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Do Movie Studios Force Smaller Gaps on Movies Feared to Have Worse Box Office Return? A Study of Movie Embargoes and Ratings

Renato da Silva Benevenuto

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Renato Da Silva Benevenuto

Dissertation presented as part of the conclusion to the Master Studies in Business and Financials Management at Angers University

Advisor

Catherine Crapsky, PhD

Rio de Janeiro

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Catherine Crapsky

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Approved by:

Prof Catherine Defains-Crapsky, PhD

Prof. Dr. Raphael de Oliveira Albergarias Lopes

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Author:	RENATO DA SILVA BENEVENUTO		
Date:	NOVEMBER 2020		
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Abstract

The main role of movie reviewers is to watch and publish a technical opinion about a movie before it comes out so it can reach the audience interested in watching it. This paper has the intention to be able to answer the question: do movie Studios force smaller gaps between the first published review of a movie and its premiere date because they fear the movie will be a failure? The critical review of a movie does not reach as many people when there are only a few days before its premiere. How does that impact the ratings? And the Box office numbers? To answer this question, it was necessary to study what is considered the success of a movie, the variables that contribute to it and then analyze if the Gap plays a role in this part. Variables related to movies were tested through regression analysis for movies released from 2014 until the end of 2019 to understand how strong the correlation between them and the profitability of a movie is. The results are show through R^2 F-tests and p-values for reliability.

Key words: movie, film, gap, critic, review, box office, ROI, budget, MPAA, studio

Dedication

To my parents, Renato and Denise, who raised and cared for me with all their heart.

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To my Master’s degree Class, which made the journey a lot fun and worthy.
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Abbreviation

MPAA – Motion Picture Association of America

ROI - Return of Investment

TBO – Total Box Office

US/USA – United States of America

V.O.D. – Video on Demand

Glossary

Gap - The time (in days) counted from the first published review of a movie until the day the movie premiered in the US movie system.

1 Introduction

1.1 On Critics, Success and Box Office

The study of film criticism has been very productive and provides alternative interpretation for what determines a movie success. In this field, research has offered controverted opinions. There are both: those who say that reviews have a positive relationship with box office performance (Litman & Kohl, 1999); (Wyatt J. , 1991); (Wallace, Seigerman, & Holbrook, 1993); (Sochay, 1994)); and authors who find no relationship between film reviews and box office performance (Ravid, 1999); (Zufryden, 2000)).

Finally, and following (Eliashberg & Shugan, 1997) proposal, critics have been treated sometimes as influencers (Basuroy, Chatterjee, & Ravid, 2003) and other times as predictors of movie success (Eliashberg & Shugan, 1997); (Basuroy, Chatterjee, & Ravid, 2003); (Reinstein & Snyder, 2005). (Wyatt & Badger, 1984) also found that critics' evaluations of movies could affect viewers' interest in those movies and their following appraisal for them.

Critics' impact is a vast research field and always centered on an aggregate level because the empirical analysis has been driven to the effects on box office movie performance. Under these circumstances, studying how reviews influence spectators' decision process is a key point, and this is part of the objective of our paper.

It has been widely tested by previous research just like budget or star power ((De Silva, 1998); (Jedidi, Krider, & Weinberg, 1998); (Litman B. , 1983); (Litman & Ahn, 1998); (Litman & Kohl, 1989); (Prag & Casavant, 1994); (Ravid 1999); (Sochay, 1994);

(Wallace, Seigerman, & Holbrook, 1993); (Wyatt & Badger, 1984, 1990) , and with the exception of a limited number of studies, at is usually supported (Ravid, 1999) Regarding the functions of movie critics, (Austin, 1984) suggested that critics help people choosing a movie, understanding the it's content, helping develop an initial opinion of the film, and "spreading the word" of the movie to others.

1.2 On GAP as a Variable

The main variable which will be the focus of this study and was not shown in any other studies seen is what will be called a **GAP**.

The gap is the time interval between the first published professional critical review of a new movie that could be retrieved online and the main premiere date of a movie in the United States, since its release date will be the reference for this study. Since gap is a variable related to another variable that has been studied before, which is rating by critics, it is a somewhat new way to study it and will follow the steps by authors that once worked with it.

The gap will be studied in days and its's influence will be studied related to other classical variables used by many researchers quoted in this paper, such as Budget, Box Office numbers, critics grades on reviews, and other that may show relevance.

1.3 Research Question

The research question which will guide the path of this paper is the following:

Are movie studios forcing smaller gaps on movies that they fear are going to have worse box office return?

When a movie becomes available for a critic to watch it, the studio may not allow a review to be submitted immediately online or in another type of media for whatever reason. Whatever this reason is, the amount of time it takes between this release and the grand public premiere of a movie may be significantly related to the rating of the critic and the box office number. If that is the case, the studio could be interfering with public opinion by suppressing them information about the movie before it becomes publicly available and this could be a marketing strategy to maximize profits it the reviews are negative.

A brief research made by Mashable journalist (Dickey, 2017) made noticeable that movies that had negative reviews on Rottentomatoes were the ones with longer embargoes. This brief analysis was the main inspiration for this paper.

1.3.1 General Objectives

The general objectives are the ones directly related to answering the research question and how the main variables work together. Given the relevance of critics' reviews to the box office numbers the way they interact with the gap might be very elucidative to draw conclusions.

1.3.2 Specific Objectives

Some specific objectives involved are to define what is a successful movie, and how much/if a professional movie critic is able to influence on the box office numbers of a movie. Discovering which variables regarding a movie can influence on its revenue is a specific objective that other authors have attempted to do and is important in order to understand how gap can also be a variable.

2 Literature Review

2.1 Regarding Movie Critics' Influence in the Movie Industry

2.1.1 The Role of Movie Critics

Since critics' review movies for a living they have some sort of expert status and their opinions are frequently presumed to be objective, even though they are not. It means that their reviews can carry special weight with others, mainly with normal people who have not yet seen a movie. Ordinary people will not necessarily agree with the opinion of a professional reviewer. However, since they are seeking out information to decide whether to watch a movie or not, critics' opinions can make a difference.

Given the wide coverage their opinions can receive, critics may be able to have considerable influence over how well movies perform at the box office. They carry authoritative information about films that is made available to spectators before a movie goes on general release or shortly afterwards (Buor, 1990); (Eliashberg & Shugan, 1997). Good reviews can drive people to theatres and give assurance to distributors and exhibitors that a movie should have a longer run or be given more theatre space.

However, critics' opinions might be dismissed. They focus on aspects that tend not to concern ordinary people who watch films, often paying attention, particularly, to the technical aspects of filmmaking. The publication for which they write might have a target audience with a particular taste. So how reviews are written is influenced considering the types of commentaries that type of audience could expect. Hence, professional critics' thoughts often diverge from regular audiences (King, 2007).

Empirical research into predictors of movies' box office performance showed that there is influence of professional critics' reviews, but this has not always been consistent (Basuroy, Chatterjee, & Ravid, 2003); (Faber & O'Guinn, 1984); (Levene, 1992); (Wyatt & Badger, 1984, 1987, 1990). There is evidence that positive reviews help to raise a box office performance and negative reviews to pull it down. There is also evidence to show that any review is better than nothing at all and that the amount of reviews overall, regardless of positive or negative is what matters most (Ravid, 1999).

More evidence was found that the nature of critics' reviews of movies correlate with the movie ratings given by regular spectators. Critics tended to agree with each other. In this instance, data from about 568 movies was gathered from a movie review website and the six critics were found to agree with each other about 92% of all the movies in the sample. Ratings by ordinary spectators showed moderate to high correlations ($r = 0.43$–0.73) with professional critics (Boor, 1992)

Researchers tried to manipulate spectators' opinions about movies through controlled exposures to advance reviews. In one study, people who were in line to see a movie overheard other people who had apparently seen it offer positive or negative views. The exposure to positive comments led participants to rate the movie in much more positive terms than the ones who had heard negative comments. The positive reviews of a movie heard before watching it did not significantly enhance opinions of it compared with those offered by other spectators who heard nothing (Burzynski & Bayer, 1977). This study showed that the experience of a movie can be influenced by hearing the opinions of others, experts or not. Since reviews of experts are accorded more authority and credibility, it is expected that their influences are even stronger.

Another study has confirmed the influence potential of advance reviews. Participants were divided into groups and were given a specially built review that was either positive, negative or mixed in nature, while controls received no review before seeing the movie. The movie that was chosen was selected because it had attracted an equal distribution of positive, negative and mixed reviews by professional critics. The review was given with other paper-and- pencil materials to disguise the main purpose of the experiment.

The ones that received the negative review gave the movie more negative ratings compared with controls. However, the same did not happen with the positive review in significant results, although they did give the movie more positive ratings than the ones in the mixed review condition. Since participants in the control group, by chance, held mostly positive views about the movie, this ended up canceling out the positive review effect (Wyatt & Badger, 1984).

Another relevant investigation of the effects of professional movie reviews gathered data about 1687 movies released from 1956 to 1988. This study clarified that a movie's performance at the box office was likely to be influenced a lot by the rating it deserved. It was not a matter of a movie that was condemned by critics not performing as well as another that did well. It was inferred that when a generally poorly rated movie got a positive review, that outlier would reduce its performance further on. Whereas positive reviews for a movie that was on balance well regarded each further boosted its performance (Wallace, Seigerman, & Holbrook, 1993).

2.1.2 Variances Between Critics and Their Influence

Many academics working in this area contest the significance of professional critics' reviews on movies' box office performance. As seen, positive and negative reviews can have different outcomes. When a movie gets both positive and negative reviews, things are hard to analyze. Another acting factor is the standing of the critic (Reinstein & Snyder, 2005). Some researchers say that professional critics are not so alike. They have relative influence, with some critics accumulating a certain "impact capital" and being able solely to decide a movie's prospects. Some critics are identified as "influencers" and others as "predictors" being distinguished in the specific role they adopt for themselves in their reviews (Eliashberg & Shugan, 1997). As it happens with other products and services, evidence also shows that any publicity, positive or negative, can help with a movie's box office performance (Azula-Flores, Fernandez-Blanco, & Sanzo-Perez, 2012).

The Influencer critics are apparently able to affect a movie's box office performance through reviews. Their reviews may have strong impact with potential spectators and negative criticism might discourage them from going to see the movie. Other critics' reviews attempt to predict how well the movie will perform at the box office, but what they write may not have impact on spectators' decisions about whether to pay to watch the movie.

(Eliashberg & Shugan, 1997) showed that critics' reviews were associated only with late and cumulative box office results, but not with early results. That led the research to assume that critics do not really influence box office success, but simply predict it. But some evidence points to the opposite. That movie critics do not simply forecast how successful movies will be at the box office. They might have power to influence the performance. A study found that the demand for some movies can be shaped less by the entire group of professional critics rather than just a few whose opinions are given a lot of credit by cinema audiences (Reinstein & Snyder, 2000).

This evidence of impact of professional critics' reviews has not always confirmed an obvious effect on box office. Research into Dutch films shows that reviews in 13 Dutch newspapers were about the performance of art house films, a niche audience, and had insignificant impact on demand for mainstream films. The greater the attention given to art house films by critics, the more audience felt interested (Gemser, Van Oostrum, & Leenders, 2007).

(Zuckerman & Kim, 2003) studied box office results for 396 films released in 1997. Among them there were movies by major studios and smaller producers. They found that critics' reviews were related to audience sizes, but mainly when the critics were specialists in reviewing blockbuster movies. This publicity may reduce the limitations placed on a movie's distribution by exhibitors. Particularly, when famous reviewers of big movies reviewed a new movie as a good fit for the mass movie market, it would bring more people to go and watch it even when a movie could have had a better distribution. This effect did not act the same way on the art house films.

2.1.3 The Status of Critics and How They Impact the Market

Analyses of movie critics' influences based on aggregates of critics' reviews drives us to think that each critic has equally weighted influences. Yet, there are critics more influent than other critics.

There are professional movie critics that gather special status over other critics. They are not all equivalent. These reviewers attribute greater weight by the movie industry and by spectators. Critics with higher status might therefore be more influential than others (Boatwright, Kamakura, & Basuroy, 2007).

The status of a critic does not guarantee consistent impact in their reviews. A study found that when spectators were handed fictional movie reviews elaborated by a researcher in which the critics' style was manipulated, along with the reputation of the film's director, the reputation of the critic and the consent level with other critics, a critic's reputation only made the review more influential if it was negative. At the same time, a film director's reputation was important to test subjects only when a review was positive. It was beneficial to a singular critic's influence if their review mostly agreed with other critics (d'Astous & Touil, 1999).

(Basuroy, Chatterjee, & Ravid, 2003) acknowledged that expert reviewers can influence consumers of many product and services. Professional reviewers have played an crucial role in the movie world for many years and many spectators recognize consulting with these reviews before deciding to watch a movie. It would be expected that expert critics could serve as potential gatekeepers who could discourage people from watching a movie if the review is negative.

Movie critics can also be predictors of a movie's success. If they can make an impact on regular spectators' decisions on which movie to watch, then it may be possible to determine the consequence of certain types of review in terms of box office performance.

(Basuroy, Chatterjee, & Ravid, 2003) and his team tested these hypotheses with a sample of approximately 200 movies released in the United States. They also considered factors like the production budget and the casting of big-name star actors in it. Even considering this, critical reviews appeared as being statistically significant on their own in relationship with box office revenues. The way of the reviews was particularly influential.

Negative reviews appeared to decrease audience attendance levels while positive reviews persuaded people to the theatre. The discouragement of negative reviews, however, was more effective than the beneficial effect of positive ones.

(Boatwright, Kamakura, & Basuroy, 2007) and his team made an analysis of 466 films released in the United States in order to study movie attendance. Each movie was categorized in terms of budget, advertisement, whether it was a sequel, the number of screens, the casting of big-name stars, its MPAA rating and the number and nature of audience and professional critics' reviews it received. It became apparent that spectators' reviews were not very influential for movies that were widely available. Reviews by expert critics did not seem to affect the attendance levels of first premiere dates, but they were strongly related to overall box office results considering how long a movie was being showed. The higher the attention from professional critics was, the higher were the box office returns.

(Chakravarty, Liu, & Mazumdar, 2010) contrasted professional critics' and audiences' reviews with box office performance. It was a different study since it focused on reviews published before a movie premiere. They were based on prior information released about a movie in the days before its release. All reviews had appeared in online settings and in this setting these reviews may be informed by earlier reviews. This will unavoidably happen when reviewers are faced with limited information about a movie with no opportunity yet to watch the movie itself.

The reviews were gathered from two important review websites, Metacritic and IMDb. Both publish data on review volumes for professional critics and regular spectators. One could imagine that regular users of these sites are likely to be enthusiastic movie fans and maybe also review movies in a similar way to professionals than with most amateur users. The study showed that the most effective influences of online reviews were felt among occasional spectators rather than by frequent spectators. Also, negative critics' reviews were more likely to prevent occasional spectators from watching a movie more than frequent ones. Regular spectators, however, gave more credit to the reviews of professionals rather than amateurs.

2.1.4 How Critics Act as Mediators of Exhibition Strategy

The first reviews written for a new movie represent an early feedback method for producers and distributors. If it gathers a negative response, although the movie cannot generally be re-made at this point, there are other strategic changes that are possible. Initial consumer feedback can help manufacturers and suppliers adjust their marketing strategy according to research into product reviews. One could adjust pricing structures, but this rarely turns into a profitable move. Decisions about differential promotional messages and where to put them can be made. Since some reviews are evaluative and have recommendations for consumers, while others are purely descriptive, it's better for an enterprise to examine the nature of a review and define what value to add to its information. The differences between these two reviews might have different outcomes on consumers and better be used in alternative ways to favor changes in brand marketing strategy (Chen & Xie, 2005).

