Word-of-Mouth in Movies with Platform Release: Theory and Evidence

By

Yijuan Chen
Australian National University

Xiaojing Ma
Holy Family University

Qiang Pan
University of Pennsylvania

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Word-of-Mouth in Movies with Platform Release: Theory and Evidence*

Yijuan Chen[†], Xiaojing Ma[‡], Qiang Pan[§]

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Abstract

We study the word-of-mouth effect on movies with platform release, a common marketing strategy in the motion picture industry. We construct a theoretical model which shows that the word-of-mouth effect together with a sliding-percentage contract between the movie distributor and exhibitors gives rise to the usage of platform release. Using the data in the U.S. motion picture industry from 2000 to 2005, we quantify the word-of-mouth scales and estimate the information transmission process in the movies featuring platform release.

Key words: Word-of-Mouth, Platform Release, U.S. Motion Picture Industry

JEL codes: L82, M31,

1 Introduction

When a movie distributor considers releasing a new movie, two patterns most often used are wide release and platform release[1]. The former, usually supported by an extensive national advertising campaign, has a large number of theatres showing the movie at the outset. In contrast, with platform release the movie distributor first shows the movie in a small number of theatres (platforms), often only in big cities. Weeks later, the movie will expand to more theatres and to more areas.

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[†]Australian National University, Email: yijuan.chen@anu.edu.au

[‡]Holy Family University, E-mail: jma@holyfamily.edu

[§]University of Pennsylvania, E-mail: panqiang@econ.upenn.edu

[1]It is also called "limited release".

As shown in the Data section, from 2000 to 2005, among the movies in the yearly Top-200 box-office chart, 238 movies adopted platform release. The conventional wisdom is that this pattern suits best the movies that do not appeal to the mainstream audiences because of, for example, an unknown cast or a too controversial topic, or that have small production budget and thus cannot afford a nationwide advertising campaign. The movie distributor relies on the audiences from the first weeks to spread information about the movie's true quality, and then increases the number of theatres in anticipation of a demand boosted by good word-of-mouth. There are, however, three questions remaining:

First, naturally a larger number of theatres will imply a larger scale of word-of-mouth, then if the distributor relies on word-of-mouth to reveal the movie's true quality, why doesn't he choose wide release from the beginning?

Secondly, given a sequence of information sources, how to estimate the scale of word-of-mouth? In other words, given the weekly admission during the platform-release period, can we estimate how many potential audiences have known about the movie via word-of-mouth?

Thirdly, how is word-of-mouth spread? After seeing a movie, will an audience inform a fixed number of acquaintances regardless of the movie's theatrical run, or will she inform a certain amount of friends each week?

We show that the answer to the first question lies in a special feature of the industry-standard contract form between the movie distributor and exhibitors. The contract entails a sliding percentage of the profit the distributor has right to during the theatrical run. Given such a contract, although wide release helps to spread information about a movie's true quality faster, the increase of the profit from the increase of audiences on the later weeks will be offset by the decrease of the distributor's share of profit. In contrast, although platform release results in a smaller audiences in the first weeks and a smaller word-of-mouth effect, the larger share of profit from expanding the screening to new theatres helps to increase the distributor's total profit.

Using data that cover the movies released in the U.S. from 2000/1/1 to 2005/12/31, we address the second and the third questions from an empirical approach. The estimation entails dividing each movie's data into a platform-release part and a wide-release part. In the first stage, using the wide-release-period data, we treat each movie's word-of-mouth scale as a fixed effect and estimate it from a first-difference approach. In the second stage, using a two-step GLS estimator, we combine the estimate in the first step with the platform-release-period data and estimate the information transmission process. Two main results are, first, the potential audiences that have known about the movie through word-of-mouth on average is about 60% larger than the actual admission during the wide-release period, and second, during the platform-release period each week's audiences will spread information about the movie for only 1 week. On average each audience will inform 6 potential audiences.

We believe our results are of not only theoretical but also practical value. Especially, estimating the word-of-mouth scale will be important in designing a movie's non-theatrical run such as introducing the movie in DVD, because the consumers who want to watch the movie but have not done so in theaters are a compelling, if not dominating, proportion of the movie's non-theatrical market. Though one may approximate a movie's word-of-mouth scale by either the whole population or the theatrical admission, neither approximation serves the decisions about the non-theatrical run better than a formal estimation.

Undoubtedly, word-of-mouth exists in virtually all movies, thus it is reasonable to exam the influence of word-of-mouth on every movie's box office. However, due to the extensive advertising campaign, the fame of the cast, and the large number of theatres since the beginning of the release, the word-of-mouth effect will be less significant in movies using wide release. In particular, in the "movie franchises" such as "Star Wars", "Harry Potter" and "007", the movies' true quality and the consumers' expectation are rather consistent, and thus one may imagine word-of-mouth plays a minimum role in such movies. On the other hand, to study all the movies, one needs to take into account not only the competition among the movies aiming at the same audiences but also seasonality exhibiting in the demand of the mainstream audiences, introducing more complications. All of these reflect the advantage of restricting the study to movies with platform release, as the characteristics of those movies (i) on the demand side minimize the impact from factors such as advertising and thus naturally single out word-of-mouth for study and (ii) on the supply side allow us to assume away competition from other movies.

While literature studying the motion picture industry has been rather rich, so far we have not found any work directly addressing the questions we propose, either theoretically or empirically. A closely related paper is Moul (2006). He employs a nest logit model to structually analyze the effect of word-of-mouth on admission by decomposing the disturbance component. The questions addressed in the present paper can be seen as a complement to his work. In addition, our paper differs from his in four accounts: First, the estimation in Moul (2006) is based upon assuming the combined population of the U.S. and Canada to be each movie's market size, with 25% of that number later used for robustness check. In contrast, the present paper directly aims at estimating the marker size of each movie. Secondly, though Moul (2006) discusses two alternative word-of-mouth patterns, he instead characterizes word-of-mouth by the probability an average consumer hears about the movie. In the present paper, we directly address the natural word-of-mouth patterns, and find one of them prevails. Thirdly, a movie's weekly performance is recorded in the data of Moul (2006) only if it enters the weekly Top-50 box-office chart, and thus a movie's age in his study is not necessarily equal to the actual number of weeks since its release. Though this approach may suit well the movies using wide release, it tends to underestimate the word-of-mouth effect in the movies using platform release, since the box office during the platform-release period can be so small that it falls below Top-50. In contrast, in the present paper, for each movie we record the weekly performance of its complete life span. Fourthly, Moul (2006) restricts the attention to weekly Top-50 movies, while we extend it to the yearly Top-200 movies. The extension is not simply a matter of scale: Our data show that, among all the movies characterized as using platform release, only 5% enter the Top-50 territory, hence restricting the attention to only Top-50 movies excludes a very large proportion of movies of interest.

Among other recent literature, Einav (2006) estimates seasonality in demand by separating it from movie qualities. Although in the data he identifies movies with platform release, he does not consider the data during the platform-release period, arguing that the first weeks are only a method of advertising. Differently, in our paper the data during a movie's platform-release period are indispensable for our estimation.

The rest of the paper is organized as follows: Section 2 briefly describe the U.S. motion picture industry. In Section 3 we provide a theoretical framework that explains why the movie distributor may choose platform release over wide release. Data description is given in Section 4. Section 5 shows our estimation framework, with the estimation results discussed in Section 6. Section 7 concludes.

