Social Learning and Optimal Advertising in the Motion Picture Industry

Hailey Hayeon Joo

Department of Economics
Ohio University

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Motivations

- This paper analyzes the demand for movies and the supply of movie advertising.

- Social learning is important:
  - Potential movie-goers learn about the quality of a movie from critics, other viewers and observing box office performance.

- Social learning:
  - Improves consumer welfare.
  - A double-edged sword for the motion picture distributors.
Figure: Weekly Box Office Performances

- Catch Me If You Can
- Ballistic: Ecks vs. Sever
Main Question

How does social learning influence the motion picture marketplace?

To answer this question, I develop an equilibrium model of consumer decisions about whether and when to watch a film and movie distributor decisions about how much to spend on movie advertising.
Model Overview

- A structural model for:
  - The optimal advertising strategies of studios, forecasting movie demand by anticipating the effect of social learning.
  - The movie demand of consumers, given an indicator of movie quality and an initial level of advertising.

- Consumers are assumed to have uncertainty about movie quality that is resolved over time through Bayesian updating. The updating process depends on the number of previous viewers and their ratings.
## Key Features

- 236 *wide-release* films shown in U.S. theaters from 2002 to 2003. The dataset combines information from multiple sources.

- The prior distribution for a movie’s quality is the same as the distribution of its initial critics’ ratings. The posterior distribution is obtained by Bayesian updating, using the number of previous moviegoers and their ratings reported over the Internet.

- The model is estimated by the Simulated Method of Moments, following Berry, Levinsohn and Pakes (2004).

- To evaluate the out-of-sample fit of the model, I leave out random subsamples at the estimation stage and then assess how well the estimated model forecasts the decay patterns for them.
Literature

- Social learning in the movie industry
  - De Vany and Walls (1996): Positive information feedback among moviegoers captured by a dynamic updating process.

- The effect of advertising in the movie industry
  - Moul (2006): Measuring it by the size of newspaper ads.
Preview of Findings

- The simulation results show that for good movies, producers spend 4.2% more on advertising with learning than they would without learning. For bad movies, social learning makes a 1.4% increase in the level of advertising expenditure.

- Uncertainty about movie quality causes studios to spend 3.6% more on advertising for good movies, but 1.4% more for bad films. With uncertainty, the box office revenue for good films goes up by 1.2%, while that for bad movies increases by 5.9%.
Dataset

- The dataset combines information from multiple sources:

<table>
<thead>
<tr>
<th>Types of Information</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Box Office Revenue</td>
<td>Variety</td>
</tr>
<tr>
<td>Total Advertising Expenditure</td>
<td><em>Brandweek’s Superbrand Report</em></td>
</tr>
<tr>
<td>Critics’ Ratings</td>
<td><em>Metacritic</em></td>
</tr>
<tr>
<td>Viewers’ Ratings</td>
<td><em>Internet Movie Database (IMDb)</em></td>
</tr>
<tr>
<td>Production Budget Estimate</td>
<td><em>Several Internet Movie Sites</em></td>
</tr>
<tr>
<td>General Movie Information</td>
<td>Variety</td>
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<td>Annual Average Ticket Price</td>
<td><em>Box Office Mojo</em></td>
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<td>Census</td>
<td><em>Integrated Public Use Micro Series (IPUMS)</em></td>
</tr>
<tr>
<td>Consumer Survey</td>
<td><em>Simmons National Consumer Survey (NCS)</em></td>
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</tbody>
</table>
## Critics’ Ratings and Viewers’ Ratings

<table>
<thead>
<tr>
<th></th>
<th>Critics’ Ratings</th>
<th>Viewers’ Ratings</th>
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<tbody>
<tr>
<td>Data</td>
<td>Metascores</td>
<td>IMDb User Ratings</td>
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<td>Data Source</td>
<td><em>Metacritic</em></td>
<td>IMDb</td>
</tr>
<tr>
<td>Scale</td>
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<td>0 to 10</td>
</tr>
<tr>
<td>Mean of Average</td>
<td>50.0</td>
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</tr>
<tr>
<td>Mean of SDs</td>
<td>14.5</td>
<td>2.15</td>
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</tbody>
</table>

