

MOVIE BUZZ & INFORMATION CASCADES

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ABSTRACT

When it comes to predicting the success of Hollywood movies, there's an adage that "Nobody knows anything." Even though big data can inform investment decisions, research has found that there is no formula studios can use to guarantee a movie's success. This is because people don't know whether they'll like a movie until they see it. Hence, the best determinant of success is word-of-mouth and whether viewers recommend a film or not. Since there are very few reliable leading indicators in this business, this article analyzes word-of-mouth, or buzz, as a lagging indicator and its impact on a movie's performance. This article also examines the effects of information cascades, or herd behavior, on movies.

INTRODUCTION

"Nobody knows anything" is a common refrain in the movie business. It's a quote from William Goldman's book, *Adventures in the Screen Trade*, and in some circles has become known as the Goldman Rule. In his book, Goldman argues that no one really knows for certain what's going to work and that, at best, it is based on an educated guess. (Goldman, 1989) Though this assertion has diminished with the rise of predictive analytics firms for the movie industry such as Nash Information Services, LLC, the business of producing movies is not without risk (Fulton, 2016).

For instance, Goldman's assertion was later quantified through a study conducted by Arthur De Vany of the University of California at Irvine and David Walls of the University of Hong Kong (Cassidy, 1997). De Vany and Walls analyzed 300 movies released between May 1985 and January 1986 and found that audiences were attracted to a small number of films. For example, they discovered that 20 percent of the films accounted for 80 percent of the revenue. However, there was no way to determine why audiences were attracted to some films and not to others – not the genre, the cast or the budget. The best predictor they found was how the movie performed the previous week (Cassidy, 1997).

That is, because people won't know if they like a movie until they see it, many rely on the recommendations of others. These recommendations, in turn, can have a positive or negative effect on a film. In fact, De Vany and Walls argued that a hit was generated by what economists call an information cascade. They also argued that an information cascade could kill a film as well (Cassidy, 1997).

Information cascades can occur for a variety of reasons and include decisions people make based on their own private information and/or observing other people's behavior (Easley & Kleinberg, 2010). As a result, we wanted to evaluate the effects of both word-of-mouth and information cascades on movies.

Therefore, we developed two hypotheses. The first was that if word-of-mouth was a primary determinant of movie success then there should be a significant difference in revenue from week to week between high-performing films versus low-performing films. The second hypothesis was that if information cascades could be driven by private information and/or observing other people's behavior then instances where these two conditions conflicted should be evident in the week to week revenue of highly anticipated movies.

To that end, in the fall of 2015, we first analyzed the role of word-of-mouth, or buzz, on both successful and unsuccessful movies over the previous 20 years. Specifically, we wanted to see whether there were any patterns or trends in the revenue reports that would reflect this process. What we found was remarkably consistent.

Then, in a separate study conducted in the spring of 2016, we compared successful movies, or high performers, to movies with the biggest opening weekends. That is, we wanted to know if movies with the biggest opening weekends could live up to their hype and to what extent they were affected by information cascades. These results were revealing as well.

DISCUSSION

Characterizing successful and unsuccessful films in terms of revenue is a challenging task. For example, not everyone defines success the same way. Is success defined as box office performance? If so, how much revenue would be considered a success? Moreover, if revenue is the metric, is it total revenue or is it return on investment? We could go on and on but you get the picture.

In addition, we needed a standard measure; one that could be used to compare apples to apples and oranges to oranges over a significant period of time. Therefore, we decided to use two common standards to assess good and bad movies. These standards are far from perfect but they are better than all the rest.

For good movies, we used those films that were nominated for an Academy Award as Best Picture. While this might seem to be a fairly noncontroversial standard, there have been a number of criticisms about this process. First, the awards are chosen by the Academy of Motion Picture Arts and Sciences, which is comprised of more than 7,000 industry professionals. The nominees are chosen by professionals in each category with the exception of Best Picture, whose nominees are chosen by all academy members. In addition, all members vote for the winners in each category (Garofalo, 2015).

Though there is considerable merit in having film professionals evaluate their peers, the academy came under fire in 2015 for its lack of diversity. The controversy emerged after the Civil Rights movie “Selma” failed to receive any Oscar nominations for its director, Ava DuVernay, or its star, David Oyelowo. Fortunately, steps had started to be taken to increase the ranks of women and minorities in the academy (Olson, 2015). However, according to the Hollywood Diversity Report conducted by the Ralph J. Bunche Center for African American Studies at UCLA, this lack of diversity not only exists behind the camera but in front of it as well (NPR, 2015).

