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Can Tweets Kill a Movie? An Empirical Evaluation of the *Bruno* Effect

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Abstract

On Friday, July 10th 2009, the movie *Bruno* was number one at the box office and took in over $18.8 million in revenue. Based on this initial performance, analysts predicted the movie would rake in over $50 million in its opening weekend. By Saturday, however, the movie experienced an unusually sharp 38% decline in box office receipts. Several prominent journalists speculated that comments on the social media site Twitter.com may have amplified negative word-of-mouth about the movie and caused the dramatic fall-off in revenue. We investigate this '*Bruno* effect' and, contrary to popular accounts, find that the valence of comments on Twitter, without accounting for other factors, is only weakly associated with changes in box office performance. We do find evidence, however, of a "midnight effect," in which movies with cult-like followings that open Thursday at midnight see significant drops in revenue between Friday and Saturday. In addition, we find strong evidence that, after accounting for a few factors like midnight openings and the volume of tweets, twitter sentiment is positively associated with increases in Friday-to-Saturday revenue. While we cannot show online word-of-mouth is causing changes in offline consumer behavior, these models could still be useful for estimating important outcomes like opening weekend box office performance.

Keywords

Twitter, Movies, Word-of-Mouth, Box office

ACM Classification Keywords

H.5.2 Information Interfaces and Presentation: User interfaces – Evaluation/ methodology

Introduction

Over the last decade, online social media has grown explosively and transformed how people communicate, transact, organize and are entertained. Twitter is a leading social media site in which users can post short, 140 character messages or "tweets" for public viewing. The site was founded in 2006 and is now the thirteenth most popular site on the Internet [1]. Over the last three years, Twitter has been credited with playing an important role in a wide variety of contexts including political campaigns, legal proceedings, citizen activism, news reporting and emergency response. Twitter has also been described as dramatically amplifying the effects of word-of-mouth feedback among consumers. In the summer of 2009, the movie *Bruno*, was released and was number one among movies released that weekend. Between Friday and Saturday, however, the movie experienced a 38% drop-off in revenue, substantially more than other new movies. Widespread speculation among journalists and bloggers suggested that word-of-mouth on twitter might have "killed *Bruno*" [3, 6, 8, 4]. The evidence for these assertions, however, was largely anecdotal.

This paper investigates if comments on Twitter exhibit any relationship to box office revenue over opening weekend. Echoing the questions posed by journalists and bloggers, we focus particularly on whether tweets on the Friday of opening weekend are associated with future changes in revenue, especially changes in the percent change in box office receipts between Friday and Saturday.

On a broader level, we look at whether Twitter microblogging for a film has any explanatory power for box office gross above existing models. We also investigate the relationship between a movie's Twitter presence and various other measures of its success (e.g. critical reception). More specifically, we investigate whether sentiment expressed on Twitter could plausibly influence movie box office performance in the way suggested by commentators around Bruno's opening weekend.

Literature Review

Standard predictive models of movie performance do not include word-of-mouth data; Basuroy, Chatterjee & Ravid (2003) concluded that critical reviews, budgets and star power are the strongest predictors of box office success[2]. Using weblog data, Mishne & Glance (2005) found that positive sentiment in posts is a better predictor of box office success than the volume of discussion alone [7]. Using IMDB movie information and the Blogpulse index, they concluded that positive sentiment in the pre-release period was better correlated with movie success than pre-release blog post count was. Zhang & Skiena (2009) used IMDB and movie news data to predict box office grosses, and found that the volume and sentiment of movie news coverage improved the predictive performance of a model based only on IMDB data (budget, number of screens, etc.) [9]. In addition, a market research firm conducted a small analysis of Twitter's influence on *Bruno*. Hampp (2009) reported on a comparison between Twitter traffic for *Bruno* and three other summer movies during their opening weekends [5]. Although it was found that *Bruno* had the highest number of negative tweets and negative percentage change between first- and second-day grosses, Hampp emphasized that the analysis cannot attribute causal influence to Twitter.

Data

This project used three sets of data on Twitter and three on movie performance to address our questions of interest. The first Twitter dataset was approximately 200,000 downloaded tweets that each mentioned one of 58 different current movies. This data came from the website TwitCritics.com, which aggregates tweets by their referenced movie and performs a sentiment analysis on each tweet, evaluating it as either a positive or a negative review. Table 1 presents summary statistics for the movie and twitter data.

