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On enjoying watching movies in a theatre versus at home: a comparative analysis

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Abstract

For most major movies, consumers have a choice to watch them in a theater or on home video. While each viewing channel has its own advantages and disadvantages, consumers are watching the same underlying product—a specific movie. An unanswered question is whether consumers enjoy watching a specific movie more in a theater or video setting. Using IMDb rating data, we find that for most wide-release movies, ratings are higher during the theater window than during the video window. The differences are particularly high for movies with relatively large production budgets and for sequels.

Keywords Movie theaters · Streaming · Product review ratings · Stochastic dominance

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1 Introduction

Streaming of movies on home video and mobile devices (referred to hereafter as "home video") has dramatically taken off over the last few years. Home viewing is appealing because consumers can watch movies at home in a convenient setting, at a time that they choose, and at a (subscription) price that is per movie lower than in the theater. But theatergoing has its own advantages. In the cinema, people can have fun, immerse themselves in the movie without being disrupted by household events, and enjoy superior audiovisual experiences, while pairing well with dining out. Most often, people watch a movie in a cinema in the company of others and consumers derive value from this shared experience (Delre et al., 2016). Moreover, prominent figures in the movie industry believe that people prefer watching a movie in a theater rather than in a home video setting and explore the possibility of bringing more films into movie theaters from streaming providers (Huston, 2022). One well-known example is Tom Cruise, who insisted that *Top Gun: Maverick* be released in theaters; it became the most popular summer 2022 movie (Grimes, 2022).

This paper examines whether the alleged superiority of the cinema for watching a movie can be demonstrated with consumer rating data from a large sample of movies. In particular, for 148 movies, widely released between January 2018 and February 2020, we compare individual viewer ratings on IMDb of the same movies, watched in theater, and on video. We find that for most wide-release movies, the mean rating of a movie watched in theater is higher than for the same movie watched on video. We also compare the theatrical and home video rating distributions in terms of stochastic dominance (Hadar & Russell, 1969) and obtain similar theater favorability results. Furthermore, we examine, for a set of movie characteristics, how they affect the difference of the ratings in the theater as compared to the video window.

2 Relevant prior research

2.1 Evidence from experiments

In August 2019, Showcase Cinemas conducted an experiment, where the movie *Jumanji: Welcome to the Jungle* was watched by two groups: one in their Massachusetts-based flagship theater in Revere, Massachusetts, on August 26 and another in a simulated home video living room at a market research company in Boston on August 19 (Showcase Cinemas, 2019). Theater viewers reported enjoying the movie more than the home viewers. Biometrical data (pulse rate and skin conduction) showed that neurophysiological excitement was much higher in the theater than in the home environment. Viewers preferred the theater setting in terms of picture and sound quality, screen size, seating comfort, and atmosphere.

In an experimental study conducted in Regensburg (Germany), participants were randomly assigned to either watch the movie *Von Komischen Vögeln* ("About funny birds") in either a cinema or home environment. Overall enjoyment of the cinema experience was found to be significantly higher than in a home cinema setting (Fröber & Thomaschke, 2021).

2.2 Evidence from surveys

In November 2018, 53% of survey respondents (n = 2200) preferred ("strongly" or "somewhat") to watch a movie for the first time at a theater, whereas 30% preferred watching via a streaming device (Navarro, 2021). That preference was reversed at the start of the pandemic (June 2020) when almost all US movie theaters were closed. However, in another survey (n = 1094) conducted 6 months (Fall 2020) after the beginning of the pandemic, done in the Netherlands, 60% of the respondents preferred to watch a new movie in theater versus 40% at home (assuming that the price is the same). For a new blockbuster, 83% would prefer the movie in theater (Simon, 2021).

While the above-noted evidence is encouraging for exhibitors, they are not without limitations. Both experimental studies included only one movie. The questions in the survey studies referred to a general, abstract watching experience (e.g., "watching a movie for the first time") not to a specific movie. To move towards greater generalizability, there is a need to compare the theater and video watching experiences for a large number of movies in a more natural setting. In this paper, we report on such a study.