Movie-wise, early reviews can serve for marketing strategy purposes or to revise distribution decisions. If professional and amateur reviewers enjoy and recommend a movie, then everything is all right. If reviews take an alternative approach and criticize a movie and recommend avoiding it, this signals to distribution networks or movie producers that they need to respond in some way or maybe change their business strategy. In the environment of social media, for example, movie studios have the possibility to commandeer “brand champions,” that is, spectators who enjoy a movie, to speak out on its behalf despite the criticism that flows online. If this is not possible or predicted as ineffective, then it might be decided that a movie’s theatre run should be shortened.

A big problem for movie studios if a movie draws negative media hype and, as a result, struggles with box office numbers, individual cinemas may decide not to exhibit them anymore. It is mandatory that studios act quickly and effectively in order to take steps to neutralize the outcomes of negative reviews. When a movie is well received and has satisfying audience attendance, local cinemas might decide to extend its run (De Vany & Walls, 1996).

Consumer feedback about products and services can quickly reach large numbers of other consumers online. When the feedback is positive, the companies responsible for those products and services can have huge benefits from a supposedly “free advertising”, also leaving behind an enduring record that others can revisit later, while word-of-mouth reactions to brands in the offline world are usually spoken and so are temporary. When consumers are unsatisfied with the quality of brands on the internet, therefore, the effects of messages on other consumers can be enduring over time. That makes it even more important that online consumer feedback is positive other than negative. If negative, companies must react quickly to prevent any long-term damage to business that it could cause.

As another important element to online feedback, the source of the it might not always be identifiable. This can lead to dishonest appraisals of products and services by people with private concerns. This issue applies to movie reviews in the same way as to reviews about products in different fields. Despite these concerns, it is without a doubt that online feedback is now normative in the consumer world as even more consumers engage to consume information, products and services online (Dellarocas, 2003).

2.1.5 Relative Effects of Critics' Reviews

The effects of critics' reviews do not happen in a business and social vacuum. The box office success of movies can have numerous reasons. What is important to know is whether critics' reviews relate with any of these other factors and in what ways. A study to answer this question examined two samples of movies released in the United States in the early 1990s and late 1990s. The data collected from each movie was box office performance, familiarity of its genre, use of big-name film stars and whether it received positive or negative reviews (Desai & Basuroy, 2005).

Many factors intermingled with each other. The way in which critics' reviews have differential effects on a movie's box office fortunes when combined with certain other movie attributes is the main aspect. For instance, the star power improved its box office results only when the movie was from an uncommon genre. For the popular genres, star power made little difference. Something similar happened between genre and critics' review effects. Negative reviews could dissuade spectators but only with unusual genres. Critics' reviews did not matter much to box office performance with relatively unknown actors, but when positive reviews were merged with big film stars, box office results were substantially improved.

The general financial significance of professional reviews stems from observations that the first reviews can have an impact on box office results during the first days of screening of a movie. This importance of the general financial fortune of a movie stem from information that a movie that can drive big audiences from the start is more likely to have great numbers across its entire theatre run. If within the first days audience volume has many negative reviews upon release, this could be a bad sign for the overall financial prospects of the movie.

Movies that drive big audiences from the start usually have big production budgets, extensive promotional campaigns and a helpful age-related classification (MPAA rating) that does not restrict audiences a lot. Movies like this are also likely to attract much early attention from reviewers. It is vital then that critical acclaim compensates rejection. The number of reviews might drop fast after the first days, but if many negative reviews are among them, it is probably an unreversible situation (Duan, Gu, & Whiston, 2008).

According to a Dutch study, both the number of reviews and size of reviews (in cm^2 on a newspaper page) made a contrast to the level of impact they had on box office results made by art house films and this happened both for first days of release as well as over the longer term. So the physical size of a review can also be a factor. This did not happen the same way for mainstream movies, as this effect was not felt at the outset, but it did help with long run movies (Grewal, Cline, & Davies, 2003).

A study of 175 movies made in Hollywood and abroad from 1991 until 1993 classified movies in terms of the number of positive and negative reviews they received and other variables like age-related classification, how widely they were distributed, budget, whether they were sequels, date of release and their “star power” (Boatwright, Kamakura, & Basuroy, 2007).

The conclusion was that positive reviews were linked to a tad better box office results, while negative reviews were related to much worse performance numbers. Since the effect of negative reviews was much stronger than that of positive reviews, the researchers described this as “negativity bias”, no matter the budget size and star power. This effect was more prominent during the first few days after a movie’s release.

2.1.6 How Online Movie Reviews Relate to the Box Office

Recent research has shown that online reviews of movies can alter their box office performance. It happens over the period of a movie’s release but might have a particular impact on the amount of people watching right after a movie has been released. It is known that professional critics’ reviews of movies in traditional media can have an immediate impact on how successful movies can be as they hit their cinemas. On the Internet, their potential to influence more people is even stronger by reaching more readers more rapidly and gathering influence.

Studying the scale of online movie reviews for their opinions is a hard task because of the utter magnitude that they reached. Softwares were developed by scientists to be able to “read” large portions of text online and sort it into groups. These tools, called “sentiment analysis,” can also detect the shape of emotional sentiments.

These linguistics tools have been applied to study movie critics’ reviews. An analysis scanned reviews linked to 1718 movies released in the United States between the years 2005 and 2009. The data collected were texts of reviews from the Metacritic website (www.metacritic.com) along with data about movies’ scriptwriters, director, cast production studios, genre, release date, Motion Picture Association of America (MPAA) rating and running time. Other data like production budget, gross revenue and number of screens playing a movie were collected from the website (www.thenumbers.com). The

Critics' opinions as measured by sentiment analysis were able to predict movies' box office revenues even amongst other variables (Joshi, Das, Gimpel, & Smith, 2010).

In another study, sentiment analysis was used on movie review blogs both before and after movies were released. It uncovered that the opinions stated about movies showed a stronger relationship with movies' box office results than did the general number of reviews a movie received. As far as direct influences on movie attendance could be presumed to happen out of these data, it looked like that the positive or negative review was the main factor at play (Mishne & Glance, 2006).

Another way to study this effect of reviews on results was to analyze the amount and sentiment of news coverage received online. Researchers used a news aggregation method to know when some movies were mentioned and to measure and classify the nature of the sentiments being expressed. Once more, the nature of online attention received by the movies that premiered were statistically related in a positive way to how each movie performed at the box office (Zhang & Skiena, 2009).

Another study gathered data on film critics' online reviews on the opening weekend box office results from seven review websites of movies released from 2005 until the end of 200. The movie genre, the star power of the cast and director were confirmed to be crucial factors linked to higher box office results. Positive evaluations of a movie were statistically related to how well a movie performed over its first weekend (Joshi, Das, Gimpel, & Smith, 2010).

2.1.7 Mediators of Critics' Reviews and Their Outcomes

According to evidence, critics' reviews can influence spectators' decisions about going to see a movie. However, these effects are not the same everywhere. There is variation from country to country (d'Astous, Caru, Koll, & Sigue, 2005); (d'Astous, Colbert, & Norbert, Effects of country-genre congruence on the evaluation of movies: The moderating role of critical reviews and moviegoers' prior knowledge., 2007). Evidence shows that critics themselves may have prejudice with a movie company that made and distributed a movie before giving their opinion (Ravid, Wald, & Basuroy, Distributors and film critics: It takes two to tango?, 2006).

Professional critics were given a special status because they could publish reviews on platforms that ordinary people who went to the cinema could not share. With the arrival of the internet, however, ordinary movie consumers could post their own reviews to many people. As soon as anybody could gain access to a mass audience of spectators to voice their opinion, the status given to critics was gone (Holbrook, 1999). From this moment regular spectators represented not only a second opinion but also competition for them (Gao, Gu, & Lin, 2006). Regular movie viewers still relied on professional critics for advice about whether to see a new movie, however attention was paid to what a critic said as much as to who the critic was. Critics used to have undisputed authority as sources of consultation. Comparisons became even more frequent. A well-known critic's review of a movie could be dismissed if confronted with many different opinions (Tsang & Prendergast, 2009).

Cultural aspects between countries seemingly can influence how spectators react to professional critics' reviews. Hofstede's framework of cultural values was implemented by some researchers and it distinguishes five types of cultural values: power distance, individualism/collectivism, masculinity/ femininity, uncertainty avoidance and long/short-term orientation (Hofstede, 1980, 2001, 2005).

According to (d'Astous, Caru, Koll, & Sigue, 2005) there are differences between spectators in Austria, Canada, Colombia and Italy in terms of power distance mediated the strength of influence of critics' reviews on movie attendance. Spectators in Austria and Canada were more given to influence by reviews than in Colombia and Italy. Moreover, spectators from Canada tended to enjoy a larger variety of movie genres than did their equivalents in the other three countries. This was found consistent with differences between these countries in observance to uncertainty avoidance principles.

Hofstede says that the power distance value variable indicated the level to which people in a variety of societies have more or less tolerance for hierarchical structures with certain people having much more power than others. Some societies are very tribal-like and some families/tribes have gathered more social status than others over time, with lower tolerance for people from different status. In these societies, there is not much tolerance for people from different social status levels to interact. Societies with strong faithfulness to power distance conventions are expected to have less taste for entertainment that goes against deeply rooted social structures.

As for uncertainty avoidance, societies diverge in how they deal with unpredictable scenarios. Some societies are strict in their social structures while others are more open to different ways of doing things, with tendency to display more creativity among their people. This tolerance for new things can show an effect on the types of entertainment tastes showed by people in these different societies. Those with low uncertainty avoidance are expected to show a larger variety of tastes in entertainment.

2.1.8 Long-Term Consequences of Critics' Reviews

Film critics are given a status as "experts", with different opinions from those that might be given by normal spectators. Their opinion is usually regarded as a much more credible measuring device of quality. Awards are also devices for quality, but the critics can give indicators early in a movie's post-release lifetime about whether it is good or not. A complicator on this subject of quality is that different sources of opinion may disagree. This may confuse spectators who rely on it in order to choose which movies to watch.

Comparisons of movies that won OSCARS, Cannes or other big awards and those named by professional critics as the best movies do not always yield completely overlapping lists. There are clear agreements but also considerable differences. Awards and good reviews from critics do not guarantee a long run in cinemas for a movie. There is some evidence that regular spectators' opinions about movies can be better indicators of a movie's box office performance. The popularity of a movie among regular spectators is a better indicator than experts' judgments because it can attract large audiences when shown on television and re-exhibitions (Ginsburgh & Weyers, 1999).

When movies showed up on best movie lists that spanned over a very long period were compared to others in revenue returns (from box office, rentals and etc) , it became clear that the experts picks were usually not the most profitable. Also, movies on these lists were not big winners at the Oscars or other big awards. Usually, movies that win many awards are found on many critics lists as best movies, but that does not translate well into money (Ginsburgh, 2003).

2.1.9 Are Critics Critical to the Box Office?

Given the fact that spectators have not seen a movie, professional movie critics could represent an important source of information about the quality of movies. The critics have been a part of the movie business for a very long time. Within the motion picture industry, the well renowned critics can acquire a status that renders them quality devices of movies in general. Though this status can be debatable, there is some good empirical evidence that people are often influenced by critics.

A new movie can generate expectations based on advertising, the actors known to be starring in it, the director's reputation, genre and so on. These expectations may be powerful enough to drive spectators into seeing a new movie. A critical review of a movie by a known and respected reviewer could make people change their minds completely. Spectators have said that critical reviews of movies do help them decide whether to watch a movie sometimes. So, they do turn to and even rely on them. On the other hand, there are also spectators that like to make up their own minds.

Critics are put in a pedestal of knowledge, being given specialist expertise. Yet, their judgments are not all that different from regular spectators (d'Astous & Touil, 1999). Professional critics, however, usually provide deeper analyses of a movie's qualities than regular spectators (Plucker, Kaufman, Temple, & Qian, 2009). For that matter, they give important data and evaluation that goes alongside other types of recommendation used by spectators.

Studies of quantitative measures of positive and negative reviews about movies alongside other predictive variables on critics' reviews has indicated that they can statistically predict a movie's box office performance. Since critics can watch and review a movie with antecedence, they can have an impact right at the start of a new movie's cinema run. If reviews are bad, they can be strong enough to discourage audiences to watch a movie. In order to see a movie getting off to a good start at the box office, opening weekend reviews can be good indicators of longer-term performance, and negative critics' reviews at that time could have awfully bad effects.

2.2 How Each Study was Conducted

The research on factors that can have influence on the success of a movie and how to measure them shows that most of the studies to date were based on data from how the movies performed in the US.

2.2.1 Litman Research

(Litman B. , 1983) Was the first and most referenced study on multiple regression models to predict the financial success of a movie. the president of the MPAA Jack Valenti used to say that no one absolutely no one can tell you what a movie is going to do in the marketplace. And that served as an inspiration for litmus for his research. Litman broke down his research into three main decision-making areas that he believed were the most important about the determining the success of a movie. These areas were the creative sphere, the scheduling and release pattern and the marketing effort. About the creative sphere one the main areas were the story (it had to be original, believable and timely). If you look at the movies today the attributes about being believable and genuine are not that important anymore. If you look at the top 10 highest grossing movies ever nine of them are science-fiction action/adventure or superhero movies. Avengers endgame grossed a total of 2.7 billion dollars and is a superhero movie and is also the highest grossing film ever made not adjusted for inflation. Titanic is the only exception on this list having grossed 1.8 billion dollars and being only partially a true story. (Box Office Mojo, 2020).

(Litman B. , 1983) also believed in the creative sphere that the cast, director, production budget and rating as particularly important factors. When movies were in the scheduling and release phase it was seen as important for an independent producer to search a major distributor for a film release because of better bargaining power bigger Financial resources preferential access to theaters reputation of delivering high quality products in large distribution networks. Periods of greater crowds were observed around Christmas and New year summer and Easter. Littman believed in the power of holidays for film releases since Indian film industry indicates that most of their successful movies are released around holiday dates. (Litman B. , 1983) believed that marketing effort was a very important part of the media campaign since he argued that after a few was released advertisements would not reverse any effect of negative word of mouth opinions and spend money on it would be pointless. Litman explored the role of critics as influencers and explored the importance of academy awards in their ability to drive audiences to watch movies.

Litman prepared multiple regression model in order to test his variables for film success. Included genre as binary independent variable. the genres were drama action adventure comedy musical and science fiction. Another set of independent variables were binary ratings for MPAA. The next one was a binary variable for whether there was a superstar in the cast and the last variable was the budget of each film. The budget of a film is extremely hard to find in an accurately reported way nowadays as it was in 1983 when Litman wrote his work. Another variable was a binary for whether the movie was distributed by a major film company or an independent one. The next independent variable was a binary one for what he believed were the peak release periods naming Easter

Christmas and summer. For awards two independent variables were included. one for academy Award nomination and other for academy Award won. The last independent variable used by Litman was critical rating. His source was a daily newspaper that used the star rating to review movies.

Litman performed many tests to eliminate the independent variables that had no significant relationship with the dependent variable. The ones he eliminated were MPAA ratings, Superstar factor and the binary variables for summer and Easter releases. Every genre that was not science fiction or horror were eliminated as being insignificant. He discovered that production cost his head positive correlation with rentals as were the influence of critic’s reviews. Science fiction and horror movies were considered extremely popular as were films released by major companies. The Christmas release and both variables for academy awards were considered incredibly significant. Litman’s research was one of the main ones for this kind of study, including this one.

