# Analysis of the Determinants of Film Quality Considering a Risk-Averse Producer and Consumer Learning from Online Reviews

Chun-Yi Liu
School of Economics and Management, Yanshan University, Qinhuangdao, China, cyliu@ysu.edu.cn,

Fernando Siciliani Oliveira
Trade and Agriculture Directorate, OECD fernando.deoliveira@oecd.com,

Tianhui You *
School of Business Administration, Northeastern University, Shenyang, China, thyou@mail.neu.edu.cn,

This study examines a dual distribution channel through theaters and digital platforms to understand how a producer's investment strategy and pricing in these channels are influenced by risk aversion and the ability of Bayesian consumers to learn from online reviews. We develop a Stackelberg game model, where a risk-averse producer acts as the leader, investing in the film, which is then released sequentially in theaters and on digital platforms. Our findings show that online reviews are crucial due to the uncertainty of achieving the target movie quality. A risk-averse producer tends to invest in lower-quality movies with lower prices, while a risk-neutral producer invests in higher-quality films with higher ticket prices. Critic reviews significantly impact firms' decisions more than audience reviews. Interestingly, increasing the precision of online reviews lessens the effect of risk aversion on quality investment. These insights provide valuable contributions to film industry stakeholders, highlighting how online reviews and risk aversion shape investment strategies in the industry.

*Key words*: Bayesian Learning, Online Reviews, Stackelberg Competition, Risk Preferences

## 1. Introduction

Investing in the film industry can be a high-stakes game. Producers face significant risks, particularly regarding the quality of their movies. Even with a substantial investment budget, there is no guarantee that critics and consumers will perceive the movie's quality as intended, leading to a potential mismatch between spending and revenue. For instance, The Great Wall, directed by Yimou Zhang, a renowned director in China, illustrates this point. Despite its expensive ancillary and theatrical cost of 266.9 million dollars, the movie received mostly negative reviews, leading to a 74.5 million dollar loss (D'Alessandro 2018).

* Corresponding author.

Additionally, with the development of electronic commerce, movie screening is no longer limited to theaters Jiang et al. (2023). The Internet is also a popular distribution channel. Consumers can watch/download the movie via a digital purchase/rental platform, such as Amazon Instant Video, iTunes Store, or Google Play Alaei et al. (2023). The price varies depending on the type of film, production cost, release date, copyright license, market demand, etc. For this reason, producers can employ a dual-channel strategy through theaters and digital channels. More than half of the top 100 films on *rottentomatoes.com* in 2020 opted for dual-channel release. More than half of these dual-channel releases were first viewed in theaters and subsequently watched on digital channels.

### 1.1. Consumer Learning from Online Reviews

In the context of the film industry, a movie can be considered a service, and its true quality can only be known after viewing it. To help assess a movie's quality, consumers often rely on online reviews from previous viewers and critics. This process of updating prior beliefs about a movie's quality based on online reviews is known as consumer learning or social learning (Papanastasiou and Savva 2017, Ma et al. 2021). Research suggests that consumer learning from online reviews leads to better-informed purchasing decisions and fewer negative experiences (Li et al. 2023). It is important to note that the information available to earlier and later consumers may differ as online reviews evolve.

For example, let us analyze the critics' and audience ratings from Rotten Tomatoes for the film Green Book. This movie was first released in theaters on Nov 21, 2018, and subsequently released on the Internet on Mar 12, 2019. On Rotten Tomatoes, the critics' ratings are binary ('fresh' or 'rotten'), while the audience ratings are categorized on a scale from 0 to 5 stars. Therefore, we transform critics' and audience ratings into a binary system. Following the approach in Hogenboom et al. (2013), we classify 3, 3.5, 4, 4.5, and 5-star ratings as positive and 0.5, 1, 1.5, 2, and 2.5-star ratings as negative. We summarize the rating statistics in Table 1. The critics' ratings refer to those collected before the movie release, whereas audience ratings refer to those collected during the theater viewing. The audience ratings have higher averages and precision than the critics' ratings. (In this article, we use the term "audience rating" to refer specifically to the ratings provided by those who watched the movie in theaters.)

In a dual-channel sequential release, consumers in different channels receive varying information signals from online reviews due to changes in the average and volatility of the online movie ratings over time. Consequently, digital and theater consumers are exposed to different information about a movie's quality before viewing it. Digital consumers can obtain insights about a film's quality from pre-digital reviews, such as critics' and audience reviews. In contrast, theater consumers can only rely on pre-theater reviews to form their judgments.

Table 1: Statistics of ratings on Rotten Tomatoes.

| | Critics | Theater audience |
|---|---|---|
| Total reviews | 105 | 1518 |
| Positive | 86 | 1456 |
| Negative | 19 | 62 |
| Mean | 0.82 | 0.96 |
| Variance | 0.15 | 0.04 |
| Precision | 6.68 | 25.51 |

Pricing is an additional issue that merits consideration. It has been commonly perceived that movies are uniformly priced, implying that the same price is charged for films of different quality. However, differentiated pricing is gaining momentum. AMC Theaters, for example, charged a higher price for *The Batman* than any other movie playing concurrently (Isenberg 2022). Furthermore, theaters indirectly set different movie prices by exhibiting them at other times or locations. For instance, ticket prices are higher on Sundays than on weekdays (SingaporeReview 2021), and popular movies are usually shown at 'prime' times. Additionally, large productions receive more theater space with better technology, while small-budget movies are relegated to older theaters with smaller screens (Thompson 2012). As online reviews can predict a movie's success to a certain extent, theaters and platforms can leverage this information to set prices and determine how to exhibit the film.

### 1.2. Motivation and Methodology

Our primary motivation is to analyze the impact of producer risk aversion and consumer learning on quality investment. Specifically, we aim to address the following research questions:

Focusing on the film supply chain, we ask three research questions regarding the equilibrium decisions about movie quality and pricing. 1. How does producer risk aversion impact movie quality and pricing decisions? 2. How does consumer learning from online reviews, as either unbiased estimates of quality or independent of a producer's ability, influence the supply chain equilibrium? 3. How is the equilibrium affected by the interaction between the producer's risk aversion and the precision of online reviews?

To address our research questions, we use a Stackelberg game model, where a risk-averse producer is a leader who invests in the quality of the film. At the same time, the theater and the digital platform are risk-neutral followers who set their respective prices. As the film is released sequentially on both channels, consumers form beliefs about its quality based on pre-theater reviews (during the theater release period) and pre-digital reviews (during the digital release period).

We determine the game's equilibrium and explore its properties. Specifically, we analyze the equilibrium's sensitivity to key factors such as risk aversion, online ratings, and information uncertainty. We also examine the price competition between theaters and digital platforms by analyzing the difference between theatrical and digital purchase prices.

Moreover, we extend the base model, which assumes independent online ratings by critics and the theater audience, to a model where the producer's quality investment affects the expected ratings.

To further analyze the complexity of the equilibria, we conduct numerical simulations. We investigate how the impact of information precision on the optimal policy depends on the producer's degree of risk aversion. Our findings suggest that an increase in online reviews' accuracy reduces risk aversion's impact on quality and prices. Additionally, we use numerical simulations and linear regression to assess the robustness of our results.

Our research employs a comprehensive methodology to answer our research questions, which involves a Stackelberg game model, numerical simulations, and linear regression analysis. Our results shed light on the interplay between producer risk aversion, consumer learning, and quality investment in the film industry.

### 1.3. Contributions

We make a significant methodological contribution by examining the impact of the interaction between risk aversion and the learning of Bayesian consumers from online reviews on the producer's investment strategy.

Our research has important managerial implications for the film industry. We show that a producer's level of risk aversion affects their decision-making process regarding quality investment and pricing in response to online ratings. Specifically, a low-risk-averse producer invests more in quality and raises prices in response to higher ratings. In contrast, a high-risk-averse producer invests less in quality under the same conditions. Furthermore, we demonstrate the significance of online reviews in the decision-making process because of the producers' uncertainty about the film's quality. Our analysis indicates that critics' reviews carry more weight than the theater audience reviews in determining the movie's profitability, and we show that an increase in the precision of online reviews reduces the impact of risk aversion on quality and prices. Finally, to deepen our understanding of how risk aversion affects optimal policies, we develop a movie typology based on production budget size and rating uncertainty, providing a framework to assess the risks and benefits of quality investment and pricing decisions.

The remainder of this paper is organized as follows. First, we review the relevant literature in Section 2, followed by a description of the Stackelberg game in Section 3. Next, in Section 4, we derive the optimal quality and pricing decisions and analyze the properties of the equilibrium. We then focus on a case in which online reviews do not affect the average consumers' perception of the movie quality but only reduce uncertainty in Section 5. In Section 6, we provide a set of numerical analyses to explore the role of online reviews on the equilibrium, and verify the theoretical results. Finally, in Section 7, we summarize the essential findings and the managerial implications. We provide all the proofs of theorems, propositions, and corollaries in the Appendix.

## 2. Literature Review

Our study relates to three streams of research: a) quality investment by risk-averse agents, b) movie pricing, and c) consumer learning from online reviews.

### 2.1. Quality Investment by Risk-Averse Agents

Several studies have explored the relationship between product quality investment decisions and risk aversion, including the works by Wen and Siqin (2020), Chen et al. (2022), and Zhou et al. (2023). Among these, the study most closely related to ours is that of Wen and Siqin (2020). They employ the mean-variance model to investigate the impact of risk aversion on quality and pricing decisions in a sharing economy platform, finding that risk aversion reduces quality.

Our study differs from that of Wen and Siqin (2020) in several significant ways. First, we incorporate the effect of learning from online reviews. Second, we examine the interaction between information precision and risk aversion. Third, we investigate how quality and pricing affect the equilibrium outcome.

### 2.2. Movie Pricing

Some studies suggest that theaters consistently charge the same price for films, regardless of the differences in the movies (Eliashberg et al. 2009). However, in specific markets, such as Hong Kong, theaters implement differential pricing for movie tickets (Ho et al. 2018). An analysis of ticket pricing by Ho et al. (2018) found that differential pricing leads to higher profits than uniform pricing. Additionally, Gu et al. (2024) discovered that a movie's ticket price is influenced by factors such as the consumer's status (senior citizen or student). They proved the conditions when the differential pricing is optimal for competitive facilities.

Films can be distributed through various channels, such as online or home video, after their release in theaters (Berbeglia et al. 2020). Calzada and Valletti (2012) and August et al. (2015) studied the inter-temporal distribution and consumption of movies. Calzada and Valletti (2012) suggested that sequential release is a better choice when the movie studio is independent of movie distributors and exhibitors. August et al. (2015) found that at the lower (upper) range of quality, an increase in movie quality is accompanied by a longer (shorter) time window between theatrical and video channels. However, few studies have considered price competition between theater and digital platforms. While there is substantial literature on price competition in dual-channel sales (Ha et al. 2022, Pal et al. 2023), the investigation of price competition of movies sequentially released on two different channels is still in its infancy.