3 Dataset

3.1 Movie rating sample

Focusing on wide-release movies, we first identified 293 movies released between January 1, 2018, and February 29, 2020, in North America in at least 500 theaters in the opening week. The February 2020 cutoff ensures all movies have their first 2 weeks of theatrical releases before COVID-19 was declared as national emergency (March 13). For these 293 movies, we then extracted all IMDb (Internet Movie Database) reviews, written in English, that included both a numerical rating and a written review. Written reviews allowed us to trace individual reviews back to specific IMDb user identification, needed to control for possible duplicate entries. We only considered reviews that were posted on or after the Friday of the week, in which the movie was released, to control for the effects of people who write reviews based on trailers and also to limit the effect of fans who might watch the film on late night showings (e.g., Thursday midnight screenings). In each review, the user rates a movie on a 1 ("you think the title was terrible and one of the worst titles you have ever seen") to 10 ("you think it was excellent") scale. Consistent with Holbrook (2005), the ratings for each movie are considered the representation of the ordinary or non-expert consumer's evaluation of the movie. After removing a small percentage of duplicated reviews, we have 207,813 reviews.

3.2 Defining theatrical vs. home video window

Since a reviewer does not specify whether the IMDb review is based on a theatrical or home video viewing experience, the posting date of the review is used to infer the appropriate viewing channel. This may result in possible misclassification of the viewing experience window; since the theater window precedes the video window, a primary concern is that some theater reviews may be classified as video reviews. As described below, we take a number of steps to mitigate such concerns.

Based on data from *the-numbers.com*, we define the theater and video windows for each movie as follows. Let:

t1 denote the Friday of the first week of the movie's US theatrical release.

t2 denote the Thursday of the last week of the movie's reported US box office.

t3 denote the reported US video availability date of the movie.

The theatrical window is defined as t3-t1. For movies with their reported US box office ending earlier than their US video availability dates (i.e., t3 > t2), the video window is defined as t3 + 52 weeks[1]. However, if t3 < t2, we define the video window as t2 + 52, essentially excluding the problematic reviews posted after the movies were released as home video but still available at some theaters. We consider all reviews during the theatrical window as generated by users watching the movie in theaters while all reviews during the video window as home video-based reviews.

3.3 Constructing the final sample for analysis

Although users on *IMDb.com* may come from theatrical markets other than the USA and Canada (both countries are technically the same market due to common release dates), our inclusion of only ratings with written (in English) reviews would primarily only include another major English-speaking market, the UK. Usually, this market is consistent with the US market in terms of release dates of movies in theater and for home video. However, to avoid biases for the situation that this is not the case, we excluded movies having their UK release dates later than t1 + 21 days (IMDb does not specify the location of the review's author).

To ensure sufficient sample size in terms of number of reviews, we include only movies with at least 100 reviews in both the theater window and the video window[2]. For these movies, we include all available reviews.

We also compiled the following movie characteristics: production budget from IMDb.com, sequel classification from *movieinsider.com*, and genre and creative type classification from *the-numbers.com*. We excluded from our analysis seven movies that did not have publicly available production budget information, resulting in a final sample of 148 movies with 165,498 reviews. Table 1 (left hand part) presents a summary of the final sample employed in the analyses reported next.

[1] Our key results remain if we change the length of both viewing windows to 1 month.

[2] Our key results hold when we reduce the cutoff to at least 50 reviews per movie in each window.