Moreover, the academy’s choices are continuously debated for a myriad of others reasons. For instance, six of the seven movies nominated for Best Picture in 2015 faced one form of controversy or another including American Sniper, The Grand Budapest Hotel, The Imitation Game, Selma, The Theory of Everything and Whiplash (Dockterman, 2015).

At the other end of the spectrum are the Razzies, which is short for the Golden Raspberry Awards. These awards were created by copywriter and publicist John Wilson in 1980 to recognize the worst movies and performances every year. They are determined by more than 600 voters in the U.S. and more than a dozen foreign countries. Anyone is eligible to vote and memberships can be purchased online (Feeney, 2015). Though the voting universe isn’t distinct in any way such as those of the Academy Awards and the survey results are not scientific, the Razzies garner significant attention and are regularly covered by major media outlets (The Golden Raspberry Awards, 2015).

The financial data for this project was obtained via The Numbers website, which is sponsored by Nash Information Services, LLC. The site was created in 1997 and is now the largest freely available database of movie industry information online (The Numbers, 2015). Box Office Mojo (2015), owned and operated by IMDb, was also consulted for additional movie information. To examine the effects of word-of-mouth, we compared the percentage change in weekend box office revenue for Best Picture and Worst Picture nominees from 1996-2015. This resulted in a sample of over 200 movies from this period. Specifically, we began by looking at the percentage change between a movie’s first weekend after its widest release and its second weekend. We referred to this period as a movie’s first week and then looked at the movie’s percentage change in revenue over the next three weeks.

We used this metric as a proxy for word-of-mouth for primarily two reasons. First, if a movie’s success can best be determined by word-of-mouth, then revenue, or sales, is certainly a reasonable measure. Second, this approach supports the Diffusion of Innovations model. Developed by Everett Rogers, this theory states that the diffusion of new products, ideas and services is primarily a social process. Rogers (2003) also argued that diffusion follows a predictable curve as shown in Exhibit 1.

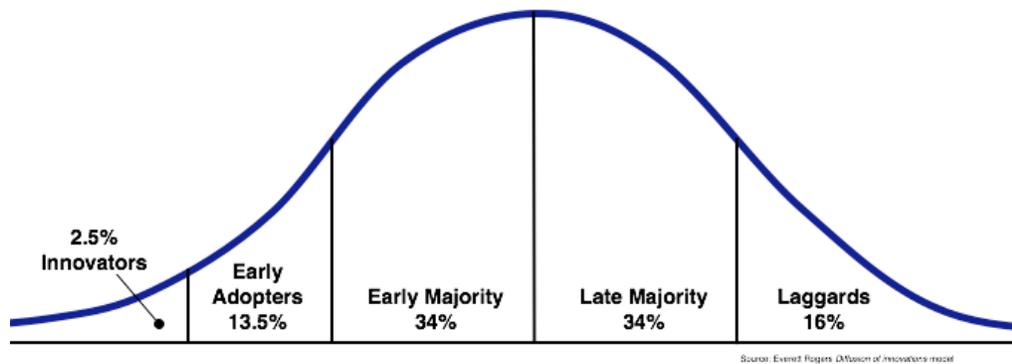


EXHIBIT 1: DIFFUSION CURVE

He characterized innovators and early adopters as opinion leaders since the early majority and others were influenced by their decisions. These opinion leaders could be recognized for their expertise on a single subject or a variety of subjects. In fact, we are all opinion leaders on one subject or another. However, we can also find ourselves at different points on this curve depending on the subject matter. For the purposes of this study, our opinion leaders are the earliest moviegoers as it is their opinions who will influence the behavior of others.

HIGH V. LOW PERFORMERS

We separated our data into two categories: high and low performers. We characterized the high performers as the Oscar-nominated movies and the low performers as the Razzie-nominated movies. We then averaged the revenue change among the movies from week to week over the 20-year period from 1996-2015, although we did remove outliers to prevent them from skewing the results. For example, the movie “New Year’s Eve,” which was nominated for a Razzie in 2012, saw a 91 percent increase in revenue in its third week because it occurred on December 30, 2011. This was a stark contrast to the declines of 44 percent and 55 percent the film experienced in its first and second weeks. While this spike in revenue was clearly the result of the movie’s holiday theme, we did use a statistical method for eliminating all of the outliers regardless of the reasons for which they might have occurred.