2.2.2 The Works of De Vany and Walls

(De Vany & Walls , 1999) gathered more than 2000 movies in their sample. There is a vague and uncertain knowledge of probabilities of consequences that is called “no one knows anything” in the industry. Based on their calculations, the average box office revenue was primarily of a few blockbuster films and the probability distribution of box office numbers had infinite variance. And it was a member of the class of distributions known as Levy stable distributions, and film revenues diverged over every possible outcome. Indicated that the average of film revenues depended almost entirely on a few extreme revenue outcomes in the upper tail whose chances were exceedingly small.

They had the persistent idea that Hollywood has not a formula for success. It didn't matter what a producer decided to make. He could try his best in making strategic choices like booking screens ideal budgets and a great cast to increase their success. However, after a film was out it was up to the audience to decide its fate. The amount of people exchanging information and interacting started a dynamic that was so complex and so unpredictable that not even an awfully expensive marketing campaign could acknowledge that kind of information. By taking in consideration the world of today where people can exchange information extremely fast in social media this is a very valid allegation. (De Vany & Walls, 1999) were of the view that:

- A movie is an overly complex product which is difficult to make well
- It was impossible to know if someone was going to enjoy a movie before watching it
- Movies are incredibly unique products and with a very small expiration date (while it was screened)
- They would enter and exit markets on a frequent basis
- Most films had one or two weeks tops to conquer the audience

The works of (De Vany & Walls, 1999) used a sample of over 2,000 movies. According to them there was a condition called no one knows anything and this condition is something that filmmakers would work under. It is a vague and uncertain knowledge of probability of consequences. The sample had a mean revenue of $17 million, which was way larger than the median of $6.9 million. The mean belonged in the 71st percentile of the revenue distribution, indicating a dominant rightward skew. Starred movies had a median box office of about $38.2 million. A movie without stars had a median box office of $20.9

million. According to their numbers the distribution of budget was very skewed, but not as much as the revenue distribution. The mean budget was $11.8 million, in the 62nd percentile. Median budgets went from $1.9 million for documentaries to $17.4 million for science-fiction. If a movie had no stars it had a median budget of $9.7 million compared to films with stars that had a median budget of $22.8 million. De Vany and Walls (1999) conclusion was that movies that had a big budget and renowned Stars were among the ones of biggest flops and on the other hand films with smaller budget and no stars could be hit successes. But it is important to point that most of the film of the sample were not profitable.

They discovered that films with very large gross returns in fact had no stars, low revenues and tiny budgets. Since their paper had the main focus of exploring star power two ways were identified as how Stars could help with profit. It could be virtue of getting a film released on many movie theaters at the opening and that would increase the initial revenue. Another way was if Stars would overperform their roles. Only 19 different stars were found to have significant impact on being a hit. The research confirmed that each star had a calculated risk associated and this would place the Levy distribution into infinite variance, so they concluded that no star was a guarantee of success. The estimation of hit coefficient for Stars also showed significant standard errors. Authors identified that stars only raised the chances of favorable events that were very unlikely.

(De Vany & Walls, 2002) emphasized that there is management model that Studios were used to adapt required Foundation in theory and more evidence. That has happened because Studios often need to make the project of one film out of many possible films. Since experience and learning are considered the more usual predictors of success in most cases, they argued that in an extremely competitive situation were not very related to the results because success depended more on getting an extreme draw in a smaller sample. According to them, future success cannot be extrapolated because movies needed a selective learning based on extreme events, and the current circumstances could not help with that. Success is considered an ability and failure is considered bad luck and this should not be a way that risks are handled in this business by studios as they currently are according to the authors.

De Vany and Walls (1999) say that having a history of past success gave Studios an 'illusion of control", however they reinforce the point that the few industries made by many complicated stochastic dynamics and it's not easier simple to find a form of causality. Success cannot be easily linked to casual factors. According to them, there was a small probability that a film would reach an extreme outcome in the upper tail, which was required for it to be lucrative. Their calculations showed that forecasts were meaningless because the possibilities wouldn't converge on a mean; they diverged over the total outcome space with an infinite variance. Their suggestion was to use the strategy of choosing a portfolio of film, instead of choosing individual movies as projects.

2.2.3 The Works of Ravid

According to the works of (Ravid, 1999) there were two possible hypotheses for the role that stars have in movies. The first one was that they were the main responsibles for a gathering value in a movie. Because of that their salaries were reflected by their market value. This is something rapid called “rent capture hypothesis”. For instance, after John Travolta worked on Pulp fiction his salary went from $150,000 to 10 million dollars for the next movie. pulp fiction only costed $8 million but made more than $212 million. The same thing happened to Alicia Silverstone her salary for her role in clueless was $250,000 and it went up to $5 million after the film started to profit. (The Numbers, 2020).

A second hypothesis of Ravid says that hiring expensive stars is a way to signal project quality by informed Insiders. This happens because, in order not to get fired, a studio executive needs to have successful movies produced by them. So, to have the commitment of hiring an expensive start is a way to not take great risks as a producer. It is a safeguard. A big commitment of a star in advance signals quality to the project which is good for the studio and its shareholders.

In order to test his hypothesis, he used sample of 200 movies released from 1991 to 1993. After doing regression models the means were compared and the ones of movies with stars were bringing higher revenue to the movies. Budget and the number of reviews were highly correlated with revenue which indicated that movies that these variables would generate big box office numbers. The correlation of TBO and stars could become zero or even negative if there were too many independent variables in the model. Sequels would also correlate positively with good revenue. An MPAA rating that was family friendly like G or PG were also associated with higher revenues. Ravid was one of the few authors who used ROI as a dependent variable, as opposed to only TBO. In his results an exceedingly high budget did not correlate directly to a big ROI. In fact, it could even be negative.

2.2.4 Awards as variables

The sample of movies studied by (Smith & Smith, 1986) released from the 1950s to the 1970s discovered a positive relationship between the number of awards that a movie received and its box office revenue. (Nelson, Donahue, Waldman, & Wheaton, 2001) also did this research and found a consistent value. An Oscar nomination could add 4.8 million dollars to box office numbers of a movie and an Oscar won could add 12 million dollars to it. These numbers are consistent with the ones of (Litman B. , 1983) who estimated an Oscar nomination of 7.34 million dollars in an Oscar one of 16 million dollars. (Dodds & Holbrook, 1988) studied the effects on academy awards both before and after the ceremony. Before the ceremony, the best actor was worth 6.5 million dollars the best actress 7 million dollars and the best picture 7.9 million dollars. After the awards, if won, the best actor would jump to 8.3 million dollars and the best picture to 27 million dollars. According to (Smith & Smith, 1986) the strength of the academy Award was not constant as it could change over time and have positive or negative effects on results depending on the time period. but the effect of an academy Award on box office numbers sure can be seen.

2.2.5 Initial Box Office as Variable

(Sawhney & Eliashberg, 1996) built a model that had the initial intention to help film theaters to foresee how much a movie could profit at box office so they can operate their exhibition capacity and negotiate license arrangements with distributors. It is a parsimonious model for Box Office data. In order to do so they used queuing theory framework. This framework divided the spectators film adoption process in two sides. They were called “time to decide”, which is the time the spectator decides to see a new film and the “time to act” as the time to adopt a decision. Both times were two independent stochastic processes and it led to interesting observations regarding filming industry:

- most of box office numbers originate from new movies;

- the “shelf life” of an ordinary movie was shorter than 15 weeks in a theatre release.
- hundreds of movies went to theatres every year.
- demand for a new movies is constantly at high levels of uncertainty;
- It was difficult for a spectator to evaluate a movie unless they have watched it

The model was capable of forecasting box office with little or almost no data of revenue. it was an adaptive approach, and the model would update itself with data after it was available after the first week second week third week etc. In order to be able to predict sales having no data was by performing a meta-analysis of parameters that were estimated from similar products. For the model to succeed the parameters for many existing products whose sales histories were available were correlated to the ones that they were trying to predict. These were the parameters used to predict the sales for the new product. This model however was limited and if the limitations were relaxed it would really find the accuracy of the model. This happened because the time to decide and time to act processes were independent from each other, but the adoption process parameters were stationary. In order to change that it would require much more data and the model would become overly complex. This cross-section analysis was benefited from the fact that there were no big changes in consumer taste and macroeconomic factors because the life cycle of the film was considered short

2.2.6 Age Rating as a Variable

In an attempt to find out if there was any correlation between MPAA ratings and film attendance (Austin, 1984) performed a study. He could not find any significant relationship within those factors. (Prag & Casavant, 1994) discovered that PG-13 and R-rated movies were not particularly good performers at the box office.

2.2.7 Genre as a Variable

There have been many attempts in studies before to try to find a relationship between genre and box office success. In the studies of. (Anast, 1967) there was a negative relationship between action and adventure movies and profit and a positive one between violent and erotic movies and profits. (Litman B. , 1983) as said before, did found positive relationship for science fiction and profit. When (Sawhney & Eliashberg, 1996) did there research off "time to act" and "time to decide" they realized that the reaction time of people was faster with the action genre and slower with drama. (Prag & Casavant, 1994) found a negative relationship between drama and revenue. (Neelamegham & Chinatagunta, 1999) Made a bayesian model predict film attendance for domestic and international markets to show that Thriller was the most popular genre and romance was the least one. Many things could have altered these results over the years for many reasons. One is because audiences could have changed over the decades. Another could be because these studies were done with sample data over different periods of time.

2.2.8 Critics Reviews as Variables

The role of a critic can be one of a predictor-influencer according to the studies of (Eliashberg & Shugan, 1997) According to their study it was possible that a critic could influence the results of box office of a movie because of their influencer or predictor role in this unique world. The role that a critic had as an influencer was more significant than the role of a predictor. The Works of (Reinstein & Snyder, 2000) concluded that there were only a few number of critics that had the power to influence consumers and because of that the Box Office return was not considerably large. (Wallace, Seigerman, & Holbrook, 1993) concluded that if a movie could gain more and more positive reviews, his box office numbers would keep increasing.

2.2.9 Seasonality

Some of the studies tried to find a relationship between the seasonality and success of films. (Litman B. , 1983) and (Einav, 2001) were both able to find a positive correlation between films released over Christmas and revenue. (Sochay, 1994) found evidence that middle of the year was better to release films, contrary to Litman's view. Einav also presented evidence that summer releases were positively related with revenue. (Radas & Shugan, 1998) found that peak season releases had better box office returns.

(Terry, Butler, & De'Armond, 2005) made a very unique study using a sample of 505 movies that were released in the USA between the years of 2001 and 2003. What made it unique was that they used a cross-section of movies and did not limit it to only big movies of big studios like many other studies did and they narrowed it down to movies opened in 25 or more place which cut 80 movies from their major sample. After doing the research the model, which used domestic growth of box office as a dependent variable, it was concluded that the critical rating variable was positive and statistically significant. In fact, at 10% increase in critical approval with that $7 million to the box office revenue. He could not reach any conclusion about holiday movies variable and no consistency with other studies were found. They believed that this happened because movies that were supposed to be of holiday season were released a little before this period. The MPAA variable for R-rated movies was negative and statistically significant to 12.5 million dollars. (Terry, Butler, & De'Armond, 2005) were also one of the few researchers that decided to analyze if the fact that a movie was a sequel was relevant to the box office. There was a positive and significant correlation of 36 million dollar of coefficient. There was a positive statistically significant correlation for action genre but a negative for children's movies. Having an academy Award nomination could make a movie increase $6 million per nomination on the box office. They also found out that the more theaters that were playing a movie the more money a movie would make at the box office as it was positive and statistically significant. His budget variable also was found to be positive and statistically significant with box office numbers. It was also suggested that in a future work a global box office revenue was used as a variable, which was done in this work.

From all the conclusions that were drawn in this literature review we can see that many authors have found contradictory results because of how the sample was restricted, meaning that there are not many factors that are definitive to Box Office success. The following variables were found to be the ones that have more impact on Box Office success according to the literature review:

- major studio involvement.
- Academy Award nominations or awards.
- timing of release.
- Critics reviews
- certain film genres.
- MPAA ratings.

- the size of the budget.

2.3 On What is Considered a Successful Movie

2.3.1 The Definition of Success

It is important to define success properly, but prior works have focused mainly on gross box office revenue (Apala, et al., 2013), (Asur & Huberman, 2010), (Gopinath, Chinagunta, & Venkataraman, 2013), (Mestyán, Yasseri, & Kertész, 2013) , (Parimi & Caragea, 2013), (Taylor, Simonoff, & Sparrow, 2014), and others have used the number of admissions (Baimbridge, 1997), (Meiseberg, Ehrmann, & Dormann, 2008). The fundamental thought for using the two as success metrics is considerably basic—a movie with huge box office numbers is considered a success. But both ignore the cost to produce a movie. The analysis of historical data shows that revenues are not directly related to profits. A better measure of success should be profitability, by numeric value of profits (De Vany & Walls, 1999) or the return on investment (ROI) (Elberse, 2007).

After selecting a success metric, many studies categorized movies as successful or not and accepted binary classifications as a predictive task; others considered the prediction as a multiclass classification problem and attempted to classify movies into many discrete categories (Parimi & Caragea, 2013). Continuous numerical values of success metrics are also predicted (Eliashberg, Jonker, Sawhne, & Berend, 2000), (Mestyán, Yasseri, & Kertész, 2013), (Walls, 2005), and many values of these metrics were logarithmized in many studies (Taylor, Simonoff, & Sparrow, 2014), (De Vany & Walls, 2019), (Zhang & Skiena, 2009).

2.3.2 Variables of Movie Success

In order to be accurate a model needs to rely on extraction and Engineering of many features which are the independent variables. There are three main types of features that have been explored regarding movie success one is audience-based other is release based and the other is about features of a movie. If audiences seem to be more optimistic or positive about a new movie it is more likely to have a better ROI. If it is possible to know the number of theaters in which a movie is available when it opens one can capture the availability at the release. The more theaters showing a movie it is more likely that it will have a higher ROI. Movie reception can be measured from data collected from media such as Twitter (Asur & Huberman, 2010), trailer comments (Apala, et al., 2013), blogs (Gopinath, Chinagunta, & Venkataraman, 2013), news articles (Zhang & Skiena, 2009), and movie reviews (Meiseberg & Ehrmann, 2013).

A way to capture the availability at release is the number of theaters a movie opens in (Mestyán, Yasseri, & Kertész, 2013), (Parimi & Caragea, 2013), (Sharda & Delen, 2006), (Taylor, Simonoff, & Sparrow, 2014), (Walls, 2005), (Zhang & Skiena, 2009). Some movies are planned to be released in specific times of the year such as holidays. And this is something used in prediction tests. (Bozdogan, 2013), (Gopinath, Chinagunta, & Venkataraman, 2013), (Parimi & Caragea, 2013), (Taylor, Simonoff, & Sparrow, 2014). There were also studies that managed to capture the competition at the time of release of a movie and this could have a negative effect on ROI. (Gopinath, Chinagunta, & Venkataraman, 2013), (Parimi & Caragea, 2013),

Some movie-based features are more directly related to what a movie is about. It includes who is part of the cast and what are the major plot points of the script. Start power is among the main features about casting. This represents how much a well-known actor or actress or ensemble can guarantee to a movie in terms of ROI. It can be measured by actor earnings (Parimi & Caragea, 2013), past award nominations (Boccardelli, Brunetta, & Vicentini, 2008), actor rankings (Taylor, Simonoff, & Sparrow, 2014), and the actor's number of Twitter followers (Apala, et al., 2013). It is possibly of common sense that a high star power helps a movie reach success, but no research has explored how profitable the actors are. And on the opposite side the role that a director has in the financial success of a movie tends to be overlooked (Lutter, 2014), Although there have been researchers that did an investigation on the individual success of directors there were not many that really tried to link a directors star power to a movies financial success. (Boccardelli, Brunetta, & Vicentini, 2008), and the value of director is less important than an actors' for movie revenues (Meiseberg, Ehrmann, & Dormann, We don't need another hero: Implications from network structure and resource commitment for movie performance, 2008).