2 The U.S. Motion Picture Industry

Borrowing from other literature, in this section we briefly describe several factors of the U.S. motion picture industry that are most relevant to the subsequent theoretical and empirical analysis. For a comprehensive and systematic review of the modern U.S. motion picture industry as well as the current research on numerous related topics we refer to Eliashberg et al. (2006).

Traditionally the U.S. motion picture industry consists of three main components: producers, distributors, and exhibitors. As the names suggest, producers produce movies, distributors are in charge of the distribution of the completed products, and exhibitors own the theatres. The modern industry has seen major studios integrating production and distribution, and some exhibitors, mostly in major cities, forming "theatre tracks" that consistently show movies of only certain studios. As the paper is focused on the release strategy, the integration of production and distribution makes it innocuous to consider the industry to be only comprised of distributors and exhibitors.

After a movie is completed and passed to the marketing stage, the distributor will make a series of decisions, including choosing a release date, deciding the initial scope and locations of the release, designing the advertisement campaign, and negotiating the contract with the exhibitors.

As it has been common for a movie's production cost to be above millions of dollars, the pressure of paying accumulating interest forces the distributor not to delay a movie's release. The scope and the locations of the initial release, however, vary significantly across the movies. Two main release patterns that have been widely adopted are wide release and platform release. In addition there is a hybrid release pattern, where the distributor adopts a national advertising campaign as well as starts showing the movie in a small number of theatres, with the movie expanded to more theatres much faster and at much larger scope than a typical platform-release movie, sometimes from less than 10 theatres to more than 1000 within one or two weeks.

Most contracts between distributors and exhibitors entail a sliding percentage of the box-office gross after subtracting the exhibitor's "nut" (house expense, which include location rents, utility, insurance, and mortgage payments, etc.). A sliding-percentage agreement may stipulate that in the first week or two 70% or more of the box-office receipts after allowance for the nut to be remitted to the distributor, with the exhibitor retaining the remaining 30% or less. Every two weeks thereafter, the split may be adjusted by 10% as 60:40, then 50:50, and so forth in the exhibitor's favor. In addition to this arrangement, should a picture not perform up to expectations, the distributor usually has the right to a certain minimum payment, which will be a direct percentage of the box-office revenue prior to the subtraction of the house expense. For example, if the house nut is $9,000 a week, and that the first week agreement on a movie with $60,000 box-office gross is 70/30 with a 60% minimum payment, then the distributor will receive the larger of $70\% \times (60,000 - 9,000)$ and $60\% \times 60,000$. Unless specified otherwise, the decision of terminating screening of a movie remains in the hands of exhibitors.

The rationale for the adoption of such a contract form, however, has not been fully studied. A conventional wisdom is that the sliding-percentage feature gives the exhibitors incentives not to terminate showing the movies too early. Typically, as documented by Eliashberg and Sawhney (1996) and Eliashberg et al. (2000), after a movie is shown in one theater, the admission per screen will fall over time. Therefore the distributor needs to give the exhibitor a larger share of the box office in order to prevent the exhibitor from switching to a new movie. Filson et al. (2005) attempt to formalize this idea based on risk sharing, but they lack a formal model that incorporates a deterministic decreasing trend into the stochastic weekly admission.

Another distinguishing feature of the motion picture industry is the uniform price: Although movies by nature are differentiated products, at any theatre, the same price is charged for all movies, with changes only applying to different group of persons, such as student discount or senior citizen discount. Orbach and Einav (2006) argue that the uniform price is primarily caused by an extreme legal constraint (namely the Paramount decrees) together with other factors such as unstable demand, high menu and monitoring cost should the price be variable, and the divergence of the interests between the distributors and the exhibitors.

A movie's theatrical run is normally followed, in sequence, by pay-cable programming, home video, network television, and local television syndication, with a market that generates higher revenue per unit of time preceding the lower ones. In general, the motion picture industry has experienced rapid growth, with the box-office revenue of major studios increasing steadily from over $1 billion in 1972 to above $30 billion in 2002 (Vogel 2004). However, soaring faster are the revenue from other channels such as sales home video and selling rights to cable and TV networks. The domestic box-office revenue now accounts for as little as 15% of a movie's revenues, down from about 35% in the early 1980's (Einav 2006).

3 Theoretical framework

In this section we provide a theoretical framework where, despite the fact that the more theatres the larger the word-of-mouth effect, the sliding-percentage contract may make the distributor, acting as a monopolist, prefer platform release to wide release. We first give a numerical example, and then discuss in detail with a parametric model.

3.1 Numerical example

A distributor is choosing a release strategy for a newly completed movie. Suppose the distributor can show the movie for three weeks. The contract stipulates that after subtraction of the theatres' house expense (nut) 90% of the first week's revenue goes to the distributor, and then 60% of the second week, and 30% of the third. There are 10 theatres available, and the ticket price is fixed at $1. The distributor has two strategies: Showing the movie in all theatres throughout the release life, or showing it in 1 theatre on the first week, and then closing that theatre[2] but expanding the screening to the other 9 theatres since week 2. Thus the first strategy resembles wide release, while the second representing platform release. For simplicity, assume the house expense is 0 for each theatre, and there is no discounting.

As to be more explicit in the following parametric model, word-of-mouth means the audiences that have seen the movie will spread information about the movie's true quality. In case the movie's true quality is higher than the expectation of the potential audiences, word-of-mouth will contribute to the increase of audiences. A larger audiences, in turn, will result in a larger scale of word-of-mouth.

First consider wide release. Denote n_t the number of theatres and A_t the number of weekly audiences from this strategy. Suppose the outcome is

t	1	2	3
n_t	10	10	10
A_t	4	10	13

Then the distributor's profit is

$$\Pi = 0.9 \times 4 + 0.6 \times 10 + 0.3 \times 13 = 13.5$$

Now consider platform release. Denote A'_t the corresponding weekly admission. Suppose the outcome is:

t	1	2	3
n_t	1	10	10
A'_t	1	7	11

Then the distributor's profit is

$$\Pi' = 1 \times 0.9 + 7 \times 0.9 + 11 \times 0.6 = 13.8$$

We can see even if a larger admission leads to a larger word-of-mouth scale, represented by the fact $A_t > A'_t$ for every t, there is $\Pi < \Pi'$, so the distributor will choose platform release over wide

[2] This simplifies the calculation of the distributor's profit, while we can show the result in this sub-section holds without this restriction.

release. The intuition lies in the sliding-percentage feature of the contract. With wide release, the increase of the profit from the increase of A_t on the later weeks were offset by the decrease of the percentage of the profit the distributor has right to. In contrast, although platform release results in a smaller admission in the first week and a smaller word-of-mouth effect, the larger share of profit from expanding the screening to new theatres increases the distributor's total profit.[3]

3.2 Parametric Model

To illustrate in the simplest way the trade-off between word-of-mouth and the percentage of profit we keep all the numbers fixed in the previous example. In this subsection we generalize the result and characterize in a discrete-time setting the conditions under which a monopolistic distributor will choose platform release over wide release.

3.2.1 Set-up

A movie distributor is considering how to release a new movie. There is a continuum of theatre areas with measure 1. Each theatre area consists of one distinct theatre and a unit mass of consumers. The ticket price is fixed at p in each theatre. The distributor knows the movie's true quality θ^*, which is unobserved by the consumers. Before the movie's premiere, the consumers share a common expectation about the movie's quality, denoted by θ.

Each consumer will only watch the movie in her own theatre area. A consumer i's expected utility from watching the movie is

$$E[u_i] \equiv \theta_i + \varepsilon_i - p$$

where θ_i is i's belief about the movie's quality, and ε_i denotes the consumer's type, which can be interpreted as the consumer's propensity to see the movie, and is a draw from an independent uniform distribution with support $[\underline{\varepsilon}, \bar{\varepsilon}]$. If the movie is shown, consumer i will go to the theatre if and only if $E[u_i] \geq 0$.

