The impact of amateur film reviews on movie theater attendance: predictors versus influencers

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May 2016

Preliminary draft

Abstract

Previous studies indicated that electronic word-of-mouth is positively related to product sales. Yet, rare studies investigated whether this positive relationship suggests causality or merely reflects the impact of unobservable product characteristics. The discussion about the impact of critic reviews in film industry suggests that if a correlation between positive reviews and good attendance reflect merely positive movie-specific characteristics, these critic reviews have only a prediction effect; otherwise, they have also an influence effect. We apply this definition on amateur online reviews, and try to distinguish these two effects by a panel dataset. We combine the information regarding amateur reviews for each film in every week and a dataset containing the theater attendance for each film in every theater and week in Taipei. We analyze this dataset by random effect and fixed effect models. Our results indicate that although only positive reviews have a positive prediction effect; the one having negative prediction and influence effects is a neutral review. Moreover, we also find that Taiwanese audience responds differently to reviews regarding native or foreign movies.

Keywords: film industry; word-of-mouth; influence effect; prediction effect **JEL classfication:** L82, M31, M37

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1. Introduction

Word-of-mouth (henceforth, WOM) is defined as oral, non-commercial communication between receivers and communicators (Arndt, 1967). Because of the rapid development of internet, electronic word-of-mouth (henceforth, eWOM) becomes a new communication model. Compared to traditional WOM, eWOM enables asynchronous feedback, which means that consumers can easily get the information even nobody present at the place where the communication occur. Therefore, eWOM is considered as having strong impact on consumers; previous studies suggested that consumers' decisions, especially online shoppers' decision, are significantly affected by online reviews (Chevalier and Mayzlin, 2006; Duan, Gu, and Whinston, 2008). However, rare studies further investigated whether the observable relationship between the valence of reviews and product sales suggests causality or reflect merely the impact of other unobservable factors.

Previous studies regarding movies indicated that professional critic reviews may serve in two different roles in consumer decisions: influencers and predictors. Eliashberg and Shugan (1997) pointed out that as an influencer, critic review provides relevant information to consumers and causally increases patronage; yet, if critic review is only a predictor, a correlation between good reviews and high demand may merely reflect some positive movie-specific characteristics, such as good film quality, which are unobservable to econometricians. The impacts of the two roles may mix together and we can only observe a total effect of them. Similarly, online consumer reviews, such as enthusiastic amateur film reviews, may also have both roles: When consumers post 5-stars online reviews for a movie, these reviews may encourage other consumers to see this movie; yet, 5-star reviews and high demand may happen simultaneously, and these two factors have no causality.

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This study empirically distinguishes between the influence effect and the prediction effect of online amateur film reviews by using panel data. Our idea is that if good reviews and high demand only reflect unobservable good movie characteristics, which are invariant over time, the change of reviews and the change of demand over time should not have a systematic relationship. Specifically, in this case, online reviews have only a prediction effect, which means that unobservable good film characteristics, such as cast, plots, or director power, simultaneously cause good reviews and high demand; because these film characteristics are constant over time, the change of (de-trended) reviews and (de-trended) demand over time should be casual. On the contrary, if the valence of online reviews can causally affect sales, the change of demand for a movie over time should be systematically related to the change of the valence of review over time.

2. Data

This study primarily combines four kinds of data. First, we collect information regarding weekly theater-level movie attendance from all theaters in Taipei; this information comes from LifeShow@movies website.¹ We collect 343 films released during the period from May to December in 2015. If there is a re-release movie, we define it as a new movie. Therefore, total number of movie collected (original plus re-release) is 490.

