Introduction

Before the prominence of social media, many works have focused on interpersonal word of mouth issues. Katz and Lazarsfeld (1995) find that interpersonal communication is important when making purchase decisions. Because of the intangible nature of service goods, word of mouth becomes important in predicting if one should make a purchase (Murray 1991; Zeithaml et al. 1993). Seeing that sentiment may be more important than the volume of the word of mouth, we examine the following question: does one company's sentiment effect the sentiment of competing company? This question engages the marketing spillover effect literature (see Sahni, 2013; Borah et al., 2016), and social media word of mouth literature (see Chevalier and Mayzlin, 2006; Duan et al., 2008; Liu, 2006).

There is extensive literature on the role of word of mouth on firm performances. Among the first works in social media and sales include Godes and Mayzlin (2004) find that the dispersion of WOM across many different news groups generates more sales (as opposed to looking at overall WOM volume). Chevalier and Mayzlin (2006), find that consumer posts on review sites can promote sales; positive reviews on these review sites strengthen sales, whereas negative reviews weaken sales.

Using Yahoo Movies Web data, Liu (2006) find that pre-release movie WOM and opening weekend WOM have the most explanatory power for movie sales. Liu also finds that WOM has more explanatory power than WOM valence. Similarly, Duan et al (2008) find that increased WOM on Yahoo!Movie (a movie review site) lead to higher movie box office performance. Dewan and Rampaprasad (2014) approach this field from an Integrated Marketing

Communications angle, and assess blog buzz and radio advertising simultaneously in a single model. They find the impact of radio advertising leads to more music sales, whereas an increase in blog buzz leads to lower sales. The negative blog effect on sales is due to people finding free music samples online, which reduce the incentive to actually buying the song.

On the predictive front of the literature, Bollen et al (2010) found that twitter moods can predict stock market performance. However, when assessing the causality claims of these approaches, there is the potential for severe omitted variable bias when other social media WOM are not included in the model. It is very likely that Facebook, Twitter, YouTube, review sites, forums, and blogs are all highly correlated with each other, and with the dependent variable, sales. It is also invalid to assume that one platform can proxy for the entire realm of social media, because each social media platform can be categorized into a broader theoretical construct, as argued by Kietzmann et al (2011).

Despite the focus on promoting WOM volume, a harsh reality is that not all consumers are admirers of a particular brand. Some consumers feel oppositional loyalty towards certain brands, which they express through purchase behavior, negative behavior towards admirers of other brands, and "trash talking" (Hickman and Ward 2007; Thompson and Sinha 2008; Thompson, Kim and Smith 2016). Some consumers go so far as to engage in protest activities and "brand terrorism" (Ward and Ostrom 2006; Klara 2014).

To test our research question, we use the airline industry—specifically when United Airline suffered from bad publicity for removing a passenger from its plane (Chicago Tribune, 2017). This is an excellent case study to examine, because United Airlines suffered from a negative shock, whereas the other airlines did not encounter any major event during the time period of our analysis.

From a managerial perspective, it is important to remind ourselves that this is not a one time incident. There are many cases where brands undergo negative events. This can be seen in the case of the #McDStories campaign, in which Mcdonald's released a hashtag campaign to invite consumers to share their positive experiences with McDonalds. This plan, however, backfired, resulting in a storm of negative tweets. Even Chipotle, known for its socially responsible source of food, suffered from several incidents of contaminated foods in 2016. Another case is when Samsung had to recall its Samsung Note 7 for catching fire. By understanding how brand harm affects competing firms, we can tell marketing managers whether they should capitalize on the windfall, or prepare to defend themselves from the coming negativity.

Hypotheses:

When a rival firm undergoes a negative event, it is unclear whether this is good news or bad news for the competing airlines. The following hypothesis are:

Hypothesis 1: United Airline's decline in sentiment improves the sentiment of competing airlines.

One could argue that United Airline's incident harmed the industry's reputation, thus bringing all the other airlines' sentiment down. This would be similar to the case of the 1984 Bhopal Chemical Disaster in which the whole chemical industry suffered severe public backlash for one company's wrongdoing. Consistent with Borah and Tellis, (2016) they argue that industries that undergo brand harm suffer from negative spillover effects. They find the negative spillover effect to be strongest for dominant brands in the industry, and that these effects diminish firm sales and stock performance. In essence, the airline industry's reputation could be viewed as a tragedy of the commons (Hardin, 1968).

Hypothesis 2: United Airline's decline in sentiment worsens the sentiment of competing airlines

Alternatively, United Airline's decline in sentiment could make other airlines seem more attractive to consumers. Based on social identity theory, those who identified negatively with United Airlines could find a new identity with competing airlines. To express their new identity, they may be motivated to speak well of the competing airlines (Turner and Oakes, 1986 ;Turner and Reynolds, 2010).

