beer brands were, in turn, inputted within the Twitter Application Program Interface (API) search engine and a number

of Tweets for each were read manually. Brands were discarded if the content of the Tweets related to areas not associated with the brand in question. Second, many tweets originate from the respective brand owner, for example, in 2013, 97.6% of monitored organisations tweeted contents about their brands (Brandwatch, 2013). These tweets will conceivably be much more positive towards the brands they represent. To minimise this bias, any tweet which has a user name relating to a brand in question was discarded.

Third, a tweet was only selected if the tweet contained an exact match to the search string fed to the search engine. In order to minimise the exclusion of capitalised or non-capitalised permutations of brand names, the text of a tweet was all capitalised for search purposes and an exact match was established on the capitalised text. This means that "Heineken", HEINEKEN" or "heinEKen" etc., were all exactly matched. Finally, some tweets contain more than one of the search criteria brands. Given the sentiment software allocated only one sentiment outcome per tweet, it would be misleading if more than one brand in question is included within the tweet as it would not be possible to allocate the sentiment to the specific brand. Therefore, only single brand Tweets were included in our sample.

Gathering Tweets

In order to gather the data from the Twitter API, an appropriate software solution is required. The three software programs considered for this purpose were TwitteR, Googledocs and Tweetarchivist. Tweetarchivist was selected on the basis that first, the package scrapes tweets every hour for a given Boolean logic search string. This feature is pertinent given the global nature, and hence multi-time zone nature of the countries selected. Second, Tweetarchivist stores circa 50,000 tweets in a .CSV text file and automatically starts a new file when this is exceeded. Finally, prevalence exists for the use of Tweetarchivist within rigorous academic research (see for example Goldie et al., 2014).

Searches were set up within Tweetarchivist containing a list of brands specific to the beer category. The considered data set was made up of eight brands of beer, Amstel, Budweiser, Fosters, Grolsch, Guinness, Heineken, Labatt and Molson. Data was gathered over a two month period using Twitterarchivist, resulting in the collection of 354,676 tweets which were deemed to be acceptable given the methodology discussed. These brands, hereafter, make up the defined category for this study.

Analysing the Tweet's Sentiment

A consistent measure was required to determine the sentiment of a brand associated tweet in order to compare across brands (Dyson et al., 1996). Given the envisaged enormity of the number of tweets, manual coding is not realistic and hence a quantitative means of analysing the sentiment of each tweet is required. The R statistical software package 'Sentiment' was selected for this purpose. This uses a Naive Bayes method to calculate sentiment scores relating to positive and negative dimensions for each tweet (for technical details see Breen, 2011; Jurka, 2012).

Each file of tweets was individually run through the R Sentiment software package and the scores assigned appended to each record (tweet). One issue with automated sentiment analysis is the accounting for sarcasm or irony of a comment. Within Twitter the "tone of voice" of a respondent is not audible on a tweet, and often a corpus symbol or emoticon is used by the tweeter to indicate any irony to its audience. Therefore, in order to clean the data further, tweets containing emoticons or corpus symbols were excluded.

In order to verify that the sentiment analysis is operating as expected, a random sample of 200 tweets was manually categorised as positive, negative or no-opinion (independent of the Naive Bayes software assignments). Comparing both categorisations, using sentiment software and manually, gave a 64.3% success rate (versus a 33%) by chance. Given some tweets could be debated on their nature even between two humans, this level was deemed an acceptable level of success for the software.

Fuzzy C-Means Clustering

The next step of analysis was to allocate the tweets into suitable groups, here termed clusters (Saunders, 1980). Clustering is a well-known technique for finding groups in data (see Frayley and Raftery, 1998). The tweets were clustered based on the sentiment calculated from the Naive Bayes process (using R Sentiment software package). The fuzzy method was employed because it is shown to represent a superior clustering technique (Hruschka, 1986). Unlike traditional clustering approaches, the fuzzy approach estimates the probability of each data point belonging to *each* cluster (Rahmani et al., 2014). In this regard, the technique allows data points to be members of multiple clusters rather than forcing them to belong to one single cluster.

Fuzzy *c*-means clustering was employed (Bezdek, 1980; 1981), which is a well-known technique for finding groups in data (see McDermott et al., 2013). Specifically, fuzzy c-means clustering requires a complex calculation wherein a full inverse-distance weighting of each point is evaluated with each cluster, thus a point does not belong to a single cluster

but rather has a weak or strong association with that cluster, pertinent here due to the results of the sentiment analysis (Ghosh and Dubey, 2013; McDermott et al., 2013). A number of cluster solutions were considered, with the tweets partitioned into n different clusters where n ranged from three clusters up to ten clusters.