As Exhibit 2 indicates, our analysis revealed very consistent findings among each movie category. That is, the average percentage change for Oscar nominees was -24 percent, -26 percent, -25 percent and -21 percent over the first four weeks. By comparison, the average percentage change for Razzie nominees was -54 percent, -56 percent, -53 percent and -54 percent. As a result, the average percentage change between Oscar nominees and Razzie nominees over this time period was -30 percent. As a caveat, this is not a hard and fast rule. For instance, there is some overlap among some of the movies in each category as percentage changes for some Best Picture nominees will hover near percentage changes for some Worst Picture nominees and vice versa. As a result, this analysis isn’t meant to serve as a predictor of a movie’s success. Rather, it is meant to identify trends among and between these movies. In that sense, it may provide another variable to evaluate a movie’s appeal.

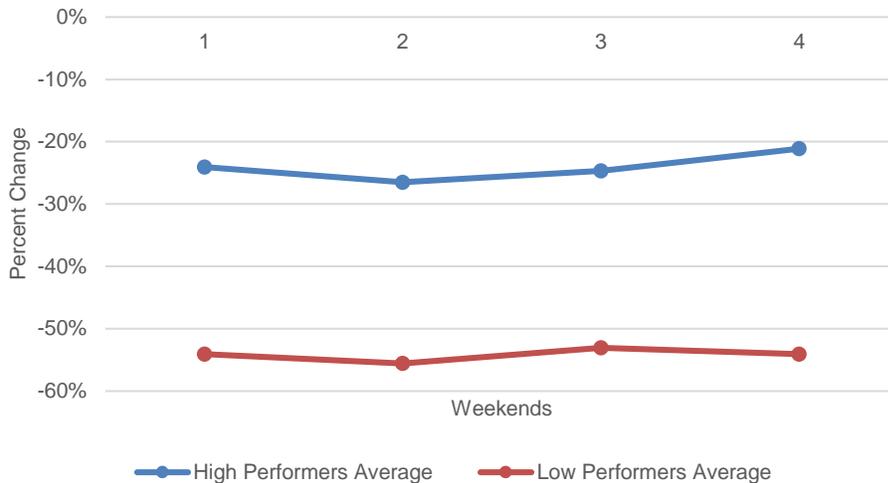


EXHIBIT 2: HIGH V. LOW PERFORMERS

Because our research period encompassed the advent of social media, we also wanted to see whether there was a difference in these results between the pre- and post-social media eras. Part of our challenge was defining not just the beginning of social media but the point at which it started to become ubiquitous. For example, Facebook was preceded by sites such as Friendster and MySpace. However, even though Facebook would eventually become the most popular social networking site, it was founded in 2004 as a site for Harvard students and remained a site for college students for two years (Digital Trends Staff, 2014). It wasn't until September 26, 2006 that Facebook opened its network to everyone (Abram, 2006).

Therefore, because this date was relatively close to the end of 2006, we chose 2007 as the delineation between the pre- and post-social media periods for this study. That is, those movies in our sample from 1996-2006 were considered part of the pre-social media era and those from 2007-2015 were considered part of the post-social media era. We then compared the average percentage change in revenue over a four-week period for both the Best Picture nominees and Worst Picture nominees in each of these periods. As we did with the full data set, we statistically eliminated outliers in these subsets as well.

As you'll see from Exhibit 3, there was some variation between these periods but it wasn't very significant. In fact, the average percentage change between Oscar nominees in the pre-social media period and post-social media period was about 5 percent, and their average percentage change compared to the entire research period was 2-3 percent. The average percentage change between Razzie nominees in the pre-social media period and post-social media period was less than 1 percent. This figure remained the same when comparing the average percentage change of these periods with the larger data set.

Moreover, the average percentage change between Oscar nominees and Razzie nominees in the pre-social media period was 33 percent, while the average percentage change between Oscar nominees and Razzie nominees in the post-social media period was 27 percent. To reiterate, the

average percentage change over the entire 20-year period between these two types of movies was 30 percent.