TwitCritics.com only provides information for movies launched since fall of 2009, and so the second Twitter dataset, which produced the information for *Bruno*, came from Tweetscan.com, an archive of tweets. We then developed a sentiment analysis model to automatically predict sentiment ratings of tweets, and to replicate the algorithm provided by TwitCritics.com.

Using the data set of 200,000 tweets and ratings from TwitCritics, we then trained the content analysis model in two stages. First, noise words (like "the," "about," "from,") and noise characters (punctuation and non-ASCII characters) were removed from the text of the tweets. We then produced a set of statistics for each word in the training data that included: percentage of total occurrences that the word appeared in a positive statement, an indicator variable for whether the word only appeared in a positive or negative statement, and the total number of occurrences of the word in the training data. In the second stage, the model was supplemented with hundreds of known positive and negative words. Due to the high sentiment reliability of these words, the model was adjusted to weight them highly.

The third set of Twitter data was used as a diagnostic for the TwitCritics sentiment analysis. The data came from Amazon Mechanical Turk (MTurk), a virtual marketplace that enables computer programs to co-ordinate the use of human intelligence to complete tasks that are difficult for computers to perform. We posted 2,787 of our TwitCritics tweets (approximately 100 per movie for 31 movies) to be evaluated as either extremely negative, negative, neutral, positive or extremely positive. Each tweet was evaluated individually by a person. We then had a human-coded sentiment to compare with the TwitCritics sentiment analysis. Table 3 presents a summary of the comparison between the human coded and algorithmic methods employed by TwitCritics.com. As a simple validation check, the MTurk data suggest that the TwitCritics ratings are fairly accurate, especially when we have a sufficient number of tweets. Further diagnostics follow later in the paper.

For movie performance data, we downloaded variables including box office total gross revenue, number of theaters opening weekend, production budget, genre, and a proxy for actors' star power. These predictors consist of all the basic information that we could obtain and which prior literature suggested was potentially relevant for predicting box office performance. Most of this information came from the-numbers.com and boxofficemojo.com, movie data aggregators. Lastly, we downloaded data on critical reception by journalists from RottenTomatoes.com, which aggregates critical reviews for films, determines whether each movie is positive or negative, and then calculates the percentage of positive reviews for each movie (its "Tmeter"). In addition, after studying a cluster of observations with very large drops in revenue between Friday and Saturday, we added a binary variable for films that have a Thursday midnight opening.

Diagnostics

Diagnostic plots (not shown) suggest that the model assumptions hold; namely, the residuals appear independent

Table 1: **Summary Statistics, Movie and Twitter Data**

	Mean	SD
# Theaters on Day 1	1,744	1,307
Budget	49,094,810	4,5638,800
Mean Critics Reviews	0.45	0.24
Num Tweets Day 1 + 2	1,189	1,515
Day 1 Revenue	6,971,092	10,603,440
Day 2 Revenue	6,440,534	7,067,621
Day 2 Percent Change	0.11	0.29
Mean Sentiment Day 1	0.73	0.12
# Tweets Day 1	447	723

and normally distributed. The Shapiro-Wilk test for normality of the residuals produces a test statistic of 0.97 with a corresponding p-value of 0.50. We cannot reject the null, and can conclude that the residuals are normally distributed. Plotting residuals against leverage, suggests the residuals all lie within an acceptable range of Cook's distance. Moreover, the model was robust to removing outlying observations.

In addition to the model diagnostics, we also evaluated the TwitCritics sentiment analysis by comparing a subsample of the exact same tweets to human coders on Amazon Mechanical Turk (MTurk). For each movie we took the average sentiment rating from MTurk and compared them to the average rating obtained from TwitCritics. Performing a paired t-test, the results show there is a statistically significant difference in the two sample means of 0.036 (on a 0-1 scale) with a two-sided p-value of 0.002. However the magnitude of this difference, for practical purposes, is quite small (see Table 3 in Appendix). Although the paired t-test shows that there may be some minor discrepancies between the TwitCritics and MTurk content analyses, in general the MTurk results appear to corroborate the sentiment ratings from TwitCritics.

Analysis

We are interested in predicting the change in revenue between the first and second day of a movie's release. Our response variable is the percentage change in revenue (the difference in revenue between day one (Friday) and day two (Saturday) divided by the day one revenue). We used two different measures of Twitter activity for each movie. The first measure was the number of tweets for each movie on the first day of release. The second variable was the mean sentiment (between 0 and 1) for each movie on the first day of release. We included these two different measures because they capture different aspects of the word-of-mouth presence, namely, the volume and positivity of Twitter attention.