In technical details, an $n \times c$ matrix $U = [u_{ij}]$, denotes initially unknown cluster membership degrees for object i with respect to cluster j, with $0 \le u_{ij} \le 1$ and $\sum_{j=1}^{c} u_{ij} = 1$, for $i = 1, \ldots, n, j = 1, \ldots, c$. Starting with $C^{(0)} = \{ c_1^{(0)}, c_2^{(0)}, \ldots, c_c^{(0)} \}$, the initial set of c centroids (centres of the clusters), and ε (a small positive constant) which controls the least level of change in the centroids to continue iterations (here set as $\varepsilon = 0.00000001$), successive centroids, in iteration $t - 1$, are found by first finding the optimal $u_{ij}^{(t)}$, for $i = 1, \ldots, n$ and $j =$

$1, \ldots, c$, using; $\sum_{q=1}^{c} \left(\dfrac{\left\| x_i - c_j^{(t-1)} \right\|}{\left\| x_i - c_q^{(t-1)} \right\|} \right)^{-2}$ except for $c_j^{(t-1)} = x_k, k \ne i$ when $u_{ij}^{(t)} = 0$, then $c_j^{(t)} =$

$\dfrac{\sum_{i=1}^{n} (u_{ij}^{(t)})^m x_i}{\sum_{i=1}^{n} (u_{ij}^{(t)})^m}$. After each iteration, if $\left\| c_j^{(t)} - c_j^{(t-1)} \right\| < \varepsilon$, for $j = 1, \ldots, c$, calculate the objective function:

$$J_{FCM}(U, C) = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{ij}^{(t)})^m \left\| x_i - c_j^{(t)} \right\|,$$

and stop. The final U matrix contains the degree of membership details of the objects to the c clusters, while the C matrix contains the centroid details.

The three-cluster solution was chosen as it posed a good representation of the data and also was considered an appropriate means of establishing a positive, negative and no-opinion termed cluster solution, which would be accessible on a practical level. Support for this theory driven choice of cluster solution approach comes from Ketchen and Shook (1996) and McDermott et al. (2013). When the clusters are established, tweets are then associated with specific clusters, through their majority degree of membership (see McDermott et al., 2013).

Results

Brand Market Volume Share and Percentage Share of Tweets

Before further discernment of the tweets is undertaken (using fuzzy c-means clustering on the sentiment analysis results), a breakdown of the brand market volume share and percentage share of tweets is exposited. Inspection of the forced-rank parallel coordinates plot, see

Figure 1, shows the rank orders of the beer brands, across market share and numbers of tweets.

Insert Figure 1 about here

Inspection of the results in Figure 1 shows the limits on the brand market volume share range from 0.704% (Grolsch) to 47.677% (Budweiser), and in terms of the percentage share of tweets, from 0.647% (Grolsch) to 30.103% (Heineken). The presented forced-rank parallel coordinates plot shows larger share brands predominantly receive a proportionally higher percentage share of tweets, and smaller share brands generally to receive a smaller percentage (the exception being Budweiser). The results in Figure 1 also show evidence of strong similarity in the ranking of the brands based on the market share of the brand and the percentage share of the tweets. The exceptions to this are the pairs of brands Heineken and Budweiser, also Amstel and Labatt, which rank exchange 1st and 2nd, and 6th and 7th places, respectively, in terms of percentage share of tweets compared to their brand share.

Recall that the DJ/NDJ effect within the context of Twitter consists of two parts, i.e. smaller brands have fewer tweets; also the sentiment amongst them will be less positive. The first part, therefore, implies smaller brands have fewer tweets than larger brands (RQ1). Thus, RQ1 can be translated as the existence of a positive relationship between the percentages of tweets received about a brand and the brand's market share. Figure 1 suggests this is the case. However in order to formally test this similarity, a test of association is required. A Spearman's rank correlation procedure (or Spearman's rho) is adopted, given the data violates parametric assumptions such as non-normally distributed data, though the procedure offered by Kendall's tau may be more suited to smaller samples (Field et al., 2012). Therefore, both Spearman's rho and Kendall's tau are adopted for analysis purposes. A two tailed test is considered in order to test the association of a positive or negative relationship within the data. The results are shown in Table 1.

Insert Table 1 about here

The associated Kendall's tau and Spearman's rho correlation coefficients show evidence to reject the test's assumption of no association between the two variables at the 0.003 level (two tailed). Therefore, brands with larger market volume share are also attracting a larger percentage share of tweets. Hence RQ1 is satisfied.

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The DJ/NDJ effect

Given that RQ1 is tested and DJ is established, i.e. larger brands have a higher number of tweets than smaller brands, the study can now seek to establish whether RQ2a or RQ2b can be demonstrated and if so, establish the existence of DJ/NDJ effect.

In order to achieve this, the sentiment of the captured tweets needs to be categorised. To allow us to undertake this analysis, the fuzzy *c*-means clustering of the sentiment described tweets is considered. The three clusters established represent groups of tweets, differentiated by the levels (scores) of positive and negative sentiment associated with them. With two dimensions of data considered in the cluster process, the results of the clustering can be presented in a scatter plot form, see Figure 2.

Insert Figure 2 about here

Figure 2 shows the scatter plot for the 354,676 tweets for the defined product category of the eight brands of beers. It is based on their levels of positive (x-axis) and negative (y-axis) sentiment scores allocated through the sentiment analysis undertaken. The breakdown (partition) of tweets, in terms of numbers in each cluster is; C1 - 127,794 (36.031%), C2 - 98,652 (27.815%) and C3 - 128,230 (36.154%), showing a good balance of tweets within each of the established clusters.[1]

Inspection of the clusters shown in Figure 2 enables a form of typology of tweet sentiment for each cluster to be constructed (here based on the three cluster solution established), next described (see Breen, 2011; Jurka, 2012, for technical details on the evaluation of positive and negative scores of sentiment).