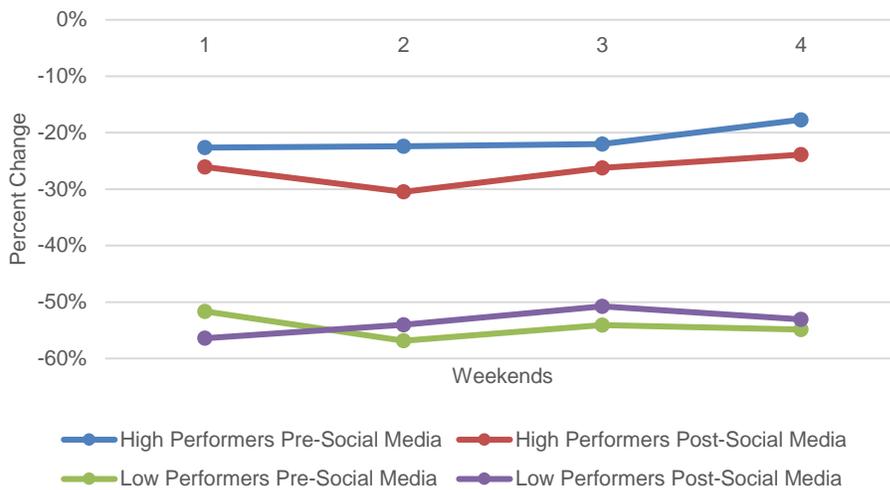


EXHIBIT 3: PRE- V. POST-SOCIAL MEDIA

Most people might have thought that there would be a more dramatic difference between these two periods due to the perceived influence of social media on word-of-mouth marketing. For instance, I routinely ask new students whether they think more word-of-mouth occurs online or offline. As you might suspect, the overwhelmingly majority of students intuitively say online. However, according to research, only 7 percent of word-of-mouth occurs online (Berger, 2013). Once you give this more thought, this makes perfect sense. For instance, most of your discussions about new ideas, products or services are likely made face-to-face among family and friends. Those are the people with whom you’re most likely to share information. After all, those are the people you most trust and the people who most trust you.

MOVIE PROFITABILITY

As Edmund Helmer of BoxOfficeQuant.com has found, Oscar winners generate far more revenue than other movies. For instance, the average movie from 2000-2009 generated roughly \$19 million domestically compared to \$143 million for a Best Picture winner. Not only do these films generate more revenue by virtue of their quality, Helmer (2011) found that the value of an Academy Award itself could boost revenue. As an example, he found that a win for Best Picture could result in an “Oscar bump” of about \$14. As an aside, Helmer (2011) also discovered that a Golden Globe win could boost earnings more than an Oscar, even though Academy Award winners earn more at the box office.

However, revenue is one thing and profitability is another. Industry analyst Harold Vogel (2011) states that on average six or seven out of 10 movies are unprofitable and one might break even. Given the unpredictability of the movie business, this is certainly understandable. To shed a little

more light on this issue, we examined the production costs and worldwide revenue for all of the Best Picture and Worst Picture nominees in our sample. We then calculated the gross profit for each movie using these figures. It is important to note that the production budget figures from this data source do not include marketing expenses. As of 2014, these costs could be as much \$200 million to market a film internationally according to movie studios. To market a movie in the U.S. alone, the average cost was \$4.3 million in 1980. This figure rose to nearly \$36 million in 2007, the last year for which this data was available through the Motion Picture Association of America (McClintock, 2014).

Exhibit 4 demonstrates the relationship between the production budgets and gross profits of the Best Picture and Worst Picture nominees. As you'll see, many of the Worst Picture nominees were in the red even before marketing expenses are factored. Conversely, all but two of the Best Picture nominees were in the black. You'll also notice a few outliers among the high performers. They are the Titanic, which won the Oscar for Best Picture in 1998, and Avatar, which was nominated for Best Picture in 2010. The Titanic was produced for \$200 million and earned \$2.2 billion in worldwide revenue, resulting in a gross profit of \$2 billion. Avatar was produced for \$425 million and garnered \$2.8 billion worldwide for a gross profit of \$2.4 billion.