Besides from individual actors and directors, the teamwork of a cast of a movie has also been explored (the "team chemistry") (Meiseberg & Ehrmann, 2013). were studies in the past that argued that star directors do not affect the way a movie will perform financially, and that the director has smaller value than that of an actor in terms of ROI. (Guimera, Uzzi, Spiro, & LAN, 2005), (Uzzi & Spiro, 2005). Having a diverse and familiar cast does help a director receiving awards and helps achieving bigger numbers at the box office. (Lutter, 2014), and the movie's box office revenues (Meiseberg & Ehrmann, 2013). Cast members' former experience also helps with revenues (Meiseberg, Ehrmann, & Dormann, 2008).

There are other features worthy of study like the MPAA rating the fact of whether a movie is a sequel and runtime. These can all be studied for success predictions., (Abassi, et al., 2015). The power of the script is also very important to measure the success for a movie and it has been studied in two papers (Eliashberg, Hui, & Zhang, 2014), (Eliashberg, Hui, & Zhang,2007) The problem is that the informative textual features in these studies rely on manual annotations done by experts and they are bow to subjectiveness. it may be subjective to say how logical a story or hero is and whether it has a believable or satisfying ending. Other problems with this analysis rely on difficulties such as the fact that movie scripts can be very long the manual annotations can be time-consuming and very few movie scripts are available online in a uniform and professional format. Besides that, a model that is able to predict script features can be applied only to a very small sample of movies and thus reducing the possible predictive power for movies in the future. An automated way to analyze movie content that is text based and it is available online is something that is necessary for a decision support system to learn from data sets of large-scale.

3 Research Methodology

3.1 Set up for Research

In order to perform this research according to the rules of (Litman B. , 1983), the following procedures were stablished:

The movies which had their data collected were chose with the following criteria: movies released in the US from the beginning of 2014 until the end of 2019 that had a budget of at least 20 million dollars. The budget is important because a bigger budget may involve higher risks to guarantee a well expected ROI from a project. So, a cheaper movie does not have to make as much revenue as an expensive movie in order to break even. Of any 10 major theatrical films produced, on the average 6 or 7 are unprofitable, and 1 will break even. (Vogel, 1990). Also, the movies that are more significant in financial results in the movie industry are the ones that spend more and earn more money. (Follows, Do Hollywood Movies Make Profit?, 2016) (Follows, How movies make money: $100m+ Hollywood blockbusters, 2016)

The reason for the 2014-2019 period was for mainly four reasons. The first is to minimize the effect of money value over time (adjustment for inflation of movie revenues) since the inflation of US Dollar was under control for this period (US Inflation Calculator, 2020). The second is to minimize the effect of usage of internet communication through the years and the power of reach of big reviews websites used in this research like Metacritic and Rottentomatoes. The third reason is to analyze if this in an ongoing trend and if has increased decreased or kept stable through the years of research. And the fourth reason is to make sure there would be a sample that was numerous, diverse and consistent enough to be analyzed according to reliable margins of error in statistical treatment.

The data collected for each movie were: studio by which it was produced, MPAA Rating, wide release premiere date (according to BoxOfficeMojo), data of first published review page found online from a well renowned website, the score given to this movie by critics on IMDB, Metacritic and Rottentomatoes, the budget and the worldwide box office (all data from BoxOfficeMojo).

The genre of the movies is also hard to categorize for some movies, so they may have an additional genre to be taken in consideration. Because of this factor of films having multiple genres, a deep analysis for genre results was discarded for this research.

In order to understand the numbers collected in this research, an arithmetic mean was taken from the score of the three websites for each movie in order to level the differences from each website.

Since the idea behind this research is to discover if there is a correlation between the size of gaps of the first published review of a movie and its premiere date and a the score of the review, those dates were collected for each movie and their difference was calculated.

3.2 About the sample

3.2.1 About the Gap Determination

In order to find the gap associated with each movie, a research was done with the 331 movies of the sample in order to find the premiere date (according to boxofficemojo) of each film. To find the date of the first published review, a research with many renowned entertainment websites such as Variety and Hollywood reporter, which usually have a vast number of reviewers and are usually present in the first press screenings, was done. Since the overall population of movies released in US from 2014 until 2019 was around 4555 (Statista, 2020). This gives an error around 5% for a 95% reliability of results.

The gap number is the difference between the day of the premiere and the day of the first published review and is an integer number. The main goal of this research is to find out if lower ratings are associated with lower ratings by critics. The gap exists essentially because studios promote a review embargo to prohibit outlets and organizations that have seen the film / TV show from posting reviews until a specified time. Sometimes studios and TV networks also set embargoes for social media reactions from critics and journalists.

3.2.2 About Colleting the Ratings

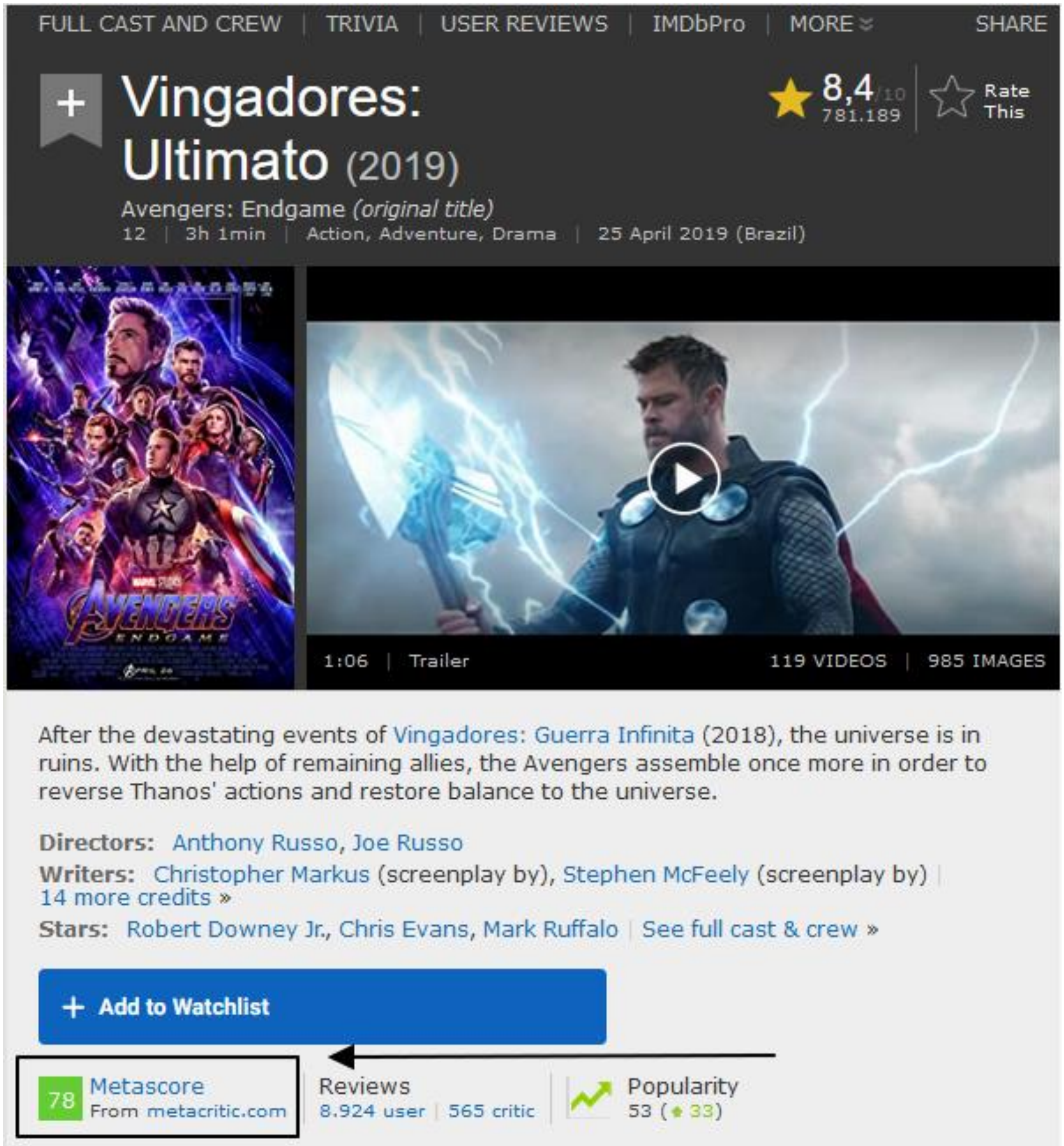
Three renowned websites were used to gather information regarding critic review. Metacritic gathers reviews that range from 0 to 100. IMDB gathers reviews that range from

0 to 10,0. And Rottentomatoes gathers reviews that range from 0 to 10,00. In order to standardize the results and to find an average rating for each movie, the ratings from IMDB and Rottentomatoes were multiplied by 10 in order to find the average result by arithmetic mean. These results are the one to be used in every statistical treatment forward.

A curation of a large group of the world’s most respected critics have assigned scores to their reviews and are applied a weighted average to summarize the range of their opinions. The result is a single number called Metascore, which summarizes all opinions.

The metascore is a weighted average in which is assigned more importance, or weight, to some critics and publications than others, based on their quality and overall stature. The data was gathered either from the Metacritic website or directly through a link in IMDB website as seen in figure 1 (Metacritic, 2020)

Figure 1: Metacritic score collected from IMDB

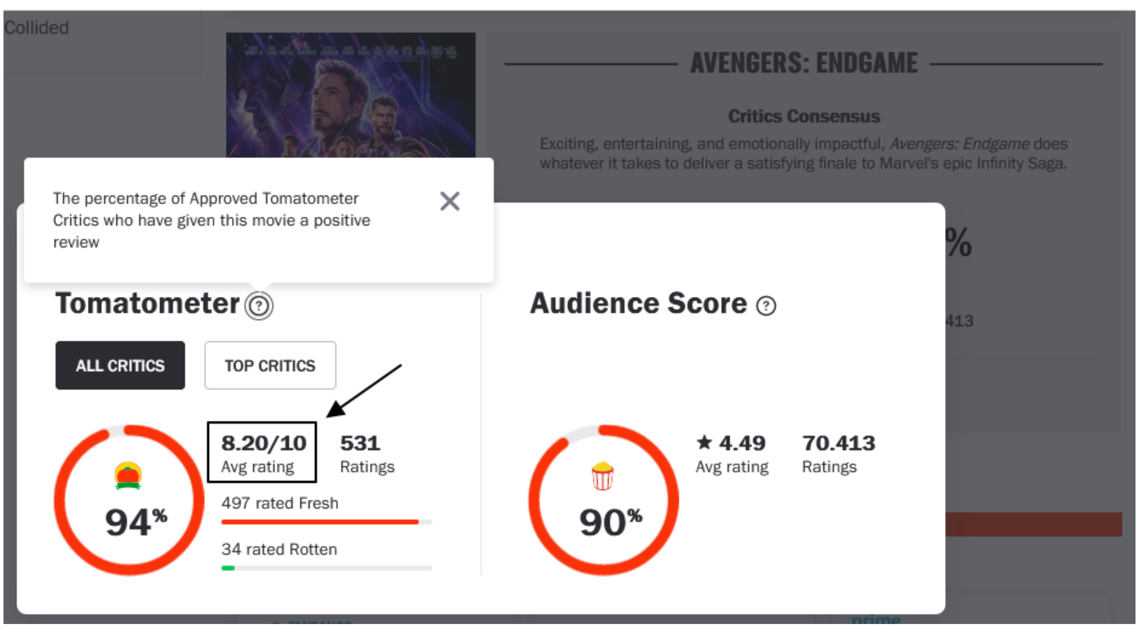


Source: (IMDB, 2020)

The Rotentomatoes score was taken from the average score within the Tomatometer of each film as seen in picture NUMBER below. The Tomatometer score is based on the opinions of numerous film and television critics and is a trustworthy measurement of critical recommendation for many stakeholders. (Rottentomatoes, 2020)

The Average Rating of Rottentomatoes measures the overall quality of a film or TV show based on an average of individual critic scores. It is an average of the individual critic scores, based on a 1-10 scale. Each critic's original rating scale (e.g., star, letter grade, numeric) is converted to a number between 1 and 10, and then the numbers are averaged. Reviews that do not have individual ratings are not counted in the Average Rating calculation, and a minimum of five reviews with individual ratings is required to be calculated within the average rating. (Rottentomatoes, 2020). Figure 2 shows how an average rating is exhibited on Rottentomatoes.

Figure 2: The average Rating from Rottentomatoes



Source: (Rottentomatoes, 2020)

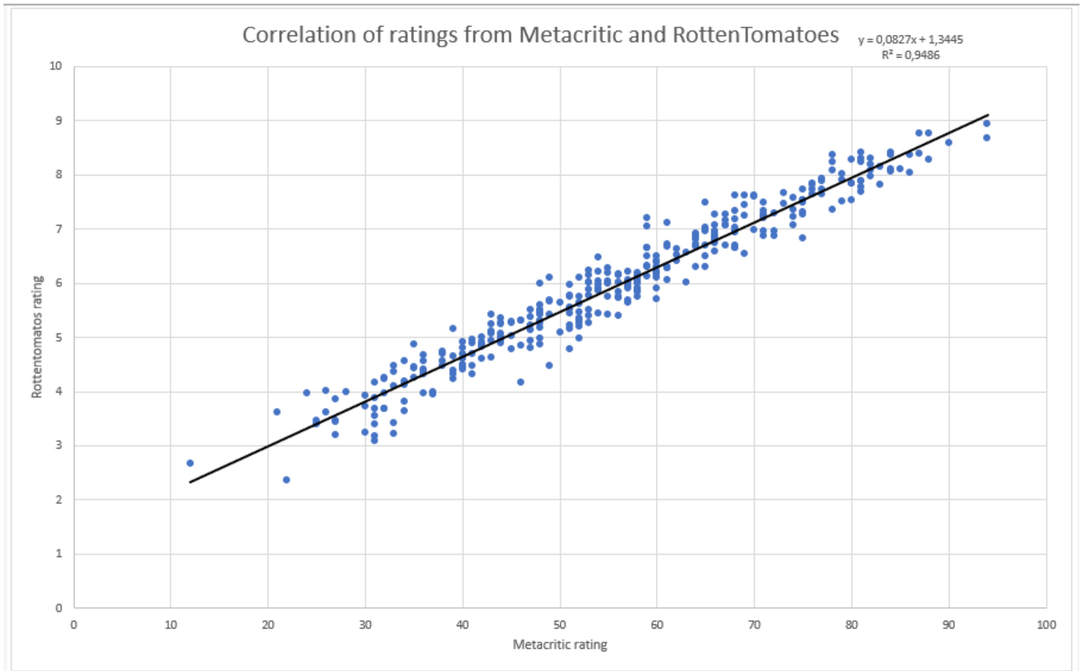
IMDb publishes weighted vote averages rather than raw data averages. Although they accept and consider all votes received by users, some votes have more impact/weight on the final rating.