C1 - This cluster is associated with both the lowest positive and negative sentiment values from the sentiment analysis, hence is termed No-Opinion (NOP). The positive sentiment and negative sentiment mean (standard deviation) scores for tweets in the NOP cluster were 1.031 (0.000) and 0.445 (0.000). The positive/negative mean (standard deviation) ratio score for NOP is 2.315 (0.000). Finally, the cluster size (36.031%) of total tweets is similar to the 40% figure which Pearanalytics (2009)

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[1] The breakdown of clusters, found from a crisp *k*-means based cluster analysis, in terms of percentage share of tweets in each cluster is (cluster indexes given are those which match those of clusters found using fuzzy *c*-means), C_1 - 285,974 (80.630%), C_2 - 37,566 (10.592%) and C_3 - 31,136 (8.779%).

expressed as opinion-less. This demonstrates the importance of creating a cluster of no-opinion tweets rather than allocating all to a positive or negative grouping.

C2 - This cluster is associated with relatively high positive and low negative sentiment values from the sentiment analysis, hence is termed Positive Sentiment (POS). The positive and negative mean (standard deviation) scores for tweets in the POS cluster were 12.867 (5.547) and 1.750 (3.153). The positive/negative mean (standard deviation) ratio score for POS is 22.867 (13.502).

C3 - This cluster is associated predominantly with relatively low positive and high negative sentiment values from the sentiment analysis, hence is termed Negative Sentiment (NEG). We note the positive and negative mean (standard deviation) scores for tweets in the NEG cluster were 5.143 (4.993) and 11.900 (5.118). The positive/negative mean (standard deviation) ratio score for NEG is 0.456 (0.416) (inverse = 6.643 (6.047)).

The findings from the three cluster solution, based on the positive and negative scores from the sentiment analysis show an interesting partitioning of the tweets, with an established no-opinion tweet cluster (NOP), allowing two further groups of tweets to be discerned which are more positive (POS) and negative (NEG) in sentiment. The descriptive statistics given for the clusters of tweets NOP, POS and NEG, also support, that while the scatter plot diagram in Figure 2 suggest cluster membership will not hold strictly to the POS and NEG terms, in particular, see where C2 and C3 border each other, inspection showed there were very few tweets represented at the border between these clusters.

The discernibility of the clusters, in their representation of NOP, POS and NEG sentiment is also validated by confirming their statistical difference based on their descriptive statistics (cluster means), in terms of ANOVA and post-hoc results, separately on the positive and negative scores the clusters were based on. The ANOVA results show significant differences in the clusters means on both the positive and negative scores across the three clusters, C1, C2 and C3 (POS - $F_{(2, 355)} = 224442.272$, p = 0.000, and NEG - $F_{(2, 355)} = 400383.652$, p = 0.000). Post-hoc analyses were conducted, given the statistically significant ANOVA tests, with Bonferroni tests conducted on all pairs of clusters (see McDermott et al., 2013), see Table 2.

Insert Table 2 about here

Post-hoc results (see Table 2) separately across the positive and negative scores, showed (at p < 0.001) each cluster was significantly different from each other cluster.

We next consider the grouping of the tweets in the clusters (NOP, POS and NEG), broken down by their association with the considered brands of beers, see Table 3.

Insert Table 3 about here

The results in Table 3 show variations in the percentage share of tweets associated with different beer brands across the three clusters. For example, for Budweiser, with 31.243% of tweets associated with it in the NOP cluster, this is above the general 28.583% of all tweets associated with that brand. This presence of Budweiser tweets in NOP is balanced by its lesser presence in the POS and NEG clusters. Moreover, with regard to Budweiser, while slightly more tweets have no opinion towards it (in NOP cluster), this has meant a slightly lesser association to positive tweets (in POS) rather than negative tweets (in NEG).

Returning to brand share, to effectively compare percentages of brands' tweets (brand share and tweet sentiment), across clusters, we consider forming an index (see Gaski and Etzel, 1986), for a brand's presence in an established cluster (NOP, POS and NEG). That is, the index value (I), say for brand h in cluster k, termed $I_{h,k}$, represents its deviation away from the total (or average), given by:

$$I_{h,k} = \frac{\text{Percentage share of brand } h \text{ tweets in cluster } k}{\text{Percentage share of brand } h \text{ tweets in population}} - 1.$$

In summary, the larger the value of the index $I_{h,k}$ the more presence that brand h has in cluster k and the value "0" indicates no deviation from the total. As in our consideration of brand share and percentage share of tweets, shown in Figure 1, the index values with respect to brands in an individual cluster can be rank compared with the market volume share of each brand.

For the established three clusters of tweets, NOP, POS and NEG, the sets of index values for the respective brands and the respective brand shares can be compared. This comparison enables the second part of the DJ/NDJ to be assessed, i.e. RQ2a/RQ2b. First RQ2a is considered which questions if smaller brands attract less positivity online from the relatively fewer number of posts compared with larger brands (if this were evidenced and combined with the findings of RQ, it would suggest the presence of DJ, since smaller brands are attracting less posts (RQ1) and there is less positivity from this smaller set of posts (RQ2a)).