Assumption 1: $\bar{\varepsilon} > p - \theta > \underline{\varepsilon} > p - \theta^*$

[3] Though we assume 0 house expense, the result does not rely on it. More exactly, adding house expense will give the distributor more incentive to turn to platform release. Mathematically, the 1st and the 2nd week's house expenses in wide release will cancel out those of the 2nd and the 3rd week in platform release, with the 3rd week's house expense in wide release reducing more of the profit than the 1st week's house expense does in platform release.

Assumption 1 implies that without knowing θ^* only a positive measure of consumers will see the movie, while every consumer will go to the theatre after knowing θ^*.

Time is discrete. If the movie has been shown in a theatre area for one period, then in the next period by word-of-mouth all the consumers in the theatre area know θ^*. Moreover, if movie theatres with measure n_1 show the movie in the first period and consumers with measure A_1 see the movie, then in the beginning of the second period a mass of consumers with measure $\min\{W(A_1), 1 - n_1\}$ in the remaining $1 - n_1$ theatre areas will know θ^* by word-of-mouth. If $W(A_1) < 1 - n_1$, we assume $W(A_1)$ spreads evenly in the $1 - n_1$ areas with the consumers with higher ε_i knowing θ^* earlier than the lower ones.

Assumption 2: $W(.)$ is strictly increasing and differentiable with $W(0) = 0$.

The movie distributor's strategy is to choose a mass of theatre areas with measure $n_1 \leq 1$, where the movie will be shown for one period before it is shown elsewhere. Hence $n_1 = 1$ represents wide release and $n_1 < 1$ represents platform release.

The figure below summarizes the above set-up.

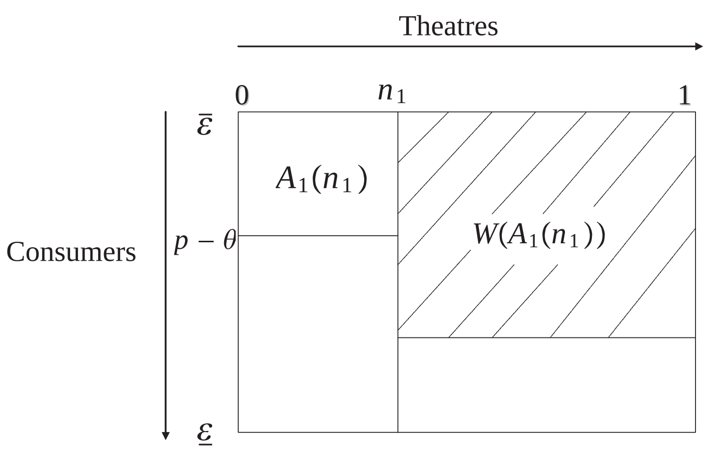


Figure-1

We assume an identical contract form across the theaters. For each theatre, a percentage ϕ_t of the theatre's periodic profit will go to the movie distributor if the movie has been shown there for t periods. By Assumption 1 and our specification of word-of-mouth, once a movie is put on screen, all the consumers in that theater area will see the movie within two periods, therefore only ϕ_1 and ϕ_2 are of concern.

Denote δ the discounting factor, and for simplicity assume the per period cost of each theatre is 0.

3.2.2 Analysis

For ease of notation in the following analysis denote $\alpha \equiv \frac{\bar{\varepsilon}-(p-\theta)}{\bar{\varepsilon}-\underline{\varepsilon}}$, the measure of consumers per theater area that will see the movie without knowing θ^*. If in the first period the movie is shown in n_1 theatres, then the first period admission is

$$A_1(n_1) = n_1\alpha$$

The distributor thus chooses $n_1 \in [0,1]$, to maximize his profit:

$$\max_{n_1\in[0,1]} \pi_1(n_1) + \delta\pi_2(n_1) + \delta^2\pi_3(n_1)$$

where

$$\begin{aligned}
\pi_1(n_1) &= \phi_1 n_1 \alpha p \\
\pi_2(n_1) &= \phi_1 \min\left\{\max\{W(A_1(n_1)), \alpha(1-n_1)\}, 1-n_1\right\} p + \phi_2 n_1(1-\alpha)p \\
\pi_3(n_1) &= \phi_2\left[(1-n_1) - \min\left\{\max\{W(A_1(n_1)), \alpha(1-n_1)\}, 1-n_1\right\}\right] p
\end{aligned}$$

We break the analysis into two cases: (i) $\phi_1 < \delta\phi_2$ and (ii) $\phi_1 \geq \delta\phi_2$.

(i) $\phi_1 \leq \delta\phi_2$

$\phi_1 \leq \delta\phi_2 < \phi_2$ implies that the movie distributor would like to have as many consumers as possible to see the movie in the second week, thus it wants to minimize word-of-mouth. As a result the movie distributor will choose $n_1 = 1$, i.e. wide release, at the first week.

(ii) $\phi_1 > \delta\phi_2$

We can first reduce the movie distributor's choice set before characterizing the optimal choice.

Lemma 1 *The movie distributor will restrict his choice to* $[n_1^*, 1]$, *where* n_1^* *uniquely solves* $W(A_1(n_1)) = 1 - n_1$.

Proof. Let $F(n_1) = W(A_1(n_1)) + n_1 - 1 = W(n_1\alpha) + n_1 - 1$. Since $F(0) = -1 < 0$ and $F(1) = W(\alpha) > 0$, by the Intermediate Value Theorem there exists a n_1^* such that $W(A_1(n_1^*)) = 1 - n_1^*$.

Moreover, by Assumption 2 $\frac{\partial F(n_1)}{\partial n_1} > 0$, so n_1^* is unique. For $n_1 < n_1^*$, $W(A_1(n_1)) < 1 - n_1$, and for $n_1 > n_1^*$, $W(A_1(n_1)) > 1 - n_1$.

In a similar way one can show that there exists a unique $\hat{n}_1 < n_1^*$ such that $W(A_1(\hat{n}_1)) = \alpha(1 - \hat{n}_1)$. Because of δ, the movie distributor prefers $n_1 = 1$ to any $n_1 < \hat{n}_1$, as word-of-mouth that comes from a too small $A_1(n_1)$ will virtually have no effect on the admission of the subsequent periods. Hence we can restrict n_1 to $[\hat{n}_1, 1]$.

Suppose the movie distributor chooses $n_1 \in [\hat{n}_1, n_1^*)$, then $W(A_1(n_1)) < 1 - n_1$, and there is

$$\begin{aligned}
\pi(n_1) &\equiv \pi_1(n_1) + \delta\pi_2(n_1) + \delta^2\pi_3(n_1) \\
&= p\left\{\phi_1 n_1 \alpha + \delta\left[\phi_1 W(A_1) + \phi_2 n_1(1-\alpha)\right] + \delta^2\phi_2\left[1 - n_1 - W(A_1(n_1))\right]\right\} \\
&= p\left\{\delta W(A_1(n_1))(\phi_1 - \delta\phi_2) + \left[\phi_1\alpha + \delta\phi_2(1-\alpha) - \delta^2\phi_2\right] n_1 + \delta^2\phi_2\right\}
\end{aligned}$$

Since $\phi_1 > \delta\phi_2$, $\phi_1\alpha + \delta\phi_2(1-\alpha) > 0$. Therefore

$$\frac{\partial \pi}{\partial n_1} = p\left[\delta\frac{\partial W(A_1(n_1))}{\partial n_1}(\phi_1 - \delta\phi_2) + \left[\phi_1\alpha + \delta\phi_2(1-\alpha) - \delta^2\phi_2\right]\right] > 0$$

Hence any $n_1 \in [\hat{n}_1, n_1^*)$ is not optimal. So the distributor will restrict its choice to $[n_1^*, 1]$. ∎

The intuition of Lemma 1 is that, since $\phi_1 > \delta\phi_2$, if the movie distributor would like to use word-of-mouth to promote the movie, then it will make full use of it so that each target consumer will be reached by word-of-mouth after platform release.