When unusual voting activity is detected, an alternate weighting calculation is used in order to preserve the reliability of the rating system. IMDB does not disclose the method used on the rating for it to remain effective.

The top 1,000 voters consist of the 1,000 people who have voted for the most titles in the ratings poll. (IMDB, 2020)

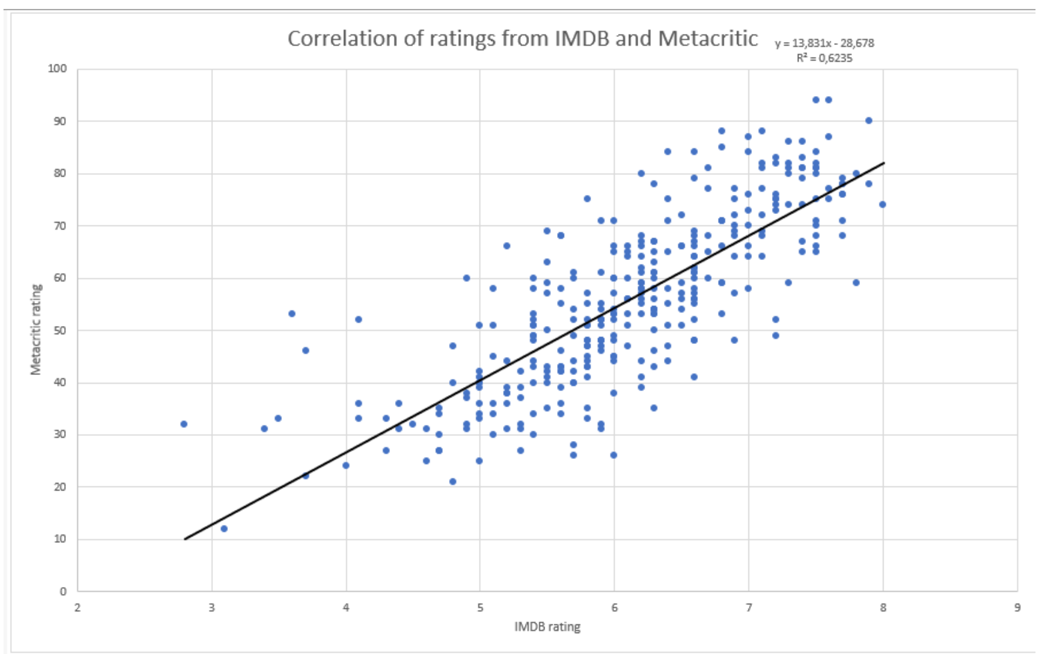
The graphs shown in figures 3,4 and 5 show how well the ratings of IMDB, Metacritic and Rottentomatoes correlate with each other. It is noticeable that Metacritic and Rottentomatoes share a very high level of similarity with an R^2 of 0,94. IMDB however has a somewhat inferior correlation with each other. This may be because in order to find the most reliable critics ratings on the website it was necessary to look up that ratings for the top 1000 voters, which are users who are a lot more dedicated to giving rates than the ordinary visitors of the site, and giving that, also have a more similar behavior with professional critics from Rottentomatoes and Metacritic.

Figure 3: Correlation of Metacritic and Rottentomatoes Ratings



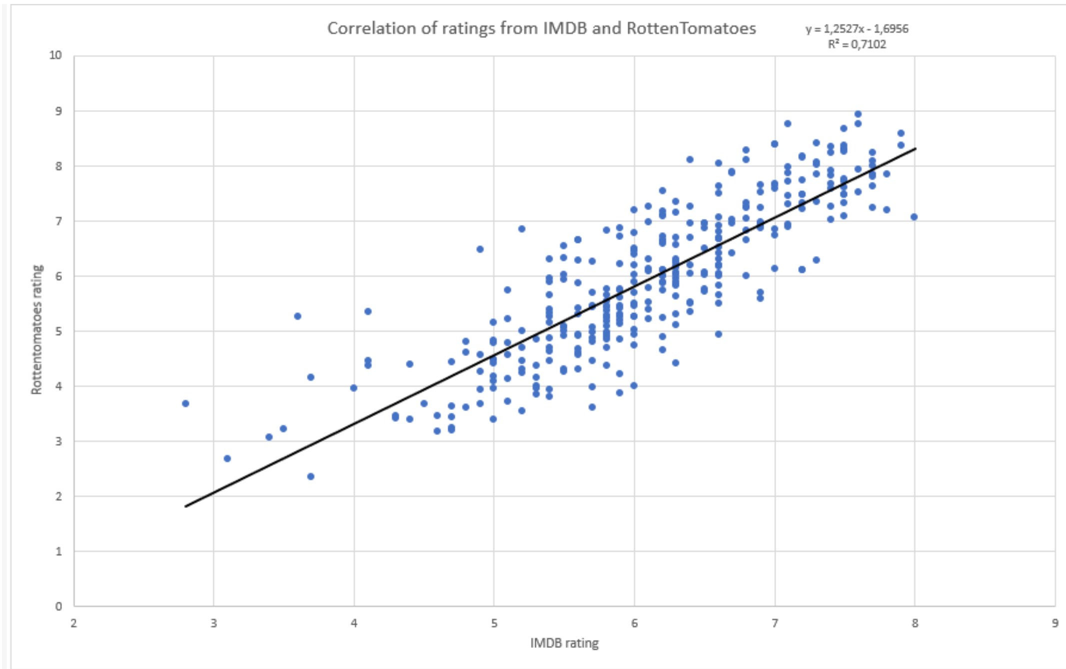
Source: Prepared by the Author

Figure 4: Correlation of IMDB and Metacritic Ratings



Source: Prepared by the Author

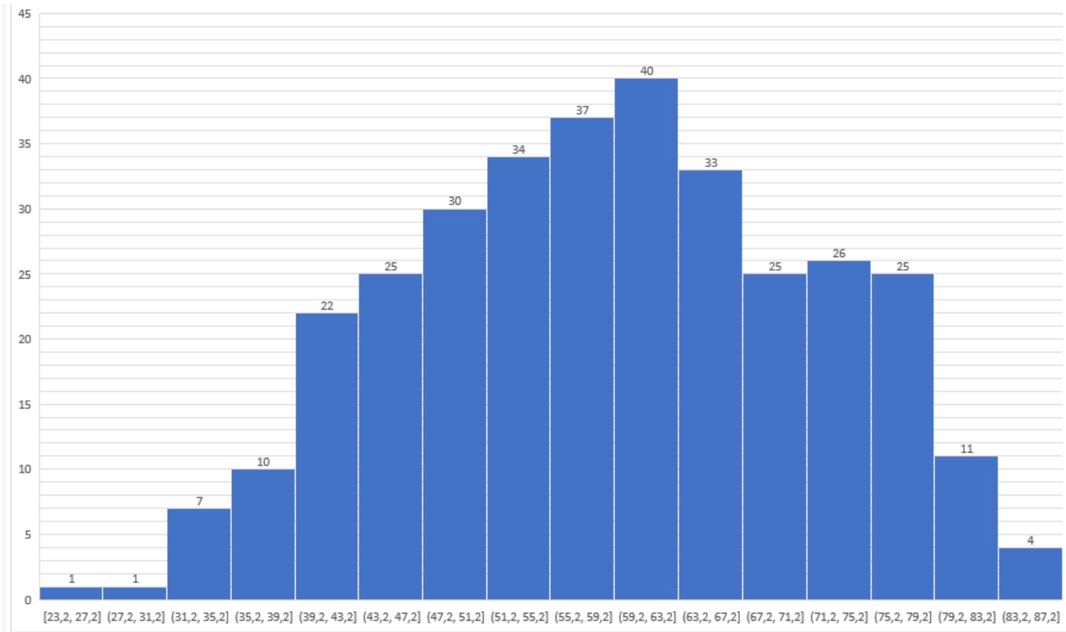
Figure 5: Correlation of IMDB and Rottentomatoes Ratings



Source: Prepared by the Author

After finding an average rating using the 3 websites, a histogram was set up with the 331 movies of the sample and they were sorted as shown in figure 6. The shape of the histogram indicates a well sorted sample in terms of range of ratings, with most movies around 60, a minimum of 23,2 for The Emoji Movie (2017) and a maximum of 86,4 for Inside Out (2015).

Figure 6: Distribution of the sample per Rating

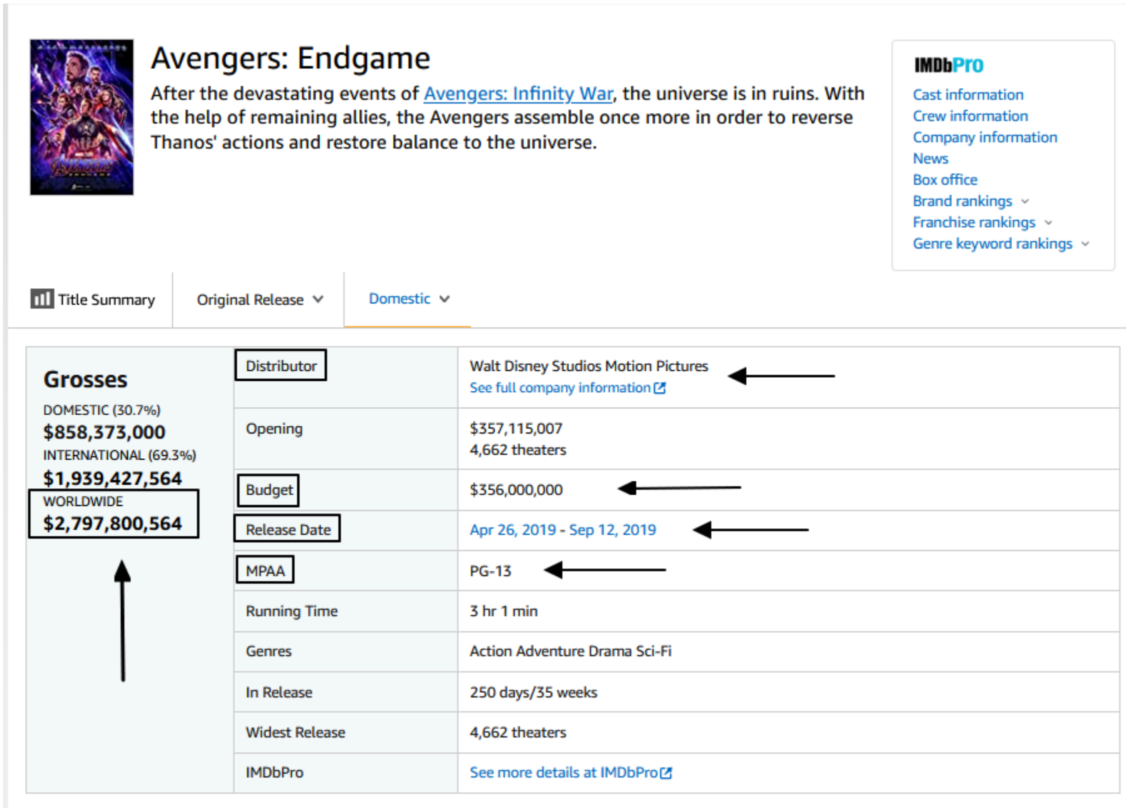


Source: Prepared by the Author

3.2.3 How the other variables were collected

The website used in order to collect the data of Distributor, Budget, Worldwide Box Office, Release date and MPAA rating was BoxOfficeMojo, which is part of the IMDB group. The figure 7 shows how this information is displayed for one of the movies of the sample.

Figure 7: Variables collected from BoxOfficeMojo

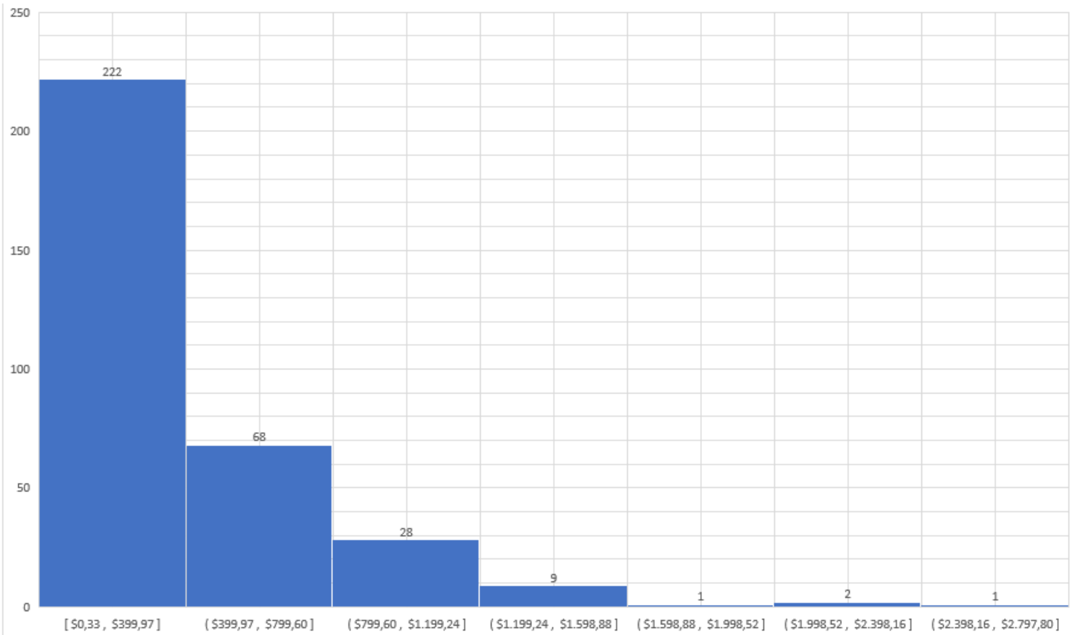


Source: (BoxOfficeMojo, 2020)

3.2.4 How the Sample is Sorted in Budget, Total Box Office and ROI (%)

The sample was sorted for the total box office gathered (from domestic and International movie theatres) and the histogram for that data is shown in figure 8. The lowest TBO belongs to the movie Lucy in the Sky (2019) with U$325.950,00, the only movie in the samplethat could not break even U$1,000,000.00, and the highest to the movie Avengers: Endgame (2019) with U$2.797.800.564,00, which is also the highest overall TBO ever for a movie (not adjusted for inflation).