Secondly, information regarding amateur online reviews comes from the biggest non-commercial online forum in Taiwan, which is a bulletin board system (BBS) and called "PTT". PTT has over 1.5 million registered users (around 6.5% of the population of Taiwan), and during peak time, there are always over 150,000 users logging in PTT. The feature of PTT is that users can express "like" or "dislike" label to a particular article or review; most of other online forums or social media, such as Facebook, do not have this characteristic. Label can help us distinguish the quality of article. In this study, we

¹ <u>http://movies.lifeshow.com.tw/</u>. Retrieved 25 February 2016.

focus on the Movie board in PTT, where enthusiastic film audience posts their reviews. In that board, users have to markup "positive", "neutral" or "negative" in the topic for their reviews. We also collect information regarding professional film reviews which were released on Next Magazine, the most popular magazine in Taiwan. On Next Magazine, professional critics regularly published their reviews and gave a score from 0 to 100 for each film in the first or second week. Some cult movies received no professional reviews; we have a variable indexing whether the film received a score assigned by professional critics.

Thirdly, we collect information regarding official trailers for each movie in Youtube. We calculate the number of official trailers, cumulative viewers, like or dislike clickthrough rates and cumulative feedback amount.

Finally, we gather information regarding film characteristics, including film nationality, genre, rating, production budget, star power (measured by Google Trend for leading and supporting actor and actress), winners or nominees for awards, and whether the film was subsidized by Taiwan government. We also collect information about theater genre, whether the theater held a sneak preview for a film, and weekly number of theaters screening a film.

3. Methodory

Below is the reduced form of our basic regression model:

$$Y_{ijt} = \beta_0 + \beta_1 PTT_{it} + \beta_2 X_{ijt} + \beta_3 Z_i + u_i + w_j + \varepsilon_{ijt}$$

where Y_{ijt} is the number of audience for film i in theater j of week t. PTT_{it} is a vector containing variables measuring the accumulated numbers of "positive", " neutral" and "negative" amateur online reviews from PTT for each film in previous weeks. X_{ijt} is a vector containing control variables changing over time or over theaters; for example, information about trailers in Youtube are variables changing over time, and whether the theater held a sneak preview for a film is a variable changing over theaters. Z_i is a vector containing observable movie-specific variables, which are invariant over time and theaters, such as film production budget or star power. u_i is the impact from unobservable movie-specific variables, such as plots or camera movement. w_j is the impact from unobservable theater-specific variables, such as equipment for each theater; we use theater dummies to catch the effect of w_j .²

We first estimate coefficients in this model by random effect models and control for observable variables in Z_i . In this regression, the estimated β_1 usually includes prediction and influence effects except for the case where unobservable film characteristics are unrelated to PTT_{it} (that is, u_i is uncorrelated with PTT_{it}); if u_i is uncorrelated with PTT_{it} , the estimated β_1 contains only an influence effect.

To get rid of the prediction effects (the impact of u_i on the estimation of β_1), we then estimate coefficients in this model by fixed effect models. Specifically, by demeaning the variables, we construct a new regression model below:

$$(Y_{ijt} - \overline{Y}_i) = \beta_1 (PTT_{it} - \overline{PTT}_i) + \beta_2 (X_{ijt} - \overline{X}_i) + (w_j - \overline{w_i}) + (\varepsilon_{ijt} - \overline{\varepsilon}_i),$$

where \overline{Y}_{l} is the average attendance over time and theaters for the movie i. \overline{PTT}_{l} are the average numbers of "positive", "neutral" and "negative" amateur reviews for movie i over time. \overline{w}_{l} is the average impact from unobservable theater-specific variables over theaters for the movie i, such as the impact of average equipment over theaters screening movie i.

4. Results

Table 1 shows the result of the regression. In this table, the variables "week" and "week²" are designed to control for general time-trend for attendance; "week" variable indicates

 $^{^{2}}$ Actually, we can reasonably assume that w_{j} is uncorrelated with PTT_{it}. Our regression results, which we do not show here, suggest that the main results do not change too much if we do not include theater dummies.

the number of weeks after the movie was released. From Model B, one can find that under a random effect model, positive (negative) reviews are significantly and positively (negatively) related to the attendance, and a "negativity bias" exists; that is, the impact of negative reviews (37.13) is greater than the impact of positive reviews (14.40). The finding of "negative bias" here is similar to previous finding regarding professional reviews in the literature (Basuroy, Chatterjee, and Ravid, 2003). Moreover, through a comparison between Model A and B, one can find that the results about positive and negative reviews do not change too much after we control the influence of observable movie-specific variables.