**Note:** Metascores and IMDb ratings use different scales, so I transform the Metascores to the same scale as the IMDb ratings.
## Summary Statistics

<table>
<thead>
<tr>
<th>Quality</th>
<th>All</th>
<th>High</th>
<th>Low</th>
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</thead>
<tbody>
<tr>
<td>Total Box Office Revenue ($Mln)</td>
<td>69.2</td>
<td>91.1</td>
<td>50.9</td>
</tr>
<tr>
<td>Opening-week’s Box Office Revenue ($Mln)</td>
<td>26.9</td>
<td>35.6</td>
<td>22.8</td>
</tr>
<tr>
<td>Total Advertising Expenditure ($Mln)</td>
<td>22.9</td>
<td>25.5</td>
<td>20.8</td>
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<tr>
<td>Production Budget ($Mln)</td>
<td>47.1</td>
<td>54.8</td>
<td>42.9</td>
</tr>
<tr>
<td>Metascore</td>
<td>50.0</td>
<td>57.9</td>
<td>38.5</td>
</tr>
<tr>
<td>IMDb Rating</td>
<td>6.28</td>
<td>7.01</td>
<td>5.33</td>
</tr>
<tr>
<td>Duration (Wks)</td>
<td>15</td>
<td>16</td>
<td>13</td>
</tr>
</tbody>
</table>
Primitives

- In the model:
  - Each movie has sufficient monopolistic power.
  - The total advertising spending is determined by the studio’s profit maximization based on the expected movie demand.
  - The advertising campaigns are given before a film’s release.
  - The duration of a movie is both given and known.

- Indices:
  - Households by \( i \in \{1, 2, \ldots, I\} \).
  - Movies by \( j \in \{1, 2, \ldots, J\} \).
  - Screened weeks of movie \( j \) by \( t \in \{1, 2, \ldots, D_j\} \), where week 1 is the opening week of movie \( j \) and \( D_j \) is the duration of release for movie \( j \).
Household’s Indirect Utility

- In $t$, $1 \leq t \leq D_j$, household $i$’s payoff to see movie $j$ is given as:

$$u_{ijt} = \sum_k x_{jkt} (\beta_k + \gamma_k v_{ik}) + \sum_k \rho_k T_{jkt} - \alpha_i \ln (p_{ij}) + \xi_{jt} + (\varepsilon_{ijt} - \varepsilon_{i0t}),$$

where:

- $x_{jkt}$ is the movie characteristic (e.g., indicator of movie quality, adjusted advertising effect ($(1 - \eta)^{t-1} \cdot AD_j$), cumulative market share, genres and Oscar nomination & receipt),
- $\beta_k$ is the common taste parameter,
- $\gamma_k$ is the parameter measuring the heterogeneity in tastes,
- $v_{ik}$ is the household attribute,
- $\rho_k$ is the parameter associated with the seasonal variable,
- $T_{jkt}$ is the seasonal dummy variable,
Household’s Indirect Utility

- In $t$, $1 \leq t \leq D_j$, household $i$’s payoff to see movie $j$ is given as:

$$u_{ijt} = \sum_k x_{jkt} (\beta_k + \gamma_k v_{ik}) + \sum_k \rho_k T_{jkt} - \alpha_i \ln(p_{ij}) + \xi_{jt} + (\varepsilon_{ijt} - \varepsilon_{i0t}),$$

where:

- $\alpha_i$ is the marginal utility of the household’s income that varies according to income groups ($\alpha_i \in \{\alpha_1, \alpha_2, \alpha_3\}$),
- $p_{ij}$ is the total price that the household has to pay,
- $\xi_{jt}$ is the unobserved characteristic decomposed into a permanent component, a time since release effect, and a random I.I.D. error, i.e., $\xi_{jt} = \xi_j + \xi_t + \Delta \xi_{jt}$, and
- $\varepsilon_{ijt}$ and $\varepsilon_{i0t}$ are the idiosyncratic error terms when the household watches and when it does not.
Household Movie Demand

- Each household:
  - Watches a movie no more than once.
  - Repeatedly but myopically decides to see a film, if it has not.
- Notations:
  - \( l_{ijt} \) by the information set of movie \( j \) given to household \( i \) in \( t \).
  - \( d_{ijt} \) by household \( i \)'s movie watching decision in \( t \).
  - \( d_{ijt} \) as 1, when it goes to movie \( j \) and as 0, when it does not.
- For household \( i \) with the history \( \{d_{ij\tau}\}_{\tau=1}^{t-1} = 0 \), its decision problem in \( t \) can be given as:

\[
V(l_{ijt} | \{d_{ij\tau}\}_{\tau=1}^{t-1} = 0) = \max \{u_{ijt}, 0\}, \ 1 \leq t \leq D_j.
\]
Social Learning

- Notations:
  - $q_{jt}$ by the indicator of movie $j$’s quality in $t$, where $q_{jt} \in \mathbb{X}_{jkt}$.
  - $n_{jt}$ by the total number of people who see movie $j$ up to $t - 1$.
  - $\phi_{\iota,j}$ by the perceived quality of the $\iota$-th film-goer, $1 \leq \iota \leq n_{jt}$.
  - $N(m_{\phi_{j}} , \sigma_{\phi_{j}}^2)$ by the true distribution of $\phi_{\iota,j}$, ex-ante unknown.

- Since $n_{j,t=1} = 0$, the initial prior for movie $j$ is given as:

$$q_{j1} \sim N(m_{cr_{j}} , \sigma_{cr_{j}}^2),$$

where $m_{cr_{j}}$ is the average of critics’ ratings for movie $j$ and $\sigma_{cr_{j}}^2$ is their variance.
Social Learning
Posterior Distribution

- In $t$, $t > 1$, a potential consumer receives the updated information about movie quality.

- According to the Bayesian rule, the posterior distribution is given as:

$$ q_{jt} \sim N(m_{jt}, \sigma_{jt}^2), $$

where:

$$ m_{jt} = \sigma_{jt}^2 \left( \frac{m_{cr_j}}{\sigma_{cr_j}^2} + \frac{w}{\sigma_{\phi_j}^2} \sum_{i=1}^{n_{jt}} \phi_{i,j} \right) \quad \text{and} \quad \sigma_{jt}^2 = \left( \frac{1}{\sigma_{cr_j}^2} + \frac{w}{\sigma_{\phi_j}^2} n_{jt} \right)^{-1}, $$

and $w$ is the velocity of the information update, $w \in [0, 1]$. 
Probability of the Household’s Movie-Watching

- If $\varepsilon_{ijt}$ and $\varepsilon_{i0t}$ are I.I.D. extreme-valued random variates, the probability for the potential consumer to view movie $j$ is given as:

$$
\Pr \left\{ d_{ijt} = 1 \mid \{ d_{ij\tau} \}_{\tau=1}^{t-1} = 0 \right\} = f_{ijt} \cdot \prod_{t'=1}^{t-1} (1 - f_{ijt'}) ,
$$

where

$$
f_{ijt} = \Pr\{d_{ijt} = 1\} = \int_q \frac{\exp(u_{ijt}(q))}{1 + \exp(u_{ijt}(q))} g(q) dq ,
$$

where $q$ means $q_{jt}$ and $g(\cdot)$ is the density of $q_{jt}$.
Aggregate Movie Demand

