Audience v Critics: the Effect of Reviews on Box Office Revenue

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Motivation

- **Uncertainty** about product quality
- **Reviews** as a signal of quality

→ Different effects of reviews?
## Industry Background

### 2 types of reviews: critics & audience
- Pre-release: (critic reviews)
  → Cold opening: no critic review before release
- Post-release: critic reviews + audience reviews
  → Difference opinions from critics and audience

### Research Questions:
- Different effects of critic & audience reviews on learning?
- How do consumers react to a cold opening?
Literature Review

Social Learning

- Newberry & Zhou (2016)

Effect of Reviews

- Critic: Reinstein & Snyder (2005), Brown et al. (2012)
- Audience: Liu (2006), Duan et al. (2008)
- Comparison: Chakravarty et al. (2010), Mollick & Nanda (2015)

Product Discovery

- Ackerberg (2003), Crawford & Shum (2005)
Preview of Results

My result shows that consumers:

(1) have higher prior mean for cold-opened movies
(2) rely more on both types of reviews for minor studio movies
(3) ↑ weight on critic reviews, ↓ weight on audience reviews for cold-opened movies and highly advertised movies
(4) Overall effectiveness of critic and audience reviews depends

Counterfactuals:

- Forcing movies to be screened hurts cold-opened movies.
- Taking away audience reviews hurts good movies and benefits bad movies.
Dataset: Top 200 highest grossing movies per year in 2011-2015

- **Box Office Revenue**
  Box Office Mojo: weekly revenue, # of theaters for 25 weeks

- **Critic & Audience Reviews**
  Metacritic & Rotten Tomatoes: chronologically ordered

- **Movie Characteristics**
  IMDb / IMDbPro: studios, actors, production budget, etc.

- **Advertising Expense**
  Kantar AdSpender: weekly advertising expenditure

→ 665 movies, 249 weeks, 8211 obs. with an average life of 12 weeks (min:1 max:20)
TABLE 1 Weekly Average

<table>
<thead>
<tr>
<th></th>
<th>Market</th>
<th>Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of movies</td>
<td>120</td>
<td>33</td>
</tr>
<tr>
<td>Revenue (mln)</td>
<td>209.3</td>
<td>188.8</td>
</tr>
</tbody>
</table>

Box Office Performance

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Audience v Critics: the Effect of Reviews
Critic & Audience Reviews

- Critics: average # of reviews about 6(pre)/35(post)
- Audience: average # of reviews about 26(w2)-103(w20)
- Correlation between reviews: 0.6200
FE Model

I regress weekly revenue on reviews, controlling for movie characteristics and movie fixed effect. (SE clustered by movie)

\[ E[R_{jt}| \cdot] = -0.0013cr_{jt} + 0.00006crn_{jt} + 0.0993ur_{jt} + 0.00028urn_{jt} + \cdots \]

(0.00366) (0.00006) (0.0197) (0.0001)

- Critic reviews do not have significant effect, while audience reviews have significant positive effect.
Overview

Pre-release Period
- Movie characteristics are revealed
- (Critics review the movie) $\leftarrow$ regular / cold-opened

Opening Week
- Consumers make choices $\leftarrow$ using prior and/or critic reviews
- (Critics review the movie)
- Consumers review the movie

Week 2 and After
- Consumers make choices $\leftarrow$ using prior + both reviews
- Consumers review the movie
Model

Individual \(i\)'s utility of watching movie \(j\) in period \(t\):

\[ U_{ijt} = \beta X_j + \gamma D_{jt} + \xi_j + \varepsilon_{ijt} \]  

- \(X_j\): movie characteristics including studios and advertising
- \(D_{jt}\): week dummies
- \(\xi_j\): true quality of the movie, unobserved before viewing
- \(\varepsilon_{ijt}\): taste shock, i.i.d type I extreme value
- Price does not enter utility (uniform price)

Utility of outside option: \(U_{i0t} = \varepsilon_{i0t}\)

Consumer choice based on expected utility:

\[ E_t[U_{ijt}] = \beta X_j + \gamma D_{jt} + E_t[\xi_j] + \varepsilon_{ijt} \]
Learning from the Reviews

Pre-release Period

Movie characteristics are revealed. Prior of movie \( j \)'s quality:

\[
\xi_j \sim N(\mu_j, \sigma_j^2)
\]  

(3)

If the movie is screened by the critics, the signal of experience is:

\[
x_{cj} \sim N(\xi_j, \sigma_{cj}^2)
\]  

(4)

Critics transform this signal to a score:

\[
cr_{jt} = \alpha_c x_{cj} + y_c
\]  

(5)
Learning from the Reviews

Opening Week

Expected quality of a cold-opened movie is:

$$\mathbb{E}[\xi_j | Z_j] = \mu_j$$ (6)