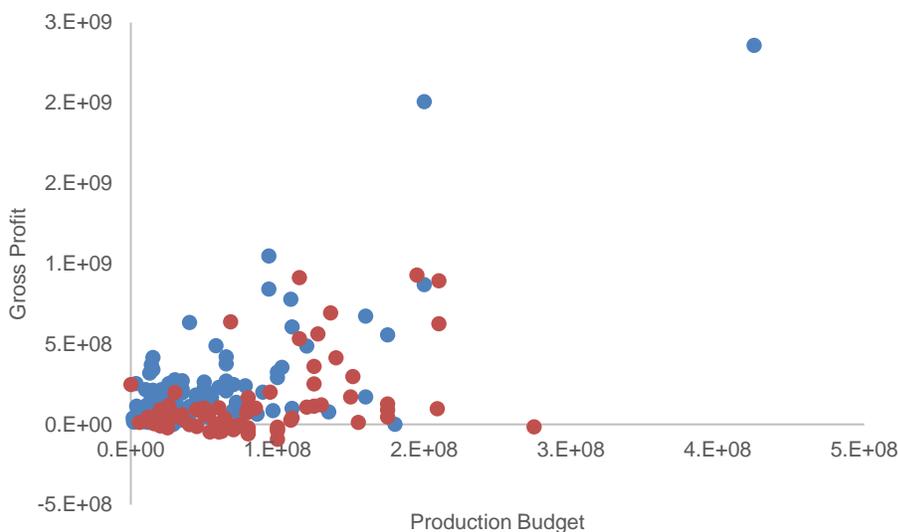


EXHIBIT 4: GROSS PROFIT V. PRODUCTION BUDGET

While these movies realized the most money in terms of gross profit, many others realized a higher return on their investment. That is, this figure represents the percentage gain between a movie's production budget and its gross profit. For example, the return on investment for Titanic and Avatar was 904 percent and 455 percent, respectively. However, there were 18 movies that received returns of more than 1,000 percent and nine that received returns of more than 2,000 percent. The Full Monty even received a return of 7,167 percent. But, by far, the movie that realized the highest return on investment was The Blair Witch Project. This movie was produced for \$60,000 and earned gross revenue of \$248 million for a return of 413,633 percent.

Not only was this return on investment unusual for a Worst Picture nominee but it was so far beyond any of the others in either category that we couldn't even present this data graphically in any meaningful way. It was literally off the chart. It suffices to say that this movie was an anomaly but, despite its success, it was still outperformed by Paranormal Activity which is the most profitable movie ever made (Avila, 2010; Frankel, 2009). This movie had a production budget of just \$15,000 yet earned \$194 million, resulting in a return of 1,294,454 percent.

Recent research has found that scary movies might be the most profitable as a genre. Despite the fact that they generate only a small percentage of the overall box office draw, they are extremely profitable because they are relatively inexpensive to make and have strong international appeal. Nevertheless, these movies generally don't have huge revenue-generating potential and are not immune to risk (Hickey, 2015).

BIGGEST OPENING WEEKENDS

There are a number of factors in the pre-release activity of the movies with the biggest opening weekends that contribute to their success. For instance, these movies are not only highly anticipated due to their subject matter but they also tend to attract large audiences due to their significant marketing campaigns and the amount of earned media that they garner.

Moreover, social media is continually providing new ways to serve as a predictive model as demonstrated in its ability to predict changes in the Dow Jones Industrial Average (Keller, 2010). Researchers have even used Wikipedia activity to forecast the first weekend box office revenue of movies (Mestyán, Yasseri, & Kertész, 2013). But what happens in the aftermath of these movies' debut? That is, do these movies continue to attract record audiences?

For this study we analyzed the top 100 movies on each of the biggest opening, second, third and fourth weekends. We then calculated their average percentage change in weekend box office revenue in their first four weeks. We also eliminated the outliers as we previously did with the high and low performers to prevent the data from being skewed. Extremely high performers such as Best Picture nominee Avatar, for example, experienced very little revenue loss in its initial weeks and were removed from the sample.

As shown in Exhibit 5, movies with the biggest opening weekends had an average percentage change of -54 percent, -48 percent, -42 percent and -43 percent. Movies with the biggest second weekends were -45 percent, -47 percent, -39 percent and -41 percent; the biggest third weekends were -41 percent, -38 percent, -38 percent and -38 percent; and the biggest fourth weekends were -36 percent, -35 percent, -31 percent and -38 percent. This resulted in an average percentage change in revenue of -47 percent, -43 percent, -39 percent and -35 percent over this period.