Combined with the result in case of $\phi_1 < \delta\phi_2$, we obtain our main result in the proposition below.

Proposition 1 *The movie distributor will choose platform release if and only if (i) $\delta > \alpha$ and (ii) $\frac{(\delta-\alpha)}{(1-\alpha)}\phi_1 > \delta\phi_2$. The optimal measure of platform-release theaters is n_1^*.*

Proof. Suppose the movie distributor chooses an $n_1 \geq n_1^*$, then all the consumers will see the movie in two periods. Thus

$$\begin{aligned}
\pi(n_1) &= \pi_1(n_1) + \delta\pi_2(n_1) \\
&= \phi_1 n_1 p\alpha + \delta\left[\phi_1(1-n_1)p + \phi_2 n_1 p(1-\alpha)\right]
\end{aligned}$$

which implies

$$\begin{aligned}
\frac{\partial \pi}{\partial n_1} &= \phi_1 p\alpha - \delta\phi_1 p + \delta\phi_2 p(1-\alpha) \\
&= p\left[\phi_1(\alpha - \delta) + \delta\phi_2(1-\alpha)\right]
\end{aligned}$$

Since $\frac{\partial \pi}{\partial n_1}$ is a constant, the movie distributor will choose platform release if and only if $\frac{\partial \pi}{\partial n_1} < 0$, which is equivalent to $\delta > \alpha$ and $\frac{(\delta-\alpha)}{(1-\alpha)}\phi_1 > \delta\phi_2$. Moreover, $\frac{\partial \pi}{\partial n_1} < 0$ implies that n_1^* is the optimal choice. ■

The intuition of the first condition in Proposition 1 is straightforward: $\delta > \alpha = \frac{\bar{\varepsilon}-(p-\theta)}{\bar{\varepsilon}-\underline{\varepsilon}}$ implies that as θ increases, we need larger δ for platform release to be used. Put in another way, it means the lower the consumers' expectation about the movie's quality, the more likely platform release will occur. When consumers' expectation is sufficiently high, platform release looses its appeal.

The intuition of $\frac{(\delta-\alpha)}{(1-\alpha)}\phi_1 > \delta\phi_2$ can be best understood from assuming $\delta = 1$, which is nonetheless close to reality as normally the length per period is only one or two weeks. With $\delta = 1$, the condition $\delta > \alpha$ is automatically satisfied. We can see that a sliding percentage contract corresponds to $\phi_1 > \phi_2$, so it exactly means this special contract feature together with word-of-mouth gives rise to the usage of platform release. When $\delta < 1$, $\delta\phi_2$ can be interpreted as the "virtual percentage" the movie distributor has right to in the second week. Since $\phi_1 > \frac{(\delta-\alpha)}{(1-\alpha)}\phi_1$, the condition $\frac{(\delta-\alpha)}{(1-\alpha)}\phi_1 > \delta\phi_2$ once again means choosing platform release entails the contract feature sliding percentage.

The optimal choice being n_1^* when using platform release is also intuitive. At n_1^*, word-of-mouth from platform release just fills the remaining market. Any $n_1 > n_1^*$ implies a waste of information sources, and the distributor can do better by cutting back to n_1^*, so that those audiences that would see the movie in the second week in the $n_1 - n_1^*$ theater areas will now see the movie in the first week, leading to an increase of profit.

It is worth noting that Proposition 1 is robust with respect to the specific value of ϕ_t and the specific scale of $W(.)$. Though in reality the specific contract clauses are subject to negotiation between the distributor and the exhibitor, the sliding percentage feature has been preserved (Filson et al. 2005), which makes platform release possible. On the other hand, for Proposition 1 to hold we only assume $W(.)$ to be strictly increasing and differentiable, a rather weak assumption.

To emphasize the relation between platform release and the sliding percentage contract, the present model is abstracted from other factors such as marketing budget, stochastic demand, and demographic variation, etc. However, we believe our framework based on theater areas and consumer propensity offers a good departure point for further extensions, among which two are discussed as follows:

Advertising Budget: Suppose the movie distributor can afford a lump-sum cost K to launch an advertising campaign, say a nationwide TV commercial, which will convincingly inform the consumers about θ^*. In addition, suppose the two conditions of Proposition 1 are satisfied. Then the movie distributor will choose platform release over wide release if $\pi(n_1^*) > \phi_1 - K$. In this direction, one can further endogenize the advertising expenditure and make the consumer's awareness of the movie's quality a function of the distributor's marketing effort.

Length of Platform Release: In the present model the length of platform release is exogenous, but in reality, as we describe in detail in the Data section, the length has typically been multiple weeks. Stochastic demand offers an explanation. After one consumer has decided to see a movie, she may be available only at a random time, as each week her opportunity cost may be a draw from a probability distribution. Therefore during platform release the movie distributor will have to wait until the source of word-of-mouth accumulates to a sufficiently high level before expanding to a larger scale of theaters. This then suggests two ways to endogenize the length of platform release: One is to have the movie distributor decide the platform-release length before the movie's premiere, with the other allowing the platform-release length to be alternated when actual admissions are realized over weeks.

4 Data

We obtain the movie data from http://www.boxofficemojo.com. The data set contains information of every movie released from 1/1/2000 to 12/31/2005, including: movie title, distributor, production budget, weekly box office, weekly theatre-number count, open / close date, total box office, cast list, genre, the MPAA rating, awards and nominations. The production budgets are available for only a small part of the movies[4]. In addition, we obtain the yearly average price from http://www.natoonline.org/statisticstickets.htm, the web site of National Association of Theatre Owners.

On average each year there are 505 movies on the box-office chart. However, we restrict each year's data to the movies whose box offices are among the top 200 in that year, because first the movies in the lower part of the box-office chart are shown in a significantly smaller number of theatre and thus are hard to distinguish between platform release and wide release, and secondly each year the 200th movie's box office is around only 7% of the average box office, implying the

[4] According to Einav(2005), the marketing expenditures are almost all funded by distributor. And aside of the marketing cost, the cost of copying and shipping copies is also on the distributors' side, which is comparable to the marketing cost.

movies with lower ranking are commercially insignificant.

For ease of data description we first outline some notations: Suppose a movie j is shown for a total of $\tilde{T}$ weeks, including T weeks of platform release. The admission of week t is denoted by a_{jt}, and the number of theaters in week t is denoted by n_{jt}.

As the present study is focused on platform release, we classify all the movies in our data set into three categories:

Wide release: A movie j's release pattern is wide release if $\frac{n_{j1}}{\max\{n_{jt}\}} > \frac{1}{2}$. We adopt this criterion since normally in each theatre a movie will be shown for more than 1 week, while $\frac{n_{j1}}{\max\{n_{jt}\}} > \frac{1}{2}$ implies $n_{j1} > \max\{n_{jt}\} - n_{j2} \geq n_{j2} - n_{j1}$, that is, there are fewer new theatres in the second week than in the first week.