Table 1 Summary of data, analysis, and findings

Sample size and notation	• $k \equiv$ total number of movies; ($k = 148$) • $n_{jw} \equiv$ number of reviews for movie j ($1 \leq j \leq k$) in window w ($w = T$ if theatrical window, V if video window) • $n_w \equiv$ total number of reviews in window w, $n_w \sum_{j=1}^{k} n_{jw}$; ($n_T = 109{,}154$; $n_V = 56{,}344$) • $n \equiv$ total number of reviews, $n = n_T + n_V$; ($n = 165{,}498$) • $x_{ijw} \equiv$ the numeric rating for ith review for movie j in window w ($1 \leq i \leq n_{jw}$)							
	Data		Data breakdown, analysis, and findings					
Average numeric rating of IMDb reviews	Average rating of movie j, aggregating both the theatrical and video windows, $\overline{x_j} = \frac{1}{n_{jT}+n_{jV}}\left(\sum_{i=1}^{n_{jT}} x_{ijT} + \sum_{i=1}^{n_{jV}} x_{ijV}\right)$		Average rating of movie j in the theatrical window ($w = T$), $\overline{x_{jT}} = \frac{1}{n_{jT}}\sum_{i=1}^{n_{jT}} x_{ijT}$		Average rating of movie j in the video window ($w = V$), $\overline{x_{jV}} = \frac{1}{n_{jV}}\sum_{i=1}^{n_{jV}} x_{ijV}$		Change of average rating of movie j from the theatrical to the video window, $\overline{x_{jV}} - \overline{x_{jT}}$	
	Mean, $\frac{1}{k}\sum_{j=1}^{k}\overline{x_j}$:	6.056	Mean, $\frac{1}{k}\sum_{j=1}^{k}\overline{x_{jT}}$:	6.293	Mean, $\frac{1}{k}\sum_{j=1}^{k}\overline{x_{jV}}$:	5.680	Mean, $\frac{1}{k}\sum_{j=1}^{k}\left(\overline{x_{jV}} - \overline{x_{jT}}\right)$:	− 0.613
	Min	3.185	Min	3.218	Min	3.061	Min	− 2.436
	Max	8.698	Max	8.942	Max	8.592	Max	0.819
	Std. Dev	1.115	Std. Dev	1.141	Std. Dev	1.097	Std. Dev	0.570
Stochastic dominance of rating distributions			Theater dominates video 118 (80%) Video dominates theater 12 (8%) No stochastic dominance 18 (12%)					
Conclusion based on the two analyses			In general, people enjoy watching the same movie in the theater more than on video at home					
Movie characteristics	Summary statistics and frequencies of categories in the sample of 148 movies		Model-free pattern between change of average rating from the theatrical to video window and a movie characteristic (details are in the online appendix)					
Production budget	Mean:	75062162	Movies with larger budget tend to have larger drop in average ratings from the theatrical to the video window (Pearson correlation = − 0.277)					
	Min:	3500000						
	Max:	400000000						
	Std. Dev:	71241354						

Table 1 (continued)

Sequel	Sequel:	38 (25.7%)	Sequels have larger drop in average ratings from the theatrical to the video window (– 0.866) than non-sequels (-0.525)
	Non-sequel:	110 (74.3 %)	
Genre	Action	40 (27.0%)	Action movies have the biggest drop in average ratings from the theatrical to the video window (– 0.885) while thriller movies have the smallest drop (– 0.391)
	Adventure	26 (17.6%)	
	Thriller	23 (15.5%)	
	Horror	22 (14.9%)	
	Comedy	20 (13.5%)	
	Drama	14 (9.5%)	
	Musical	3 (2.0%)	
Creative types	Contemporary Fiction	71 (48.0%)	Superhero movies have the biggest drop in average ratings from the theatrical to the video window (– 0.954) while historical fiction is the genre with the smallest drop (– 0.069)
	Sci-Fi	24 (16.2%)	
	Kid Fiction	13 (8.8%)	
	Superhero	13 (8.8%)	
	Dramatization	11 (7.4%)	
	Historical fiction	9 (6.1%)	
	Fantasy	7 (4.7%)	

4 Analyses: differences in ratings

To examine which window (theater or video) generates higher evaluations, we conduct two different analytical comparisons: average ratings and stochastic dominance. The multiple methods allows us to examine the robustness of the results, which is important, given that online product reviews are known to have non-symmetrical distributions like a J-shaped one (Hu et al., 2009).