- The proportion of *individuals* going to movie $j$ in $t$, $s_{jt}$, can be written as:

$$s_{jt}(\delta(\theta), \theta|x, \mathcal{P}_V) = \frac{H}{N} \int hh_{ij} \Pr\left\{d_{ijt} = 1 | \{d_{ij\tau}\}_{\tau=1}^{t-1} = 0\right\} \mathcal{P}_V,$$

where $\theta = (\beta, \alpha, \gamma, \rho, \mu)$, $V_i$ is the vector of all household attributes, and $\mathcal{P}_V$ is the distribution of $V_i$. $H$ is the total number of households in the U.S., $N$ is the total population in the U.S. and $hh_{ij}$ is the number of potential movie consumers that may see movie $j$ in household $i$. 
Studio’s Net Profit

- The studio’s net profit for movie $j$ in $t$ is given as:

$$
\pi_{jt} (ad_j) = \begin{cases} 
- ad_j, & \text{if } t = 0, \\
\psi \left( p \cdot s_{jt} \cdot N - c \cdot sc_{jt} \right), & \text{if } 1 \leq t \leq D_j,
\end{cases}
$$

where $\pi_{jt} (\cdot)$ is the net profit, $ad_j$ is the total advertising spending, $\psi$ is the distributor’s share, $p$ is the price of one ticket, $c$ is the “nut” per screen and $sc_{jt}$ is the number of screens.

**Note:** $s_{jt}$ comes from the demand side. And, $s_{jt} = \lambda (ad_j|j, t)$ and $sc_{jt} \equiv \Lambda (s_{jt}) \equiv \Lambda' (ad_j|j, t)$. 

Studio’s Profit Maximization Problem

- The studio’s profit maximization problem is given as:

$$\max_{adj} \pi_j = \sum_{t=0}^{D_j} \gamma^t \pi_{jt}(adj),$$

where $\gamma$ is the discount factor.

- The studio can forecast:

$$E\left[ m_{\phi_j} \right] = \mu_0 + \mu_1 cr_j + \mu_2 (cr_j)^2 + \mu_3 pc_j$$ and

$$E\left[ \sigma_{\phi_j} \right] = \frac{1}{j} \sum_{j'} \sigma_{\phi_{j'}},$$

where $pc_j$ is its production cost.
Moments & Instruments

- Two sets of moments:
  1. Both studio-side and demand-side disturbances.
  2. Two relationships between household attributes and movie characteristics using consumer-level data, NCS 2002 fall set.

- Instruments ($z_{jt}$):
  - $x_{jkt}$ except weekly adjusted advertising effects.
  - $p_j$, $T_{jt}$, $(cr_j)^2$ and $pc_j$.

Note: The price of a movie ticket is fixed regardless of movies, so the prices themselves are not correlated with the disturbances.
The First Set of Moments

- The first set of moments can be derived from:

\[ E [\Delta \xi_{jt} (\theta_0) | z_{jt}] = E [\omega_j (\theta_0) | z_{jt}] = 0. \]

- The first set of moments can be written as:

\[ G_1 (\theta_0) = E \left[ H_j (z_{jt}) T_j (z_{jt}) \begin{pmatrix} \Delta \xi_{jt} (\theta_0) \\ \omega_j (\theta_0) \end{pmatrix} \right], \]

where \( H_j (z_{jt}) \) is the matrix of \( z_{jt} \) and \( T_j (z_{jt}) \) satisfies:

\[ T_j (z_{jt})' T_j (z_{jt}) = \left( E \left[ (\Delta \xi_{jt}, \omega_j)' (\Delta \xi_{jt}, \omega_j) | z_{jt} \right] \right)^{-1}. \]
The Second Set of Moments

- The second set of moments matches:

1. the model’s prediction of the movie-going probability conditional on household income levels with that of the NCS 2002 fall data set. (Equations)