This can be translated into a mathematical association which then can be statistically tested. Therefore, if the POS cluster is positively correlated with brand share then a DJ effect

is apparent (i.e. *larger* brands have *more* positivity). Alternatively the same conclusion would be established if a negative relationship existed between the NEG cluster and brand share (i.e. *smaller* brands have *less* positivity). Again this would indicate a DJ relationship is apparent. Therefore, if either of these were true, then the question posed by RQ2a is answered positively, hence smaller brands are suffering by attracting less positive (or more negative) associations online than larger brands.

Alternatively, RQ2b may be shown to exist, i.e. compared to smaller brands, larger brands attract more negativity online from the larger number of posts (which combined with the existence of RQ1would indicate a NDJ effect, i.e. larger brands are suffering by attracting more posts than smaller brands and more negativity amongst the larger number of posts). RQ2b can also be translated into a mathematical association and then tested statistically as follows. If a negative relationship exists between the POS cluster and brand share (i.e. *larger* brands have *less* positivity) *or* if a positive relationship exists between the NEG cluster and brand share (i.e. *smaller* brands have *more* positivity). If RQ2b is demonstrated, (in conjunction with existence of RQ1, demonstrated earlier) this would indicate a NDJ relationship, i.e. larger brands are suffering by having a larger number of posts and more negativity amongst this larger number.

These associations (or not) can be formally tested through a correlation analysis and a Kendall's tau and Spearman's rho correlation analysis is conducted to test this. The results are shown in Table 4.

Insert Table 4 about here

From the analysis presented in Table 4, for the NEG, POS or NOP clusters, there is very little evidence to reject the underlying assumption of the tests which is that of no association, and hence no bivariate correlation between the brand shares and the brand sentiment index for either of the NEG, POS or NOP clusters. Therefore, there is no evidence to support RQ2a or RQ2b and hence for the total tweets captured for this defined category, no evidence to suggest either a DJ or a NDJ effect is present.

Splitting the tweets into original tweets and retweets
As discussed in the literature, there is a need to identify whether the lack of pattern seen within the total tweet profile also exists when the tweets are split into original tweets (those which have not been retweeted) and retweets (those which have been retweeted). From the

original 354,676 of all tweets it was found 258,622 (72.918%) and 96,054 (27.082%) were original tweets and retweets, respectively. This noticeable variation in proportion of original tweets and retweets is in line with portion of retweets recorded during the US health care reform debate (27%) and the proportion recorded during the International Semantic Web Conference (24%) (see Nagarajan et al., 2010).

Original Tweets

Considering only the original tweets, the breakdown of the brand percentages of tweets within the NOP, POS and NEG clusters is reported in Table 5.

Insert Table 5 about here

In general, from Table 5, the percentages of original tweets in each cluster (top row, NOP - 36.796%, POS - 25.562% and NEG - 36.642%) are not too dissimilar than when considering all tweets (NOP - 36.031%, POS - 27.815% and NEG - 36.154% in Table 3).

For these original tweets, the index ($I_{h,k}$) values are constructed as before for each brand in each of the NOP, POS and NEG clusters. These index values, along with the respective shares of the brands, enable consideration of RQ3a, which states that a DJ effect exists within the original tweets. With the same logic used as with the total tweets, this would mean that either the brand share would be positively associated with the POS cluster (i.e. *larger* brands have *more* positivity), *or* brand share would be negatively associated with the NEG cluster (i.e. *smaller* brands have *less* positivity). If either of these are demonstrated, then a DJ effect would be observed.

Alternatively an NDJ effect may be observed using RQ3b. Again this can be translated into a mathematical test in the same way as the total tweets. As before, the association between the brand share and brand indices is formally tested for all three clusters, NOP, POS and NEG, separately using a correlation analysis. Both the Kendall's tau and Spearman's rho are employed in this test, and the results shown in Table 6.

Insert Table 6 about here

The analysis presented in Table 6 shows no evidence to reject the tests' underlying assumption of no association between the brand share and the brand sentiment index within the NOP or POS cluster. This implies there is no evidence to suggest an association between

the brand share and the brand indices within the NOP cluster or the POS cluster. In contrast, for the original tweets in the NEG cluster, significance levels of 4.8% and 1.5% for the Kendall's tau and Spearman's rho respectively show there is evidence to reject the underlying assumption of no association, at the 5% level. Hence, there is evidence to suggest a positive association between the brand share and the brand indices of the NEG cluster. This implies the larger the brand, the more negativity they will experience from original Twitter posts. This would offer agreement with our research question RQ3b. This combined with acceptance of RQ1 suggests evidence of NDJ within this defined category. Therefore, larger share brands attract a larger percentage share of tweets which have a more negative sentiment amongst the larger number of tweets. This is the NDJ effect.

With the significant results found, substantiating the presence of NDJ, further elucidation of the relationship between index values and respective shares of the brands is given in Figure 3, using a series of forced-rank parallel co-ordinates plots (as employed in Figure 1).

Insert Figure 3 about here

Inspection of the paired rank orders of brands in Figure 3 shows little evidence of an association between brand share and brand $I_{h,k}$ index values for any of the NOP and POS clusters (as suggested in the correlation results in Table 6). Supporting evidence of the identified significant correlation between the brand share and the brand $I_{h,k}$ index values within the NEG cluster is exhibited, with four brands having the same rank and the others forming two exchangeable pairs of brands (Fosters and Budweiser, and Labatt and Guinness).