4.1 Rating comparison

We compare the ratings of movies in the theatrical (average rating (across all reviews for a movie first and then across all movies) = 6.29) and video (average rating = 5.68) windows (see Table 1 for more details). To do this comparison, we first calculate the average ratings for each movie in the theatrical window and in the video window; we then conduct a paired two-tailed t-test comparing the 148 pairs of average ratings. The resultant t-statistic (H_o: the across-movie average difference between ratings in the theatrical and the video window = 0; H_a: the across-movie average difference ≠ 0) is 13.086, df = 147 ($p < 0.001$). This implies that, overall, the ratings in the theater window are higher than in the video window. Moreover, 88% of the 148 movies in our sample have higher ratings in the theatrical vs. video window.

4.2 Comparing the distributions of the reviewer ratings: stochastic dominance approach

To focus directly on a comparison of the distribution of movie ratings in the theatrical and video windows, we apply stochastic dominance. Stochastic dominance, a widely accepted ordering approach employed in various fields, has been applied as guidance when a decision maker needs to choose between two or more alternatives, based on the distributions of outcomes (Levy, 1992). For our setting, in notation form, let T denote the average rating across all reviewers randomly drawn from the theatrical window and V denote the average rating across all reviewers randomly drawn from the video window; then, T first-order stochastically dominates V when $\Pr[T \leq x] \leq \Pr[V \leq x]$ for all x with strict inequality for some x. Applying the Bayes factor test (Heathcote et al., 2010), three possible outcomes can be obtained: (1) the movie theatrical window rating distribution stochastically dominates that of the video window rating distribution, (2) there is no stochastic dominance, and (3) the movie video window rating distribution stochastically dominates that of the theatrical window rating distribution.

For 118 (80%) of the 148 movies in our sample, the distribution in the theatrical window stochastically dominates the distribution in the video window. No stochastic dominance between distributions in the two windows is observed for 18 (12%) movies. The rating distribution in the video window stochastically dominates the rating distribution in the theatrical window for 12 (8%) of the movies.

In sum, both approaches discussed above show converging results; for the majority of wide-release movies, the same movie generates more favorable reactions when watched in theater relative to on video.

4.3 Possible effect of choosing the theater watching for a priori most favorite movies

It may be possible, since the theater window comes first, that some consumers who watched a particular movie in a theater have done so because the movie was of special interest to them or one of their favorite types of movies (for movies of lower interest, these people would wait until it becomes available on video). To the extent that a priori favorite movies receive comparatively higher ratings, this would produce higher overall ratings for theaters. We conduct two empirical analyses to assess whether the effects of people choosing to see particular movies at a theater rather than waiting for it to be released to video could be an important driver of our results, i.e., higher ratings of movies in theater.

First, we track each review to its unique IMDb user identifications (totaling 104,292 users) and focus on 1177 IMDb users, who posted at least 10 reviews. Although these frequent users represent only 1.13% of the users in our sample, they posted 15.31% (25,339 reviews) of the 165,498 reviews. We define three different groups of these frequent movie consumers, on the basis of whether their reviews come from (1) theater primarily (TP) consumers with > 90% of their reviews coming from the theater window, (2) video primarily (VP) consumers with < 10% of their reviews coming from the theater window, and (3) balanced (BAL) theater and video consumers with between 45 and 55% of reviews coming from the theater window. A possible phenomenon that consumers choose selectively the theater for the movies they a priori like most and give it a comparatively high rating would be most visible in the group of BAL consumers, because they switch most easily from video to theater whereas the TP and VP consumers are window loyal. However, this does not appear to be the case in the data. For each of the three groups we calculated the average ratings for movies they see in theaters and find the following averages: TP consumers 6.88, VP 6.79, and BAL 6.30 (lowest). BAL viewers' ratings are significantly lower than those of TP consumers ($t = 6.795$, p-value < 0.001) and (although not significantly) lower than those of VP consumers ($t = 1.428$, p-value $= 0.158$).