2. the model’s estimate for the ratio of the movie-watching probability in each group categorized by the youngest child’s age to the movie-going probability in the population with that of the NCS 2002 fall set. (Equations)
\[ s_{j'}^{NCS} (y < \bar{y}_1) - \int_{y < \bar{y}_1} \left( 1 - \Pr \left\{ \{d_{ij'}t\}^{D_{j'}}_{t=1} = 0 \right\} \right) dV = 0 \]

\[ s_{j'}^{NCS} (\bar{y}_1 \leq y < \bar{y}_2) - \int_{\bar{y}_1 \leq y < \bar{y}_2} \left( 1 - \Pr \left\{ \{d_{ij'}t\}^{D_{j'}}_{t=1} = 0 \right\} \right) dV = 0 \]

\[ s_{j'}^{NCS} (y \geq \bar{y}_2) - \int_{y \geq \bar{y}_2} \left( 1 - \Pr \left\{ \{d_{ij'}t\}^{D_{j'}}_{t=1} = 0 \right\} \right) dV = 0 \]
\[
\frac{1}{J'} \sum_{j \in F} \left( \frac{s_{j'}^{NCS} (\text{age} < 6)}{s_{j'}^{NCS}} \right) - \frac{\int_{\text{age} < 6} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]

\[
\frac{1}{J'} \sum_{j \in F} \left( \frac{s_{j'}^{NCS} (6 \leq \text{age} < 17)}{s_{j'}^{NCS}} \right) - \frac{\int_{6 \leq \text{age} < 17} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]

\[
\frac{1}{J'_{NF}} \sum_{j \notin F} \left( \frac{s_{j'}^{NCS} (\text{age} \geq 17)}{s_{j'}^{NCS}} \right) - \frac{\int_{\text{age} \geq 17} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]

\[
\frac{1}{J'_{NF}} \sum_{j \notin F} \left( \frac{s_{NCS} (\text{age} < 6)}{s_{j'}^{NCS}} \right) - \frac{\int_{\text{age} < 6} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]

\[
\frac{1}{J'_{NF}} \sum_{j \notin F} \left( \frac{s_{j'}^{NCS} (6 \leq \text{age} < 17)}{s_{j'}^{NCS}} \right) - \frac{\int_{6 \leq \text{age} < 17} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]

\[
\frac{1}{J'_{NF}} \sum_{j \notin F} \left( \frac{s_{j'}^{NCS} (\text{age} \geq 17)}{s_{j'}^{NCS}} \right) - \frac{\int_{\text{age} \geq 17} \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV}{\int \left( 1 - \Pr \left\{ \left\{ d_{ij'}^t \right\}_{t=1}^{D_j'} = 0 \right\} \right) \, dV} = 0
\]
Objective Function

- Moment conditions can be assumed to be zero at the true $\theta_0$:

$$E \left[ G (\theta_0) \right] = E \left[ \begin{array}{c} G_1 (\theta_0) \\ G_2 (\theta_0) \end{array} \right] = 0.$$

- The SMM estimator, $\theta_{SMM}$, can be defined as:

$$\theta_{SMM} = \arg \min_{\theta \in \Theta} G^* (\theta)' G^* (\theta),$$

where $G^* (\theta) = A(\tilde{\theta}) \hat{G} (\theta)$, $\hat{G} (\theta)$ is the sample analogue to $G (\theta)$, and $A(\tilde{\theta})$ is a consistent estimate of the square root of the inverse of the asymptotic variance-covariance matrix of the moments.
<table>
<thead>
<tr>
<th>Parameters</th>
<th>Variables</th>
<th>Parameter Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Means of Movie Characteristics ($\beta_k$'s)</td>
<td>Family Movie</td>
<td>0.5785</td>
<td>0.2165</td>
</tr>
<tr>
<td>Action Movie</td>
<td></td>
<td>0.3588</td>
<td>0.1761</td>
</tr>
<tr>
<td>Market Share of Cumulative viewers</td>
<td></td>
<td>0.6548</td>
<td>1.2286</td>
</tr>
<tr>
<td>Updated Reputation of Movie Quality</td>
<td></td>
<td>0.7530</td>
<td>0.0041</td>
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<tr>
<td>Adjusted Advertising Effects</td>
<td></td>
<td>0.1658</td>
<td>0.0751</td>
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<tr>
<td>Oscar Nomination</td>
<td></td>
<td>0.3395</td>
<td>0.1752</td>
</tr>
<tr>
<td>Oscar Winning</td>
<td></td>
<td>0.1227</td>
<td>0.1097</td>
</tr>
<tr>
<td>SDs of Movie Characteristics ($\gamma_k$'s)</td>
<td>Family Movie</td>
<td>0.5295</td>
<td>0.0198</td>
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<tr>
<td>Action Movie</td>
<td></td>
<td>0.3127</td>
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<td>Market Share of Cumulative viewers</td>
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<td>0.2302</td>
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<td>Updated Reputation of Movie Quality</td>
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<td>0.1073</td>
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<td>Adjusted Advertising Effects</td>
<td></td>
<td>1.9835</td>
<td>0.0171</td>
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<tr>
<td>Oscar Nomination</td>
<td></td>
<td>2.9289</td>
<td>0.0102</td>
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<tr>
<td>Oscar Winning</td>
<td></td>
<td>1.8114</td>
<td>0.1317</td>
</tr>
<tr>
<td>Family Movie Preferences ($\zeta_k$'s)</td>
<td>Dummy for the Household with a Youngest Child Under 6</td>
<td>0.0334</td>
<td>0.0229</td>
</tr>
<tr>
<td></td>
<td>with a Youngest Between 6 and 17</td>
<td>0.0563</td>
<td>0.0130</td>
</tr>
<tr>
<td>Price Sensitivity of 1st Income Cohort, $\alpha_1$</td>
<td>Price to Watch a Movie</td>
<td>8.3002</td>
<td>0.1249</td>
</tr>
<tr>
<td>Price Sensitivity of 2nd Income Cohort, $\alpha_2$</td>
<td>Price to Watch a Movie</td>
<td>5.9757</td>
<td>0.0146</td>
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<tr>
<td>Price Sensitivity of 3rd Income Cohort, $\alpha_3$</td>
<td>Price to Watch a Movie</td>
<td>3.8889</td>
<td>0.0014</td>
</tr>
<tr>
<td>Time-Specific Characteristics ($\rho_k$'s)</td>
<td>Holiday Weekend Dummy</td>
<td>0.1514</td>
<td>0.0550</td>
</tr>
<tr>
<td></td>
<td>Summer Season Dummy</td>
<td>0.0634</td>
<td>0.1033</td>
</tr>
<tr>
<td>Discount Rate of Advertising Effects ($\eta$)</td>
<td>Constant</td>
<td>-0.9964</td>
<td>0.3671</td>
</tr>
<tr>
<td>$\mu_l$'s</td>
<td>Standardized Media Critic</td>
<td>1.5963</td>
<td>0.7218</td>
</tr>
<tr>
<td></td>
<td>(Standardized Media Critic)$^2$</td>
<td>-0.0686</td>
<td>0.0753</td>
</tr>
<tr>
<td></td>
<td>Production Cost</td>
<td>0.0087</td>
<td>0.0096</td>
</tr>
</tbody>
</table>

Note: For estimation, both the movie-specific fixed effects and the time-specific unobserved heterogeneities are included.
Decay Patterns: Within-Sample Fit

(A) Catch Me If You Can (2002)

(B) Ballistic: Ecks vs. Sever (2002)
Decay Patterns: Out-of-Sample Fit

(A) Road to Perdition (2002)

Weeks

Market Shares

(B) Serving Sara (2002)

Weeks

Market Shares

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# Model Fit: Average Market Shares