Retweets

The analysis continues by using the same analytical process on only the retweeted data. Table 7 explores the breakdown of the brand percentages of tweets (or retweets) within the NOP, POS and NEG clusters.

Insert Table 7 about here

From Table 7, there is noticeable increase in the percentages of retweets in POS cluster (31.188%), against original tweets (25.562% in Table 5) and all tweets (27.815% in Table 3), resulting in a fewer number of retweets in the NOP and NEG clusters

As with the original tweets, for the retweets, the index ($I_{h,k}$) values are constructed for each brand within the three clusters NOP, POS and NEG. These index values, along with the respective shares of the brands, enable consideration of RQ4a, which states that a DJ effect exists within the retweets. Using the same logic as with total and original tweets, a DJ effect would mean either the brand share would be positively associated with the POS cluster, *or* brand share would be negatively associated with the NEG cluster. Alternatively an NDJ effect may be observed using RQ4b, where the brand share would be positively correlated with the NEG cluster *or* negatively correlated with the POS cluster.

The association between the brand share and brand indices is formally tested for all three clusters, NOP, POS and NEG, separately using correlation analysis. Both the Kendall's tau and Spearman's rho are employed in this test, and the results shown in Table 8.

Insert Table 8 about here

The analysis presented in Table 8 shows no evidence to reject the tests' underlying assumption of no association between the brand share and the brand sentiment index within the NOP, POS or NEG clusters. This implies there is no evidence to suggest an association between the brand share and the brand indices within any of the clusters. Therefore, there is no evidence of either a DJ or a NDJ effect within the retweets.

Discussion

This research is the first to theoretically apply and empirically test the presence of both DJ and NDJ in an online environment. Only very limited understanding of DJ and NDJ online exists, and typically such studies examine the presence of either DJ or NDJ in a separate and detached perspective.   By utilising Twitter data, we contribute to the theoretical, methodological and practical understanding of DJ and NDJ dynamics.

Theoretical and Methodological Implications

This study is one of the first to explore the presence of both DJ and NDJ in a single setting. The current research adds to our theoretical understanding of DJ and NDJ because the study findings show that the theory does not perform in the same way in an online environment as was originally conceived for offline settings (Ehrenberg et al., 1990). To detail, the current study demonstrates that online settings can exhibit a NDJ effect. In particular, NDJ is revealed to be pertinent within the online environment wherein the DJ effect is reversed.

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That is, larger beer brands (according to market share) were found to suffer by experiencing higher volumes of original negative tweets. Thus, in investigating DJ and NDJ effects, the current study contributes to theoretical understanding of the constructs and their associated dynamics. In examining the effects of DJ and NDJ in a simultaneous and holistic way, the current study also adds to theory in demonstrating the bi-directional effect of the constructs.

Additionally, this study represents the first attempt to analyse the sentiment of consumer-authored tweets to explore DJ and NDJ effects. Previous studies in this area draw on data from hate-sites. However, such sites are biased towards larger brands. Consequently, Twitter data is utilised to, in part, remedy this bias and gain access to a diverse sample and rich dataset of relevant tweets. Thus, we argue that sentiment analysis using consumer-authored Twitter data enables researchers to further drill down into DJ and NDJ effects within an environment that reflects the full spectrum of positive and negative consumer behaviour. Additionally, the current research also utilises fuzzy c-means clustering, which is a rarity in this field. Specifically, as demonstrated in our study, this form of clustering recognises that observations may belong to more than one cluster.

This study demonstrates that it offers more dimensionality to the previously employed ratio (positive/negative, e.g. Breen, 2011) or difference (positive – negative, e.g. Jansen et al., 2009) based sentiment scoring. Further, the application of forced-rank parallel co-ordinates plots to a consumer dataset is a unique addition to this field of study elucidating the similarity/variation in rank order of beer brands in terms of market share and number/sentiment of tweets.

Our study also contributes to broader understanding of Twitter dynamics because our findings demonstrate that not all tweets are equal. Indeed, our study findings highlight the need to separate original tweets from retweets in that our data shows that jeopardy dynamics differ in these different domains. That is, we find statistical evidence of a strong negative double jeopardy effect for original tweets. By contrast, our findings also reveal that this effect is diluted for retweets which are more positively orientated. That is, there are marked differences in original tweets in comparison to retweets which are important when investigating and acting upon double jeopardy and negative double jeopardy dynamics.

Managerial Implications

This study demonstrates that for original tweets, there is a NDJ effect. This indicates that consumers are actively communicating with their social network and for larger share brands, the sentiment of these communications are negative.

The implications of the sentiment of tweets has been demonstrated in several studies (e.g. Aurier and Séré de Lanauze, 2012; Tumasjan et al., 2010). However, for the first time, this study suggests the practitioner will benefit if the sentiment received from these tweets is analysed within the well-established theoretical construct of DJ. Specifically, this study demonstrates the need for practitioners to be aware of the NDJ effect's implications towards their brands based on the sentiment of tweets they receive. Awareness of the issue can lead to taking steps to minimise the risk to the brand or, conversely, to use the NDJ effect as a way of benefitting the brand.