In our second analysis, we consider the possibility that when VP consumers choose to go to theaters, they go to see particular types of movies, in this case sequels.[3] While sequels account for 25.7% of the movies in our sample, for VP consumers, 40.0% of the movies they post reviews for in the theater window are sequels. This suggests that they indeed choose the theater for movies that they are a priori most interested in, which could produce an upward effect on the theater ratings.

[3] We thank Aidan Lieberman for suggesting this analysis.

Therefore, we excluded sequels from the analyses we conducted in Sections 4.1 and 4.2 and again found that the average rating was still significantly (t = 10.219, p-value < 0.001) higher in the theater window (mean = 6.250) than the video window (mean = 5.725) and that stochastic dominance was achieved for 77% (85 of 110 non-sequels) of the movies in the theater window (for more details, please see the Online Appendix).

While we recognize that some consumers may choose to watch movies they particularly want to see in theaters as compared to on video, the effects of this behavior on ratings seem to be limited in our sample.

5 Movie characteristics and differences in ratings

As indicated by the findings above, not all movies generate higher average ratings nor achieve stochastic dominance in the theatrical relative to the video window, and if they do, the theater's advantage differs by movie. We next study movie characteristics that might be associated with these differences.

We consider four characteristics that have received previous attention by researchers and practitioners. First, production budget has long been associated with motion picture box office success (Eliashberg et al., 2006) and a number of industry observers have suggested that primarily high production budget movies will get national releases and attract large audiences (e.g., Follows, 2019). Second, sequels are typically based on movies that achieved high box office success (Dhar et al., 2012) and thus might be thought to have a particular advantage with regard to viewer ratings as compared to non-sequel movies. Third, genre is another frequently studied variable (e.g., Gehring, 1988), and again, industry observers have suggested that only certain types of movie genres (e.g., Action movies) are likely to earn box office revenues that would justify widespread national distribution (Galloway, 2019). Fourth, we study creative type. While there has been limited attention to this characteristic in the academic literature, it receives attention in movie websites (e.g., the-numbers.com) as well as in media outlets targeting industry practitioners (e.g., Davis, 2022) and the general public (e.g., Eliashberg et al., 2022). See Table 1 for summary statistics of these variables. We approached this issue using multilevel modeling. Consistent with a number of studies in the literature (e.g., Moon et al., 2010), we treat the rating data as being interval scale.

5.1 Multilevel modeling

Multilevel modeling (MLM) is used to examine relations between variables measured at different levels of the multilevel data structure (Hox et al., 2018). In our case, there are two levels: level 1 (individual review) and level 2 (movie). Mathematically, for review i of movie j, the following equation is specified:

$$\text{Rating}_{ij} = \beta_{0j} + \beta_{1j}\text{VIDEO\_RUN}_{ij} + r_{ij} \tag{1.1}$$

where

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{LN\_Budget}_j + \gamma_{02}\text{Sequel}_j + \gamma_{03}\text{Genre}_j + \gamma_{04}\text{CreativeType}_j + u_{0j} \tag{1.2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}\text{LN\_Budget}_j + \gamma_{12}\text{Sequel}_j + \gamma_{13}\text{Genre}_j + \gamma_{14}\text{CreativeType}_j + u_{1j} \tag{1.3}$$

where Rating_{ij} is the rating of review i for movie j and $\text{VIDEO\_RUN}_{ij} = 1$ if review i for movie j comes from the home video window and 0 if from theatrical window.

Movie j variables are as follows:

LN_Budget_j is log of production budget of movie j, after mean-centering.

Sequel_j is an indicator variable for movie j being a sequel (= 1) or not (= 0).