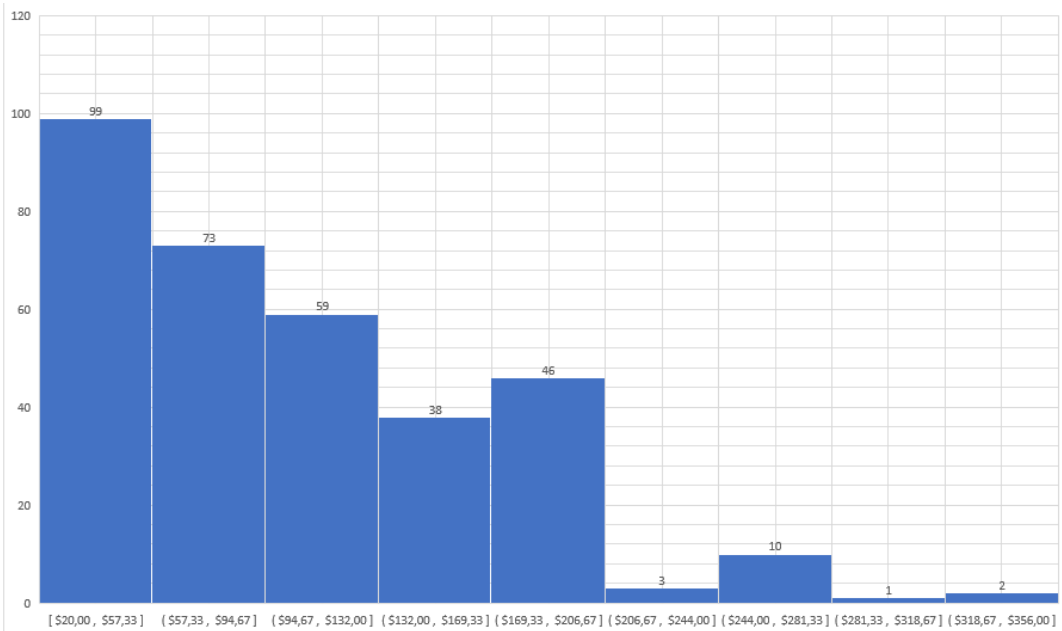
Figure 8: Distribution of the sample per Total Box Office(In millions of Dollars)



Source: Prepared by the Author

The histogram of budget data has a similar shape to the TBO one as can be seen in figure 9. Since U$20,000,000.00 was stablished as the lower limit to gather sample with statistically significant financial numbers, there are four movies within this limit. The movie with the biggest budget on the list is the same as the biggest box office numbers, costing U$356,000,000.00, almost 1700% more expensive than the cheapest movies within the sample.

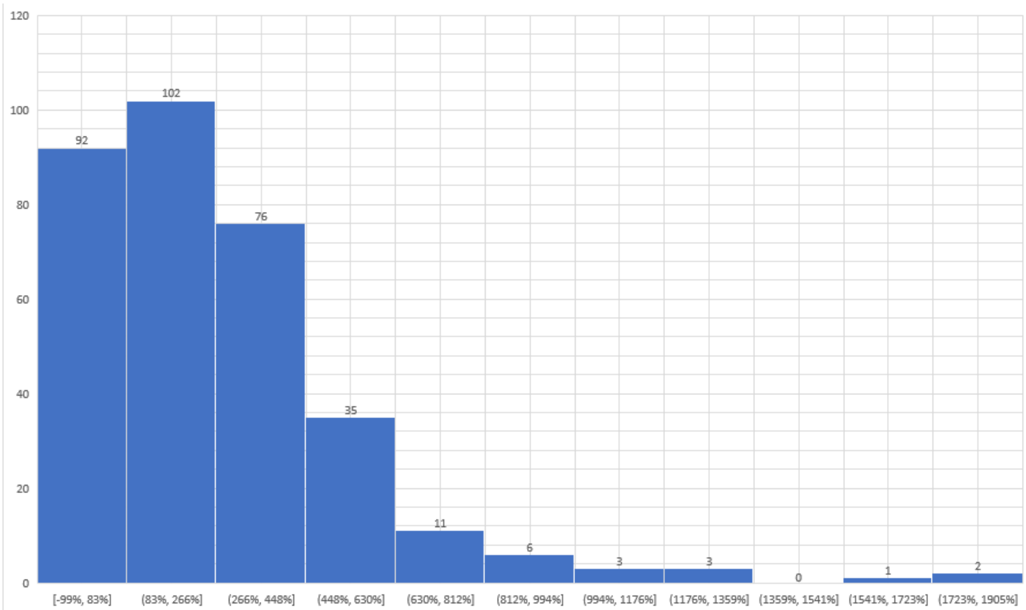
Figure 9: Distribution of the sample per Budget (in millions of Dollars)



Source: Prepared by the Author

Given the data on budget and TBO, a calculation for Return of Investment was made and presented in % for each movie and presented as an histogram in figure 10. The movie with the lowest ROI was Lucy in the Sky (2019) with -99% and the one with the highest ROI was It (2017) with 1905%.

Figure 10: Distribution of the sample per ROI (%)

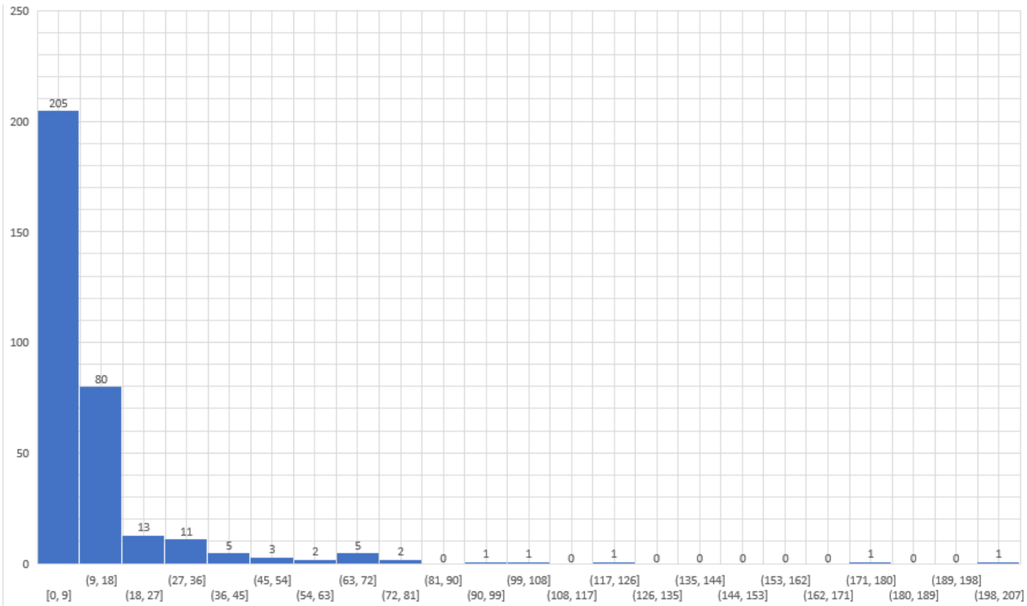


Source: Prepared by the Author

3.2.5 How Gap is Sorted Through the Sample

As done with budget, TBO, and ROI (%), a histogram shown in figure 11 to sort the gap distribution throughout the sample was also constructed. The movies with smallest gaps were four and they had 0 days, which means that their first published review was only found on premiere date and not a day earlier than that. The movie with largest gap was Macbeth (2015) with 202 days of gap.

Figure 11: Distribution of the sample per Gap (in days)



Source: Prepared by the Author

As can be seen is also confirmed by a more detailed look at the data, over 86% of the sample falls within the 18th day of gap and almost 94% are below 40 days.

As can be seen, gap, TBO, ROI, and even a few movies budgets have some subjects that soar scattered towards higher values. In order to analyze well distributed the sample is, boxplots for each of these variables were also built and shown in the following chapter.

3.2.6 About Outliers of Gap, Ratings and Percentual Results

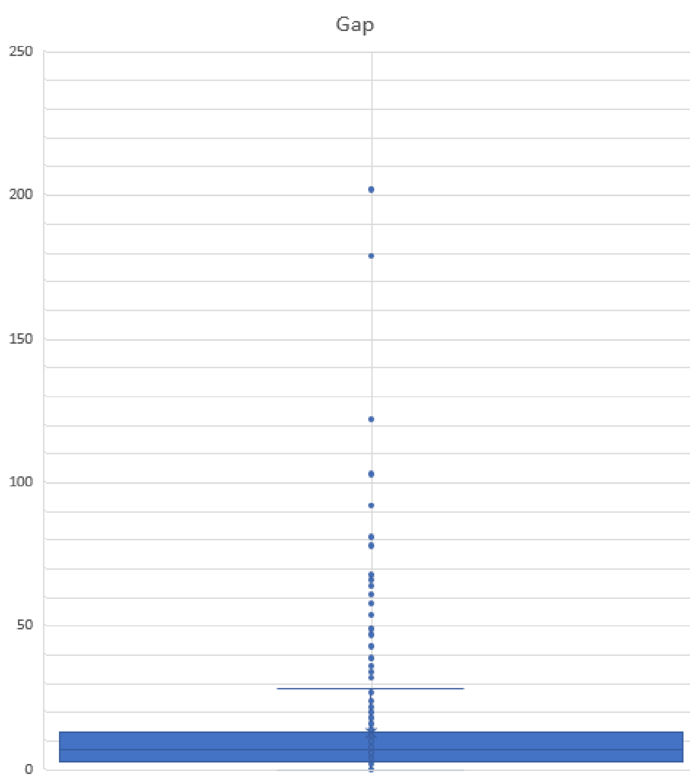
Correlations can be difficult to be perceived. Arranging numbers into categorized scales can be useful to find correlations, but learning more about the sample is also necessary, so outliers can be spotted and excluded from certain analysis.

In order to discover the outliers within gap, ROI (%), budget, TBO and ratings, a boxplot was built from each variable

Although ROI and TBO have some movies that stretch beyond the boxplot limits, the do not represent even 10% of the size of the sample, which should not be a problem. Since gap is also an object of study for minimum values the dispersion that happens for upper values shall not represent a problem to validate further analysis.

The boxplot for gap in figure 12 has an upper limit of 28 days. There are 31 movies that are beyond this threshold and this will be a limitation further on.

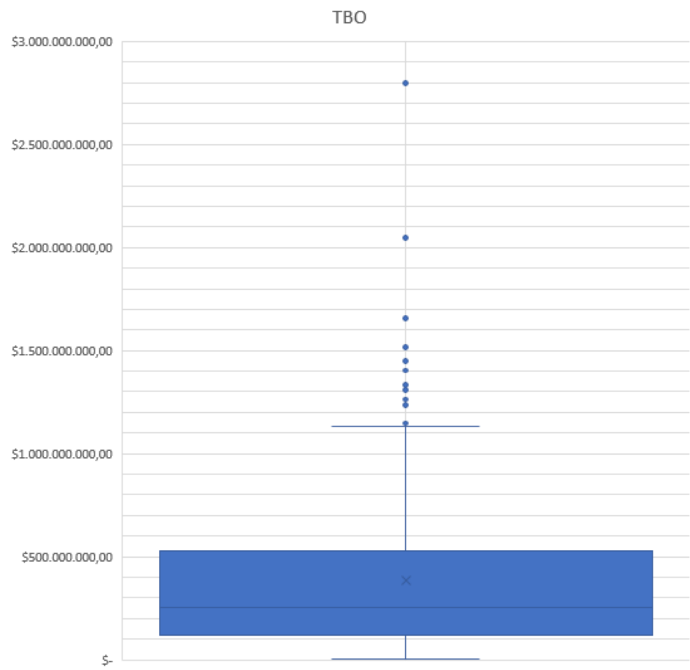
Figure 12: Gap Boxplot



Source: Prepared by the Author

The TBO boxplot in figure 13 has over 10 movies beyond the upper limit of more than 1 billion dollars. 26 movies broke the 1-billion-dollar barrier and only 3 movies broke the 2-billion-dollar barrier.

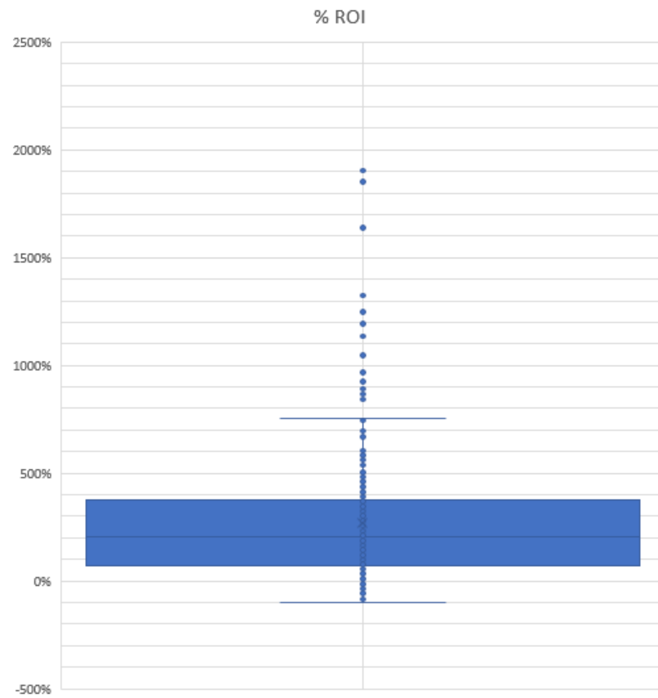
Figure 13: Total Box Office Boxplot



Source: Prepared by the Author

The boxplot for ROI in figure 14 does have outliers within the highest grossing movies of the sample. The upper limit is 756% and there are 15 movies that surpassed this limit.

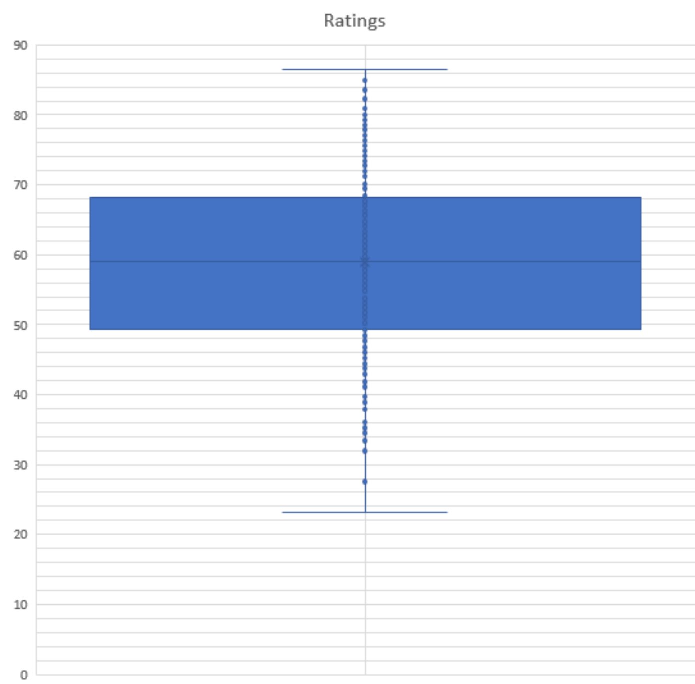
Figure 14:ROI (%) Boxplot



Source: Prepared by the Author

Since the ratings are set within a limited range and fluctuations were diminished by making an average rating, no movie fell beyond the stablished limits as seen in figure 15.

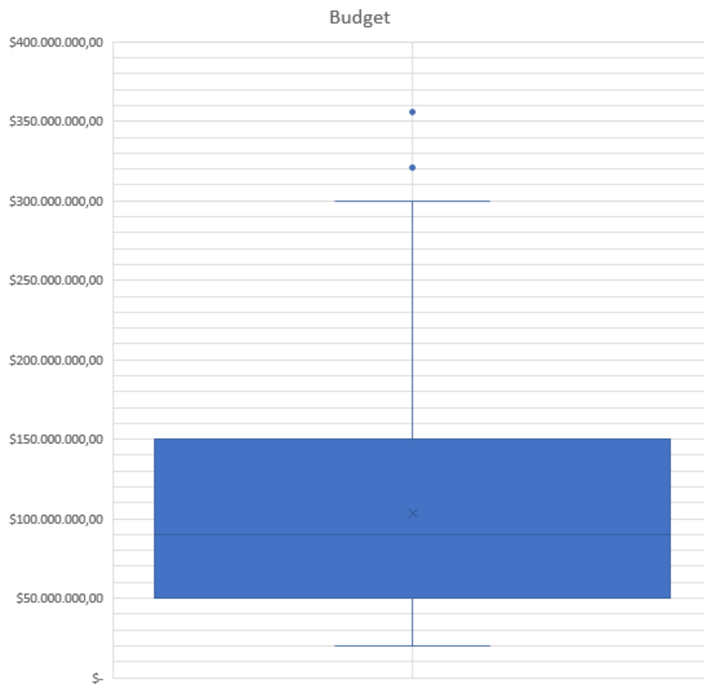
Figure 15: Critics Average Rating Boxplot



Source: Prepared by the Author

The budget boxplot in figure 16 has only two movies beyond the U$300,000,000.00 upper limit and a good margin for the interquartile range.