Due to uncertainty regarding the quality of the film, strategic consumers may delay viewing the movie until receiving word-of-mouth recommendations. Online reviews and the expected price difference are two crucial factors in consumer choices regarding different channels for viewing. For this reason, we investigate the impact of different types of online reviews on the pricing strategy of two channels for a movie sequentially released in theater and on digital channels.

### 2.3. Consumer Learning from Online Reviews

Consumer learning refers to how consumers acquire knowledge and experience of products or services and apply them to their purchasing decisions. Empirical studies have proven that online reviews are an important source of information for consumers to learn about products or services prior to making a purchase (Huang et al. 2023). Therefore, developing mathematical models to capture consumer learning from online reviews is crucial. For instance, Zhou et al. (2023) considers that consumers learn about product quality from online reviews and past sales volume information and finds that neither of these two types of information can guarantee higher firms' profit. Other studies, such as those conducted by Li et al. (2019), Wang et al. (2022), and Li et al. (2023) have modeled how consumers update their expectations of how well a product fits their needs based on online reviews. Jiang and Yang (2019) has modeled how consumers learn the firm's type of cost efficiency from online reviews.

In Bayesian learning, when the prior beliefs and information signals follow a normal distribution, the updated posterior beliefs of consumers also follow a normal distribution. The mean of this posterior distribution is the weighted average between the prior belief and the signal. For example, Papanastasiou and Savva (2017), Ma et al. (2021), and Shin et al. (2023), have included the number of reviews and the average rating by early consumers as information signals in the consumer learning process. In contrast, Keppo et al. (2022) has extended the updating process to $t$ periods.

We adopt a similar consumer learning model but assume consumers in different channels can access additional review information. Specifically, theater consumers only read online reviews by professional critics, while digital channel consumers read online reviews by both critics and theater viewers. We analyze the impact of these two types of review information on the investment in movie quality and retail pricing.

### 2.4. Summary

In summary, several articles on investment in quality consider risk aversion, focusing on demand uncertainty (e.g., Li and Qi 2021, Wen and Siqin 2020). However, the situation in the film industry is different. The revenue from a film is strongly related to online reviews, which, together with the producer's quality investment, influence consumer perceptions. Therefore, investigating the joint impact of the producer's risk-averse behavior and consumer learning on movie quality, ratings, and pricing is a significant contribution.

Furthermore, films are often released sequentially in theaters and on digital platforms, so consumers in different channels observe different online review signals. However, existing articles on consumer learning from online reviews assume that all consumers observe the same review signals and, therefore, learn only once (e.g., Papanastasiou and Savva 2017, Ma et al. 2021). For this reason, we also contribute to studying the impact of different online review signals on film quality investment and pricing decisions.

## 3. Modeling the Film Distribution Channel Structure

This section presents a Stackelberg model that captures the interactions between a producer, a theater, and a digital platform in the film industry. The dual-distribution channel consists of a producer (she), a theater (he), and a digital platform (he), as shown in Figure 1. The producer invests in and produces movies and then screens them sequentially in the theater and through the digital platform. Let the retail prices for watching the film be $p_r$ at the theater and $p_s$ on the digital platform. The theater and the platform share a portion of their box office revenues, $\alpha_r$ and $\alpha_s$, respectively, with the producer.

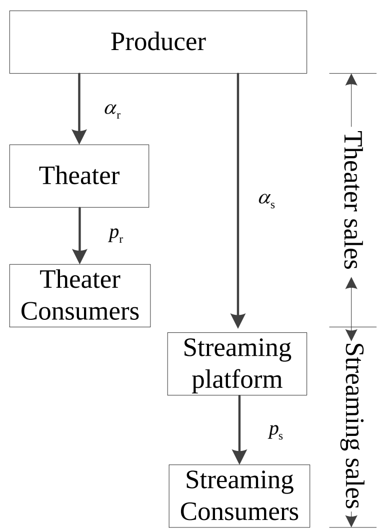



**Figure 1 Channel structure.**

### 3.1. Modeling Consumer Learning

Prior to release, the actual quality of the movie is unobservable to the agents (i.e., consumers, theater, digital platform, and producer). However, we assume that they all share a common and public prior belief about $\tilde{q}_0$, which is represented by equation (1). Specifically, $q_0$ is the producer's target quality, while $\tau_0$ represents the precision of the prior belief and captures the producer's ability to meet the quality target. This precision is the inverse of the variance (e.g., Lynch 2007, chap. 3). A high value of $\tau_0$ indicates that the difference between the perceived quality of the movie among various consumers before reading online reviews is slight, which implies that the producer has a high ability to meet the consumers' expectations.

$$\tilde{q}_0 \sim N(q_0, 1/\tau_0) \tag{1}$$

Consumers can enhance their understanding of quality by reading online reviews. The object of consumer learning is represented by $\tilde{q}_0$. Consumers combine their prior beliefs with online review information to re-evaluate the movie's quality, deriving their posterior beliefs, which form the basis for their viewing decisions. Meanwhile, the producer can influence $q_0$ by deciding how much of the budget to invest in advertising, which actors to hire, who should write the plot, which technicians to employ, and which studio facilities to use.

Consumers can access pre-theater reviews to help them decide whether to purchase theater tickets and pre-digital reviews to guide their choices when watching a movie on a digital platform. Pre-digital reviews supplement pre-theater reviews by including the opinions of the general audience. As a result, pre-theater reviews are typically written by professional critics, while pre-digital reviews come from both critics and theatergoers.

In reality, even though theater releases may last around a month or longer, box office contributions are largely based on the first week's box office. For this reason, reviews about theater releases rely more on pre-release reviews. Moreover, to keep a complex model analytically tractable, we condensed all theater consumers to a single point and considered the reviews they learned to be primarily critics' reviews.

Let $\tilde{q}_a$ and $\tilde{q}_b$ denote the movie's quality signals revealed by critics' early reviews and theater audience reviews, respectively. We assume that $\tilde{q}_a \sim N(q_a, 1/\tau_a)$ and $\tilde{q}_b \sim N(q_b, 1/\tau_b)$, where $q_a$ and $q_b$ are the corresponding average ratings and $\tau_a$ and $\tau_b$ capture the precision of these reviews. A higher precision parameter (larger $\tau_a$ or $\tau_b$) indicates lower dispersion among individual reviews and therefore more reliable information. Therefore, following Bayes' rule (Feldman et al. 2019, Guo et al. 2022), theater audiences update their beliefs about movie quality to $\tilde{q}1$ in (2), combining their prior beliefs $\tilde{q}_0$ with the critics' early reviews $\tilde{q}_a$.

$$\tilde{q}_1 \sim N\left(\frac{q_0\tau_0 + q_a\tau_a}{\tau_0 + \tau_a}, \frac{1}{\tau_0 + \tau_a}\right) \tag{2}$$

As online releases typically occur after the theatrical run (often about a year later), we postulate that online viewers have access to more review information than theater audiences: they can consider both critics' early reviews and subsequent theater audience reviews. Digital consumers then update their beliefs about the movie's quality to $\tilde{q}_2$ in (3), based on their prior beliefs $\tilde{q}_0$, critics' reviews $\tilde{q}_a$, and theater audience reviews $\tilde{q}_b$. Here, $\tau_0$, $\tau_a$, and $\tau_b$ represent the weights attributed to prior beliefs, critics' reviews, and theater audience reviews, respectively. The greater the precision of the information, the more influential it is in shaping consumers' perceptions of product quality (Papanastasiou and Savva 2017).

$$\tilde{q}_2 \sim N\left(\frac{q_0\tau_0 + q_a\tau_a + q_b\tau_b}{\tau_0+\tau_a+\tau_b}, \frac{1}{\tau_0+\tau_a+\tau_b}\right) \tag{3}$$

The theater observes $\tilde{q}_a$ before setting the price $p_r$. The platform observes both $\tilde{q}_a$ and $\tilde{q}_b$ before setting price $p_s$. Therefore, the theater's pricing is based on $\tilde{q}_1$, and the platform's pricing is based on $\tilde{q}_2$, the posterior distributions. Formulas (2) and (3) show that the mean values of $\tilde{q}_1$ and $\tilde{q}_2$ are positively correlated, and the coefficient is $\frac{\partial q_2}{\partial q_1} = \frac{\partial q_2}{\partial q_0}\frac{1}{\frac{\partial q_1}{\partial q_0}} = \frac{\tau_0+\tau_a}{\tau_0+\tau_a+\tau_b}$. Let $\rho$ be the correlation between $\tilde{q}_1$ and $\tilde{q}_2$. As the residual of $\tilde{q}_1$ and $\tilde{q}_2$ are independent and identically distributed, then the correlation between $\tilde{q}_1$ and $\tilde{q}_2$ is same as the correlation between $q_1$ and $q_2$, i.e., $\rho = \frac{\tau_0+\tau_a}{\tau_0+\tau_a+\tau_b}$.

### 3.2. Modeling the Demand Function

Our model postulates that the linear demand functions depend on the retail prices in both channels and the consumers' posterior beliefs about movie quality. Equations (4)-(5) represent the demand functions in the theater and the digital platform, where $a$ is the potential market size, $z$ represents the consumers' preference for the theater (with $1-z$ for digital channel), $b_1$ is the price sensitivity coefficient, $b_2$ is the cross-price sensitivity coefficient, and $b_q$ is the quality sensitivity coefficient. Following Ha et al. (2022), we assume $b_1 > b_2$, as the price of each channel has a greater effect on its demand than on the demand of the competing channel.

$$\tilde{D}_r = za - b_1 p_r + b_2 p_s + b_q \tilde{q}_1 \tag{4}$$

$$\tilde{D}_s = (1-z)a - b_1 p_s + b_2 p_r + b_q \tilde{q}_2 \tag{5}$$

From Eqs. (4) and (5), we obtain the properties of the demand functions in the theater ($\tilde{D}_r$) and digital channel ($\tilde{D}_s$), as summarized in Proposition 1.