Genre_j represents a set of six indicator variables for seven genres for movie j (action is the base case).

CreativeType_j represents a set of six indicator variables for seven creative types for movie j (contemporary fiction is the base case).

r_{ij}, u_{0j}, and u_{1j} are unobserved random variables.

To better understand the incremental effects of the variables, the following models were estimated:

MLM1: only review-level variables (i.e., setting γ_{01}, γ_{02}, γ_{03}, γ_{04}, γ_{11}, γ_{12}, γ_{13}, and γ_{14} all equal to zero)

MLM2: production budget and sequel model (setting γ_{03}, γ_{04}, γ_{13}, and γ_{14} all equal to zero)

MLM3: production budget, sequel, and genre model (setting γ_{04}, and γ_{14} all equal to zero)

MLM4: production budget, sequel, and creative types model (setting γ_{03} and γ_{13} all equal to zero)

MLM5: production budget, sequel, genre, and creative types model

Table 2 presents the estimation results. The focal models are MLM2, which is the best model in terms of the BIC information criteria measure, and MLM5, which is the best model in terms of the AIC measure, but MLM3 and MLM4 have very similar AIC values. For a discussion of these metrics, see Vrieze (2012).

5.2 Results of MLM

In all five models (see Table 2), the coefficient of VIDEO_RUN is negative and significant[4]. This confirms our earlier finding that, overall, the ratings are lower in the video than in the theater window.[5]

[4] As a robustness check on our results, we also estimated a fixed effect (for each movie) model in which the variable VIDEO_RUN is included. The coefficient of VIDEO_RUN is negative and statistically significant. See the Online Appendix for these results.

[5] To allow for the possibility that ratings may decline over time, in addition to the VIDEO_RUN variable, we added a variable to capture the decay rate in the theatre and video windows to models MLM1-5. We found that the decay rate for the theatre window was significant and negative, but that the coefficient of VIDEO_RUN was still negative and significant. See the Online Appendix.

Table 2 Results of the multilevel models

Estimate (standard error)	MLM1	MLM2	MLM3	MLM4	MLM5
Intercept (γ_{00})	6.306*** (0.093)	6.318*** (0.103)	6.401*** (0.187)	6.402*** (0.152)	6.440*** (0.215)
Main effect					
VIDEO_RUN$_{ij}$ (γ_{10})	− 0.633*** (0.047)	− 0.559*** (0.052)	− 0.734*** (0.099)	− 0.616*** (0.078)	− 0.784*** (0.116)
LN_Budget$_j$ (γ_{01})		0.359*** (0.087)	0.121 (0.124)	0.431*** (0.108)	0.151 (0.130)
Sequel (γ_{02})		− 0.082 (0.209)	0.135 (0.200)	− 0.042 (0.203)	0.118 (0.195)
Genre$_j$ (γ_{03}) (base: action)					
Adventure			0.147 (0.250)		0.541 (0.340)
Thriller			− 0.282 (0.297)		− 0.162 (0.286)
Horror			− 1.104** (0.354)		− 1.029** (0.336)
Comedy			− 0.045 (0.322)		0.002 (0.315)
Drama			0.653* (0.330)		0.567 (0.381)
Musical			− 0.483 (0.590)		− 0.087 (0.608)
Creative_Type$_j$ (γ_{04}) (base: contemporary fiction)					
Sci-Fi				− 0.620* (0.269)	− 0.555* (0.264)
Kid fiction				0.143 (0.338)	− 0.204 (0.428)
Superhero				0.158 (0.351)	0.419 (0.341)
Dramatization				0.665* (0.334)	0.161 (0.383)
Historical fiction				− 0.412 (0.363)	− 0.439 (0.347)
Fantasy				− 0.933* (0.429)	− 1.124* (0.468)
Interaction effect					
VIDEO_RUN$_{ij}$_x LN_Budget$_j$ (γ_{11})		− 0.125** (0.044)	− 0.080 (0.067)	− 0.140* (0.056)	− 0.076 (0.072)
VIDEO_RUN$_{ij}$_x Sequel$_j$ (γ_{12})		− 0.253* (0.104)	− 0.250* (0.106)	− 0.233* (0.104)	− 0.216* (0.106)
VIDEO_RUN$_{ij}$_x Genre$_j$ (γ_{13})					
Adventure			0.261* (0.132)		0.117(0.182)