Hypothesis 3: United Airline's decline in sentiment has no effect on competing airlines

Lastly, United Airline's decline in sentiment could be an isolated incident. Exit and Voice theory (1970) argues that those who cannot exit will protest. Seeing that airline tickets are bought weeks and months in advanced, many customers cannot resell their tickets and exit. This may lead to current customers protesting and posting negative tweets about United Airlines, while those who are not United have already "exited" so they do not do not need to voice their concern about United's competitors.

By performing sentiment analysis on this case study, we seek to understand whether or not competitor performances have spillover effects, and whether or not competitors should be wary of their rivals' downfalls.

Data and Methods:

Data

We collected customer tweets data about the nation's major airlines (namely, United Airline, Virgin America, and American Airline) from two different sources for two distinct purposes.

First, we used customer tweets sentiment data downloaded from *Kaggle.com* to build up a classifier model, which, in turn, will be applied for the estimation and prediction of customer tweets sentiment of the second dataset.

There are 11,222 unique tweets from 11,222 distinct Tweeter IDs, with a timeframe from 2/16/2015 through 2/24/2015. In terms of sentiment, 60% of the tweets were classified as positive, 23% neutral, and 17% positive. The longest tweet among them have 144 characters, while the shortest has only 12. With regards to airline, 34% of these tweets were about United Airline, followed by American Airline – 25%, Southwest – 22% and Delta – 20%.

In addition to aforementioned fields, the dataset also provides information, including number of retweets, geo-source of the tweets, user time zones, etc. However, given the objective of this study, we would only focus on fields of actual tweet texts, tweet created date, and airlines covered.

The second source of the dataset is directly from Twitter.com, where we used an R function 'twitteR' and scraped textual data covering three major airlines to be concerned: United Airline, American Airline, and Virgin Airline. 51,906 tweets were collected from 51,906 distinct Tweeter IDs, with a timeframe from 4/11/2017 through 4/19/2017. The reason we selected this timeframe is to align with the timeline of United Airline crisis progress starting from 4/11/2017.

Among these 51,906 tweets, not surprisingly, almost 63% are related to United Airline, 34% about American Airline, and only 3% is about Virgin Airline.

Method:

As aforementioned, the major objective of this study is to estimate the impact of customers' WOM sentiment on the wellness of both focal firm and its competitors in the industry ecosystem. In order to get sentiment data, we first utilize Naïve Bayes method in the realm of machine learning to create a textual sentiment classifier based on its learning from *Dataset One*. As step two, we applied the classifier to the *Dataset Two* to analyze the dispersion of customers' sentiment on the three major airlines.

Naive Bayes, in general, is a method dealing with binary (two-class) and multi-class classification problems. Compared to logit regression, its algorithm is based on Bayes Theorem. However, the calculation of the probabilities for each hypothesis, by Naïve Bayes, is pretty simplified. Rather than attempting to calculate the values of each attribute value $P(d1, d2, \dots dn|h)$, they are assumed to be conditionally independent given the target value and calculated as $P(d1|h) * P(d2|H)$, and so on. This is a very strong assumption which requires no attributes interaction in the real dataset, but many studies show that the model still performs well even the assumption does not hold stringently.

Representation used by Naïve Bayes model is comprised of: 1). Class Probabilities: The probabilities of each class in the training dataset; and 2). Conditional Probabilities: The conditional probabilities of each input value given each class value.

The class probabilities are simply the frequency of instances that belong to each class divided by the total number of instances. For example, in a binary classification the probability of an instance belonging to class 1 would be calculated as:

$$P(class = 1) = \frac{count(class = 1)}{count(class = 0) + count(class = 1)}$$

In the simplest case each class would have the probability of 0.5 or 50% for a binary classification problem with the same number of instances in each class.

Compared to class probabilities, the conditional probabilities are the frequency of each attribute value for a given class value divided by the frequency of instances with that class value.

In our case, for example, if a 'tweet' attribute had the values 'love' and "hate" and the class attribute had the class values "positive" and "negative", then the conditional probabilities of each tweet value for each class value could be calculated as:

$$P(tweet = love|class = positive = \frac{count(instances\ with\ tweet{=}love\ and\ class{=}positive)}{count(instances\ with\ class{=}positive)}$$

$$P(tweet = love|class = negative = \frac{count(instances\ with\ tweet{=}love\ and\ class{=}negative)}{count(instances\ with\ class{=}negative)}$$

$$P(tweet = hate|class = negative = \frac{count(instances\ with\ tweet{=}hate\ and\ class{=}negative)}{count(instances\ with\ class{=}negative)}$$

$$P(tweet = hate|class = positive = \frac{count(instances\ with\ tweet{=}hate\ and\ class{=}positive)}{count(instances\ with\ class{=}positive)}$$