Expected quality of a screened movie is:

$$\mathbb{E}[\xi_j | Z_j, cr_{jt}] = \frac{\sigma^2_{cj}}{\sigma^2_j + \sigma^2_{cj}} \mu_j + \frac{\sigma^2_j}{\sigma^2_j + \sigma^2_{cj}} \cdot \frac{(cr_{jt} - y_c)}{\alpha_c}$$ (7)

Generating audience score:

$$x_{aijt} \sim N(\xi_j, \sigma^2_{aj})$$ (8)

$$ur_{ijt} = \alpha_a x_{aijt} + y_a$$ (9)
Learning from the Reviews

Week 2 and After

Expected quality after seeing critic and audience reviews:

\[
E[\xi_j | Z_j, cr_{jt}, ur_{jt}, n_{jt}] = \mu_j \cdot \frac{\sigma_c^2 \sigma_a^2}{n_{jt} \sigma_j^2 \sigma_c^2 + \sigma_j^2 \sigma_a^2 + \sigma_c^2 \sigma_a^2} + \frac{\sigma_j^2 \sigma_a^2}{n_{jt} \sigma_j^2 \sigma_c^2 + \sigma_j^2 \sigma_a^2 + \sigma_c^2 \sigma_a^2} \cdot \frac{cr_{jt} - y_c}{\alpha_c} + \frac{n_{jt} \sigma_j^2 \sigma_c^2}{n_{jt} \sigma_j^2 \sigma_c^2 + \sigma_j^2 \sigma_a^2 + \sigma_c^2 \sigma_a^2} \cdot \frac{ur_{jt} - y_a}{\alpha_a}
\]

(10)
Expected Quality

Opening Week, Cold-opened:

\[ \mathbb{E}[\xi_j | Z_j] = \mu_j \]  \hspace{1cm} (11)

Opening Week, Regular:

\[ \mathbb{E}[\xi_j | Z_j, cr_{jt}] = \frac{\tilde{\sigma}_{cj}^2}{1 + \tilde{\sigma}_{cj}^2} \cdot \mu_j + \frac{1}{1 + \tilde{\sigma}_{cj}^2} \cdot \frac{(cr_{jt} - y_c)}{\alpha_c} \]  \hspace{1cm} (12)

Week 2 and After:

\[ \mathbb{E}[\xi_j | Z_j, cr_{jt}, ur_{jt}, n_{jt}] = \frac{\tilde{\sigma}_{cj}^2 \tilde{\sigma}_{aj}^2}{n_{jt} \tilde{\sigma}_{cj}^2 + \tilde{\sigma}_{aj}^2 + \tilde{\sigma}_{cj}^2 \tilde{\sigma}_{aj}^2} \cdot \mu_j + \frac{\tilde{\sigma}_{aj}^2}{n_{jt} \tilde{\sigma}_{cj}^2 + \tilde{\sigma}_{aj}^2 + \tilde{\sigma}_{cj}^2 \tilde{\sigma}_{aj}^2} \cdot \frac{(cr_{jt} - y_c)}{\alpha_c} + \frac{n_{jt} \tilde{\sigma}_{cj}^2}{n_{jt} \tilde{\sigma}_{cj}^2 + \tilde{\sigma}_{aj}^2 + \tilde{\sigma}_{cj}^2 \tilde{\sigma}_{aj}^2} \cdot \frac{(ur_{jt} - y_a)}{\alpha_a} \]  \hspace{1cm} (13)
Model (cont.)

Parameterization: \((Z_j: \text{major/minor, cold-opened, adspend})\)

\[
\begin{align*}
\mu_j &= \mu Z_j \tag{14} \\
\frac{\sigma^2_{c_j}}{\sigma^2_j} &= \tilde{\sigma}^2_{c_j} = \exp(\sigma_c Z_j) \tag{15} \\
\frac{\sigma^2_{a_j}}{\sigma^2_j} &= \tilde{\sigma}^2_{a_j} = \exp(\sigma_a Z_j) \tag{16}
\end{align*}
\]

Expected quality entering utility:

\[
E_t[\xi_j] = E[\xi_j |.] + \epsilon_{jt} \tag{17}
\]

→ Expected utility:

\[
E_t[U_{ijt}] = \beta X_j + \gamma D_{jt} + E[\xi_j |.] + \epsilon_{jt} + \varepsilon_{ijt} \tag{18}
\]
Estimation

Market share of movie $j$ in period $t$:

$$s_{jt} = \frac{\exp(\beta X_j + \gamma D_{jt} + \mathbb{E}[\xi_j | \cdot] + \epsilon_{jt})}{1 + \sum_j \exp(\beta X_j + \gamma D_{jt} + \mathbb{E}[\xi_j | \cdot] + \epsilon_{jt})}$$

(19)

Estimation equation:

$$\log(s_{jt}) - \log(s_{0t}) = \beta X_j + \gamma D_{jt} + \mathbb{E}[\xi_j | \cdot] + \epsilon_{jt}$$