Figure 16: Budget Boxplot



Source: Prepared by the Author

3.2.7 How Gap Relates to ROI (%) and Ratings

In order to know more about how Gap correlates to variables it was decided to measure what was the average gap for movies within certain ranges of critics ratings and ROI(%) The average Gap and standard deviation for ratings were calculated for movies with less than 35, then between 35 and 50 then between 50 and 65 then between 65 and 80 and then greater than 80. The same was done for Roy of movies below 100%, then between 100% and 180%, then between 180% and 260%, then between 260% and 340%, then greater than 340% The results are shown in table 1. The table was color graded for each line from red (low) to green (high) of average gap to help see the differences.

Table 1: Average gap X Ratings and ROI (%)

Ratings	<35	≤35<R≤50	50<R≤65	65<R≤80	>80
average gap	1,43	5,42	9,56	22,24	29,67
sd	0,98	8,83	11,40	31,89	32,70
ROI(%)	**<100%**	**100%≤ROI≤180%**	**180%<ROI≤260%**	**260%<ROI≤340%**	**>340%**
average gap	12,70	9,52	11,77	14,25	13,90
sd	27,71	14,49	18,52	18,39	17,99

Source: Prepared by the Author

It is pretty clear that the average gap is very small for movies with lower ratings and grows continually as ratings follow. However, this could not be observed directly for ranges of gaps.

3.2.8 The Model Used to Understand How Variables Relate to Each Other

In order to be able to detect the parameters and how they occur, several analyzes with distinguished variables were attempted in order to find out if a certain studio endorses this practice more than others, or if it depends on the MPAA rating, on having a sequel, etc.

The empirical model used to examine the determinants of global box office revenue and ROI for films is specified as:

$$TBO = \beta_0 + \beta_1 Budget_i + \beta_2 Gap_i + \beta i Variable_i + e_i$$

$$ROI\ (\%) = \beta_0 + \beta_1 Budget_i + \beta_2 Gap_i + \beta i Variable_i + e_i$$

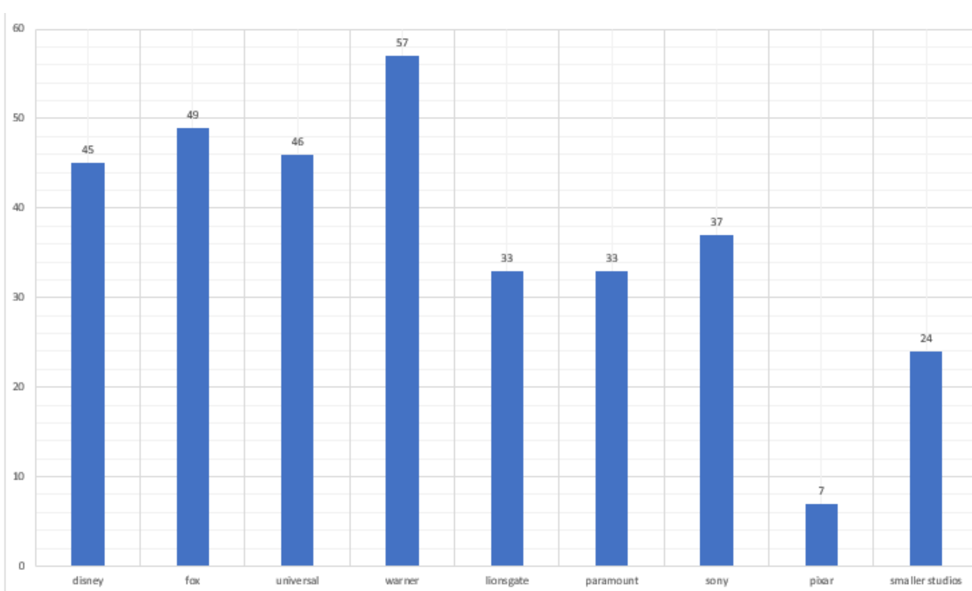
The equation was estimated with Stepwise regression, where:

- Gap is the number of days of gap of a movie (the number of days between the first published review and the premiere date in the US)

- Disney, Fox, Universal, Warner, Lionsgate, Paramount, Sony and Pixar are dummy variables, each representing a studio
- Smaller Studios is a dummy variable representing smaller studios
- Sequel is a dummy variable representing whether the movie is a sequel
- G, PG, PG-13 and R are dummy variables indicating the MPAA rating of a movie
- Average rating is the average of the rating of the top 1000 IMDB voters, the metascore and the Rottentomatoes average of a movie.
- Budget is the production cost of a movie in US Dollars
- TBO is the global box office revenue earned by a film in US Dollars
- ROI is the difference of TBO and budget of a movie, divided by the budget of a movie, in %.

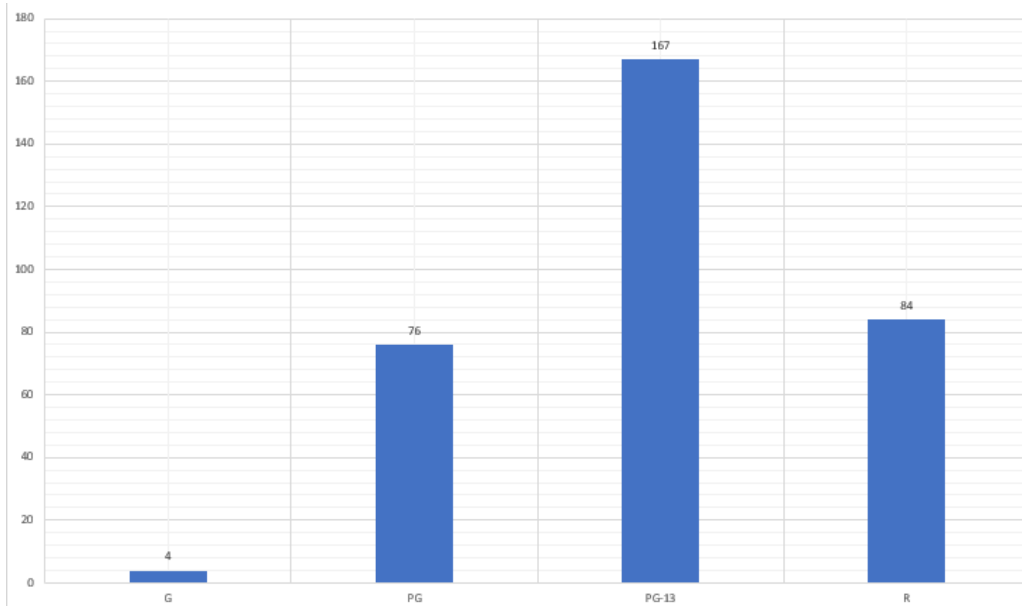
The sorting of the sample among studios and the MPAA rating is show in figures 17 and 18. Sequels represent 127 of the 331 movies in of the sample (a bit over 38%).

Figure 17: Studios sample distribution



Source: Prepared by the Author

Figure 18: MPAA Rating sample distribution



Source: Prepared by the Author

In order to eliminate multicollinearity and find out how the variables interact with each other; a Pearson Correlation Matrix was set up with all the variables in this study. It was color coded from red (-1) to green (+1) for a more identifiable correlation. The table is in table 2.

Table 2: Correlation Matrix

all movies	*gap*	*disney*	*fox*	*universal*	*warner*	*lionsgate*	*paramount*	*sony*	*pixar*	*smaller studios*	*sequel*	*G*	*PG*	*PG-13*	*R*	*average rating*	*budget (>=20mi U$)*	*total box office*	*% result*
gap	1																		
disney	-0,0563	1																	
fox	0,068414	-0,16535	1																
universal	0,004839	-0,15936	-0,16747	1															
warner	-0,07879	-0,18092	-0,19012	-0,18324	1														
lionsgate	0,007066	-0,132	-0,13871	-0,13369	-0,15178	1													
paramount	-0,05233	-0,132	-0,13871	-0,13369	-0,15178	-0,11074	1												
sony	0,03211	-0,14072	-0,14788	-0,14252	-0,1618	-0,11805	-0,11805273	1											
pixar	0,010977	-0,0583	-0,06127	-0,05905	-0,06704	-0,04891	-0,048913119	-0,05214	1										
smaller studios	0,096173	-0,11091	-0,11655	-0,11233	-0,12753	-0,09304	-0,093043336	-0,09919	-0,0411	1									
sequel	-0,13409	0,085815	0,020982	0,096095	-0,08014	-0,07593	-0,013720251	0,055279	0,056748	-0,148737362	1								
G	-0,0245	-0,04387	0,109612	-0,04443	-0,05045	-0,0368	-0,036804842	-0,03924	**0,368098**	-0,030923778	0,083315	1							
PG	0,0429	0,265496	-0,00507	-0,03243	-0,09679	-0,15769	-0,085764925	0,011502	0,169387	0,013556991	-0,07622	-0,06038	1						
PG-13	-0,13613	-0,01241	-0,0293	0,031295	0,051881	0,067575	0,08774396	-0,05116	-0,14832	-0,09573791	0,110895	-0,11161	-0,5509	1					
R	0,121089	-0,23132	0,011044	0,006548	0,046608	0,084009	-0,008680974	0,057511	-0,08572	0,104657739	-0,07466	-0,0645	-0,31837	-0,58847	1				
average rating	**0,353438**	0,218804	0,034591	-0,13575	0,033635	-0,11175	-0,103908935	-0,04299	0,184254	-0,005295383	0,07434	0,059537	0,047728	-0,12799	0,085976942	1			
budget (>=20mi U$)	-0,13703	**0,411988**	-0,02737	-0,12158	0,021159	-0,15291	0,008934501	-0,10241	0,19521	-0,193174848	**0,348884**	0,073426	0,043342	**0,319249**	**-0,427117618**	0,176502379	1		
total box office	-0,05462	**0,419023**	-0,03891	0,005172	-0,03715	-0,16513	-0,086195144	-0,0425	0,168281	-0,204698481	**0,374479**	0,048286	0,04392	0,186686	**-0,269060149**	**0,369532722**	**0,709109604**	1	
% result	0,03626	0,078686	0,042417	0,18242	-0,0021	-0,10874	-0,124861803	0,008424	0,030574	-0,159666962	0,185714	-0,00012	0,008049	-0,03181	0,028796958	**0,29643677**	0,015077477	**0,589456419**	1

Source: Prepared by the Author

Some observations are important to be made. There is a good correlation of gap and average rating, of 0,353. This is important to answer this projects research question, as it indicates that the bigger the gap, the higher are the rates given to a movie.

It also shows that Disney is a studio that constantly has higher budgets (0,411) and gets high levels of TBO (0,419) and fairly good ratings (0,265), especially due to Marvel Cinematic Universe movies, Star Wars movies and remakes of classical animations.

Sequels are also shown to have a good correlation with budget (0,348) and TBO (0,374), which shows that studios usually spend more money on them and make more money. Since audiences would be more familiar with a previous movie, a decision about watching a sequel seems something to be expected. It is also expected that a producer would agree on making a sequel if its predecessor was successful. Then making the sequel movie is expected to be well received at the box office.

Smaller studios also show a negative correlation with budget (-0,193) and TBO (-0,204) which makes sense since the have less money to invest in movies and make less money since are relatively unknown.

The matrix also shows a correlation of PG-13 movies with budget (0,319) and TBO (0,186), since this category usually attracts more younger people, so a producer would feel safe to spend more and, possibly, make more money. R rated movies go the opposite way, with a negative correlation for budget (-0,427) and TBO (-0,269), since it has a more restricted audience, it is less capable of making much money, and so usually does not spend much either.

Average rating showed a good correlation with TBO (0,369) and ROI (0,296), which is consistent with all the literature reviewed on the subject matter. The strongest correlation in the matrix is budget and TBO (0,709).

A stepwise regression analysis was performed to eliminate any correlated independent variables and to define the relative explanatory power of each variable. A regression was made using TBO as dependent variable and a second one with ROI (%).

Only three independent variables (budget, rating, and sequel) exhibited a highly significant linear relationship with TBO, and all other independent variables did not exhibit a significant linear relationship. Results are shown in tale 3.

Table 3: Stepwise Regression Analysis for TBO

OVERALL FIT							
Multiple R	0,762854176		AIC	12793,15845			
R Square	0,581946494		AICc	12793,34306			
Adjusted R Squar	0,57811114		SBC	12808,36692			
Standard Error	245549046,9						
Observations	331						
ANOVA				Alpha	0,05		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	3	2,74458E+19	9,14859E+18	151,732175	1E-61	yes	
Residual	327	1,97162E+19	6,02943E+16				
Total	330	4,7162E+19					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*vif*
Intercept	-477387373,3	65087248,27	-7,334576065	1,76593E-12	-6E+08	-3E+08	
budget (>=20mi l	3,722912206	0,233746801	15,9271151	1,11741E-42	3,2631	4,1827	1,1689
average rating	7443740,609	1080089,022	6,891784339	2,84368E-11	5E+06	1E+07	1,0324
sequel	109492517	29618320,77	3,696783413	0,000255959	5E+07	2E+08	1,1388

Source: Prepared by the Author

As for ROI (%) as dependent variable, only average rating and sequel were significative to a 0,05 alpha. However, the R^2 associated was 0,114 which is exceptionally low to make up for a good correlation, as seen on table 4. This indicates that there is not a variable good enough to guarantee a good ROI within this sample.

Table 4: Stepwise Regression Analysis for ROI (%)

Regression Analysis		ROI(%)					
OVERALL FIT							
Multiple R	0,338842		AIC	674,3583458			
R Square	0,114814		AICc	674,4810452			
Adjusted R Square	0,109416		SBC	685,7647009			
Standard Error	2,757039						
Observations	331						
ANOVA				Alpha	0,05		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	2	323,3840305	161,6920152	21,27173326	2,05915E-09	yes	
Residual	328	2493,213898	7,601261884				
Total	330	2816,597928					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*vif*
Intercept	-1,49888	0,722310035	-2,075116595	0,038754917	-2,91982233	-0,077932752	
average rating	0,065297	0,011968881	5,455600898	9,6319E-08	0,04175198	0,08884289	1,005557074
sequel	0,987309	0,312495137	3,159438049	0,001727907	0,372561459	1,602056592	1,005557074

Source: Prepared by the Author

3.2.9 Making an Average of Ratings, Budget, TBO and ROI (%) per Gap

In order to discover about the relation between gap and the main variables, a table was set up to rank the numbers of days of gap in crescent order and the main data for the movies that had that gap was leveled by simple arithmetic mean, with the standard deviation on the side and, within the 3 last columns, the amount of movies on each gap, it’s size in % with the total sample a last column to show how many movies are within the first days compared to the total sample. Each column was color coded from red (for lowest values) to green (for higher values) to show their differences more easily. This information can be seen in table 5.