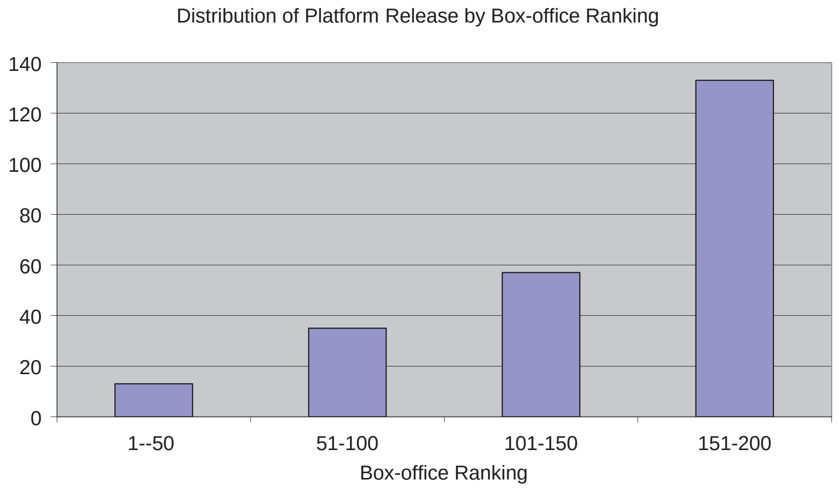
Hybrid release: $\frac{n_{j1}}{\max\{n_{jt}\}} \leq \frac{1}{2}$ and there exists a t such that $\frac{n_{jt+1}}{n_{jt}} > 100$. Though the best way to identify hybrid release is to check the proportion of marketing budget in the total production budget, the corresponding data are not available. The present criterion is obtained from the fact that hybrid release means that only a small number of theatres will be used as platforms and the platform-release period will be rather short.

Platform release: A release pattern that is neither wide release nor hybrid release is classified as platform release.

For a movie using platform release, we set T, the week platform release ends, to be the week of which the number of theatres is (i) less than 90% of the maximum number of theatres and (ii) less than 600. Using this criterion instead of setting T to be the week with maximum number of theatres takes into account the possibility that some theatres may have run at full capacity when a movie is scheduled to be shown there and thus postpone the release by one or two weeks. Moreover it takes into account the fact that in some theatre areas there are more than one theatre.

In total there are 3033 movies in the box-office charts and the average box office for each movie is \$17.37m. Applying our criterion we obtain 238 movies categorized as platform release.

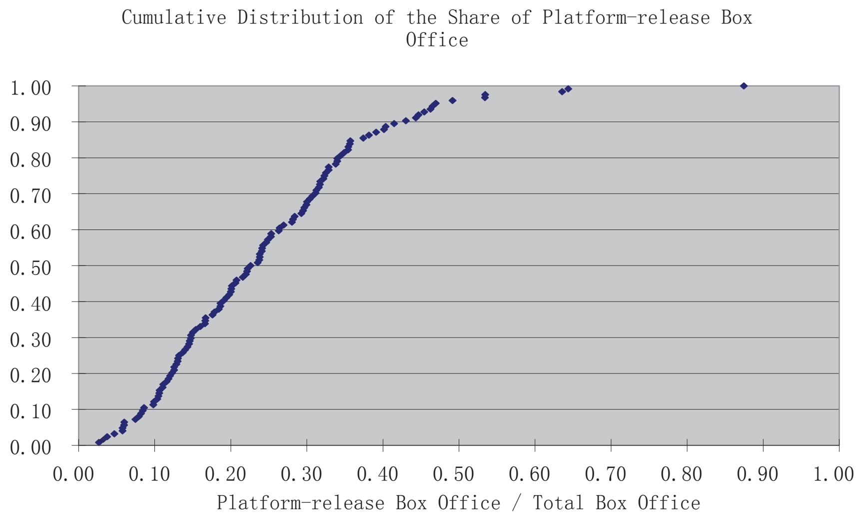
Though the data do not contain marketing budget and only contain production budget for a small proportion of the movies, as the figure below indicates, more movies in the lower part of the box-office chart use platform release than those in the upper part of the chart, suggesting that movies with low production budget tend to use platform release more often.



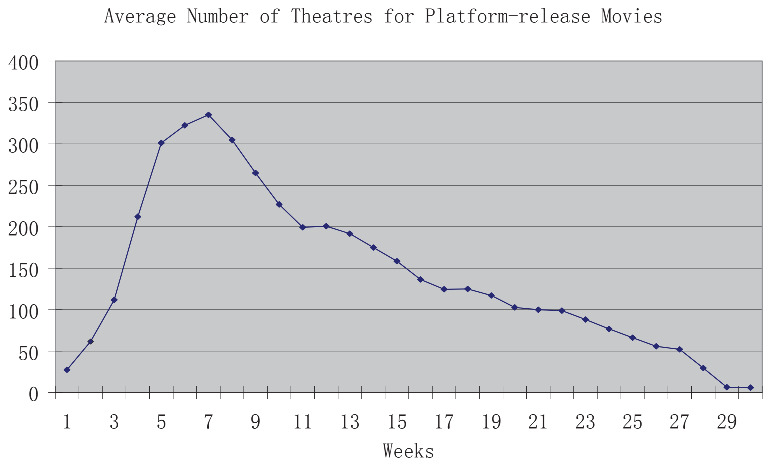
The table below summarizes some statistics of concern:

	mean	median	min	max	std
Number of Theaters in Platform Release	170	104	5	1174	180
Maximum Number of Theaters	479	221	22	3001	598
Length of Platform Release	6	5	1	53	5
Length of Whole Release	19	19	5	72	9

As the figure below shows, for about 70% of the movies with platform release, the box office from the platform-release period counts less than 30% of the total box office, suggesting that platform release is more important in spreading word-of-mouth than contributing to box office.



As explained in previous sections, once a movie is shown in one theatre, when to terminate the show is up to the exhibitor. While it is reasonable to assume identical distribution of consumer propensity in different theatre areas, the theatres in different areas do differ in construction costs, the ages of the theatres and thus the maintenance costs, the number of screens they have, and the capacity for each screen. Due to the heterogeneity of theaters' opportunity costs, in the data we observe that after wide release the number of theatres in general decrease gradually. The assumption of identical distribution of consumer propensity then suggests us base the estimation on per theatre term. For ease of computation, we restrict our attention to the movies whose theatre numbers decrease after reaching peak. Finally in total we have 124 movies and 2194 observations. The figure below shows the average number of theatres during the a movie's release period.



The average annual ticket prices are as follows:

Year	2000	01	02	03	04	05
Ticket Price ($)	5.39	5.65	5.80	6.03	6.21	6.41

5 Specification and Estimation Strategy

Following our previous notations, movie j's word-of-mouth scale from its platform release is, at the beginning of week $T+1$, the number of potential audiences that have heard θ_j^* from the previous audiences, denoted by $W(a_{j1}, ..., a_j)$ with the following specification

$$
\begin{aligned}
W(a_{j1}, ..., a_j) &= \beta_0 + \beta_1 a_{j1} + \beta_2 a_{j1} + ... + \beta_T a_{j1} \\
&\quad + \beta_1 a_{j2} + \beta_2 a_{j2} + ... + \beta_{T-1} a_{j2} \\
&\quad \cdots \\
&\quad + \beta_1 a_{jT} + \eta_j \\
&= \beta_0 + \beta_1 \sum_{t=1}^{T} a_{jt} + \beta_2 \sum_{t=1}^{T-1} a_{jt} + \cdots + \beta_T a_{j1} + \eta_j \qquad (1)
\end{aligned}
$$

where β_0 is a constant and β_t measures the effect of word-of-mouth from the audiences that see the movie t weeks ago, and η_j is an error term that is i.i.d. across the movies. Hence, for instance, $\beta_1 a_{j1} + \beta_2 a_{j1} + ... + \beta_T a_{j1}$ are the total amount of potential audiences informed by the first week's audiences during the movie's platform release. This specification therefore encompasses two possible information transmission processes: An audience may inform a fixed number of acquaintances regardless of the movie's theatrical run, implied by $\beta_1 > 0$ and $\beta_t = 0$ for $t > 1$, or an audience may inform a certain number of audiences in each week, with $\beta_t > 0$ for every t.