Initial analyses showed that models with all movie performance variables included too many confounders to reveal meaningful relationships, and subsequently we investigated more parsimonious models more appropriate for our questions of interest. In particular, the indicator variable we constructed for sequel had little explanatory power. We also attempted to incorporate a variable for "star power," a measure of the box office success of the particular actors in each movie. Although RottenTomatoes.com provides a variable for this, it is calculated from the same set of critical review sentiments as the Tmeter variable, and to avoid multicollinearity, we omitted the star rating from the model.

After the preliminary data analysis exploration (not shown) we then constructed a full model including all variables that seemed substantively important and not obviously confounded. This model included the following covariates: the log of the number of tweets on day one, the mean tweet sentiment, the log of the production budget, the number of theaters on day one, the Tmeter (the RottenTomatoes.com measure of critical reception) and whether the opening weekend began on Thursday at midnight.

Full model for percent change in revenue from Friday to Saturday

$$\begin{aligned} \hat{y}_{\%chg} &= \beta_1 log(x_{\#tweets}) + \beta_2 x_{sentiment} + \\ &+\beta_3 log(x_{budget}) + \beta_4 log(x_{\#thtrs}) + \\ &+\beta_4 sqrt(x_{tmeter}) + \beta_5 x_{midnight} + \epsilon \end{aligned} \quad (1)$$

Table 2: **Change in Revenue vs Number and Sentiment of Tweets**

	Dependent variable:					
	Percent Change in Revenue, Fri to Sat					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Number Tweets Day 1)	-0.13^{***}		-0.13^{***}	-0.15^{***}	-0.09^{***}	-0.11^{***}
	(0.02)		(0.02)	(0.02)	(0.02)	(0.02)
Mean Sentiment Day 1		0.49^{*}	0.67^{***}	0.62^{***}	0.84^{***}	0.84^{***}
		(0.29)	(0.23)	(0.22)	(0.22)	(0.21)
log(Budget)				0.09^{***}		0.10^{***}
				(0.03)		(0.04)
Midnight Release					-0.27^{***}	-0.27^{***}
					(0.08)	(0.07)
Number Theaters						-0.0000
						(0.0000)
sqrt(Critical Rating)						-0.11
						(0.13)
Constant	0.83^{***}	-0.21	0.39^{*}	-1.10^{*}	0.09	-1.52^{**}
	(0.14)	(0.21)	(0.20)	(0.58)	(0.20)	(0.61)
Observations	57	57	57	57	57	57
R^2	0.32	0.05	0.41	0.49	0.52	0.61
Adjusted R^2	0.31	0.03	0.39	0.46	0.50	0.56
Residual Std. Error	0.22 (df = 55)	0.26 (df = 55)	0.21 (df = 54)	0.19 (df = 53)	0.19 (df = 53)	0.17 (df = 50)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2 presents the regression results for six specifications. Models (1) and (2) present naive bivariate models of the two Twitter metrics. The number of tweets (logged) is negatively and significantly correlated with the change in box office revenue. Figure 1 presents a plot of this relationship. While we might expect a higher tweet volume to be associated with increasing revenue between Friday and Saturday, the result is robust across a variety of specifications. One possible explanation is that a large volume of tweets before a film opens is associated with aggressive marketing campaigns that help generate outsize excitement for opening night but, relatively speaking, contribute to declines in revenue on following nights.

Model (2) shows that the mean tweet sentiment, on its own, is positively but only weakly associated with an increase in revenue between Friday and Saturday. See Figure 2 for a visualization of this relationship. When both Twitter metrics are included in Model (3), the magnitude of the coefficient on tweet sentiment increases and becomes statistically significant. Adding the film's budget, in Model (4), does not substantively change either of the coefficients on the Twitter metrics but, as measured by Adjusted R^2, the overall explanatory power of model does improve. Similarly, in Model (5), the Twitter metrics are robust to inclusion of the binary variable for a Thursday midnight release. With the indicator for midnight opening, the magnitude of coefficient for sentiment increases substantively on the zero to one scale. Finally, in Model (6), again the main Twitter metrics are robust to inclusion of the number of theaters on opening night and measures of critical acclaim.