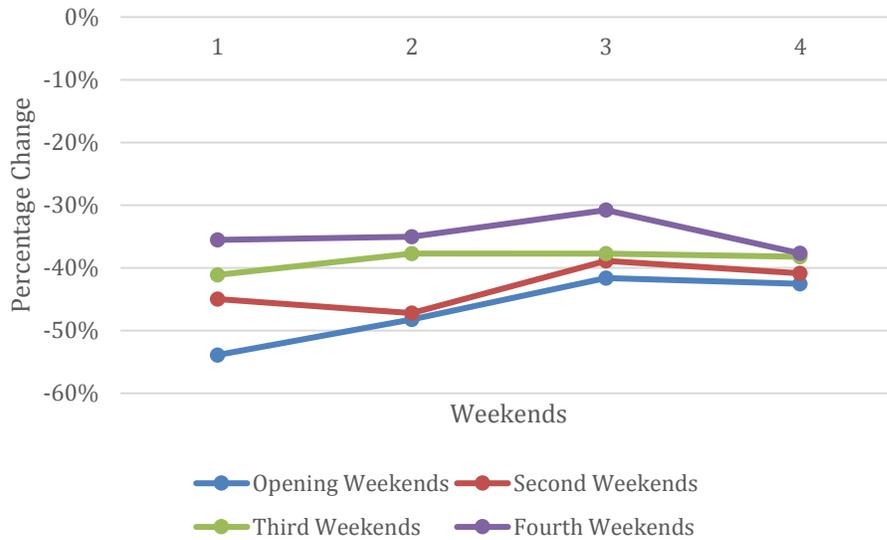


EXHIBIT 5: BIGGEST WEEKENDS

We also analyzed the average of critics and audience reviews of these movies based on ratings from Rotten Tomatoes, the web's leading aggregator of movie and TV reviews from professional critics. The critics rating is based on the published opinions of hundreds of film and television critics and represents the percentage of reviews that are positive. The audience rating is the percentage of positive reviews from Flixster.com and RottenTomatoes.com users (Rotten Tomatoes, 2016).

Hollywood studios are becoming increasingly fixated on these types of scores as they have been shown to be reliable indicators of a movie's performance. These scores are even sometimes promoted in advertisements and shareholder communications (Fritz, 2016).

What we found was an inverse relationship for critics and audience ratings among the movies with the biggest, second, third and fourth weekends. That is, as illustrated in Exhibit 6, as the weekends progressed, the average ratings of both the critics and the audience improved.

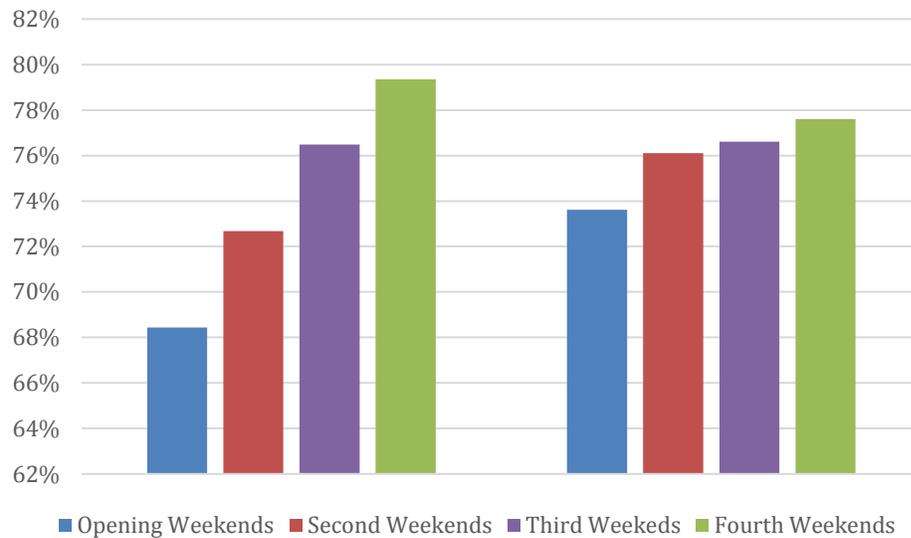


EXHIBIT 6: CRITICS & AUDIENCE RATINGS

This is also consistent with our finding that only 73 movies from the biggest opening weekends were included among the movies from the biggest second weekends, and just 53 among the biggest third weekends and 39 among the biggest fourth weekends. This downward trend, coupled with the upward trend in favorable reviews, suggests that other movies were propelled by positive word-of-mouth from moviegoers.