What measures the practitioner takes, and whether the NDJ effect is viewed as an opportunity or a threat, depends on the size of share the brand being managed enjoys. This study demonstrates managers of larger brands, within the Twitter environment, will suffer by attracting more tweets relating to their brand and these tweets will much likely be of a more negative sentiment towards their brand. Thus, consumers are actively tweeting negative sentiments about their brands. Conversely, managers of smaller share brands find themselves in a position of enjoying proportionally less negative sentiment about their brands within the Twitter environment. They are receiving less tweets (which would be expected), but the sentiment within these tweets are relatively less negative than if their brand was larger in share.

Web2.0 has changed the nature of modern communication, empowering the voice of the consumer and managers have lost control of the online content which can be communicated about their brand. This loss of control can only be magnified further when considering the enormity of the Twitter population. The vast number of tweets captured within this study over a relatively short time period, relating to just eight brands in one category underlines this point. Consequently, practitioners need to take heed of this NDJ effect and the importance can only intensify as the amount of tweets online increase. The sooner the practitioner can define a strategy to defend against, or embrace this NDJ effect, the sooner they may steal a march on their competition.

The importance of adapting an organisation's structure and strategy to adapt and change as the environment changes is by no means a new concept (e.g. Waterman et al., 1980), and the same applies for the advent of the new online environment of Twitter. Embracing the NDJ effect can help minimise the negative impacts which are brought about through being a larger brand but also be used to leverage the less negative sentiment which smaller share brands may expect.

Research shows the more successful businesses are those with a dedicated online function (Kane et al., 2009). This can only be done through equipping staff with the skills required to adapt to the new environment (Fournier and Avery, 2011), and allowing them to engage with consumers (Kim et al., 2008). Despite the more technical nature of this online environment, practitioners should note it is easier for a socially active employee to learn web technology than it is for a technical employee to learn to be socially active (Page, 2010). It is argued therefore the business which adapts their social strategy to embrace the NDJ effect will gain competitive advantage. Based on the current study findings, larger brands should adopt an engagement strategy to reduce the negative sentiment around them. This strategy may be at a corporate level in order to affect the brand image globally but also through engaging positively with consumers online to address the negativity.

The study findings also indicate that smaller share brands should embrace the benefit of less negativity and nurture relationships online and rely on word of mouth from their socially active consumers to promote the brand within their social networks. Additionally, the NDJ effect is only prevalent in original tweets, therefore that first communication by a consumer is more likely to be opinion forming. It is important, therefore for brand managers to nurture socially active users to ensure the first communication is positive.

The practitioner's paradox of DJ/NDJ

A paradox emerges from the existence of NDJ within the Twitter environment. Consider a larger share brand. Within the offline sales environment, DJ states this larger share brand will benefit twice, more consumers and more loyalty amongst the larger consumer base. However, as this larger share brand increases offline, it will simultaneously incur more negativity online, based on this study. This negativity online can only lead to longer term detrimental effects on the brand's equity. Therefore, where does the balance of the positive effects of offline DJ versus the negative effects of online NDJ lie? This is the paradox.

Contrast this with the strategy of managing a small share brand. In this case, the brand would suffer offline under the DJ effect through less consumers and less loyalty amongst the smaller number. However, the same brand would benefit online from less negativity (again based on this study). Whether this online negativity translates to a more positive financial performance requires further research. However, if there is a positive correlation between online sentiment and financial performance then this could represent an opportunity to use the online environment to nurture and gain a more positive outlook for the brand and hence increase off line share performance. As the brand grows offline, it will

attract DJ effects which will help to further grow the brand. However, as the brand grows, it will start to incur more negativity online which has implications on longer term equity. Hence, the balance or tipping point is again desired to address this. This demonstrates the paradox. Addis and Podesta (2005) argue that the changes being introduced to marketing after the advent of Web2.0 which are creating a new 4Cs of marketing, i.e. change, complexity, chaos and contradiction. Could the paradox of DJ/NDJ also be contributing to these new challenges the practitioner will face in the future?

Future Research and Limitations

While the current study deepens and broadens theoretical and managerial understanding of the DJ/NDJ constructs, five limitations highlight pertinent areas for future research in this area. First, the current study focuses on the occurrence and mechanisms of DJ and NDJ within a single product category. While beer is shown to be a fitting and useful product category within which to study this phenomenon, future research should examine the generalizability of the DJ and NDJ effects across multiple diverse product categories and online platforms. Second, an inherent limitation in Twitter-derived data is the software's inability to accurately and reliably determine the geographical location of sample members. Although the current study took steps to minimise such bias, future research should seek to explore means by which to precisely capture the physical location of the tweet source. Such information may help inform a deeper understanding of DJ and NDJ rhythms according to time and space.

Third, this study recognises some countries within the sample frame of gathered tweets are multi-lingual, though only English based tweets are being analysed. Clearly, the multilingual nature of most countries means that picking a single language is a limitation. The countries chosen are those where the English language is predominant. However, with a tweet having an identifier which expresses the language it is written in, future research may attempt to try and undertake multi-language based sentiment analysis. Fourth, a further future dimension to consider this form of Twitter based analysis of the presence of the DJ/NDJ effect is to consider the evidence qualitatively. It may be possible in future research work to combine our approach with further netnography oriented approaches (see for example, Camiciottoli et al., 2014). Fifth, sentiment analysis, more specifically, automated sentiment analysis, is still in its infancy, how many factors, such as cultural and linguistic

nuances, may be impacting of the sentiment derived, will be very much worth considering in future research.