The results in Table 2 Model (6), suggest that a doubling in the number of tweets is associated with a 10 percentage point decrease in the percentage change in revenue from day one to day two ($p < 0.01$). Also results in Model (6) suggest a one unit increase in mean sentiment, from a uniformly negative rating of zero to a uniformly positive rating of one, is associated with an approximately 84 percent increase in revenue from Friday to Saturday ($p < 0.01$).[2]

Discussion

Is there a '*Bruno* effect'? Overall, evidence does suggest the valence of tweets is positively associated with increases in Friday-to-Saturday revenue, suggesting that word-of-mouth can improve a film's weekend box office. Further, the volume of tweets appears to be independently and negatively associated with the percent change in revenue between Friday and Saturday.

For the film *Bruno*, however, our results suggest that the popular interpretation that the film tanked due to negative tweets is wrong. The simple bivariate relationship between change in revenue and sentiment, as presented in Figure 2, does initially suggest a '*Bruno* effect.' Specifically, in the lower left-hand corner of the Figure 2, *Bruno* has both a low mean Friday sentiment score of 0.58 and an atypically large decrease in Friday-to-Saturday revenue of about 39 percent. In Figure 2, *Bruno*'s revenue metrics are far below the predicted values in the linear model.

As Figure 3 shows, however, a subset of films including *Bruno* open on Thursday at midnight. Consequently, Friday revenue includes many Thursday night / Friday morning screenings that appear to boost Friday ticket sales but that result in large decreases going in to Saturday. Figure 3 presents two separate models, one for films with and one for films without midnight screenings. As can be seen in Figure 3 along the linear model for non-midnight openings (black line), Many films actually receive worse mean sentiment ratings than *Bruno* but do not experience dramatic reductions in Friday-to-Saturday revenue. When midnight screenings are accounted for in

[2] The observed values of the sentiment measure range from 0.38 to 0.95 so, in these data, there are no films with mean sentiment scores close to zero.

the model (red line in Figure 3), Twitter sentiment still matters but *Bruno* actually outperforms the predicted Friday-to-Saturday percent change in revenue given its below average sentiment measure. In short, while word-of-mouth on Twitter is associated with significant changes in day-to-day box office revenue, the specific claim of '*Bruno* effect' actually appears to be detecting a distinct midnight opening effect.