Table 2 (continued)

Estimate (standard error)	MLM1	MLM2	MLM3	MLM4	MLM5
Thriller			0.315* (0.158)		0.313* (0.156)
Horror			0.255 (0.188)		0.246 (0.183)
Comedy			0.216 (0.175)		0.243 (0.175)
Drama			0.085 (0.177)		0.151 (0.208)
Musical			0.145 (0.310)		0.059 (0.330)
VIDEO_RUN$_{ij}$_x Creative_Type$_j$ (γ_{14})					
Sci-Fi				0.093 (0.137)	0.099 (0.142)
Kid fiction				0.223 (0.178)	0.213 (0.234)
Superhero				− 0.113 (0.175)	− 0.049 (0.180)
Dramatization				− 0.129 (0.175)	− 0.108 (0.210)
Historical fiction				0.512** (0.188)	0.533** (0.189)
Fantasy				0.134 (0.221)	0.111 (0.256)
Var(r_{ij})	8.006*** (0.028)	8.005*** (0.028)	8.005*** (0.028)	8.005*** (0.028)	8.005*** (0.028)
Var(u_{0j}) (intercept)	1.242*** (0.147)	1.114*** (0.132)	0.951*** (0.113)	0.979*** (0.116)	0.852*** (0.101)
Var(u_{1j}) (VIDEO_RUN$_{ij}$)	0.269*** (0.036)	0.234*** (0.032)	0.224*** (0.031)	0.214*** (0.030)	0.208*** (0.029)
AIC	814934.3	814908.3	814902.5	814902.3	814902.0
BIC	814949.2	814935.2	814965.5	814965.3	815000.9

***p-value ≤ 0.001, **p-value ≤ 0.01, and *p-value ≤ 0.05

5.2.1 Movie budget

The coefficient (0.359) of LN_Budget is positive and significant in MLM2, suggesting that movies with larger budgets in general get better ratings. This is consistent with Karniouchina et al. (2022, Web Appendix B) who report a significant pairwise positive correlation between production budget and IMDb ratings. However, when the dummy variables for the genre categories are included in MLM5, the significance disappears, probably because of multicollinearity with one or more genre categories. Genres such as adventure and action tend to have higher production budgets than the others (see Online Appendix). Model MLM2 shows a significant negative interaction of production budget with VIDEO_RUN (− 0.125), implying that the drop in ratings from the theatrical to video window would be amplified for movies of higher production budget.

5.2.2 Sequel

SEQUEL does not have a significant main effect on the ratings. However, the significant negative interaction with VIDEO_RUN in both MLM2 and MLM5 suggests that sequels do relatively worse than a non-sequel in the video window.

5.2.3 Genre and creative type effects

Turning to the issue of whether the difference in ratings between the theater and video windows is associated with genre and creative types, we focus on MLM5. The genre horror tends to have a statistically lower rating (− 1.029) as compared to the base case of action. With regard to the interactions with VIDEO_ RUN, there is a significant positive coefficient for thriller (0.313). This positive effect is smaller than the negative effect (− 0.784) of VIDEO_RUN, for thriller movies, so it does not compensate fully for this. Yet, the gap between theater and video ratings is smaller for thriller movies than for action movies. Overall, there is no genre which is significantly associated with higher movie ratings in the video window than for theater.