Therefore, based on Bayes Theorem, we can make predictions for a new dataset as follow:

$$MAP(h) = \max(P(d|h) * P(h))$$

In terms of this study, we can use the classifier result to calculate:

$$positive = P(tweet = love|class = positive) * P(class = positive)$$

$$negative = P(tweet = love|class = negative) * P(class = negative)$$

Based on the results of the above calculation, we can choose the class that has the largest value and turn these values into probabilities by normalizing them as follows:

$$P(positive|tweet = love) = \frac{positive}{positive + negative}$$

$$P(negative|tweet = love) = \frac{negative}{positive + negative}$$

Result:

We extracted tweets and initially analyzed the percentage of tweets that belongs to United, Virgin and American airlines and we found the below results in Table 1.

Table 1

	11-Apr	12-Apr	13-Apr	14-Apr	15-Apr	16-Apr	17-Apr	18-Apr	19-Apr	Average
American (total %)	1.4%	44.4%	33.9%	35.1%	36.4%	24.6%	34.4%	32.6%	30.0%	30.3%
Negative	1.4%	41.6%	31.1%	32.4%	33.7%	22.4%	32.0%	30.2%	27.8%	28.1%
Positive	0.0%	2.8%	2.8%	2.7%	2.7%	2.2%	2.4%	2.4%	2.2%	2.2%
United (total %)	98.4%	52.2%	61.5%	62.3%	61.7%	73.2%	62.8%	64.1%	65.9%	66.9%
Negative	96.0%	50.7%	60.3%	60.1%	61.0%	71.7%	61.1%	61.7%	63.8%	65.2%
Positive	2.4%	1.5%	1.2%	2.2%	0.7%	1.5%	1.7%	2.4%	2.1%	1.7%
Virgin (total %)	0.1%	3.4%	4.6%	2.6%	1.8%	2.2%	2.8%	3.3%	4.1%	2.8%
Negative	0.1%	2.9%	3.9%	2.2%	1.7%	1.9%	2.5%	3.0%	3.5%	2.4%
Positive	0.0%	0.4%	0.7%	0.4%	0.2%	0.4%	0.3%	0.2%	0.6%	0.3%

As we can see above, we have on average 67% tweets for United everyday and around 30% for American airlines. We can also see that the negative reviews are higher in percentage compared to the positive reviews. Since Virgin airlines is not as frequently used by travelers as compared to American or United, they also have lower percentage of reviews. As a next part in our analysis we found the split between the positive and negative reviews for all the airlines. The results are given below in table 2:

Table 2

		11-Apr	12-Apr	13-Apr	14-Apr	15-Apr	16-Apr	17-Apr	18-Apr	19-Apr	Average
American	Negative	100.0%	93.7%	91.8%	92.4%	92.6%	91.2%	93.1%	92.6%	92.5%	92.6%
	Positive	0.0%	6.3%	8.2%	7.6%	7.4%	8.8%	6.9%	7.4%	7.5%	7.4%
United	Negative	97.5%	97.1%	98.1%	96.5%	98.8%	98.0%	97.3%	96.3%	96.9%	97.4%
	Positive	2.5%	3.0%	1.9%	3.5%	1.2%	2.1%	2.7%	3.7%	3.1%	2.6%
Virgin	Negative	100.0%	87.5%	84.7%	85.7%	91.5%	83.6%	90.9%	92.6%	86.3%	87.6%
	Positive	0.0%	12.5%	15.3%	14.3%	8.5%	16.4%	9.1%	7.4%	13.7%	12.4%

From the table above we find that the percentage of negative reviews for United airlines have been quite high from the 11th of April and this is attributed to the negative event that occurred with the passenger. We can also see a slight drop in the percentage of negative reviews on the 14th of April which could be attributable apology that the CEO asked using social media and news channels but this needs to be further tested. In general we can see that the negative reviews do not go down significantly and there is still a high percentage of negative reviews throughout the time period. We then calculated the cross elasticity of negative reviews on positive reviews. This is given by the below formula:

$$\frac{\%\ change\ in\ the\ positive\ reviews\ of\ airline\ 2}{\%\ \text{change in the negative reviews of airline 1}}$$

In our scenario, the airline 1 is United airlines and the airline 2 can be either American airlines or Virgin airlines. To calculate the percentage change, we took the difference in the percentages across 2 consecutive days divided by the average of the percentages of the two days given by:

$$\frac{\%\ of\ day\ 1 - \%\ of\ day\ 2}{0.5 * (\%\ of\ day\ 1 + \%\ of\ day\ 2)}$$