Since $W(a_{j1}, ..., a_{jT})$ is unobservable and needs to be estimated, (1) cannot be directly used for estimating β. Hence we turn to the movies' wide-release part.

After hearing θ_j^*, a potential audience i's utility from seeing the movie at week t is

$$u_{ijt} = \theta_j^* - p + \varepsilon_i - \kappa_{ijt}$$

where κ_{ijt} is i.i.d. across i, and measures the opportunity cost of i seeing j at week t. Assume

$$\kappa_{ijt} = \begin{cases} 0 \text{ with probability } q_j \\ c \text{ with probability } 1 - q_j \end{cases}$$

where $c > \bar{\theta} - p + \bar{\varepsilon}$, implying that, due to discounting, i will see the movie at the first t with $\kappa_{ijt} = 0$.

The assumption of a movie-specific q_j is consistent with our monopoly framework, as it implies each movie is targeting a niche market, with the consumers' common characteristic in the same market represented by q_j. At the same time, heterogeneity among consumers exists due to ε_i. It is worth noting that q_j is not in conflict with seasonality in demand. The assumption only entails q_j being constant throughout the movie's theatrical run, which normally lasts only a few months, so q_j can vary from season to season. One may further decompose q_j into a season-invariant part and a part that varies across seasons, but we skip such a step here since an unbiased estimator of q_j suffices for our main purpose, estimation of $W(a_{j1},...,a_{jT})$ and β.

As we show in the Data section, after wide release, the number of theatres normally decreases gradually, indicating that we should focus on the theater areas that still show the movie. Define $w_j = \frac{W(a_{j1},...,a_{jT})}{n_{jT+1}}$ and $\bar{a}_{jt} = \frac{a_{jt}}{\min\{n_{jt},n_{jT+1}\}}$ for $t \geq T+1$. Thus w_j is the number of potential audiences in each theater area at the beginning of wide release, and $\bar{a}_{jt}$ is the number of audiences that see the movie in one of the remaining theater areas at week t. The reason we use $\min\{n_{jt}, n_{jT+1}\}$ is that by our criterion of T we set the measure of the theater areas to be n_{jT+1}, which is allowed to be less than $\max\{n_{jt}\}$. In other words, we allow around 10% of the theater area to have more than one theater.

By our specification of the consumer's utility function, we can derive the evolution of $\bar{a}_{jt}$:

$$\begin{aligned}
\bar{a}_{jT+1} &= w_j q_j + \xi_{jT+1} \\
&\vdots \\
\bar{a}_{jt'} &= (w_j - \sum_{t=T+1}^{t'-1} \bar{a}_{jt}) q_j + \xi_{jt'} \\
&\vdots \\
\bar{a}_{j\tilde{T}} &= (w_j - \sum_{t=T+1}^{\tilde{T}-1} \bar{a}_{jt}) q_j + \xi_{j\tilde{T}} \qquad (2)
\end{aligned}$$

where $\xi_{jt'}$'s are i.i.d. disturbance with $E[\xi_{jt'}] = 0$.

Despite w_j being unobservable, we can estimate q_j by taking first difference of the above system, which leads to, for $t' \in \{T+1,...,\tilde{T}-1\}$,

$$\bar{a}_{jt'} - \bar{a}_{jt'+1} = \left[\left(\bar{a}_{jt'} - \xi_{jt'}\right)\right] q_j + \xi_{jt'} - \xi_{jt'+1}$$

After simplification we arrive at an ARMA(1,1) process

$$\bar{a}_{jt'+1} = (1-q_j)\bar{a}_{jt'} + \xi_{jt'+1} - \xi_{jt'}$$

Let $Y_j = \begin{pmatrix} y_{jT+2} \\ \vdots \\ y_{j\tilde{T}} \end{pmatrix}$ with $y_{jt'} = \bar{a}_{jt'+1}$ and let $X_j = \begin{pmatrix} x_{jT+1} \\ \vdots \\ x_{j\tilde{T}-1} \end{pmatrix}$ with $x_{jt'} = \bar{a}_{jt'}$.

The endogeneity problem is implied by the fact $E[x_{jt'}(\xi_{jt'+1} - \xi_{jt'})] \neq 0$. Use an instrumental variable $z_{it'} = \bar{a}_{jt'-1}$ and define $Z_j = \begin{pmatrix} z_{jT+1} \\ \vdots \\ z_{j\tilde{T}-1} \end{pmatrix}$. The estimator for q_j is

$$\hat{q}_j = 1 - (Z_j' X_j)^{-1} (Z_j' Y_j)$$

Since the sample for each movie is small and an unbiased estimator suffices for the estimation of W_j and β, we neglect the autocorrelation problem.

(2) implies the estimator of $W(a_{j1}, ..., a_{jT})$

$$\hat{W}(a_{j1}, ..., a_{jT}) = (\frac{\bar{a}_{j\tilde{T}}}{\hat{q}_j} + \sum_{t=T+1}^{\tilde{T}-1} \bar{a}_{jt} - \frac{\xi_{j\tilde{T}}}{\hat{q}_j}) n_{jT+1} \tag{3}$$

(3) together with (1) then leads to the estimation equation for $\{\beta_t\}$:

$$(\frac{\bar{a}_{j\tilde{T}}}{\hat{q}_j} + \sum_{t=T+1}^{\tilde{T}-1} \bar{a}_{jt}) n_{jT+1} = \beta_0 + \beta_1 \sum_{t=1}^{T} a_{jt} + \beta_2 \sum_{t=1}^{T-1} a_{jt} + \cdots + \beta_T a_{j1} + \zeta_j \tag{4}$$

with $\zeta_j = \eta_j + \frac{\xi_{j\tilde{T}}}{\hat{q}_j} n_{jT+1}$.

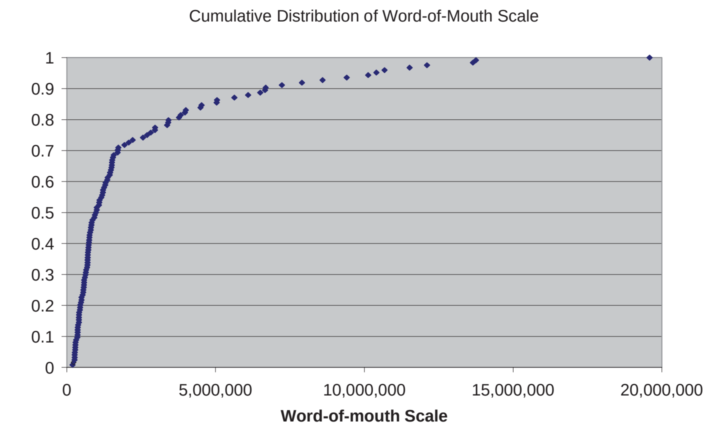
Heteroskedasticity in (4) is indicated by $Var[\zeta_j] = E[\eta_j^2 + \xi_{j\tilde{T}}^2 (\frac{n_{jT+1}}{\hat{q}_j})^2] = Var[\eta_j] + Var[\xi_{j\tilde{T}}] (\frac{n_{jT+1}}{\hat{q}_j})^2$, and so we adopt a two-step feasible GLS estimation, assuming $\hat{\zeta}_j^2 = l_1 + l_2 (\frac{n_{jT+1}}{\hat{q}_j})^2 + \upsilon_j$, with $\hat{\zeta}_j$ being the OLS residual and υ_j being an i.i.d. disturbance.