Further, it sheds light on the effect of certainty on information cascades. That is, though information cascades can be influential, they can also be fragile (Easley & Kleinberg, 2010). As a result, movies provide a good case study on the emergence of certainty in the herding process. Herding is an actual term in behavioral science which can be used interchangeably with information cascades. These conditions occur when our decision-making is influenced by the actions of others. There are innumerable situations in which this happens from deciding which restaurants to patronize to deciding which political candidates to support (Banerjee, 1992).

In addition, herding, or information cascades, can occur when information that we possess conflicts with the information we observe. For example, suppose you had intended to go to restaurant *A* based on your own research. However, when you arrived, you saw that restaurant *A* was empty but restaurant *B* next door was full. As a result, you might choose restaurant *B* if you thought that patrons in that restaurant had tastes similar to yours (Easley & Kleinberg, 2010).

There is a mathematical model for decision-making under conditions of uncertainty. This is done by using Bayes' Rule which provides a formula for determining the probability of various events. Specifically, this formula helps us understand the probability of event *A* given that event *B* has occurred.

One of my favorite examples of Bayes' Rule is one offered by David Easley and Jon Kleinberg in their book *Networks, Crowds, and Markets: Reasoning about a Highly Connected World*. This example involves eyewitness testimony of a hit-and-run accident involving a taxi cab. The witness says that the taxi cab was yellow but 80 percent of the taxi cabs in the city are black and

20 percent of the taxi cabs are yellow. Also, let's suppose that eyewitness testimony is imperfect, and that if a taxi is yellow witnesses will identify it as yellow 80 percent of the time and if a taxi is black witnesses will also identify it as black 80 percent of the time.

In this case, the witness has identified the taxi as yellow. So, we need to know the statistical probability that the witness's testimony is accurate. To that end, we refer to the prior probability of event A as $\Pr [A]$ and the posterior probability of A given B as $\Pr [A / B]$. This is determined by using the following formula.

$$\Pr [A | B] = \frac{\Pr [A] \cdot \Pr [B | A]}{\Pr [B]}$$

For this problem, let's denote *true* as the true color of the taxi, *report* as the reported color of the taxi, Y as yellow and B as black. Therefore, we want to know the value of $\Pr [true = Y | report = Y]$, which results in the equation below.

$$\Pr [true = Y | report = Y] = \frac{\Pr [true=Y] \cdot \Pr [report=Y | true=Y]}{\Pr [report=Y]}$$

We know that $\Pr [true = Y]$ is 0.2 since this is the frequency of yellow taxi cabs and is the probability of the event being true. We also know that $\Pr [report = Y | true = Y]$ is 0.8 since this is the accuracy of eyewitness testimony.

For the denominator, there are two ways in which an eyewitness can report a taxi as yellow. The first way is for a taxi to actually be yellow and the second is for it to actually be black. The probability of being yellow is represented as follows.

$$\Pr [true = Y] \cdot \Pr [report = Y | true = Y] = 0.2 \cdot 0.8 = 0.16$$

And the probability of being black is represented by the formula below.

$$\Pr [true = B] \cdot \Pr [report = Y | true = B] = 0.8 \cdot 0.2 = 0.16$$

The probability of a report of yellow is determined by the sum of these probabilities.

$$\begin{aligned} \Pr [report = Y] &= \Pr [true = Y] \cdot \Pr [report = Y | true = Y] + \\ &\Pr [true = B] \cdot \Pr [report = Y | true = B] \\ &= 0.2 \cdot 0.8 + 0.8 \cdot 0.2 = 0.32 \end{aligned}$$

We can now enter this data into the following equation.

$$\begin{aligned} \Pr [true = Y | report = Y] &= \frac{\Pr [true=Y] \cdot \Pr [report=Y | true=Y]}{\Pr [report=Y]} \\ &= \frac{0.2 \cdot 0.8}{0.32} \\ &= 0.5 \end{aligned}$$

As a result, we can see that the actual likelihood of the taxi being yellow is equally likely to have been yellow or black.