Regarding creative type, as compared to the base case of contemporary fiction, both Sci-Fi and fantasy have significantly lower ratings. Considering interactions with VIDEO_RUN, a significant positive coefficient occurs for historical fiction (0.533), suggesting the drop in ratings from the theatrical to the video window would be less severe for historical fiction than for contemporary fiction. However, analogous to genre, there is no creative type that is significantly associated with higher movie ratings in the video vs. theater window.[6]

[6] Other papers, e.g., Godes and Silva (2012), treat product ratings as ordinal. As a robustness check, we follow Bauer and Sterba (2001) and run an estimation of multilevel cumulative logit model treating the ratings as ordinal for models MLM1–5 and find that the coefficient of VIDEO_RUN is negative and significant. The results for other independent variables are generally consistent. See the Online Appendix for these results.

6 Discussion

In a study of 148 wide-release movies, released between January 1, 2018, and February 29, 2020, we found that on average, the same movies watched in theater receive higher ratings than when watched on video. Interestingly, several movie characteristics affect the advantage of theater over video. For example, large production budgets and sequels are associated with even lower ratings in the video window, thus increasing the advantage of the theater window over the video window.

Major Hollywood studios are increasingly moving from being movie producers with strong theatrical distribution to becoming ones with streaming services. They are also experimenting with releases to theaters and videos on the exact same day, or in very close proximity to each other (day-and-date release). Warner Bros, for instance, released its 2021 movies in theaters and on HBO Max simultaneously, hoping that audiences would enjoy these movies at a sufficiently high level to motivate purchasing and renewing a subscription to their streaming service. However, based on the results of this paper, studios should realize that in most cases, making a movie available on video implies a loss of enjoyment on the part of the consumer, as expressed by lower rating.

The analyses reported in this paper imply that movie theaters remain an indispensable element in the movie distribution channel, as a shared consumption experience in a setting that is largely devoid of distractions and with high levels of sound and picture quality. At the same time, the convenience, low price per movie watched, and instant availability of a wide range of movies will continue to make streaming a popular outlet. The willingness of people to go to movie theaters and the economics of the exhibition industry in the post-pandemic world will greatly influence the future of the movie-theater business.

As ratins differences vary by movie characteristics, movie theaters should attempt to create a viewing experience which enhances the satisfaction of moviegoers. Additionally, just as movie theaters have been able to charge higher prices for 3D movies, they may consider charging higher prices for movies which are more likely to be differentially rated higher when seen in movie theaters as compared to streaming. One way to do this is by booking such movies into “luxury” screening rooms.

7 Future research

As with all empirical data studies, some questions remain. For example, we find that, on average, the same movies watched in theater gets higher ratings than when watched on video. However, the ratings are given by different groups of respondents. It may well be that the theater respondents a priori give a movie a higher rating in theater because they like theater more. However, *mutatis mutandis*, the same can be said for the video respondents.

It is possible, as long as the theater window comes first, that people who choose to go to a movie theater are those who are most interested in that movie.

It is unclear, however, whether these people would be more supportive or more critical of such movies. We provide some empirical evidence suggesting that such movie selection issues are not the main drivers of our results, but we suggest that future work examine the reasons underlying the differences we found in ratings between theater and video viewing.

The present study offers initial insights into the difference in movie experience between watching a movie in the home video and in the traditional movie theater. There are still interesting issues that remain to be studied. For example, how does the consumer decide between watching a film at a theater or on home vide, and to what extent does this decision depend on factors such as the type of movie and setting-specific conditions, for example, the available companions with whom to watch the movie, and the differences between socio-economic groups? Another interesting issue is how the enjoyment of home video would be affected if people are opting for ad-supported variants of streaming services.

Watching movies is an interesting and important research domain in consumer behavior that has spawned an extensive literature. The pandemic period, technological advances, and innovative management strategies have resulted in changes in the way people choose, consume, and enjoy movies. These developments raise new and challenging questions for both researchers and practitioners.

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Declarations

Ethical approval Not applicable.

Informed consent Not applicable.

Competing interests The authors declare no competing interests.

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