Proposition 1. *$\tilde{D}_r$ and $\tilde{D}_s$ follow normal distributions: $\tilde{D}_r \sim N\left(D_r, \frac{b_q^2}{\tau_0+\tau_a}\right)$ with mean $D_r = za - b_1 p_r + b_2 p_s + \frac{b_q(q_0\tau_0+q_a\tau_a)}{\tau_0+\tau_a}$; $\tilde{D}_s \sim N\left(D_s, \frac{b_q^2}{\tau_0+\tau_a+\tau_b}\right)$ with mean $D_s = (1-z)a - b_1 p_s + b_2 p_r + \frac{b_q(q_0\tau_0+q_a\tau_a+q_b\tau_b)}{\tau_0+\tau_a+\tau_b}$. The correlation between $\tilde{D}_r$ and $\tilde{D}_s$ is $\rho(\tilde{D}_r, \tilde{D}_s) = \frac{cov(\tilde{q}_1,\tilde{q}_2)}{\sqrt{\tilde{q}_1}\sqrt{\tilde{q}_2}} = \rho$.*

### 3.3. Defining the Profit and Utility Functions

Moreover, consumers' prior beliefs about movie quality depend on the producer's investment in film quality. To model the diminishing returns from investment, we adopt a quadratic cost structure. Specifically, to produce a movie with an average quality level $q_0$, the producer incurs a cost of $kq_0^2$ (Wen and Siqin 2020), where $k$ is the quality improvement cost coefficient. A higher $k$ indicates greater difficulty (and thus higher costs) in improving movie quality, causing producers to aim for lower target quality levels. Movie genres vary in their associated $k$ values. For instance, horror films typically have lower $k$, while science fiction films often have higher $k$. Section 6.2 discusses the interplay between the cost coefficient $k$ and information precision across different movie genres. The producer's profit function is given by equation (6), and the profit functions for the theater ($r$) and digital platform ($s$) are provided in equation (7).

$$\pi_p(q_0) = \sum_{i=r,s} \alpha_i p_i \tilde{D}_i - k q_0^2 \tag{6}$$

$$\pi_i(p_i) = (1-\alpha_i) p_i \tilde{D}_i \qquad \forall i = r, s \tag{7}$$

Uncertainty surrounding consumer reactions makes it highly challenging for producers to ensure movie profitability. Producers' revenues heavily depend on box office performance, placing them at substantial financial risk. Even in Hollywood, only about half of all films turn out to be profitable for producers (Pokorny and Sedgwick 2012). In contrast, theaters operate with relatively greater stability. Rather than investing in film production, theaters secure profits by allocating more screenings, premium auditoriums, and prime-time slots to popular films. Additionally, theaters generate revenue through complementary sales, such as beverages and popcorn. Similarly, digital platforms mitigate risk by offering a variety of popular movies. For example, during the 2025 Spring Festival, the film "Creation of the Gods II: Demon Force" generated revenues of around RMB 456 million, significantly less than its production cost of RMB 800 million (TencentNews 2025). However, the poor performance of this film did not significantly impact theaters, as they compensated by scheduling more screenings of other popular movies like "NeZha 2". Indeed, according to a recent survey, revenues for some theaters in China have already surpassed last year's total (Dai 2025). Given the substantial investment risk faced by producers, we examine how their risk aversion influences investment decisions, while assuming that theaters and digital platforms are risk-neutral.

We adopt the mean–variance framework to model the producer's risk-averse behavior (Wen and Siqin 2020). The producer aims to maximize her utility function (8), where $E(\pi_p(q_0))$ represents the expected profit, $Var(\pi_p(q_0))$ denotes the profit variance that measures the risk faced by the producer, and $\eta$ reflects the producer's degree of risk aversion, i.e., the weight assigned to the variance in the producer's utility. A higher value of $\eta$ indicates a more risk-averse producer, reflecting a greater concern for potential losses and a higher weight assigned to the variance in her utility. The producer is risk-neutral when $\eta = 0$.

$$E(U_p) = E(\pi_p(q_0)) - \eta Var(\pi_p(q_0)) \tag{8}$$

On the other hand, the risk-neutral theater and digital platform aim to maximize their expected profits, represented by $E(\pi_r(p_r))$ and $E(\pi_s(p_s))$, respectively.

The decision process is formalized as a Stackelberg game, which has been used to analyze similar problems (e.g., Wang et al. 2019). The game sequence is the following: the producer, acting as the Stackelberg leader, first makes the movie and determines the target quality $q_0$. The risk-neutral theater then observes the pre-theater reviews by professional critics and decides the retail price $p_r$. Next, the film is released in the theater, and the audience reviews are observed. Finally, the movie is released through the risk-neutral digital platform that chooses the retail price $p_s$.

## 4. Derivation and Analysis of the Closed-Form Equilibrium

Section 4.1 describes in detail the process for deriving the equilibrium, while Section 4.2 analyzes its properties.

### 4.1. Deriving the Equilibrium of the Stackelberg Game

The producer's optimization model is represented by Eq. (9).

$$\begin{aligned} &\max_{q_0} E(U_p(q_0)) \\ &s.t. \quad \begin{cases} \max\limits_{p_r} E(\pi_r(p_r|q_0)) \\ s.t. \quad \max\limits_{p_s} E(\pi_s(p_s|p_r, q_0)) \end{cases} \end{aligned} \tag{9}$$

Following Wang et al. (2019), we use backward induction to derive the equilibrium. First, we analyze the problem of the digital platform, where the risk-neutral platform maximizes the expected profit function (10).

$$\max_{p_s} E(\pi_s(p_s|p_r, q_0)) = (1-\alpha_s)p_s \left[(1-z)a - b_1 p_s + b_2 p_r + \frac{b_q\left(q_0\tau_0 + q_a\tau_a + q_b\tau_b\right)}{\tau_0+\tau_a+\tau_b}\right] \tag{10}$$

Since $E(\pi_s(p_s|p_r, q_0))$ is concave in $p_s$, we can use this property to derive the digital platform's optimal retail price ($p_s$) in Eq. (11). It should be noted that, as this equilibrium is obtained through backward induction, $q_0$ and $p_r$ are considered parameters from the platform's perspective.

$$p_s(q_0, p_r) = \frac{a(1-z) + b_2 p_r + \frac{b_q(q_0\tau_0 + q_a\tau_a + q_b\tau_b)}{\tau_0+\tau_a+\tau_b}}{2b_1} \tag{11}$$

Next, we analyze the theater problem. As a risk-neutral follower, the theater aims to maximize the expected profit function, as shown in Eq. (12).

$$\max_{p_r} E(\pi_r(p_r|q_0)) = (1-\alpha_r)p_r \left[za - b_1 p_r + b_2 p_s + \frac{b_q\left(q_0\tau_0 + q_a\tau_a\right)}{\tau_0+\tau_a}\right] \tag{12}$$

To account for the platform's reaction to its decisions, the theater's problem is solved by substituting Eq. (11) into Eq. (12). Being a risk-neutral follower, the theater maximizes the expected profit function in Eq. (12), which is concave in $p_r$. This allows us to derive the theater's best response function, given by Eq. (13).

$$p_r(q_0) = \frac{1}{2\left(2b_1^2 - b_2^2\right)} \left\{ a\left[\left(2b_1 - b_2\right)z + b_2\right] + \frac{2b_1 b_q\left(q_a\tau_a + q_0\tau_0\right)}{\tau_a+\tau_0} + \frac{b_2 b_q\left(q_a\tau_a + q_b\tau_b + q_0\tau_0\right)}{\tau_a+\tau_b+\tau_0} \right\} \tag{13}$$

Third, we analyze the producer's problem. As the producer is a Stackelberg leader, she maximizes the utility function that incorporates risk aversion, Eq. (14).

$$\begin{aligned}\max_{q_0} E(U_p(q_0)) = {} & \alpha_r p_r \left[ za - b_1 p_r + b_2 p_s + \frac{b_q\left(q_0\tau_0 + q_a\tau_a\right)}{\tau_0+\tau_a} \right] \\ & + \alpha_s p_s \left[ (1-z)a - b_1 p_s + b_2 p_r + \frac{b_q\left(q_0\tau_0 + q_a\tau_a + q_b\tau_b\right)}{\tau_0+\tau_a+\tau_b} \right] \\ & - kq_0^2 - \eta b_q^2 \left[ \frac{\alpha_r^2 p_r^2}{\tau_a+\tau_0} + \frac{\alpha_s^2 p_s^2}{\tau_a+\tau_b+\tau_0} + \frac{2\rho\alpha_s p_s \alpha_r p_r}{\sqrt{(\tau_a+\tau_0)\left(\tau_a+\tau_b+\tau_0\right)}} \right]\end{aligned} \tag{14}$$

As the equilibrium is derived by backward induction, the producer substitutes the reaction functions of the platform (11) and theater (13) into her profit function (14). By optimizing (14), the producer obtains the optimal $q_0^*$. (Note that the parameters must meet the requirements described in Lemma 1 to ensure an interior point solution.)

LEMMA 1. *The utility function $E(U_p)$ is concave in $(q_0)$ and has a unique maximum value only when $k > k_m$. Furthermore, $q_0^* > 0$ only when $\eta < \eta_m$. (All threshold values, such as $k_m$ and $\eta_m$, are defined in Table A3 in the Appendix.)*

Upon solving the model in Eq. (9), the producer can obtain the optimal policy outlined in Theorem 1. The values of the parameters $\Phi_1$, $\Phi_2$, $\Phi_3$, $\Phi_4$, and $\Phi_5$ are provided in Table A2 of the Appendix.

THEOREM 1. *The producer's optimal target quality ($q_0^*$), the theater's optimal retail price ($p_r^*$), and the digital platform's optimal retail price ($p_s^*$) in the Stackelberg equilibrium are represented by Eqs. (15), (16), and (17), respectively.*

$$q_0^* = \frac{b_q\tau_0\left[2b_1\Phi_1\Phi_5\alpha_r\left(2b_1^2 - b_2^2 - \frac{2\eta b_1 b_q^2\alpha_r}{\tau_0+\tau_a}\right) + \Phi_2\Phi_6\alpha_s\left(b_1 - \frac{\eta b_q^2\alpha_s}{\tau_b+\tau_0+\tau_a}\right) - \eta\Phi_3\Phi_4\right]}{16kb_1^2\left(2b_1^2-b_2^2\right)^2 - b_q^2\tau_0^2\left[2b_1\alpha_r\Phi_1^2\left(2b_1^2 - b_2^2 - \frac{2\eta b_1 b_q^2\alpha_r}{\tau_a+\tau_0}\right) + \alpha_s\Phi_2^2\left(b_1 - \frac{\eta b_q^2\alpha_s}{\tau_a+\tau_b+\tau_0}\right) - \eta\Phi_1\Phi_2\Phi_3\right]} \tag{15}$$

$$\begin{aligned}p_r^* = {} & \frac{16k\Phi_5 b_1^2\left(2b_1^2-b_2^2\right)^2 + b_q^2\tau_0^2\left[\alpha_s\Phi_2\left(\Phi_1\Phi_6 - \Phi_2\Phi_5\right)\left(b_1 - \frac{\eta b_q^2\alpha_s}{\tau_b+\tau_0+\tau_a}\right) - \eta\Phi_1\Phi_3\left(\Phi_4 - \Phi_2\Phi_5\right)\right]}{16kb_1^2\left(2b_1^2-b_2^2\right)^2 - b_q^2\tau_0^2\left[2b_1\alpha_r\Phi_1^2\left(2b_1^2 - b_2^2 - \frac{2\eta b_1 b_q^2\alpha_r}{\tau_a+\tau_0}\right) + \alpha_s\Phi_2^2\left(b_1 - \frac{\eta b_q^2\alpha_s}{\tau_a+\tau_b+\tau_0}\right) - \eta\Phi_1\Phi_2\Phi_3\right]} \\ & \times \frac{1}{2\left(2b_1^2-b_2^2\right)}\end{aligned} \tag{16}$$

$$\begin{aligned}p_s^* = {} & \frac{16k\Phi_6 b_1^2\left(2b_1^2-b_2^2\right)^2 - b_q^2\tau_0^2\left[2\alpha_r b_1\Phi_1\left(\Phi_1\Phi_6 - \Phi_2\Phi_5\right)\left(2b_1^2 - b_2^2 - \frac{2\eta b_1 b_q^2\alpha_r}{\tau_0+\tau_a}\right) + \eta\Phi_2\Phi_3\left(\Phi_4 - \Phi_1\Phi_6\right)\right]}{16kb_1^2\left(2b_1^2-b_2^2\right)^2 - b_q^2\tau_0^2\left[2b_1\alpha_r\Phi_1^2\left(2b_1^2 - b_2^2 - \frac{2\eta b_1 b_q^2\alpha_r}{\tau_a+\tau_0}\right) + \alpha_s\Phi_2^2\left(b_1 - \frac{\eta b_q^2\alpha_s}{\tau_a+\tau_b+\tau_0}\right) - \eta\Phi_1\Phi_2\Phi_3\right]} \\ & \times \frac{1}{4b_1\left(2b_1^2-b_2^2\right)}\end{aligned} \tag{17}$$

From Theorem 1, by substituting equations (15) to (17) into (4), (5), (10), (12), and (14), we obtain the optimal expected demands, the producer's optimal utility, and the optimal expected profits of the theater and the digital platform, as summarized in Appendix Table A4. Interestingly, the producer's degree of risk aversion and consumer learning influence the optimal demands, expected utility, and profits.