<table>
<thead>
<tr>
<th>Week</th>
<th>High-rated Movies</th>
<th>Low-rated Movies</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Within Sample Data</td>
<td>0.0224</td>
<td>0.0027</td>
</tr>
<tr>
<td>1</td>
<td>0.0250</td>
<td>0.0019</td>
<td>0.0011</td>
</tr>
<tr>
<td>2</td>
<td>0.0096</td>
<td>0.0006</td>
<td>0.0006</td>
</tr>
<tr>
<td>3</td>
<td>0.0055</td>
<td>0.0006</td>
<td>0.0006</td>
</tr>
<tr>
<td>4</td>
<td>0.0036</td>
<td>0.0006</td>
<td>0.0006</td>
</tr>
<tr>
<td>5</td>
<td>0.0020</td>
<td>0.0011</td>
<td>0.0015</td>
</tr>
<tr>
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<td>0.0013</td>
<td>0.0006</td>
<td>0.0010</td>
</tr>
<tr>
<td>7</td>
<td>0.0009</td>
<td>0.0003</td>
<td>0.0006</td>
</tr>
<tr>
<td>8</td>
<td>0.0006</td>
<td>0.0002</td>
<td>0.0004</td>
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<tr>
<td>10</td>
<td>0.0004</td>
<td>0.0001</td>
<td>0.0003</td>
</tr>
</tbody>
</table>
Comparison of World without WOM Referrals or Learning

- A situation in which word-of-mouth referrals are not available, and uncertainty about a movie’s quality is not resolved over time by a learning process.

- Consumers still use critics’ ratings, but no longer acquire viewers’ word-of-mouth referrals.

- The prior distribution for a movie’s quality is unchanged from the benchmark case. The posterior distribution is now identical to the prior distribution, because the initial prior for a movie’s quality cannot be updated by viewers’ word-of-mouth recommendations.
Figure: Relationship Between the Original Advertising Spending and the Simulated Advertising Spending in a World without WOM Referrals

\[ y = -0.1573 + 0.9778 \times x \]
Change in Advertising Spending
In a World without WOM Referrals nor Learning

\[ ad_{j,\text{sim}} = -0.3840 + 0.9879 \cdot ad_j - 0.2202 \cdot \Delta ir_j, \]

(0.1363) (0.0002) (0.0150)

where \( ad_{j,\text{sim}} \) is the simulated optimal advertising spending, \( ad_j \) is the original advertising spending and \( \Delta ir_j \) is the difference between movie \( j \)'s IMDb rating and the overall mean.

- For good movies, producers spend substantially more on advertising in a world with learning than they would in an environment without it. For bad movies, social learning makes much less difference in the level of advertising spending.
## Perfect Certainty Vs. Uncertainty

<table>
<thead>
<tr>
<th></th>
<th>Movies</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>High</td>
</tr>
<tr>
<td><strong>Advertising Spending</strong></td>
<td>21.70</td>
<td>23.35</td>
</tr>
<tr>
<td>with Perfect Certainty ($Mln)</td>
<td>22.31</td>
<td>24.23</td>
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<tr>
<td><strong>Difference ($Mln)</strong></td>
<td>-0.61</td>
<td>-0.88</td>
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<tr>
<td><strong>Difference (%)</strong></td>
<td>-2.73</td>
<td>-3.63</td>
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<tr>
<td><strong>Box Office Revenue</strong></td>
<td>62.52</td>
<td>79.26</td>
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<tr>
<td>with Perfect Certainty ($Mln)</td>
<td>64.29</td>
<td>80.21</td>
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<tr>
<td><strong>Difference ($Mln)</strong></td>
<td>-1.77</td>
<td>-0.95</td>
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<tr>
<td><strong>Difference (%)</strong></td>
<td>-2.75</td>
<td>-1.18</td>
</tr>
</tbody>
</table>
Concluding Remarks

- Social learning can amplify or impede the effectiveness of advertising.

- The advertising expenditures of movie studios are sensitive to both consumer uncertainty about movie quality and the speed with which potential movie-goers learn about movie quality.

- For good movies, producers spend 4.2% more on advertising in a world with learning than they would without learning. For bad movies, learning makes a 1.4% increase in the level of advertising.