Simply for illustrative purposes, we can use this same equation to determine the probability that you'll enjoy a highly anticipated movie on its opening weekend. We'd like to emphasize that this is purely hypothetical as we're sure that very few, if any, people would make a decision this way.

However, let's assume that you typically trust the reviews of both critics and those of your family and friends. For our prior probability, we can use the critics' ratings from Rotten Tomatoes for movies with the biggest opening weekends, which is 68 percent.

Next, for our posterior probability, let's assume that about 60 percent of your family and friends enjoyed a particular movie. As a result, you want to know the conditional probability of whether a highly anticipated movie is worth seeing based on this conflicting evidence.

In this example, we will designate *true* as the true outcome of the movie, *report* as the reported outcome of the movie, *F* as favorable and *U* as unfavorable. Hence, we want to know the value of $\Pr [true = F | report = F]$, or the posterior probability of a favorable outcome of event *A* given *B*. This results in the following equation.

$$\Pr [true = F | report = F] = \frac{\Pr [true=F] \cdot \Pr [report=F | true=F]}{\Pr [report=F]}$$

First, based on the critics' rating, we know that the prior probability of a favorable outcome, or $\Pr [true = F]$, is 0.68. In addition, we know that $\Pr [report = F | true = F]$ is 0.60 as this is the percentage of your family and friends that felt the movie was worth seeing.

Again, there are two ways a movie can be reported as favorable. One is for the movie to actually be favorable and the other is for the movie to actually be unfavorable. Thus, we use the following formula to determine the probability of a movie being favorable.

$$\Pr [true = F] \cdot \Pr [report = F | true = F] = 0.68 \cdot 0.60 = 0.408$$

And we use the formula below to represent the probability of a movie being unfavorable.

$$\Pr [true = U] \cdot \Pr [report = F | true = U] = 0.32 \cdot 0.40 = 0.128$$

The sum of these probabilities is the probability of a favorable report.

$$\begin{aligned} \Pr [report = F] &= \Pr [true = F] \cdot \Pr [report = F | true = F] + \\ &\Pr [true = U] \cdot \Pr [report = F | true = U] \\ &= 0.68 \cdot 0.60 + 0.32 \cdot 0.40 = 0.536 \end{aligned}$$

We can now enter this data into the following equation.

$$\begin{aligned} \Pr [true = F | report = F] &= \frac{\Pr [true=F] \cdot \Pr [report=F | true=F]}{\Pr [report=F]} \\ &= \frac{0.68 \cdot 0.60}{0.536} \\ &= 0.76 \end{aligned}$$

This means that there is a 76 percent chance that you'll find going to a highly anticipated movie on its opening weekend a favorable experience using these criteria. By the same token, using the critics rating of 79 percent on the Biggest Fourth Weekend, there would be an 85 percent chance that you'd find the movie enjoyable.

CONCLUSION

This research confirmed both of our hypotheses. In regard to our first hypothesis, week to week revenue seemed to be a good proxy for estimating the influence of word-of-mouth as there were clear patterns and trends that emerged in the data. However, despite these patterns and trends, it is important to note that this research is not meant to serve as a model for predicting outcomes. It merely presents an illustration of the role of word-of-mouth and quantifies this relationship in very broad terms. As such, to some degree, this research may provide another metric to evaluate the popular appeal of a movie in addition to the metrics of gross revenue and profitability.

Our second hypothesis was found to be true by comparing highly anticipated movies with high performers to see to what degree their popularity was the result of an information cascade. As we discovered, movies with the biggest opening weekends are driven by both information that people observe publicly and information that people possess privately. However, because this information still consists of uncertainty until people see the movies, some of these movies lose their appeal if they don't live up to expectations. This was evident in the weekly percentage changes in revenue, the critics and audience ratings, and in the diminishing number of movies from the biggest opening weekends in the subsequent weekends we examined.

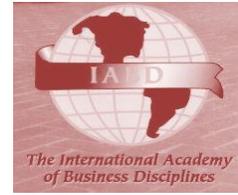
The value of the initial study was in the greater understanding it promoted relative to the success of movies and the influence of word-of-mouth. The subsequent study enhances that understanding by demonstrating the fragility of information cascades.

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