### 4.2. Characterizing the Properties of the Equilibrium

**4.2.1. Impact of Producer Risk Aversion on the Equilibrium.** Proposition 2 shows that a risk-averse producer invests less and reduces the target quality due to revenue uncertainty. Therefore, investment decreases as the producer's risk aversion increases. As a result, given the lower movie quality, the theater and the digital platform lower their retail prices to increase demand.

PROPOSITION 2. *For a risk-averse producer, higher risk aversion ($\eta$) leads to lower values of $q_0^*$, $p_r^*$, and $p_s^*$.*

Additionally, Proposition 3 shows that when a producer is risk-averse, higher demand correlation leads to lower optimal decision levels. As the correlation between the two channels' demands increases, fluctuations in demand become more synchronized. This synchronization intensifies overall demand uncertainty, elevating systemic risk within the supply chain. Producers reduce their quality investment to mitigate this heightened risk, while theaters and digital platforms lower retail prices to maintain sales and minimize the negative impacts of demand variability. Taken together, Propositions 2 and 3 demonstrate that increased risk-aversion and greater demand correlation (by amplifying uncertainty) lead to conservative supply chain decisions.

PROPOSITION 3. *Suppose the producer is risk-averse, an increase in the correlation between consumers' posterior beliefs about the movie quality in the two channels $\rho$ leads to a decrease in $q_0^*$, $p_r^*$, and $p_s^*$. In contrast, $\rho$ does not impact the equilibrium if the producer is risk-neutral.*

**4.2.2. Impact of Expected Online Ratings on Quality and Pricing.** Proposition 4.(1) and 4.(2) show the impact of critics' and theater audience ratings on equilibrium, respectively.

According to Proposition 4.(1), the influence of critic ratings on target quality depends on the producer's risk tolerance. Elevated ratings can include the danger of unmet expectations for the highly risk-averse producer. As critic ratings climb, so do consumers' expectations regarding the movie's quality. If the film fails, negative word-of-mouth ensues, and the potential profit increase does not outweigh the additional risk of loss. Thus, to avoid the potential risks associated with high expectations, high risk-averse producers reduce investment in quality, even if the expected rating from professional critics ($q_a$) is increased. Conversely, and somewhat surprisingly, a producer with lower risk aversion or a risk-neutral stance invests more in quality when the critics' rating is already high. This is because these producers are willing to gamble on creating a blockbuster with exceptionally high box-office revenue, despite the greater risk of loss.

Meanwhile, theaters and the platform adjust pricing strategies based primarily on critic ratings. When ratings are high, ticket prices increase. However, while consumers pay a premium for high ratings, the real moviegoing experience can fall short, especially if the producer is highly risk-averse.

Proposition 4. *Let the producer be risk-averse. (1). As the critics' rating ($q_a$) increases: (a) The retail prices in both markets ($p_r^*$ and $p_s^*$) increase; (b) The target quality level ($q_0^*$) decreases if the producer is highly risk-averse but increases if the producer is less risk-averse, based on a threshold level of risk aversion ($\eta_{q_a}$).*

*(2). As the theater audience rating ($q_b$) increases: (a) The target quality level ($q_0^*$) decreases if the producer's risk aversion is above a certain threshold ($\eta > \eta_{q_b-q}$), and increases if below this threshold; (b) The retail price ($p_r^*$) decreases if risk aversion is high ($\eta > \eta_{q_b-r}$) but increases if risk aversion is low; (c) Similarly, the retail price in the secondary market ($p_s^*$) decreases if risk aversion is high ($\eta > \eta_{q_b-s}$) but increases if it is low.*

Proposition 4.(2) shows that the effects of audience ratings on equilibrium depend on the producer's risk aversion. Specifically, when risk aversion is high, a positive rating leads to lower investment and retail prices, similar to the impact of critics' reviews described in Proposition 4.(1). On the other hand, when risk aversion is low, investment in quality increases when the theater audience ratings are high. After observing the high level of investment, the theater and the platform increased their respective retail prices. These results show that the impact of audience ratings on the equilibrium depends on the producer's degree of risk aversion.

For a risk-neutral producer, as shown in Corollary 1, improvements in online ratings (both critics' and theater audience ratings) lead to higher target movie quality and higher prices. This is because risk-neutral producers focus exclusively on expected returns and are indifferent to risk fluctuations. As a result, they are more willing to invest in higher movie quality to pursue greater revenues. Corollary 1 further indicates that risk-neutral producers respond positively to favorable evaluative signals in the market.

Corollary 1. *For a risk-neutral producer, an increase in the online ratings ($q_a$ and $q_b$) leads to higher values of $q_0^*$, $p_r^*$, and $p_s^*$.*

In reality, when the ratings of a movie go up, low-risk-averse producers are willing to invest more, such as expensive actors and actresses, complicated special effects, and innovative scripts, to improve the movie quality. For example, after the success of the "Ne Zha 1", the "Ne Zha 2" was made with a budget of RMB 600 million, which was more costly than the "Ne Zha 1" in terms of the quality of the picture, the number of characters, and the special effects in battles, and was a huge success as a result. However, when a movie's rating rises, high-risk-averse producers are more likely to turn to mature and low-risk production models, such as relying on existing successful IPs and adopting fixed formulaic narratives, to avoid the increased costs caused by the quality improvement. For example, the later works of the "Marvel Cinematic Universe" have gradually adopted a low-risk strategy, leading to a decline in the quality of some works.

**4.2.3. Impact of the Information Uncertainty on Quality and Pricing.** In this section, we explore how the producer's ability to meet the quality target ($\tau_0$) and the precision of reviews ($\tau_a$ and $\tau_b$) affect the optimal strategies. To better explain the impact of $\tau_0$ on the equilibrium, we consider two particular cases: a) no online reviews or those that are not trusted ($\tau_a = \tau_b = 0$); b) online reviews have an overwhelming impact on consumers' decisions ($\tau_a = \tau_b \to \infty$). Proposition 5 summarizes the analysis results.

PROPOSITION 5. *(1) When $\tau_a = \tau_b = 0$, an increase in $\tau_0$ leads to higher values of $q_0^*$, $p_r^*$, and $p_s^*$. (2) When $\tau_a = \tau_b \to \infty$, $\tau_0$ has no effect on the equilibrium.*

When the ratings are unreliable (i.e., $\tau_a = \tau_b = 0$), investment in quality increases as the precision of consumers' prior beliefs improves, as greater confidence in the film reduces the producer's risk of incurring a loss. Correspondingly, theaters and platforms raise their prices after observing the producer's higher investment in quality. This suggests that even when external rating mechanisms fail, the market can still regulate quality and prices effectively through the producer's actions. When the producer is highly capable of meeting the quality target—meaning that consumers' prior beliefs about movie quality are more accurate, the market favors high-quality movies with higher prices, thereby promoting healthy competition and encouraging the production of superior content.

On the other hand, when the precision of both critics' and audiences' reviews is exceptionally high, the accuracy of consumers' prior beliefs does not affect the equilibrium. This suggests that in a high-precision review information environment, the market equilibrium is influenced primarily by review information, as external signals adjust customers' preconceived notions. In such a scenario, the producer's ability to influence the public, even with high budgets, is insignificant.

We can further explore the impact of the precision of target quality and online ratings on the equilibrium, accounting for their interplay with the degree of risk aversion, as described in Proposition 6.

PROPOSITION 6. *(1) When $\tau_0 \to \infty$, the degree of risk aversion ($\eta$) and online ratings ($q_a$ and $q_b$) do not affect the equilibria. (2) When $\tau_a \to \infty$: (a) the degree of risk aversion ($\eta$) and the theater audience rating ($q_b$) do not affect the equilibria; (b) prices $p_r^*$ and $p_s^*$ depend only on the critics' rating ($q_a$). (3) When $\tau_b \to \infty$, the equilibria depend on the degree of risk aversion ($\eta$) and the mean of the ratings ($q_a$ and $q_b$).*

Proposition 6 presents three scenarios in which different factors affect equilibria. Proposition 6.(1) indicates that when the producer can fully meet consumer expectations about movie quality, she is no longer exposed to risk, and the ratings from both critics and the audience no longer affect demand. This is because the producer's investment aligns precisely with market demand, eliminating the need for consumers to rely on online reviews to shape their perception of the movie. Consequently, the producer can concentrate on investing in quality without the concern of fluctuating social reviews or word-of-mouth recommendations.

Proposition 6.(2) indicates that when critics' reviews are highly accurate, the movie quality and prices are based on these reviews and neither on the audience opinions nor the risky attitudes of producers. This occurs because *authoritative signals* guide the market, leading consumers to rely solely on critics' assessments, thereby reducing information asymmetry. Consequently, the manufacturer's risky actions become unnecessary as the risks are *absorbed* by the accuracy of the critics' reviews. Additionally, decentralized audience reviews lose significance as consumers are more inclined to trust the critics. In this scenario, neither the actual quality of the movie nor audience reviews are relevant; only the critics' reviews matter.

Proposition 6.(3) indicates that when consumers fully trust the theater audience reviews, the producer's risk aversion influences the equilibrium. Although digital consumers trust the reviews by the theater audience, there is still uncertainty among the latter about the movie's quality, as they can only observe the critics' reviews. Therefore, theater audience reviews cannot completely alleviate the producer's investment risk, as reflected in the equilibrium. As a result, precision in both the target quality and the critics' reviews remains essential, even when $\tau_b$ approaches infinity.

Proposition 6 also demonstrates that the impact of audience reviews on movie quality is lower than that of critics' reviews. This is because critics' reviews are released earlier, influencing a larger portion of the market. Therefore, the scheduling strategies of theaters and the recommendation algorithms of platforms tend to rely more on these *professional opinions.* This is a widely adopted industry practice. Producers typically organize limited pre-release screenings to assess market responses and cultivate early word-of-mouth recommendations.