However, the estimation under a fixed effect model (Model C and D) is quite different from that under a random effect model. From Model D, one can find that although positive reviews remain positively related to the attendance, the number of negative reviews has also a positive impact. Moreover, the number of neutral reviews has a strong negative impact.

Our estimation presented in Table 1 implies that the "negative bias" could be a result of strong prediction effect for negative reviews; and, negative reviews may actually have a positive influence effect. In other words, when a film has negative unobservable moviespecific characteristics, such as a bad story, attendance is poor and audience tends to post more bad reviews; however, these bad reviews may arouse people's interest to see that film. On the other hand, positive reviews have both positive prediction and influence effects.

Interestingly, neutral reviews have both negative prediction and influence effects.³ For movie producers, neutral reviews are worse than bad reviews.

(Table 1 around here)

³ The positive estimation for neutral reviews in Model A merely reflects the impact of observable moviespecific variables.

To understand whether audience responds differently to reviews regarding Taiwanese movies or non-Taiwanese movies, we also do regression including interaction terms between reviews and an indicator of Taiwanese films. Table 2 presents the results. From Model F, one can find that even under a fixed effect model, positive (negative) reviews for Taiwanese films are significantly positively (negatively) related to the attendance; moreover, even for influence effects, a "negative bias" also exists (|9.10+52.50| < |36.76-240.68|). However, for Taiwanese films, neutral reviews have no statistically significant impact (-179.68+110.49 = -69.19, p=0.15).

On the contrary, for non-Taiwanese films, both positive and negative reviews have a significantly positive influence effect. Moreover, for non-Taiwanese films, neutral reviews hurt. Therefore, our regression result presented in Table 1 basically reflect audience's attitude toward non-Taiwanese films.

(Table 2 around here)

5. Conclusion

This study investigates whether the relationship between eWOM and theater attendance in film industry suggests causality or reflects only impacts of unobservable movie-specific characteristics. We distinguish these two effects through a panel dataset, and compare the estimation under a random effect model and that under a fixed effect model. Our results indicate that although negative online reviews have a negative prediction effect, they have a positive influence effect. On the other hand, positive online reviews have positive prediction and influence effects. Interestingly, neutral online reviews have both negative prediction and influence effects. We have not yet found a satisfying explanation about why neutral reviews are worse than bad reviews.

Moreover, we also find that Taiwanese audience responds differently to reviews regarding Taiwanese movies or non-Taiwanese movies. For Taiwanese films, positive

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(negative) online reviews have positive (negative) prediction and influence effects;

neutral reviews have no significant impact on attendance. Why Taiwanese audience

responds differently to reviews regarding native and foreign films also needs further

investigation.⁴

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⁴ One possible explanation is that Taiwanese films are similar to "art" films, so their marketing relies on online reviews more than foreign films, such as Hollywood films, which have a high advertising budget and have more than one marketing channel. Therefore, this finding may be similar to the finding in Reinstein and Snyder (2005) and Gemser, Van Oostrum, and Leenders (2007) for art films.