(20)

Plug in expected quality based on prior and reviews:

$$\log(s_{jt}) - \log(s_{0t}) = \beta X_j + \gamma D_{jt} + \xi_{jt}(\mu, \sigma, \alpha, y) + \epsilon_{jt}$$

(21)

Use nonlinear least squares:

$$(\hat{\beta}, \hat{\gamma}, \hat{\mu}, \hat{\sigma}, \hat{\alpha}, \hat{y}) = \arg\min \sum_{j,t} (\Delta s_{jt} - f_{jt}(\beta, \gamma, \mu, \sigma, \alpha, y))^2$$

(22)
Positive effects of major studio productions
Significant budget effect, insignificant advertising effect

TABLE 2 Preference Parameters

<table>
<thead>
<tr>
<th>Coeff.</th>
<th>SE</th>
<th>Coeff.</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disney</td>
<td>0.386*** (0.117)</td>
<td>Universal</td>
<td>0.445*** (0.115)</td>
</tr>
<tr>
<td>Fox</td>
<td>0.388*** (0.114)</td>
<td>Warner</td>
<td>0.0589 (0.111)</td>
</tr>
<tr>
<td>Paramount</td>
<td>0.199 (0.113)</td>
<td>ln(Adspend)</td>
<td>0.0532 (0.0552)</td>
</tr>
<tr>
<td>Sony</td>
<td>0.626*** (0.112)</td>
<td>ln(Budget)</td>
<td>0.0733*** (0.0222)</td>
</tr>
<tr>
<td>Week</td>
<td>Y N</td>
<td>8211</td>
<td>Adj R-sq 0.892</td>
</tr>
</tbody>
</table>

Notes: *p < 0.05, **p < 0.01, ***p < 0.001
Learning Parameters

- Cold-opened movies have higher prior ex-ante
- More weight on both reviews for minor studio movies
- Weight on critics ↑, audience ↓ for cold-opened and higher advertised movies

**TABLE 3 Learning Parameters**

<table>
<thead>
<tr>
<th></th>
<th>$\mu$</th>
<th>$\sigma_c$</th>
<th>$\sigma_a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Major</td>
<td>-1.188***</td>
<td>6.222***</td>
<td>3.162***</td>
</tr>
<tr>
<td></td>
<td>(0.268)</td>
<td>(0.541)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>- Minor</td>
<td>-1.108***</td>
<td>6.024***</td>
<td>2.958***</td>
</tr>
<tr>
<td></td>
<td>(0.236)</td>
<td>(0.540)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>- Cold</td>
<td>0.611***</td>
<td>-0.324*</td>
<td>0.558***</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.145)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>- Adspend</td>
<td>0.0829</td>
<td>-1.333***</td>
<td>0.119*</td>
</tr>
<tr>
<td></td>
<td>(0.0587)</td>
<td>(0.231)</td>
<td>(0.0495)</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
1. Effect of Cold Opening

- Replace pre-release average critic score with week 2 average.
- 71% of cold-opened movies have decreased revenue.

**TABLE 4** ∆Revenue After Removing Cold Opening ($mln)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cold</td>
<td>-1.266</td>
<td>11.83</td>
<td>-2.911</td>
<td>-34.33</td>
<td>48.64</td>
<td>238</td>
</tr>
<tr>
<td>Regular</td>
<td>0.7868</td>
<td>4.144</td>
<td>0.6923</td>
<td>-26.39</td>
<td>21.57</td>
<td>387</td>
</tr>
<tr>
<td>All</td>
<td>0.0052</td>
<td>8.049</td>
<td>0.2611</td>
<td>-34.33</td>
<td>48.64</td>
<td>625</td>
</tr>
</tbody>
</table>

Graphs by cold fraction:
- Minor
- Major

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2. Benefit from Audience Reviews

- Consumers form belief with prior and critic reviews only.
- 76% of Good suffer a loss; 88% of Bad earn more.

**TABLE 5** \( \Delta \text{Revenue After Removing Audience Reviews (} \text{\$mln)} \)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>-22.72</td>
<td>40.6</td>
<td>-8.793</td>
<td>-297</td>
<td>26.15</td>
<td>129</td>
</tr>
<tr>
<td>Bad</td>
<td>9.726</td>
<td>14.12</td>
<td>7.247</td>
<td>-43.73</td>
<td>63.26</td>
<td>187</td>
</tr>
<tr>
<td>All</td>
<td>-3.259</td>
<td>29.78</td>
<td>1.996</td>
<td>-297</td>
<td>77.76</td>
<td>624</td>
</tr>
</tbody>
</table>

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Conclusion

- Critic and audience reviews have different effects
- Cold-opened movies benefit from not being screened
- Audience reviews help consumers choose good movies

Future work:
- Model score generating process
- Learning from advertising & box office performance
- Supply side: studio choice of screening and advertising