### 4.3. Price Competition Analysis

As shown in Theorem 1, the optimal pricing policies are highly complex and depend on consumer learning and the producer's risk aversion. Proposition 7 and Corollary 2 analyze the price competition between the theater and the platform by comparing the optimal retail prices in two channels.

PROPOSITION 7. *There is a threshold $\hat{q}_a$ such that $p_r^* \geq p_s^*$ if $q_a \geq \hat{q}_a$, $p_r^* < p_s^*$ if $q_a < \hat{q}_a$.*

Proposition 7 shows that the theater price is higher than the digital price only if the movie quality revealed by the critic's reviews is sufficiently large to justify a viewing in the theater (when $q_a > \hat{q}_a$). This is because consumers wishing to experience the movie at its release increase theater demand, leading to the theater charging a higher price. On the other hand, films with low critics' ratings are priced lower at the theater than on the platform as people delay seeing them, waiting to receive additional reviews from early viewers.

Corollary 2. *Let $\Delta = p_r^* - p_s^*$, then $\Delta$ decreases with the production cost coefficient ($k$), the producer's degree of risk aversion ($\eta$), and the correlation of consumers' posterior belief about movie quality between the two channels ($\rho$), and increases with the expected critics' rating ($q_a$). Moreover, $\Delta$ increases (decreases) with the expected rating by audience reviewers ($q_b$) if $\eta < \eta_\delta$ (if $\eta > \eta_\delta$).*

Furthermore, Proposition 7 and Corollary 2 demonstrate that if the quality of the movie revealed by critic's reviews justifies viewing in the theater (i.e., $q_a > \hat{q}_a$), then increasing the production cost coefficient ($k$), the producer's degree of risk aversion ($\eta$), or the coefficient of correlation between consumers' posterior beliefs about movie quality in the two channels ($\rho$) will reduce the price difference between the two channels, hence intensifying the price competition. Conversely, increasing the average movie quality revealed by critics' earlier reviews ($q_a$) will increase the price difference between the two channels. This indicates that the theater and the platform vie for distinct market niches.

However, the influence of theater audience reviews on the price differential across the two channels is shaped not only by pre-theater reviews but also by the producer's degree of risk aversion.For producers with high-risk aversion ($\eta > \eta_\delta$) and a movie with high critic's reviews ($q_a > \hat{q}_a$), increasing the average movie quality revealed by theater audience reviews ($q_b$) will decrease the price difference between the two channels, thus intensifying the price competition.

## 5. Equilibrium under Quality-Dependent Ratings

This section addresses a special case of the general model where $q_a = q_b = q_0$. In this case, consumers' posterior beliefs about the movie quality (after reading all the reviews), denoted as $\tilde{q}_1$ and $\tilde{q}_2$, change to $\tilde{q}_1 \sim N\left(q_0, \frac{1}{\tau_0+\tau_\mathrm{a}}\right)$ and $\tilde{q}_2 \sim N\left(q_0, \frac{1}{\tau_0+\tau_\mathrm{a}+\tau_\mathrm{b}}\right)$. These new beliefs imply that online reviews do not change the average perception of movie quality among consumers but only reduce the uncertainty over time regarding the actual rating the movie will receive from the population. Furthermore, the reviews are consistent in this case, and the correlation between the demands in the different channels is 1 (i.e., $\rho = 1$). Note that when $q_a = q_b = q_0$, the correlation between the channels, denoted as $\rho$, is independent of $\tau_0$, $\tau_a$, and $\tau_b$ since $\frac{\partial q_2}{\partial q_1} = \frac{\partial q_2}{\partial q_0} \frac{1}{\frac{\partial q_1}{\partial q_0}} = 1$. The equilibrium is summarized in Corollary 3.

Corollary 3. *Let $q_a = q_b = q_0$. The utility function $E(U_p)$ is concave in $q_0$ and has a unique maximum only when $k > k_0$. Similarly, $q_0^* > 0$ only when $\eta < \eta_0$. The optimal target quality ($q_0^*$) and retail prices in the theater ($p_r^*$) and digital channel ($p_s^*$) are summarized by equations (18) to (20).*

$$q_0^* = \frac{ab_q\left\{b_1\left[2(2b_1+b_2)\left(2b_1^2-b_2^2\right)(2b_1z-b_2z+b_2)\alpha_r+\left(4b_1^2+2b_2b_1-b_2^2\right)\left(2b_1b_2z+\left(4b_1^2-b_2^2\right)(1-z)\right)\alpha_s\right]-b_q^2\eta x_1\right\}}{16b_1^2\left(2b_1^2-b_2^2\right)^2k-b_1b_q^2\left[2\left(2b_1^2-b_2^2\right)(2b_1+b_2)^2\alpha_r+\left(4b_1^2+2b_2b_1-b_2^2\right)^2\alpha_s\right]+b_q^4\eta x_2} \tag{18}$$

$$p_{\mathrm{r}}^{*}=\frac{a\left\{16kb_1^2\left(2b_1^2-b_2^2\right)^2(2b_1z-b_2z+b_2)+4b_1b_q^2\alpha_s\left(2b_1^2-b_2^2\right)(1-2z)\left[\left(4b_1^2+2b_2b_1-b_2^2\right)\left(b_1-\frac{b_q^2\eta\alpha_s}{\tau_b+\tau_0+\tau_a}\right)-\frac{2b_1b_q^2(2b_1+b_2)\eta\alpha_r}{\sqrt{\tau_0+\tau_a}\sqrt{\tau_b+\tau_0+\tau_a}}\right]\right\}}{2\left(2b_1^2-b_2^2\right)\left\{16b_1^2\left(2b_1^2-b_2^2\right)^2k-b_1b_q^2\left[2\left(2b_1^2-b_2^2\right)(2b_1+b_2)^2\alpha_r+\left(4b_1^2+2b_2b_1-b_2^2\right)^2\alpha_s\right]+b_q^4\eta x_2\right\}} \tag{19}$$

$$p_{\mathrm{s}}^{*}=\frac{2ab_1\left\{2k\left(2b_1^2-b_2^2\right)\left[2b_1b_2z+\left(4b_1^2-b_2^2\right)(1-z)\right]-b_q^2\alpha_r(1-2z)\left[(2b_1+b_2)\left(2b_1^2-b_2^2-\frac{2b_q^2b_1\eta\alpha_r}{\tau_0+\tau_a}\right)-\frac{\left(4b_1^2+2b_2b_1-b_2^2\right)b_q^2\eta\alpha_s}{\sqrt{\tau_0+\tau_a}\sqrt{\tau_b+\tau_0+\tau_a}}\right]\right\}}{16b_1^2\left(2b_1^2-b_2^2\right)^2k-b_1b_q^2\left[2\left(2b_1^2-b_2^2\right)(2b_1+b_2)^2\alpha_r+\left(4b_1^2+2b_2b_1-b_2^2\right)^2\alpha_s\right]+b_q^4\eta x_2} \tag{20}$$

Proposition 8 summarizes the impact of the key parameters $k$, $\eta$, $\rho$, $\tau_0$, $\tau_a$ and $\tau_b$ on the equilibrium when $q_a = q_b = q_0$. These results are similar to Propositions 2 to 6: it is proved that the impact of producer risk aversion, and information uncertainty on the optimal policy still hold when expected ratings are determined by investment in quality (i.e., $q_a = q_b = q_0$).

PROPOSITION 8. *When $q_a = q_b = q_0$: (1) An increase in the producer's risk aversion $\eta$, or in the correlation between the consumers' posterior beliefs about the movie quality in the two channels ($\rho$) leads to lower values of $q_0^*$, $p_r^*$, $p_s^*$; (2) When $\tau_a = \tau_b = 0$ an increase in $\tau_0$ raises $q_0^*$, $p_r^*$, $p_s^*$; (3) When $\tau_a = \tau_b \to \infty$, $\tau_0$ has no effect on the equilibrium; (4) When $\tau_0 \to \infty$, or when $\tau_a \to \infty$, the degree of risk aversion ($\eta$) does not affect the equilibrium; however, when $\tau_b \to \infty$, the equilibrium depends on the degree of risk aversion ($\eta$).*

Additionally, Appendix (Table B4), summarizes the optimal target quality $q_0^*$, and optimal prices $p_r^*$ and $p_s^*$ when precision $\tau_0$, $\tau_{\mathrm{a}}$ or $\tau_{\mathrm{b}}$ converge to infinity. The formulas in Table B4 shows that when $\tau_0 \to \infty$, or when $\tau_a \to \infty$, information uncertainty (neither $\tau_0$, $\tau_{\mathrm{a}}$ or $\tau_{\mathrm{b}}$) do not affect the equilibrium, but when $\tau_b \to \infty$, the equilibria still depend on $\tau_0$ and $\tau_{\mathrm{a}}$. This verifies the qualitative conclusions in Section 4: the critics' reviews impact the product's target quality more than the theater audience reviews.

Next, Proposition 9 summarizes two conclusions regarding cases where ratings are determined by the producer's effort, which differ significantly from cases where ratings are independent of the producer's effort.

PROPOSITION 9. *(1) For a risk-neutral producer, the precision $\tau_0$, $\tau_a$ and $\tau_b$ does not affect the equilibrium. (2) For a risk-averse producer, as $\tau_0 \to \infty$, or as $\tau_a \to \infty$, the equilibrium converges to the risk-neutral equilibrium.*

On the one hand, when ratings are influenced by the producer's effort, information uncertainty no longer impacts the equilibrium if the producer is risk-neutral. In contrast, with independent ratings, information uncertainty affects the equilibrium even for a risk-neutral producer. This difference arises because, in the effort-dependent case, online reviews only reduce uncertainty without altering consumers' perception of movie quality. However, in the independent rating scenario, both the producer's ability to meet quality targets and the critics' and audience's ability to assess quality can shift consumers' perceptions.

Secondly, in cases where ratings depend on the producer's effort, as $\tau_0$ or $\tau_\mathrm{a}$ approach infinity—meaning the producer fully meets the quality target, or critics' reviews perfectly reflect the movie's quality—the optimal quality and pricing decisions for the film supply chain align with those of a risk-neutral producer. However, in the independent rating case, the equilibria when $\tau_0$ or $\tau_\mathrm{a}$ reach infinity differ from those of a risk-neutral producer, even though they are no longer influenced by the producer's risk attitude (as shown in Tables B1 and B2). Specifically, Table B3 demonstrates that optimal quality decisions tend toward zero as critics' ability to assess quality becomes infinitely precise. This phenomenon is further explored in Section 6, Figure 4.

# 6. Computational Experiments

## 6.1. Equilibrium Sensitivity to Information precision

In this section, we examine the sensitivity of the equilibrium to the information precision parameters $\tau_0$, $\tau_a$, and $\tau_b$. As the typical revenue-sharing rate between theaters and producers in China is 43% (Yang 2022), we set $\alpha_r = \alpha_s = 43\%$. (We have also analyzed the results when $\alpha_r \neq \alpha_s$ in Appendix C, and the conclusions remain valid). Because the available data do not allow us to fully parameterize movie demand and investment functions, we have assigned values consistent with the theoretical model for the base case: $a = 2$, $b_1 = 0.2$, $b_2 = 0.1$, $b_q = 1$, $\tau_0 = 3$, $k = 3$, and $z = 0.5$. This type of simulation approach is commonly used in operations management research (e.g., Zhou et al. 2024, Tian et al. 2024).