6 Results

(i) $W(a_{j1}, ...a_{jT})$

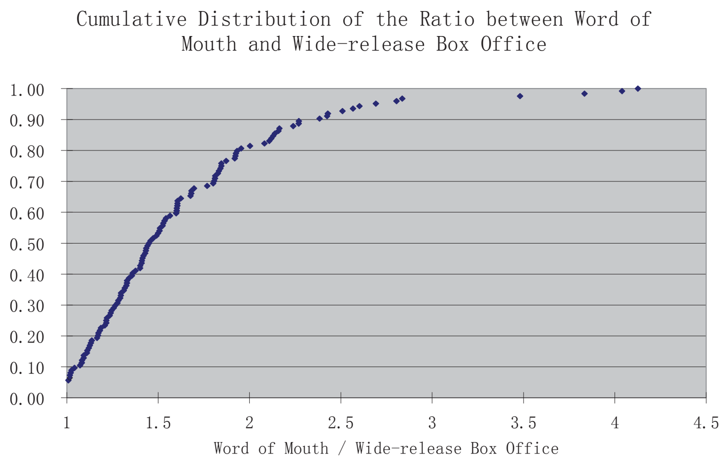
The table below shows the statistics of the estimates of word-of-mouth scale, with the following figure showing the cumulative distribution:

	mean	median	min	max	std
$\hat{W}(a_{j1}, ...a_{jT})$	$2,430,193$	$991,840$	$191,947$	$19,583,883$	$3,395,671$



The next table shows the statistics of the ratio $\frac{\hat{W}(a_{j1},...a_{jT})}{\sum_{t=T+1}^{\tilde{T}} a_{jt}}$, with the cumulative distribution displayed next.

	mean	median	min	max	std
$\frac{\hat{W}(a_{j1},...a_{jT})}{\sum_{t=T+1}^{\tilde{T}} a_{jt}}$	1.6269	1.454	0.7968	4.1257	0.607



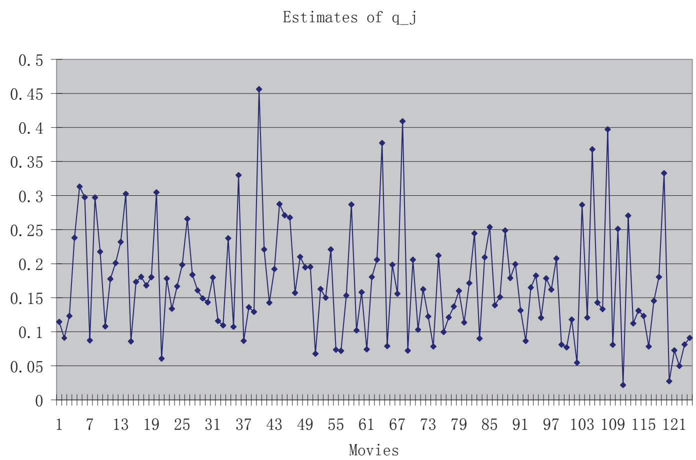
Estimating word-of-mouth scales has particular value in movies' nontheatrical windows, which nowadays have generated more revenue than the theatrical run. As Eliashberg et al. (2006) show, among all the windows, DVDs have become the largest, accounting for about $20 billion in 2003, twice of the expenditure on U.S. theatrical tickets. More strikingly, it is widely believed that most movies do not break even until DVD releases. Among the consumers of the nontheatrical windows, we believe those that want to see the movie but have not done so in theaters account for a very significant, if not the largest, proportion. Within our framework, the size of these consumers can be inferred from the difference between a movie's word-of-mouth scale and its total admission.

Previously, without formal estimation of the word-of-mouth scale, one tends to take two opposite approximations, one using the whole population or an exogenous fraction of it, and the other using the actual admission. But as our results indicate, neither approach pertains to movies with platform release. The significant variation among $\hat{W}_j$ is consistent with our assumption that movies using platform release target niche markets and thus can be better studied in a monopoly framework. On the other hand, we see that the actual admission during the wide-release period is much less than the number of potential audiences that have known about the movie through word-of-mouth. Hence we conclude that our approach results in a good alternative to estimate a movie's word-of-mouth scale and consequently its actual market size.

(ii) q_j **and** β

The table below shows the statistics of $\hat{q}_j$, with the following figure showing the estimates

	mean	median	min	max	std
$\hat{q}_j$	0.1712	0.1605	0.0217	0.4562	0.084



The estimate of β is as follows:

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
$\hat{\beta}_t$:	87.7741	6.2681*	-1.2895	-7.9289	3.4509	1.3732	-4.5661
Asymptotic t :	0.66	4.12	-0.35	-1.92	0.82	0.18	-0.53

As the result shows, only β_1 is significant at the 5% level. This suggests that after seeing a movie, the audiences will spread information about the movie for only 1 week and on average 1 audience will inform 6 people about the movie's quality. This result on the one hand answers our question about the natural pattern of word-of-mouth, and on the other hand provides empirical evidence for theoretically modelling the movie distributor's decision of the scale and length of platform release.

Moreover, the relative small value of q_j's and the result that only β_1 is significant explain why the movie distributor normally uses platform release for multiple weeks: Each week there is only a small proportion of potential audiences that are available to see the movie, and after seeing the movie the audiences will spread information about the movie for only one week, therefore before wide release the movie distributor will have to wait long enough until a sufficiently large number of audiences have seen the movie.

7 Concluding Discussion

In this paper we study the word-of-mouth effect on the movies with platform release. We construct a theoretical model and show that the word-of-mouth effect together with the sliding-percentage contract between the movie distributor and exhibitors give rise to the usage of platform release. Using the data in the U.S. motion picture industry from 2000 to 2005, we find that on average a movie's word-of-mouth scale is 60% larger than its actual admission, an audience will inform 6 friends about the movie and will spread information for only 1 week.

In the theory part, we show the conditions under which the optimal release pattern features platform release. However, there is an inconsistency between the two-period theoretical framework and the multiple-period empirical model. It is a future direction to extend the present theoretical model to incorporate multiple periods so that the movie distributor's decision include not only the scale of platform release but also its duration. Our empirical results have provided fundamental elements for such a theory.

In the empirical part, it remains to quantify the contribution to box office from using platform release, which will be measured by the difference between the real box office and the projected box office should there be no platform release. Moreover, our criterion for wide release, platform release and hybrid release calls for more accurate data on the production budget and marketing budget.

Though data are abundant in the motion picture industry and the movies with platform release are commercially less significant, we would like to reiterate the importance as well as advantage of studying movies with platform release. Among all the movies, movies with platform release are those that almost completely rely on word-of-mouth to promote themselves, so the study of word-of-mouth is of most value to these movies. Moreover, movies with platform release offer an ideal field to study word-of-mouth, since instead of studying a reduced form under the assumption that factors such as advertising are "solved out", researchers can comfortably neglect the minimum impact of these factors in movies with platform release. Furthermore, the fact that most of the movies are not mainstream allows a framework based on monopoly.