Figure 1: **Twitter Volume vs. % Change in Day 1 to Day 2 Revenue**

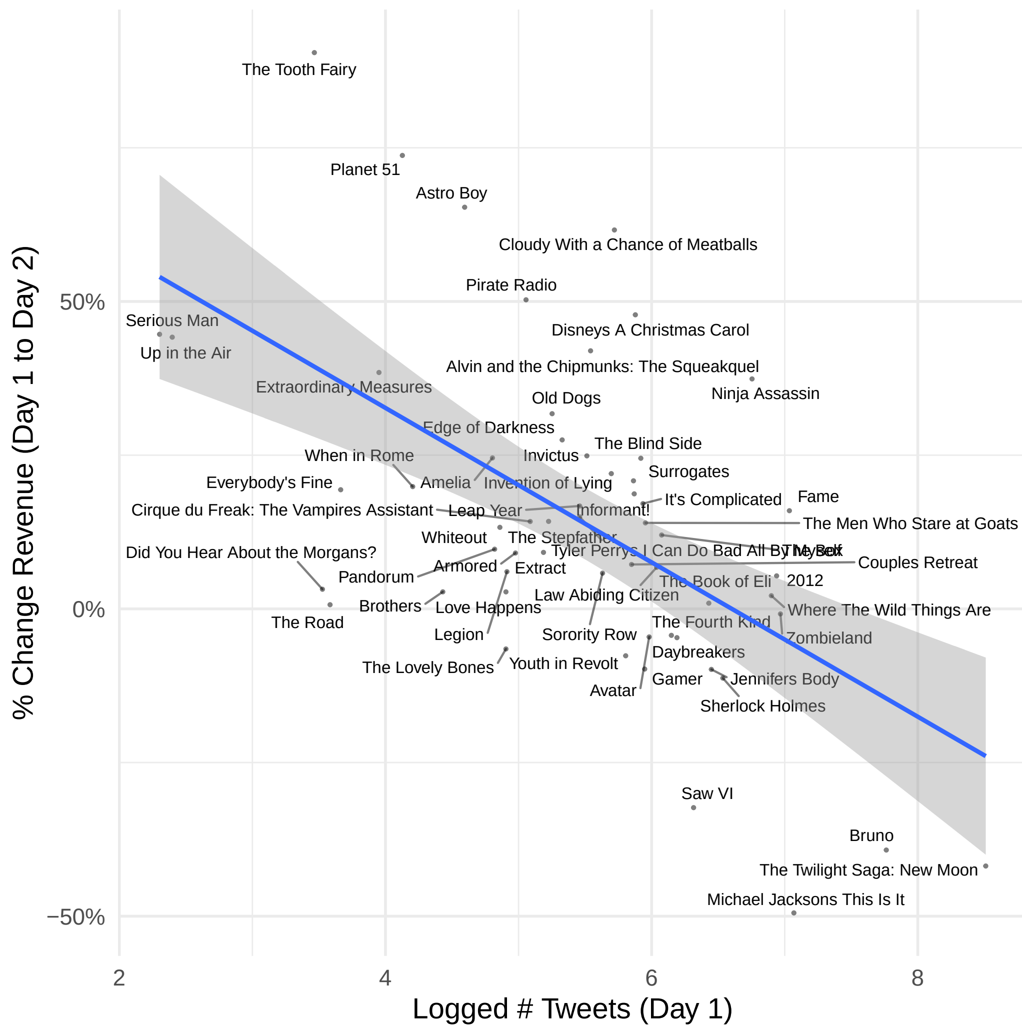


Figure 2: **Percent Change in Day 1 to Day 2 Revenue vs Twitter Sentiment**

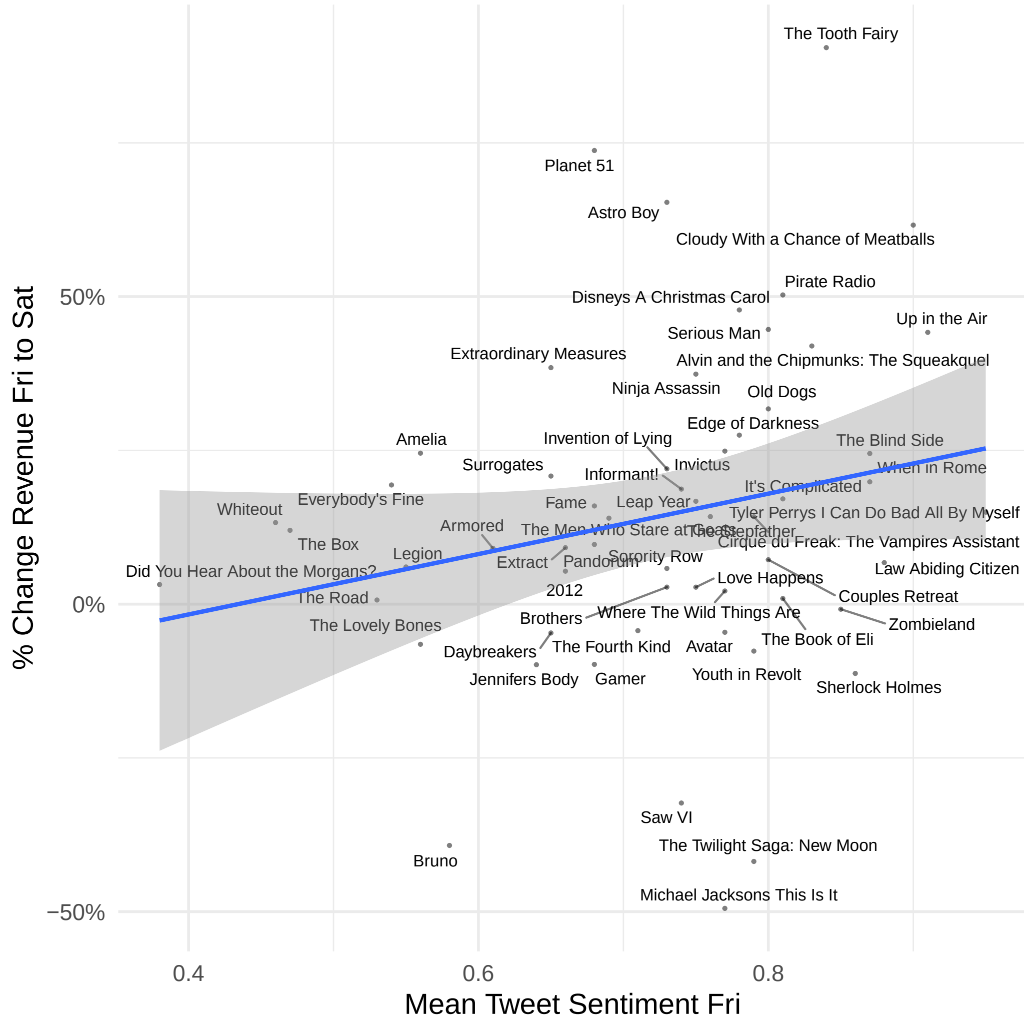
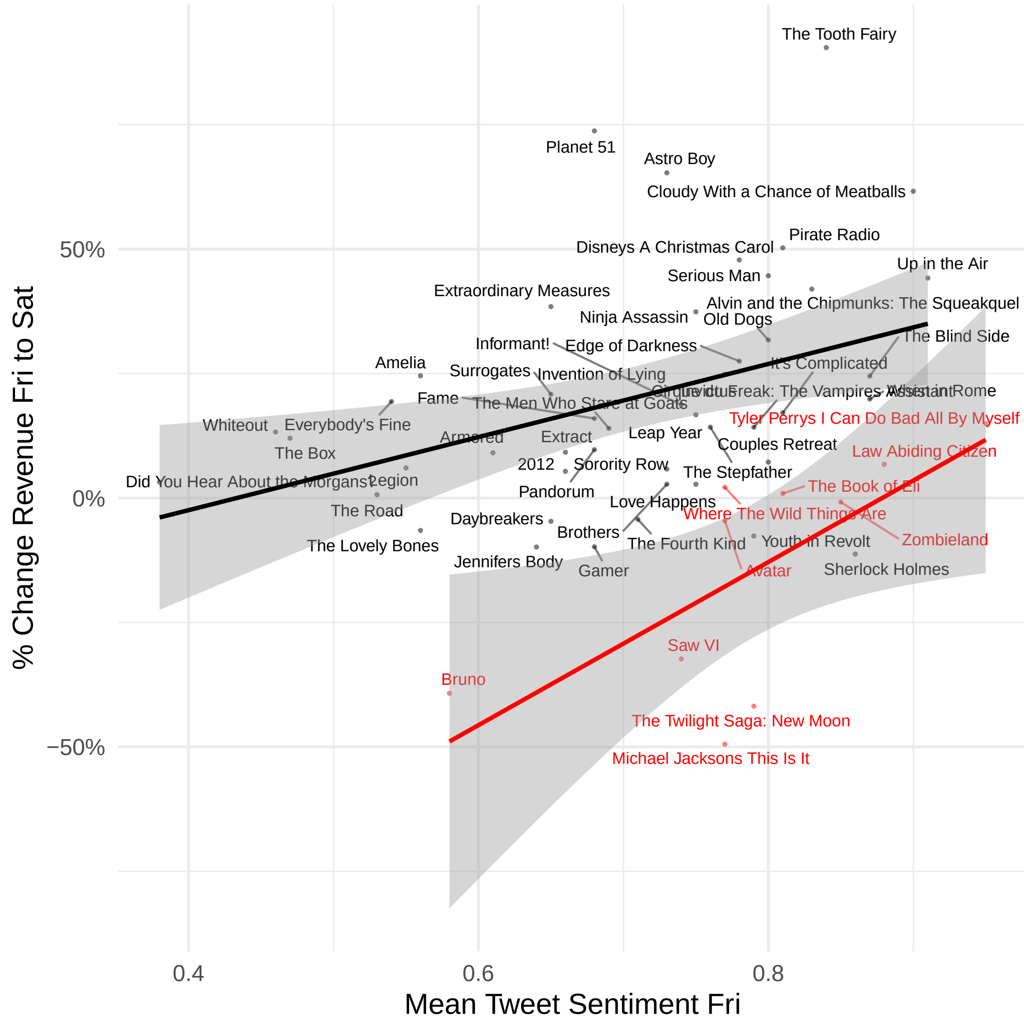


Figure 3: **Percent Change in Day 1 to Day 2 Revenue vs Twitter Sentiment. (Midnight Thursday releases in red.)**



Limitations

These results suffer from a number of important limitations. Though hundreds of thousands of tweets were used to calculate mean film sentiment, the ultimate N of the study is only 57 movies. Further data collection and analysis are necessary to validate these results In addition, some of the Twitter data was censored in that tweets were almost all mined on two dates and may not reflect the full breadth of sentiment. In addition, it was not possible to include data from much beyond opening weekend in the analysis because the different movies had been in theaters for various and non-comparable periods of time. Although it would have been preferable, it was not possible to obtain historical data on movies that had completed their entire theater runs due to limitations in the Twitter and TwitCritics archives. The necessary discarding of the majority of our Twitter data was also not ideal, and a larger data set containing more movies, collected over a longer period of time, could improve the analysis.