The online review-related information comes from the film Victoria & Abdul on Rotten Tomatoes, a comedy-drama released in 2017. We converted the critics' ratings before release and the theater audience's ratings after release into a binary rating system, where positive ratings are scored as 1 point and negative ratings as 0 points. The average rating and variance were 0.66 and 0.23 before release, and 0.83 and 0.14 after release, respectively. Therefore, we set $q_a = 0.66$, $\tau_a = 4.35$, $q_b = 0.83$, and $\tau_b = 7.14$. To generalize our analysis, we chose two different values of $q_b$ ($q_b = 0.43, 0.83$) to represent movies with low and high word-of-mouth recommendations, and three different values of $\eta$ to describe levels of risk aversion: risk-neutral (0), medium (0.5), and high (0.9). Section 6.2 further investigates the impact of $k$ on the equilibrium, by considering big-budget and small-budget movies.

**6.1.1. The Effect of $\tau_0$ (Prior Precision).** Figure 2 shows that the producer reduces the movie's quality to mitigate the increasing uncertainty by cutting production costs. The greater the value of $\tau_0$, the lower the demand uncertainty for the producer. Consequently, the producer invests in improving the movie's quality when consumers have higher confidence in the producer, which is reflected by a higher value of $\tau_0$.

Surprisingly, Figures 3 (a) and (b) indicate that the relationship between quality uncertainty and pricing is non-linear. There is always a threshold in $\tau_0$ at which the price is minimal, and this

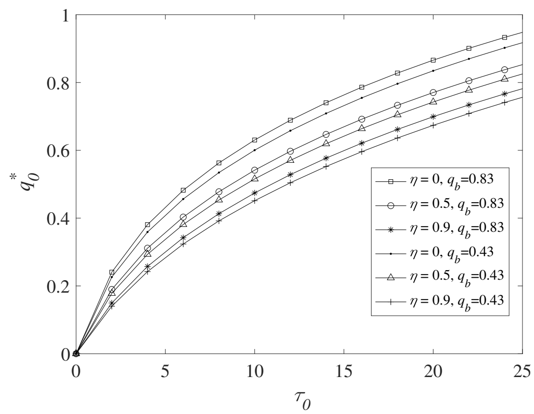
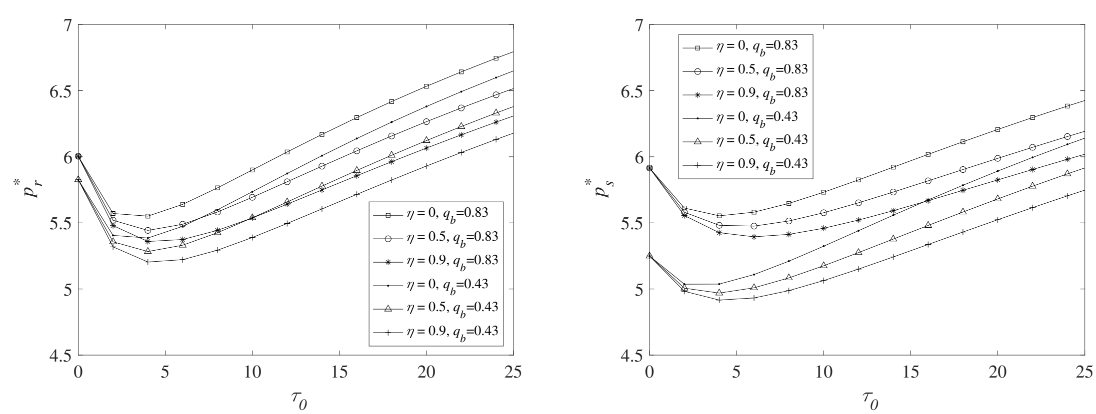



**Figure 2** **The impact of $\tau_0$ on the producer's investment in quality.**

threshold increases with $k$. As the average of consumers' posterior beliefs, $q_1$ and $q_2$, increases, the demand in both channels (the theater and the digital platform) also increases. Therefore, $\tau_0$ influences prices by affecting $q_1$ and $q_2$. Since $q_1$ and $q_2$ are composed of prior beliefs ($\tilde{q}_0$) and online rating information ($\tilde{q}_a$ and $\tilde{q}_b$), the impact of $\tau_0$ on $q_1$ and $q_2$ is non-monotonic. On the one hand, when $q_0$ is small enough, the higher the $\tau_0$, the more weight $q_0$ carries in the average consumers' perception of movie quality (i.e., in $q_1$ and $q_2$), resulting in lower values for $q_1$ and $q_2$. Therefore, lower prices help to attract additional demand. On the other hand, when $q_0$ is significant, an increase in precision (i.e., $\tau_0$) increases the average of the consumers' posterior beliefs about the movie's quality (i.e., $q_1$ and $q_2$), increasing demand. Consequently, price increases lead to a slower increase in demand and a continuous rise in profits.




(a) (b)

**Figure 3** **The impact of $\tau_0$ on theater and digital platform pricing.**

**6.1.2. The Effect of $\tau_a$ (Critic Review Precision).** Figure 4 illustrates the effect of $\tau_a$ on optimal target quality $q_0^*$ under varying levels of risk aversion and audience rating.

A surprising result is the interaction between the producer's degree of risk aversion and the precision of critics' reviews, which jointly affect the producer's optimal investment in quality. As $\tau_a$ increases, the critic rating $q_a$ plays a more important role as a signal in consumers' quality assessment. Conversely, the importance of the producer's target quality as prior information diminishes, leading to a lower $q_0^*$. On the other hand, for a risk-averse producer, a higher $\tau_a$ reduces potential losses from uncertainty and therefore leads to a higher $q_0^*$. When the first effect dominates, the producer reduces movie quality, whereas when the second effect dominates, she increases it. Although the producer's quality decision is influenced by her degree of risk aversion, $q_0^*$ approaches zero as $\tau_a$ tends to infinity, regardless of $\eta$, as shown in Table C2. Therefore, greater information precision reduces the role of risk aversion in shaping the producer's decisions.

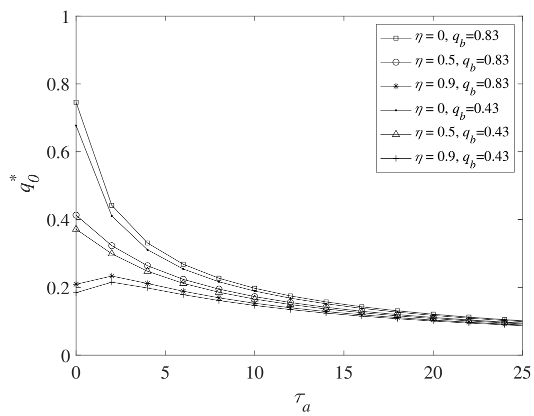
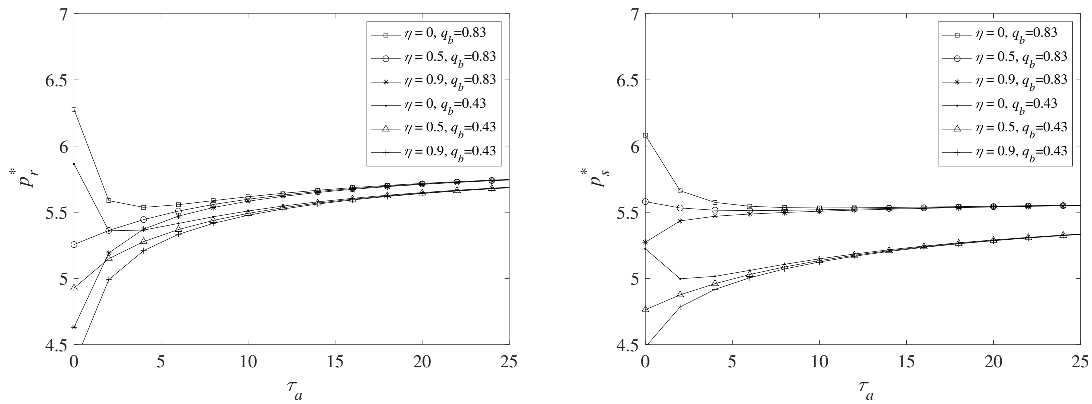



**Figure 4 The impact of $\tau_a$ on the producer's investment in quality.**

Surprisingly, Figures 5 (a) and (b) show that the relationship between retail pricing and critics' reviews depends on the producer's degree of risk aversion when the reviews are of low reliability. This occurs because the producer's investment decision—shaped by her risk aversion (see Figure 4)—influences consumers' perceived quality of the movie and, in turn, the retail price. Specifically, since $q_1 = \frac{q_0\tau_0+q_a\tau_a}{\tau_0+\tau_a}$ and $q_2 = \frac{q_0\tau_0+q_a\tau_a+q_b\tau_b}{\tau_0+\tau_a+\tau_b}$, the reduction of $q_0^*$ decreases consumers' perceived quality in both channels, which drives down prices. However, as the precision of critics' reviews increases, the influence of risk aversion diminishes. When $\tau_a$ tends to infinity, retail prices become independent of risk aversion.




(a) (b)

**Figure 5 The impact of $\tau_a$ on theater and digital platform pricing.**

**6.1.3. The Effect of $\tau_b$ (Audience Review Precision).** Figure 6 illustrates that the effect of $\tau_b$ on $q_0^*$ depends on the producer's degree of risk aversion. On the one hand, the higher the $\tau_b$, the less critical $q_0$ becomes in the consumers' posterior beliefs in the platform channel, as $q_b$ gains more weight. Thus, the producer prefers to reduce $q_0$ since it is less critical and costly. On the other hand, the higher the $\tau_b$, the lower the potential loss of the producer due to uncertainty. For this reason, if the uncertainty is low, the producer prefers to improve $q_0$ to increase the perceived quality of the movie.

The former effect dominates for the risk-neutral producer, whereas the two effects remain roughly balanced for the risk-averse producer. As $\tau_b$ converges to infinity, the investment in quality becomes similar, decreasing the importance of risk aversion, and vice versa when $\tau_b$ converges to zero. Hence, the lower the precision of information regarding the audience ratings, the more important the role of risk aversion becomes.