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List of Tables and Figures

Market Volume Share vs. Percentage Share of Tweets			
Kendall's tau		Spearman's rho	
Correlation Coefficient	Significance	Correlation Coefficient	Significance
0.857	0.003**	0.952	0.000**

** Significant at 1% level

Table 1. Correlation analysis of brand market volume share against brand percentage share of tweets, using Kendall's tau and Spearman's rho tests

	Positive				Negative	
	C_2	C_3			C_2	C_3
C_1	MD - 11.836 SD – 0.018 Sig. - 0.000	MD - 4.111 SD - 0.017 Sig. - 0.000		C_1	MD - 1.304 SD - 0.015 Sig. - 0.000	MD - 11.455 SD - 0.014 Sig. - 0.000
C_2		MD - 7.724 SD - 0.018 Sig. - 0.000		C_2		MD - 10.151 SD - 0.015 Sig. - 0.000

Note: MD - Absolute Mean Difference), SD – Standard Error, Sig. - Significance

Table 2. Bonferoni Post Hoc results for Positive and Negative sentiment scores over three clusters, C_1, C_2 and C_3

Beer\Cluster	NOP (36.031%)	POS (27.815%)	NEG (36.154%)	Total
Budweiser	39,927 (31.243%)	25,744 (26.096%)	34,889 (27.208%)	100,560 (28.353%)
Labatt	1,715 (1.342%)	1,316 (1.334%)	1,749 (1.364%)	4,780 (1.348%)
Heineken	38,656 (30.249%)	26,816 (27.182%)	41,296 (32.205%)	106,768 (30.103%)
Grolsch	1,349 (1.056%)	464 (0.470%)	483 (0.377%)	2,296 (0.647%)
Molson	6,380 (4.992%)	3,927 (3.981%)	4,413 (3.441%)	14,720 (4.150%)
Amstel	2,521 (1.973%)	4,761 (4.826%)	2,367 (1.846%)	9,649 (2.721%)
Fosters	25,609 (20.039%)	20,524 (20.804%)	35,449 (27.645%)	81,582 (23.002%)
Guinness	11,637 (9.106%)	15,100 (15.306%)	7,584 (5.914%)	34,321 (9.677%)

Table 3. Breakdown of numbers (and percentage share) of tweets in each cluster, based on brand of beers

	Market Volume Share vs. Brand Index			
	Kendall's tau		Spearman's rho	
	Correlation Coefficient	Significance	Correlation Coefficient	Significance
NOP Cluster	0.000	1.000	-0.048	0.911
POS Cluster	-0.214	0.458	-0.190	0.651
NEG Cluster	0.429	0.138	0.619	0.102

Table 4. Correlation analysis of brand market volume share against brand index in each cluster, for all tweets, using Kendall's tau and Spearman's rho tests

Beer\Cluster	NOP (36.796%)	POS (25.562%)	NEG (36.642%)	Total
Budweiser	30,204 (31.740%)	19,271 (28.053%)	27,131 (28.630%)	76,606 (29.621%)
Labatt	1,394 (1.465%)	1,044 (1.520%)	1,228 (1.296%)	3,666 (1.418%)
Heineken	28,347 (29.788%)	19,177 (27.916%)	29,356 (30.978%)	76,880 (29.727%)
Grolsch	1,232 (1.295%)	388 (0.565%)	400 (0.422%)	2,020 (0.781%)
Molson	4,902 (5.151%)	2,657 (3.868%)	3,154 (3.328%)	10,713 (4.142%)
Amstel	1,868 (1.963%)	3,307 (4.814%)	1,633 (1.723%)	6,808 (2.632%)
Fosters	19,337 (20.320%)	15,242 (22.188%)	25,987 (27.423%)	60,566 (23.419%)
Guinness	7,878 (8.279%)	7,609 (11.076%)	5,876 (6.201%)	21,363 (8.260%)

Table 5. Breakdown of numbers (percentages) of original tweets in each cluster (not final column), based on brand of beer

	Market Volume Share vs. Brand Index			
	Kendall's tau		Spearman's rho	
	Correlation Coefficient	Significance	Correlation Coefficient	Significance
NOP Cluster	-0.143	0.621	-0.190	0.651
POS Cluster	-0.071	0.805	-0.024	0.955
NEG Cluster	0.571	0.048*	0.810	0.015*

* Significant at 5% level

Table 6. Correlation analysis of brand market volume share against brand index in each cluster, for original tweets only, using Kendall's tau and Spearman's rho tests