Conclusions

Contrary to popular accounts, we do not find evidence of a specific '*Bruno* effect' in which negative word-of-mouth on Twitter about a specific film explains its notable decline in opening weekend box office performance. More generally, however, we do find that the number of tweets has a significant association with a negative change in revenue between Friday and Saturday and that the mean sentiment of the tweets on Friday is predictive of an increase in Friday-to-Saturday revenue, after accounting for factors like budget and whether the film has a Thursday midnight opening. In short, volume and valence matter, but other factors appear to matter more for the alleged '*Bruno* effect.'

More generally, if the relationship between tweet volume, sentiment and revenue during opening weekend is found to be present in larger and different data sets, then Twitter is potentially a valuable source of nearly free and real-time public opinion that could provide useful information for forecasting movie performance.

References

[1] Traffic stats for twitter.com, January 2010.

[2] S. Basuroy, S. Chatterjee, and S. Ravid. How critical are critical reviews? the box office effects of film critics, star power, and budgets. *Journal of Marketing*, 67(October):103–117, Jan 2003.

[3] R. Corliss. Box-office weekend:Brüno a one-day wonder?, July 2009.

[4] J. V. Grove. Did opening night twitter reviews sink *Bruno's* weekend box office?, July 2009.

[5] A. Hampp. Forget Ebert: How Twitter makes or breaks movie marketing today, 2009.

[6] M. Keane. Did Twitter bury "Bruno'"?, July 2009.

[7] G. Mishne and N. Glance. Predicting movie sales from blogger sentiment. *AAAI 2006 Spring Symposium on Computational Approaches to Analysing Weblogs*, 2006.

[8] A. Salkever. Did Twitter kill 'Bruno'? maybe not, July 2009.

[9] W. Zhang and S. Skiena. Improving movie gross prediction through news analysis. *wi-iat*, 1(2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology):301–304, 2009.

Appendix

Table 3: **TwitCritics and Human Coded Sentiment Ratings, Select Movies**

	Movie Name	# Tweets	MTurk Sent.	Twit. Sent.	Diff.
1	Amreeka	6	1.00	1.00	0.00
2	Extract	75	0.79	0.69	0.09
3	Gamer	78	0.71	0.74	-0.04
4	Sorority Row	79	0.86	0.82	0.04
5	Tyler Perry's I ...	92	0.95	0.98	-0.03
6	Whiteout	74	0.36	0.39	-0.03
7	Bright Star	20	0.85	0.70	0.15
8	Burning Plain	19	0.79	0.79	0.00
9	Cloudy With a ...	91	0.99	0.96	0.03
10	Informant!	70	0.83	0.73	0.10
11	Jennifers Body	77	0.74	0.69	0.05
12	Love Happens	82	0.79	0.78	0.01
13	Fame	71	0.83	0.83	0.00
14	Pandorum	75	0.87	0.83	0.04
15	Surrogates	71	0.72	0.69	0.03
16	Invention of ...	78	0.79	0.78	0.01
17	Zombieland	85	0.98	0.93	0.05
18	Serious Man	21	0.90	0.67	0.24
19	Couples Retreat	87	0.92	0.91	0.01
20	Law Abiding ...	90	0.94	0.92	0.02
21	The Stepfather	75	0.75	0.71	0.04
22	Where The Wild ...	79	0.90	0.84	0.06
23	Amelia	50	0.60	0.66	-0.06
24	Astro Boy	73	0.92	0.84	0.08
25	Saw VI	83	0.83	0.69	0.14
26	Cirque du Freak: ...	82	0.93	0.89	0.04
27	Michael Jackson's ...	80	0.96	0.90	0.06
28	The Box	78	0.46	0.49	-0.03
29	Disneys A Christmas ...	87	0.92	0.87	0.05
30	The Fourth Kind	67	0.79	0.82	-0.03
31	The Men Who Stare ...	82	0.77	0.78	-0.01

Figure 4: **Twitter Volume vs. % Change in Day 1 to Day 2 Revenue. (Midnight Thursday releases in red.)**