At last we would like to point out that "platform release" is not restricted to the motion picture industry. In the publishing industry, it has been an established strategy to first publish hardcover copies and use them as seeds for word-of-mouth before introducing the paperback edition. In the pop-music industry, a similar, though not identical, strategy entails a single song introduced to the public before the album goes on sale, and sometimes an underperformed single may cause the withdraw of the whole album. Therefore we believe the study of platform release and word-of-mouth has value beyond the motion picture industry.

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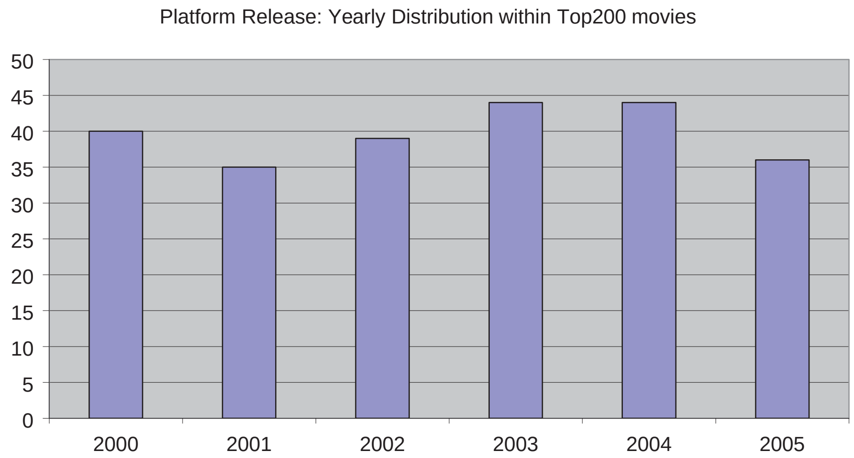
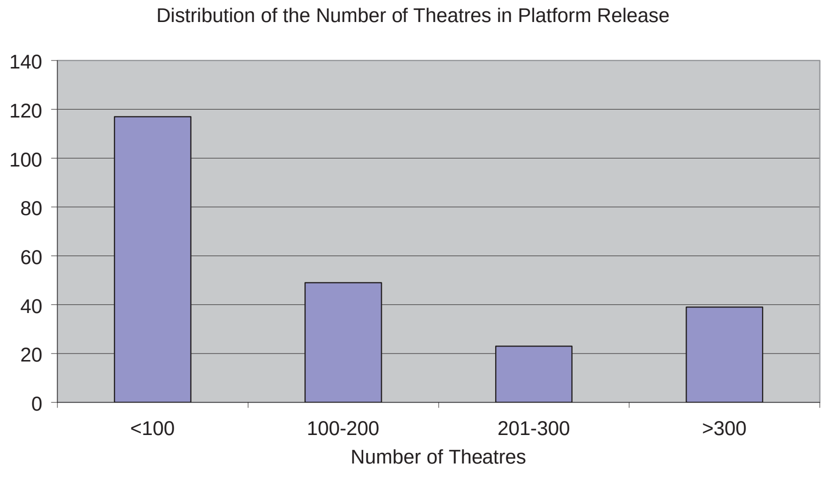
9 Appendix

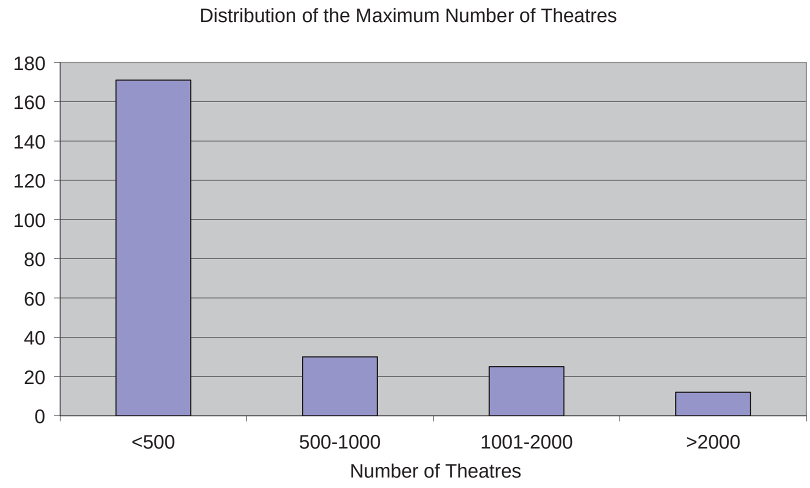
(i) Yearly distribution of the number of movies with platform release



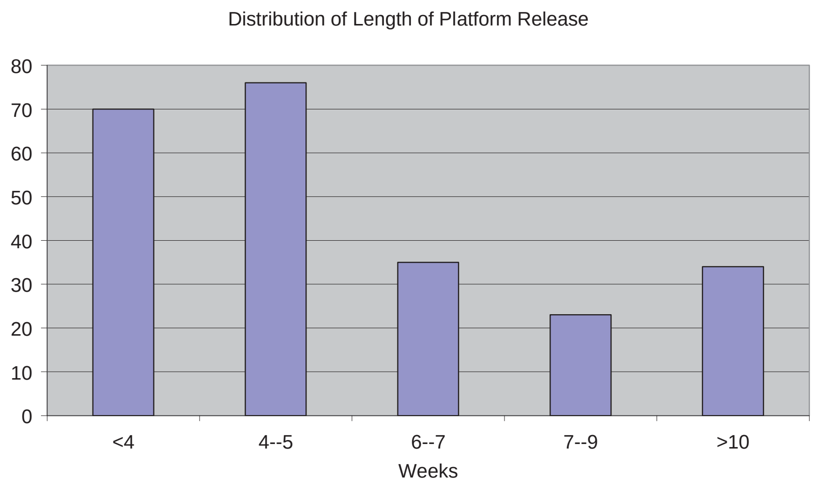
(ii) The distribution in the number of theaters in platform release



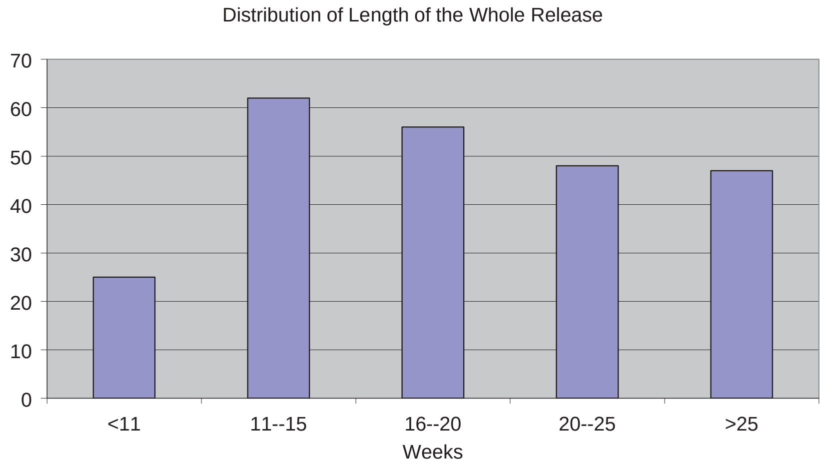
(iii) The distribution of the maximum number of theatres in movies with platform release:



(iv) The distribution of length of platform release:



(v) The distribution of the length of lifespan for movie's with platform release


Distribution of Length of the Whole Release
70
60
50
40
30
20
10
0
<11
11--15
16--20
20--25
>25
Weeks