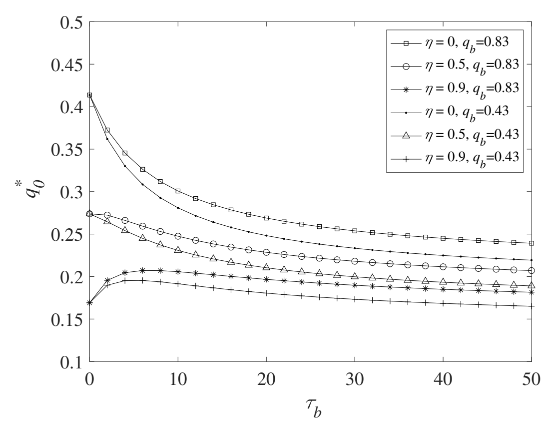
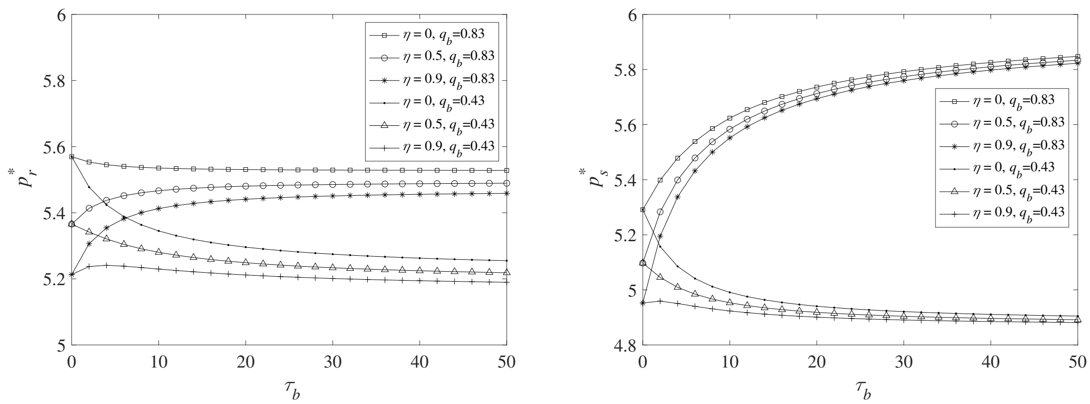



**Figure 6 The impact of $\tau_b$ on the producer's investment in quality.**




(a) (b)

**Figure 7 The impact of $\tau_b$ on the theater and digital platform pricing.**

Figure 7 shows how the theater's and digital platform's pricing policy is affected by $\tau_b$, for different degrees of risk aversion and mean rating of theater audience reviews. The optimal pricing strategy results from a combination of factors. First, the impact of $\tau_b$ on theater consumers' posterior beliefs on movie quality ($q_1$) results mainly from its effects on $q_0^*$. The risk-neutral producer reduces $q_0^*$ when $\tau_b$ increases (as illustrated in Figure 6), leading to low perceived quality of the movie for consumers. Thus, both the theater and the platform reduce prices to attract more viewers.

Second, $q_2$ may either increase or decrease with $\tau_b$. Specifically, when $q_b$ is sufficiently large (small), $q_2$ increases (decreases) as $\tau_b$ rises. As a result, demand for the digital platform also increases (decreases). Accordingly, both the theater and the platform are incentivized to raise (lower) $p_r$ and $p_s$ when $q_b$ is high (low). Consequently, Figure 7 illustrates that theater pricing is more strongly influenced by $q_1$, whereas platform pricing is more affected by $q_2$.

Additionally, Figures 7 (a) and (b) illustrate that when $\tau_b = 0$ (i.e., when the theater audience provides no reviews or when the reviews are unreliable for assessing movie quality), the producer's risk aversion becomes the primary determinant of retail prices. Specifically, retail prices decrease as the producer's risk aversion increases. However, as precision improves, the average rating provided by the theater audience becomes the main determinant of prices. In other words, prices rise with the average rating, while the degree of risk aversion plays only a minor role.

Although Proposition 4(2) demonstrates that the equilibrium decreases with audience rating $q_b$ when the producer is extremely risk-averse, Figures 2 to 7 show that, in most cases, when the market anticipates a film with a high audience rating $q_b$, the producer is inclined to invest more and improve the target quality $q_0^*$ to meet these elevated expectations. As a result, both the theater and the digital platform are incentivized to increase ticket prices ($p_r^*$ and $p_s^*$) to maximize profits.

### 6.2. Robustness Analysis

In this section, we use simulation and linear regression to test the robustness of the theoretical analysis, following the approach used in Jandhyala and Oliveira (2021).

We begin by examining the impact of information precision ($\tau_0$, $\tau_a$, and $\tau_b$) on the relationship between $q_1^*$ and $q_2^*$. Specifically, we estimate four regression models for $q_2^*$ as a function of $q_1^*$. In the base model, the decision parameters are sampled from a uniform distribution ($\tau_0, \tau_a, \tau_b \in [4.5, 5.5]$). In models 2 to 4, we increase the mean and range of the uniform distribution for the precision parameters ($\tau_0, \tau_a, \tau_b \in [13.5, 16.5]$). We randomly generate $\eta$ from a uniform distribution with a range of (0, 1) and $k$ from a range of (3, 3.5). Other parameters are kept as in Section 6.1. We randomly generated a sample of 100 films using the distributions described above for the precision and risk-aversion parameters and then tested the theoretical insight that $\rho = \frac{\tau_0+\tau_a}{\tau_0+\tau_a+\tau_b}$ in Table 2.

The regressions in Table 2 estimate the correlation between $q_1^*$ and $q_2^*$. In models (1) to (4), the estimated $\rho$ is approximately equal to $\frac{10}{15}$, $\frac{20}{25}$, $\frac{20}{25}$, and $\frac{10}{25}$. This indicates that the posterior beliefs of both theater and digital channel viewers (prior to watching the movie) are highly correlated, even when critics and audience ratings are independent. In the base case, the adjusted $R^2$ is 88.8%, which means that $q_1^*$ explains that proportion of the variation in $q_2^*$.

Furthermore, the results summarized in Table 2 indicate that the more precise the parameters' standard error, the more accurately $\rho$ can be estimated from the regression model coefficients. These results demonstrate that not all information has the same value. For instance, an increase in the precision of $\tau_0$ increases the adjusted $R^2$ to 99.5%, as the producer can significantly influence the public's perceptions, even when critics and the audience rate independently. Conversely, larger values of $\tau_a$ and $\tau_b$ reduce the adjusted $R^2$ to 58.4% and 37.4%, respectively, reflecting an increased independence of consumer posterior beliefs from earlier information and a greater reliance on critics' and audience ratings.

Table 2: Linear regression model of $q_2^*$ on $q_1^*$.

| | (1)<br>Base model | (2)<br>Large $\tau_0$ | (3)<br>Large $\tau_a$ | (4)<br>Large $\tau_b$ |
|---|---|---|---|---|
| $q_1^*$ | 0.644*** | 0.787*** | 0.651*** | 0.312*** |
| | (0.023) | (0.006) | (0.055) | (0.040) |
| Constant | 0.287*** | 0.174*** | 0.247*** | 0.539*** |
| | (0.011) | (0.003) | (0.030) | (0.019) |
| Observations | 100 | 100 | 100 | 100 |
| Adjusted R-squared | 0.888 | 0.995 | 0.584 | 0.374 |

Standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Next, to verify the results in Section 6.1, we regress the relationship between the optimal policy (target quality and retail prices) and the degree of risk aversion. We consider four different types of movies: big budget ($k \in [5.5, 6.5]$), small budget ($k \in [1.5, 2.5]$), high information precision ($\tau_0 = \tau_a = \tau_b = 10$) and low information precision ($\tau_0 = \tau_a = \tau_b = 2$). The regression results are summarized in Tables 3 to 5. The tables aim to illustrate how risk aversion ($\eta$) affects the movie quality ($q_0^*$) and retail prices ($p_r^*$ and $p_s^*$). A notable finding from these tables is that an increase in information precision decreases the adjusted $R^2$ and the risk aversion coefficient. Therefore, this result shows that increased precision leads to reduced uncertainty and a decreased role of risk aversion in decision-making.

Table 3: Linear regression model of $q_0^*$ on $\eta$.

| | (1)<br>Big budget<br>High precision | (2)<br>Big budget<br>Low precision | (3)<br>Small budget<br>High precision | (4)<br>Small budget<br>Low precision |
|---|---|---|---|---|
| $\eta$ | -0.037*** | -0.164*** | -0.111*** | -0.609*** |
| | (0.003) | (0.002) | (0.040) | (0.024) |
| Constant | 0.204*** | 0.200*** | 0.693*** | 0.703*** |
| | (0.002) | (0.001) | (0.022) | (0.015) |
| Observations | 100 | 100 | 100 | 100 |
| Adjusted R-squared | 0.605 | 0.986 | 0.062 | 0.865 |

Standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

More specifically, the results in Table 3 show that risk aversion has a negative impact on film quality, particularly for small-budget films with high rating uncertainty (type 4), where risk exposure is most significant. In contrast, risk aversion has a significant but minor impact on big-budget movies with low rating uncertainty (type 1). The highest explanatory power of film quality is observed in big-budget and low-precision movies, scenario (2).

Table 4: Linear regression model of $p_r^*$ on $\eta$.

| | (1)<br>Big budget<br>High precision | (2)<br>Big budget<br>Low precision | (3)<br>Small budget<br>High precision | (4)<br>Small budget<br>Low precision |
|---|---|---|---|---|
| $\eta$ | -0.061*** | -0.274*** | -0.185*** | -1.016*** |
| | (0.005) | (0.003) | (0.067) | (0.040) |
| Constant | 5.209*** | 5.203*** | 6.024*** | 6.040916*** |
| | (0.003) | (0.002) | (0.037) | (0.025) |
| Observations | 100 | 100 | 100 | 100 |
| Adjusted R-squared | 0.605 | 0.986 | 0.062 | 0.865 |

Standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Furthermore, Tables 4 and 5 indicate that risk aversion has a greater impact on theater pricing than digital channel, particularly when information precision is low. This conclusion is drawn from comparing the absolute values of the $\eta$ coefficient, which reflects the value of cumulative information. As there is always more information available at the time of digital viewing, the value of information reduces the role of risk aversion in decision-making, resulting in less impact on these prices. In contrast, the impact of risk aversion on theater pricing is more significant. Moreover, the higher the precision of information from the beginning of the process, the lower the differential impact of risk aversion on pricing.

Table 5: Linear regression model of $p_s^*$ on $\eta$.

| | (1)<br>Big budget<br>High precision | (2)<br>Big budget<br>Low precision | (3)<br>Small budget<br>High precision | (4)<br>Small budget<br>Low precision |
|---|---|---|---|---|
| $\eta$ | -0.046*** | -0.206*** | -0.139*** | -0.762*** |
| | (0.004) | (0.002) | (0.051) | (0.030) |
| Constant | 5.213*** | 5.209*** | 5.825*** | 5.838*** |
| | (0.002) | (0.001) | (0.028) | (0.018) |
| Observations | 100 | 100 | 100 | 100 |
| Adjusted R-squared | 0.605 | 0.986 | 0.062 | 0.865 |

Standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

The interaction between budget size and rating uncertainty (information precision) creates a film typology that provides a better understanding of how risk aversion affects quality and pricing in the movie industry. This is summarized in Figure 8.