We got the following elasticities given in table 3

Table 3

Airlines	11th and 12th	12th and 13th	13th and 14th	14th and 15th	15th and 16th	16th and 17th	17th and 18th	18th and 19th
American/United	27.80	-3.19	-0.77	2.78	10.37	-13.07	-1.79	-11.83
Virgin/United	13.67	-1.98	-0.41	0.11	1.72	-3.13	0.44	-0.18

From the above table, we can see that on the change between 11th and 12th, the elasticity value is very high and this could be possibly due to the high negative feeling of customers towards United and this would result in a high positive feeling towards the other brand. On average, found that the elasticity of positive reviews was 1.29 which is > 0 and implies that the airlines are substitutes and people would not mind switching to another airline when there is something they do not like about a particular airline. One interesting finding we see is that for both American and Virgin, the elasticity is on average positive till 16th and then becomes negative going forward. This could be possible because the customers will now feel less negative towards United and the impact goes lower.

Managerial Implication

There are many occasions when managers want to get an advantage over the competitor and if possible try to capture the customers from competitor. Negative events like what happened to United airlines provide such an opportunity to managers of competing airlines to capture customers. Although negative events may happen with the competitors' products, their customers may still have a positive sentiment towards the products and the firm. Sources like twitter will help managers to identify what is the general trend in the sentiment of people. Also, what would be a good time for a manager to send marketing messages and ads in order to get positive sentiment towards his or own brand. To answer these questions, managers need to be proactive and identify the right time and days to send the ads. This will be a more effective way of advertising than a traditional way of advertising.

References

Abhishek Borah and Gerard J. Tellis (*2016*) Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?. Journal of Marketing Research: April 2016, Vol. 53, No. 2, pp. 143-160.

Bollen, Mao, and Zeng. "Twiter Mood Predicts the Stock Market." Journal of Computational Science. 2011.

Chevalier and Mayzlin. "The Effect of Word of Mouth on Sales: Online Book Reviews." 2006.

Dewan, Sanjeev and Ramaprasad, Jui. 2014. "Social Media, Traditional Media, and Music Sales," MIS Quarterly, (38: 1) pp.101-121.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales-An empirical investigation of the movie industry. Journal of Retailing, 84(2), 233-242.

Hardin. "The Tragedy of the Commons." Science. 1968.

Hirschman, Albert O. (1993): Exit, Voice, and the Fate of the German Democratic Republic: An Essay in Conceptual History, in: World Politics, 45(2): 173-202

Katz, E. & Lazarsfeld, P.F. (1955) ‘Personal influence: The part played by people in the flow of mass communications‘, The Free Press, New York.

Kietzmann, Hermkens, McCarthy, and Silvestre. "Social Media? Get Serious! Understanding the functional building blocks of social media." Business Horizons. 2011.

Marotti and Zumbach. "United Airlines' brand takes a beating after bumped passenger dragged off plane." chicago Tribune. 2017.

Murray, K.B. (1991) A test of services marketing theory: consumer information acquisition activities. Journal of Marketing 55, 10–25.

Sahni, Navdeep (2013), “Advertising Spillovers: Field-Experiment Evidence and Implications for Returns from Advertising,”

Scott A. Thompson, Molan Kim, and Keith Marion Smith (2016) Community Participation and Consumer-to-Consumer Helping: Does Participation in Third Party–Hosted Communities Reduce One’s Likelihood of Helping?. Journal of Marketing Research: April 2016, Vol. 53, No. 2, pp. 280-295.

Scott A. Thompson, Rajiv K. Sinha (2008) Brand Communities and New Product Adoption:The Influence and Limits of Oppositional Loyalty. Journal of Marketing: November 2008, Vol. 72, No. 6, pp. 65-80.

Thomas Hickman and James Ward (2007) ,"The Dark Side of Brand Community: Inter-Group Stereotyping, Trash Talk, and Schadenfreude", in NA - Advances in Consumer Research Volume 34, eds. Gavan Fitzsimons and Vicki Morwitz, Duluth, MN : Association for Consumer Research, Pages: 314-319.

Turner and Oakes. "The significance of the social identity concept for social psychology with reference to individualism, interactionism and social influence." 1986.

Ward and Ostrom. "Complaining to the Masses: The Role of Protest Framing in Customer-Created Complaint Web Sites." 2006.

Yong Liu. “Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue.” *Journal of Marketing*. Vol. 70, No. 3 (Jul., 2006), pp. 74-89

Zeithaml, V.A., Berry, L.L. and Parasuraman, A. (1993), ``The nature and determinants of customer expectations of service", Journal of the Academy of Marketing Science, Vol. 21, pp. 1-12