Dependent variable: theater attendance for every film in each theater and each week											
Independent variables	(A)		(B)		(C)		(D)				
	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD			
PTT-positive review	14.73	1.74**	14.40	1.94**	35.42	4.20**	25.60	3.99**			
PTT-neutral review	30.14	7.53**	-43.66	7.53**	-156.05	13.26**	-194.99	12.56**			
PTT-negative review	-44.59	10.39**	-37.13	9.92**	17.60	17.23	31.98	16.23*			
Youtube trailer No.	33.29	8.20**	-38.63	9.96**	-508.24	201.06*	-721.47	188.86**			
Youtube viewer	3.7e-04	7.7e-05**	2.6e-04	7.7e-05**	-7.5e-04	1.6e-04**	-1.0e-03	1.5e-04**			
Youtube like	0.02	0.02	0.04	0.03	0.22	0.13	0.11	0.12			
Youtube dislike	-1.91	0.15**	-1.68	0.15**	-0.38	0.70	-0.87	0.66			
Youtube comment	3.36	0.28**	2.97	0.29**	0.71	1.37	1.92	1.29			
Expert reviews: score	54.85	8.79**	41.03	9.81**	-37.10	29.11	13.92	27.53			
No expert review	3927.80	712.69**	3404.95	791.50**	-3958.35	2330.35	815.30	2205.32			
Hollywood film	739.70	69.07**	-118.36	76.50							
Taiwanese film	-331.42	82.76**	-5.52	98.91							
Week	-461.78	36.11**	-358.01	34.16**	-517.48	46.55**	-261.82	44.78**			
Week ²	-11.47	3.33**	-0.34	3.18	-1.83	4.23	8.60	4.00*			
Production budget			0.37	0.02**							
No budget data			204.57	74.67**							
Star power			72.22	10.07**							
Award			36.47	70.60							
Government subsidy			-4.3e-05	5.9e-06**							
# of screening theaters			18.92	0.64**			23.43	0.74**			
Constant	-1289.00	719.06	-1526.60	894.75	11267.06	2703.37**	8320.25	2670.05**			
Random/Fixed Effect	Random		Random		Fixed		Fixed				
Theater dummies	Yes		Yes		Yes		Yes				
R-squared: within	0.21	0.21 0.33			0.30		0.38				
R-squared: overall	0.26		0.39								
No. of Obs.	8416		8416		8410	5	8416	5			

Table 1 The effect of amateur online reviews on theater attendance

Note: * p < .05; **p < .01; due to the lack of space, we do not show the results for variables of weather,

theater genre, movie release month, film genre, rating, and sneak preview in this table.

Table 2 The effect of amateur online reviews on theater attendance
Taiwanese films vs. non-Taiwanese films

Independent variables		(E)	(F)		
-	Coeff.	SD	Coeff.	SD	
PTT-positive review	15.27	2.35**	9.10	4.41*	
PTT-neutral review	-57.10	8.17**	-179.68	13.13**	
PTT-negative review	-18.73	10.52	36.76	16.70*	
Taiwanese film	95.86	100.87			
Taiwan* PTT-positive review	4.30	5.58	52.50	9.82**	
Taiwan* PTT- neutral review	44.76	29.96	110.49	49.14*	
Taiwan* PTT-negative review	-198.48	38.88**	-240.68	57.49**	
Youtube trailer No.	-43.91	10.52**	-461.68	190.93*	
Youtube viewer	3.9e-04	8.6e-05**	-4.2e-04	1.6e-04**	
Youtube like	-0.01	0.03	-0.84	0.15**	
Youtube dislike	-1.79	0.16**	-0.33	0.68	
Youtube comment	3.27	0.30**	2.16	1.31	
Expert reviews: score	26.10	10.15**	9.82	28.15	
No expert review	2197.23	818.47**	337.40	2256.27	
Hollywood film	-140.31	76.68			
Week	-347.56	35.28**	-323.85	45.09**	
Week ²	-0.73	3.30	20.73	4.16**	
Production budget	0.37	0.02**			
No budget data	172.64	75.00**			
# of screening theaters	19.09	0.64**	23.46	0.73**	
Constant	-233.51	928.51	7047.60	2748.26**	
Random/Fixed Effect	Random		Fixed		
Theater dummies	Yes		Yes		
R-squared: within	0.33		0.39		
R-squared: overall	0.40				
No. of Obs.	8416		8416		

Dependent variable: theater attendance for every film in each theater and each week

Note: * p < .05; **p < .01; due to the lack of space, we do not show the results for variables of star power, award, government subsidy, weather, theater genre, movie release month, film genre, rating, and sneak preview in this table.