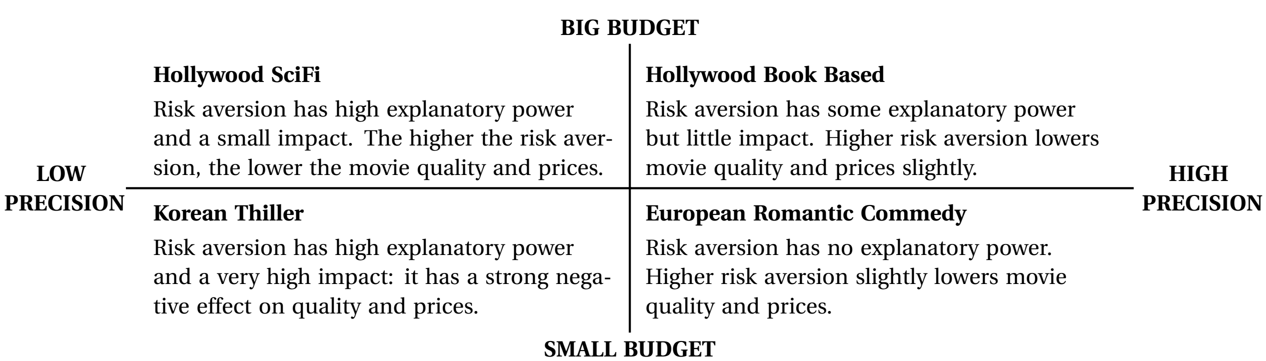



**Figure 8** **Movie Typology: Budget vs. Precision.**

## 7. Conclusion

This article examines the impact of producer risk aversion and consumer learning from online reviews on quality investment and pricing in the film supply chain. We propose a Stackelberg game with a producer as the leader and a theater and a digital platform as followers to represent this problem. We focus on films released in theaters and then on a digital platform sequentially, where consumers perceive movie quality based on pre-theater reviews during the theater release period and pre-digital studies during the digital release period.

Our primary contribution is the analysis of the interaction between risk aversion and consumer learning in determining the optimal management of a dual-channel supply chain in the film industry, considering strategic interactions using game theory.

Specifically, our main managerial contributions are as follows. Regarding the impact of producer's risk aversion on quality and pricing decisions: (a) We find that a greater degree of producer risk aversion result in lower movie quality and prices, as expected. Additionally, highly risk-averse producers tend to adopt conservative investment strategies, reducing investment in the film's quality. As a result, both theaters and platforms lower prices for lower-quality films. (b) We also show that the effect of expected ratings, including critics' and audience ratings, on quality investment depends on the producer's risk aversion. A low-risk-averse producer invests more in quality when the expected ratings are high. Interestingly, a highly risk-averse producer does the opposite, reducing investment in quality despite high expected ratings.

With respect to the way consumer learning from online reviews affects quality and pricing decisions: (a) We demonstrate that when the online ratings are an unbiased estimate of the producer's ability and determined by her efforts, the overall analysis of the interactions between the model parameters (i.e., investment costs, producer risk aversion, and information uncertainty) and the equilibrium remains the same as when we assume, more generally that online ratings are independent of the producer's ability. The reason for observing this result is that even when the critics and audience ratings are independent of the producer's ability, the posterior beliefs of both theater and digital viewers on movie quality are highly correlated. (b) We demonstrate that critics' reviews have a more significant impact on the decisions of the producer, theater, and platform than audience reviews.

Concerning the interaction between risk aversion and precision of online reviews in shaping movie quality and pricing, our analysis reveals that as the precision of online reviews increases, the influence of risk aversion on movie quality decreases. Finally, we propose a film typology based on the interaction between production budget size and rating uncertainty, providing a clearer understanding of how risk aversion should guide quality investment and pricing policies for different types of movies.

In conclusion, our study has demonstrated that the optimal distribution network in the film industry, investment in quality, and retail pricing are interdependent and a complex function of both the producer's degree of risk aversion and the precision of the information provided by online reviews, which are essential components of the film industry.

## Acknowledgements

This work is partly supported by the National Natural Science Foundation of China (Project No. 72031002), the Humanities and Social Science Fund of Ministry of Education of China 24YJC630129), the Natural Science Foundation of Hebei Province (Project No. G2024203003), and the Science Research Project of Hebei Education Department (Project No. QN2025009).

## Disclosure statement

No potential conflict of interest was reported by the authors.

## References

Alaei S, Makhdoumi A, Malekian A (2023) Optimal subscription planning for digital goods. Operations Research 71(6):2245–2266.

August T, Dao D, Shin H (2015) Optimal timing of sequential distribution: The impact of congestion externalities and day-and-date strategies. Marketing Science 34(5):755–774.

Berbeglia F, Derdenger T, Tayur S (2020) Optimal timing of home video releases: A dynamic model of movie distribution. Working paper, Tepper School of Business, Pennsylvania.

Calzada J, Valletti TM (2012) Intertemporal movie distribution: Versioning when customers can buy both versions. Marketing Science 31(4):649–667.

Chen J, Wei H, Xie L (2022) Optimal strategy in managing product quality risk for a risk-averse manufacturer: Prevention or mitigation? Naval Research Logistics (NRL) 69(2):287–302.

Dai MM (2025) Nezha's "burning" economy opens up more imagination of movie+. Accessed April 7, 2025, https://news.cctv.com/2025/03/02/ARTIOagVrDr2BCivtupodxbK250302.shtml.

D'Alessandro A (2018) What were the biggest bombs at the 2017 b.o.? deadline's most valuable blockbuster tournament. Retrieved from https://deadline.com/2018/03/king-arthur-geostorm-monster-trucks-the-promise-the-great-wall-box-office-losses-1202354934/. Accessed November 6, 2023.

Eliashberg J, Hegie Q, Ho J, Huisman D, Miller SJ, Swami S, Weinberg CB, Wierenga B (2009) Demand-driven scheduling of movies in a multiplex. International Journal of Research in Marketing 26(2):75–88.

Feldman P, Papanastasiou Y, Segev E (2019) Social learning and the design of new experience goods. Management Science 65(4):1502–1519.

Gu W, Heese HS, Kemahlıoğlu-Ziya E, Ziya S (2024) Pricing for services with cross-segment externalities, capacity constraints, and competition. European Journal of Operational Research 313(2):801–813.

Guo Q, Chen YJ, Huang W (2022) Dynamic pricing of new experience products with dual-channel social learning and online review manipulations. Omega 109:102592.

Ha AY, Luo H, Shang W (2022) Supplier encroachment, information sharing, and channel structure in online retail platforms. Production and Operations Management 31(3):1235–1251.

Ho JY, Liang Y, Weinberg CB, Yan J (2018) An empirical study of uniform and differential pricing in the movie theatrical market. Journal of Marketing Research 55(3):414–431.

Hogenboom A, Bal M, Frasincar F, Bal D (2013) Towards cross-language sentiment analysis through universal star ratings. 7th International Conference on Knowledge Management in Organizations: Service and Cloud Computing, 69–79 (Springer).

Huang H, Sunar N, Swaminathan JM, Roy R (2023) Do noisy customer reviews discourage platform sellers? empirical analysis of an online solar marketplace. Manufacturing & Service Operations Management .

Isenberg M (2022) The batman tickets will cost more than other movies at amc theaters. Retrieved from `https://www.cnet.com/culture/the-batman-tickets-will-cost-more-than-other-movies-at-amc-theaters/`. Accessed November 11, 2022.

Jandhyala S, Oliveira FS (2021) The role of international anti-corruption regulations in promoting socially responsible practices. Journal of Economic Behavior & Organization 190:15–32.

Jiang B, Yang B (2019) Quality and pricing decisions in a market with consumer information sharing. Management Science 65(1):272–285.

Jiang ZZ, Cui S, He N, Li K, Tian L (2023) Contract selection and piracy surveillance for video platforms in the age of social media. Production and Operations Management .

Keppo J, Kim MJ, Zhang X (2022) Learning manipulation through information dissemination. Operations Research 70(6):3490–3510.

Li F, Du TC, Wei Y (2023) This is what's in store for you: How online social learning affects product positioning. Transportation Research Part E: Logistics and Transportation Review 179:103317.

Li X, Qi X (2021) On pricing and quality decisions with risk aversion. Omega 98:102118.

Li Y, Li G, Tayi GK, Cheng T (2019) Omni-channel retailing: Do offline retailers benefit from online reviews? International Journal of Production Economics 218:43–61.

Lynch SM (2007) Basics of bayesian statistics. *In Introduction to applied bayesian statistics and estimation for social scientists* (Springer, New York).

Ma Q, Shou B, Huang J, Başar T (2021) Monopoly pricing with participation-dependent social learning about quality of service. Production and Operations Management 30(11):4004–4022.

Pal B, Sarkar A, Sarkar B (2023) Optimal decisions in a dual-channel competitive green supply chain management under promotional effort. Expert Systems with Applications 211:118315.

Papanastasiou Y, Savva N (2017) Dynamic pricing in the presence of social learning and strategic consumers. Management Science 63(4):919–939.

Pokorny M, Sedgwick J (2012) The financial and economic risks of film production. Film and risk 181–196.

Shin D, Vaccari S, Zeevi A (2023) Dynamic pricing with online reviews. Management Science 69(2):824–845.

SingaporeReview (2021) Movie ticket price in singapore 2022. Retrieved from `https://bestprices.sg/movie-ticket-prices-in-singapore/`. Accessed November 11, 2022.

TencentNews (2025) At a cost of 800$million, \backslash fengshen2”couldonlysell$1.2 billion at the box office, and the consequences were extremely serious as ulsan's work was lost. Accessed April 7, 2025, `https://news.qq.com/rain/a/20250210A05XL000?uid%5B0%5D=100042670174&uid%5B1%5D=100042670174&suid=&media_id=`.

Thompson D (2012) Why do all movie tickets cost the same? Retrieved from `https://www.theatlantic.com/business/archive/2012/01/why-do-all-movie-tickets-cost-the-same/250762/`. Accessed November 11, 2022.

Tian B, Lu Y, Yu L, Chang X (2024) Optimal financing strategies for a risk-averse supplier under the cvar criterion in a capital-constrained supply chain. Journal of the Operational Research Society 75(8):1643–1661.

Wang D, Liu W, Shen X, Wei W (2019) Service order allocation under uncertain demand: Risk aversion, peer competition, and relationship strength. Transportation Research Part E: Logistics and Transportation Review 130:293–311.

Wang J, Shum S, Feng G (2022) Supplier's pricing strategy in the presence of consumer reviews. European Journal of Operational Research 296(2):570–586.

Wen X, Siqin T (2020) How do product quality uncertainties affect the sharing economy platforms with risk considerations? a mean-variance analysis. International Journal of Production Economics 224:107544.

Yang X (2022) Rules and process of chinese film box office sharing. Retrieved from `https://www.douban.com/note/605608460/?\_i=7242561749RAGI`. Accessed November 11, 2022.

Zhou J, Xu R, Jiang C (2023) Sales volume and online reviews in a sequential game. Journal of the Operational Research Society 74(10):2277–2288.

Zhou P, Bu C, Zhai Y (2024) Service provision decisions of competitive manufacturers: From service spillover perspective. Journal of the Operational Research Society 1–16.