Beer\Cluster	NOP (33.973%)	POS (31.188%)	NEG (34.840%)	Total
Budweiser	9,723 (29.796%)	6,473 (21.608%)	7,758 (23.182%)	23,954 (24.938%)
Labatt	321 (0.984%)	272 (0.908%)	521 (1.557%)	1,114 (1.160%)
Heineken	10,309 (31.592%)	7,639 (25.500%)	11,940 (35.679%)	29,888 (31.116%)
Grolsch	117 (0.359%)	76 (0.254%)	83 (0.248%)	276 (0.287%)
Molson	1,478 (4.529%)	1,270 (4.239%)	1,259 (3.762%)	4,007 (4.172%)
Amstel	653 (2.001%)	1,454 (4.854%)	734 (2.193%)	2,841 (2.958%)
Fosters	6,272 (19.220%)	5,282 (17.632%)	9,462 (28.274%)	21,016 (21.879%)
Guinness	3,759 (11.519%)	7,491 (25.006%)	1,708 (5.104%)	12,958 (13.490%)

Table7. Breakdown of numbers (percentages) of retweets in each cluster (not final column), based on brand of beer

	Market Volume Share vs. Brand Index			
	Kendall's tau		Spearman's rho	
	Correlation Coefficient	Significance	Correlation Coefficient	Significance
NOP Cluster	0.286	0.322	0.190	0.651
POS Cluster	-0.071	0.805	-0.262	0.531
NEG Cluster	0.143	0.621	0.333	0.420

Table8. Correlation analysis of brand market volume share against brand index in each cluster, for retweets only, using Kendall's tau and Spearman's rho tests

Figure 1. Breakdown of brand market volume share and percentage share of tweets of brands, using forced-rank parallel coordinates plot
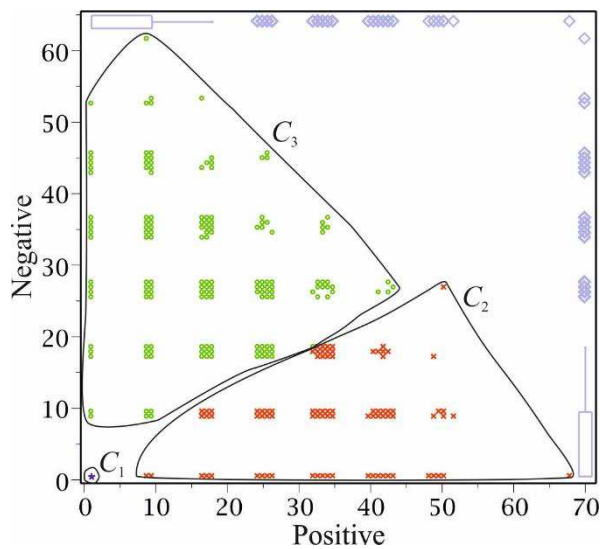

Figure 2. Scatter plot based elucidation of three cluster solution, based on sentiment analysis found positive and negative scores for each tweet
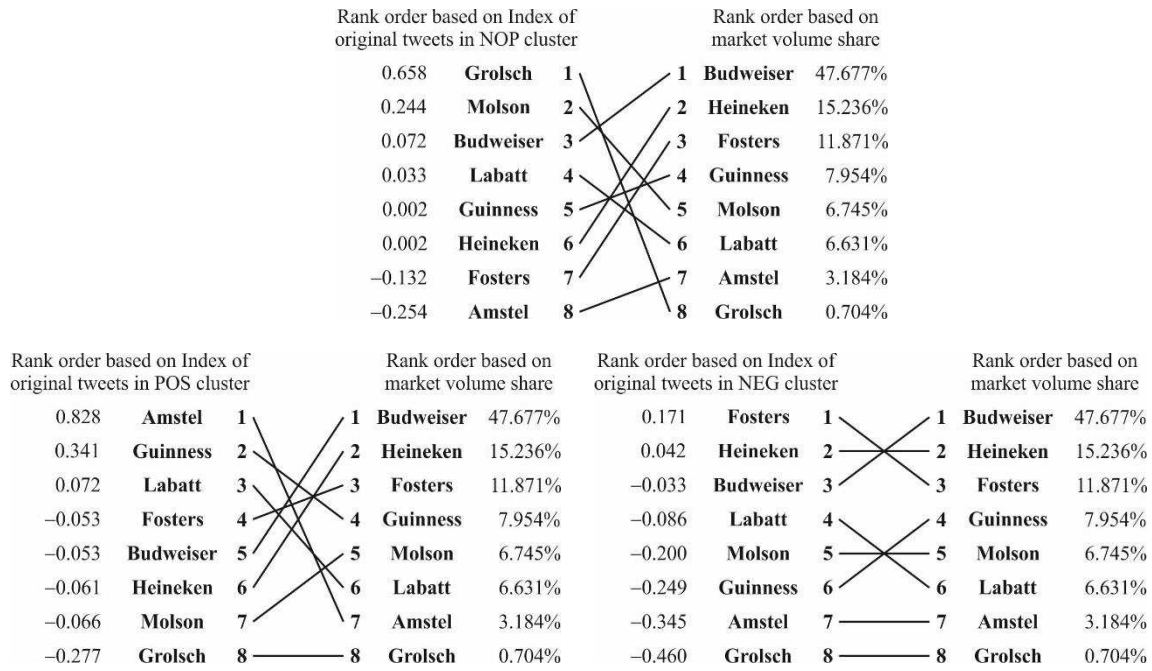
Figure 3. Forced-rank parallel co-ordinates plots of the ranking of the $I_{h,k}$ brand cluster indexes and the ranking of brands' market share volumes, for each of the three clusters, NOP, POS and NEG, for original tweets only.