Table 5: Average variables per gap

gap	avg rating	sd	avg budget	sd	avg tbo	sd	avg ROI(%)	sd	size	% (total sample)	% acum
0	39,58	12,97	$ 62.250.000,00	$ 22.954.665,47	$ 147.179.040,00	$ 193.623.918,39	93,9%	218%	4	1,21%	1,21%
1	42,42	9,22	$ 87.827.777,78	$ 68.874.171,76	$ 241.527.084,83	$ 253.014.228,93	180,5%	198%	18	5,44%	6,65%
2	50,47	9,59	$ 91.367.346,94	$ 58.440.744,16	$ 281.577.477,84	$ 334.237.099,48	203,1%	272%	49	14,80%	21,45%
3	52,61	10,06	$ 115.627.906,98	$ 76.572.413,05	$ 443.723.661,81	$ 558.731.385,50	232,5%	215%	43	12,99%	34,44%
4	59,45	13,94	$ 107.090.909,09	$ 54.823.447,44	$ 352.665.254,41	$ 311.391.095,37	217,9%	186%	22	6,65%	41,09%
5	57,10	11,61	$ 97.076.923,08	$ 64.218.976,35	$ 342.379.442,08	$ 343.244.275,06	283,3%	373%	13	3,93%	45,02%
6	61,46	10,04	$ 92.857.142,86	$ 54.879.955,57	$ 351.138.777,00	$ 282.799.208,46	243,7%	182%	7	2,11%	47,13%
7	64,54	11,33	$ 120.812.500,00	$ 50.837.281,27	$ 372.332.991,50	$ 223.401.762,24	232,4%	173%	16	4,83%	51,96%
8	64,85	8,89	$ 122.222.222,22	$ 72.441.096,20	$ 595.923.752,33	$ 479.220.389,45	364,4%	216%	18	5,44%	57,40%
9	58,87	10,67	$ 81.800.000,00	$ 41.788.925,40	$ 275.976.163,07	$ 195.584.601,38	286,9%	290%	15	4,53%	61,93%
10	66,88	8,99	$ 104.857.142,86	$ 83.380.367,68	$ 533.951.608,07	$ 494.416.945,78	512,3%	606%	14	4,23%	66,16%
11	59,85	8,33	$ 102.364.705,88	$ 64.014.538,79	$ 378.005.417,59	$ 381.898.153,50	292,4%	266%	17	5,14%	71,30%
12	73,54	5,58	$ 123.200.000,00	$ 66.904.409,42	$ 503.015.226,20	$ 317.733.999,96	336,3%	161%	5	1,51%	72,81%
13	63,93	8,50	$ 113.111.111,11	$ 36.439.828,64	$ 350.180.610,33	$ 199.388.814,00	195,7%	134%	9	2,72%	75,53%
14	63,07	6,91	$ 101.375.000,00	$ 48.385.173,35	$ 499.287.957,75	$ 424.557.130,04	365,7%	327%	8	2,42%	77,95%
15	70,50	8,06	$ 135.125.000,00	$ 55.962.838,44	$ 521.934.255,63	$ 268.767.958,62	294,0%	131%	8	2,42%	80,36%
16	62,39	10,24	$ 103.727.272,73	$ 79.202.387,48	$ 447.456.543,64	$ 379.378.078,88	309,8%	318%	11	3,32%	83,69%
17	56,31	11,92	$ 165.333.333,33	$ 8.082.903,77	$ 760.871.780,33	$ 509.996.260,18	359,4%	298%	3	0,91%	84,59%
18	65,73	15,00	$ 142.600.000,00	$ 36.691.960,97	$ 430.112.204,40	$ 168.904.141,10	199,3%	92%	5	1,51%	86,10%

Source: Prepared by the Author

The table goes up to 18 days of gap for several reasons. The main ones are that over 86% of the sample is contemplated within the first 18 days of gap, and after 18 days there is a very small number of movies for each day of gap, and the analysis will lose consistency.

It is easy to see that from 0 up to 8 or 9 days the grades from rating, budget, TBO, and ROI slowly shift from red to green, so there is an observable correlation. In order to further analyze this correlation, a graph and a regression table was setup, and each variable was treated as a dependent variable and gap was considered an independent variable.

The curve that best fits gap x average rating for 18 days is a second order polynomial. It has an R^2 of 0,79 and Adjusted R^2 of 0,76. The p-value is also within the 95% tolerance, beeing way below 5% and are significative relevant. This is shown in table 6.

Table 6: Gap Polynomial Regression of average rating

Polynomial Regression			rating					
			18 days			degree	R-square	p-value
OVERALL FIT			polynomial reg			1	0,488436982	
Multiple R	0,889857968		AIC	57,09367		2	0,791847203	0,000184952
R Square	0,791847203		AICc	59,95081		3	0,805875693	0,314299661
Adjusted R Square	0,765828103		SBC	59,92699		4	0,80708874	0,771048478
Standard Error	4,180769809							
Observations	19					opt deg	2	

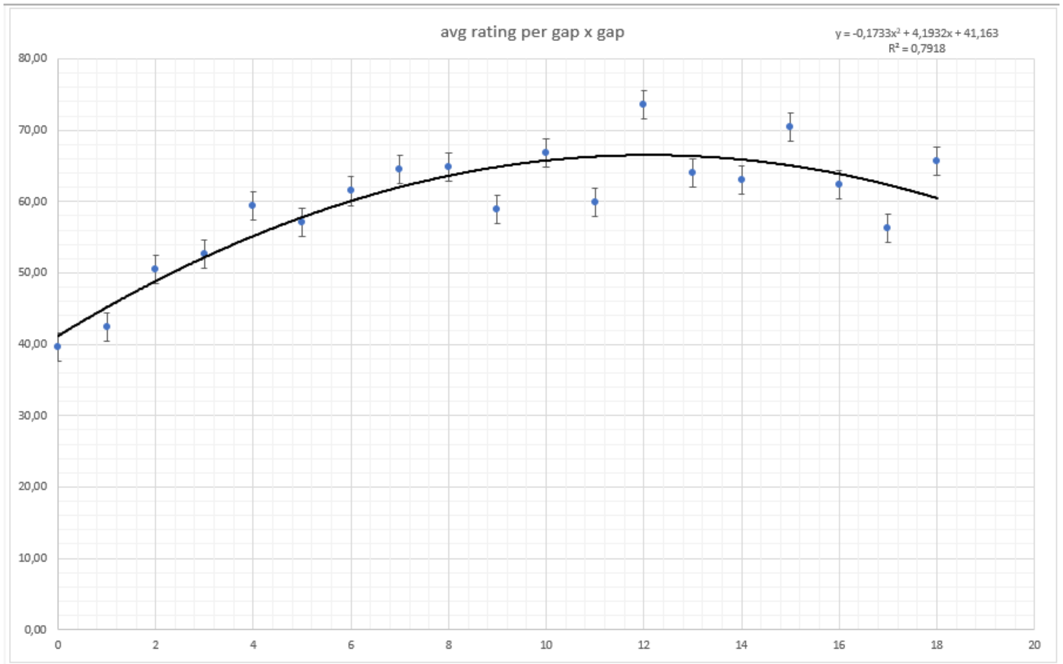
ANOVA				Alpha	0,05	
	df	SS	MS	F	p-value	sig
Regression	2	1063,878	531,9388	30,43331	3,52418E-06	yes
Residual	16	279,6614	17,47884			
Total	18	1343,539				

	coeff	std err	t stat	p-value	lower	upper
Intercept	41,16309898	2,599034	15,83784	3,37E-11	35,6533926	46,67280536
Degree 1	4,193212385	0,669415	6,264	1,13E-05	2,774116963	5,612307807
Degree 2	-0,173346197	0,035895	-4,8293	0,000185	-0,249439566	-0,097252829

Source: Prepared by the Author

The curve that describes the polynomial regression is show below in figure 19.

Figure 19: Gap x Average Rating curve



Source: Prepared by the Author

If we observe the curve closely it can be seen that the correlation beyond 9 days starts to get weaker. In order to observe the correlation in an interval closer to 0 days of gap, a new second order polynomial regression was set in the following table 7.

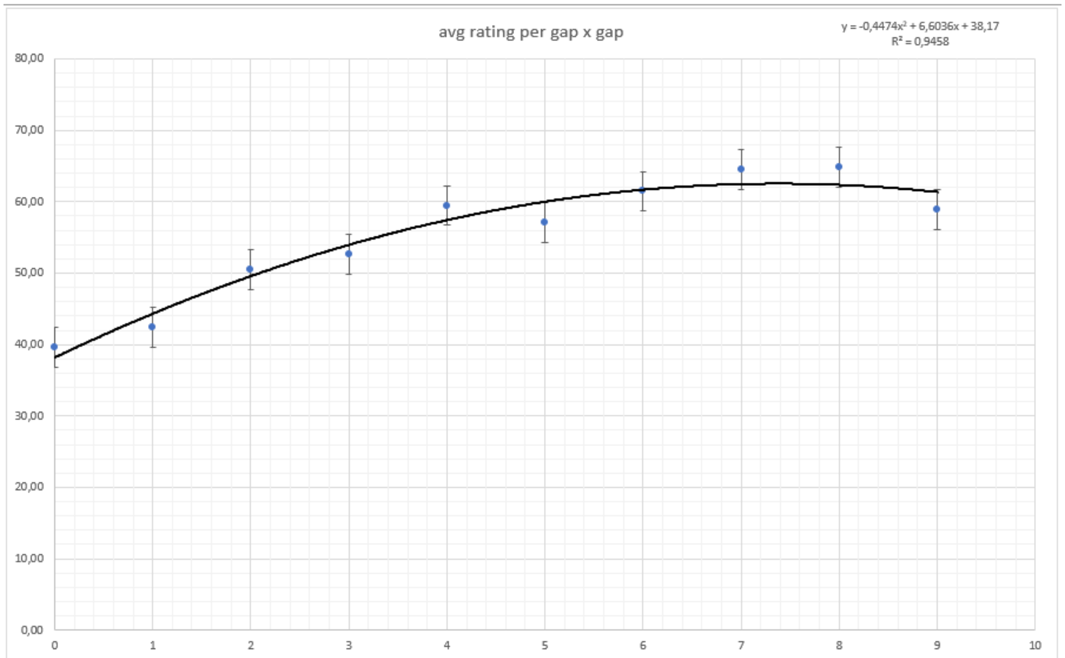
Table 7: Gap Polynomial Regression of average rating for the first 9 days

Polynomial Regression		rating						
		9 days				*degree*	*R-square*	*p-value*
OVERALL FIT		polynomial				1	0,792785484	
Multiple R	0,972500647		AIC	19,21219		2	0,945757509	0,002996505
R Square	0,945757509		AICc	27,21219		3	0,955661647	0,290987026
Adjusted R Square	0,930259655		SBC	20,11995		4	0,960997472	0,44586258
Standard Error	2,313929598							
Observations	10					opt deg	2	
ANOVA				Alpha	0,05			
	df	*SS*	*MS*	*F*	*p-value*	*sig*		
Regression	2	653,4893	326,7447	61,02506	3,71697E-05	yes		
Residual	7	37,47989	5,35427					
Total	9	690,9692						
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*		
Intercept	38,16997523	1,819316	20,98039	1,41E-07	33,86797534	42,47197511		
Degree 1	6,603604921	0,941432	7,014427	0,000209	4,377472289	8,829737553		
Degree 2	-0,447423094	0,100701	-4,44309	0,002997	-0,68554279	-0,209303398		

Source: Prepared by the Author

The correlation is much stronger with an R^2 of 0,94 and an adjusted R^2 of 0,93. The p-value is still sigficant below 5%. The curve in figure 20 describes the regression model.

Figure 20: Gap x Average Rating curve for 9 days



Source: Prepared by the Author

In order to verify the correlation between gap and ROI (%), a polynomial regression of second order was also found to be a best way to do so and can be seen in picture table 8.

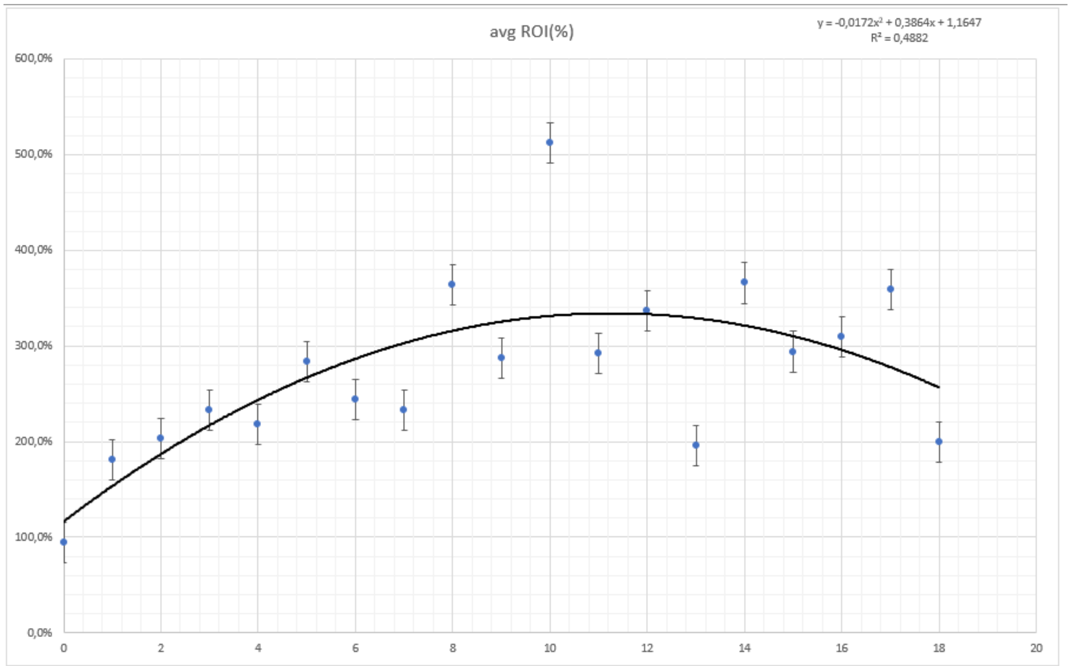
Table 8: Gap Polynomial Regression for ROI (%)

Polynomial Regression			%return					
			18 days			*degree*	*R-square*	*p-value*
OVERALL FIT			polynomial reg			1	0,226132759	
Multiple R	0,698734432		AIC	-10,93588745		2	0,488229806	0,0113
R Square	0,488229806		AICc	-8,078744591		3	0,488574882	0,9212
Adjusted R Square	0,424258532		SBC	-8,10257051		4	0,489314835	0,8888
Standard Error	0,697846496							
Observations	19					opt deg	2	
ANOVA				Alpha	0,05			
	df	*SS*	*MS*	*F*	*p-value*	*sig*		
Regression	2	7,433427128	3,716713564	7,632016283	0,004705436	yes		
Residual	16	7,791835712	0,486989732					
Total	18	15,22526284						
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*		
Intercept	1,16466227	0,433826065	2,684629544	0,016276101	0,244992096	2,084332443		
Degree 1	0,386435569	0,111737457	3,458424576	0,003235506	0,149562741	0,623308397		
Degree 2	-0,017150925	0,005991478	-2,862553164	0,011283895	-0,029852292	-0,004449559		

Source: Prepared by the Author

There is a weaker correlation than the one seen before, with an R^2 of 0,48 and an adjusted R^2 of 0,42. The p-value is still significant for a 95% reliability. The curve in figure 21 describes the regression model.

Figure 21: Gap x Average ROI (%) curve



Source: Prepared by the Author

Once again, for gaps over 9 days it seems that the correlations become weaker. So, a new second order regression was done up to 9 days of gap. However, a second order regression did not reach the p-value necessary for a 95% reliability and a linear regression was chosen instead. The results are in picture table 9

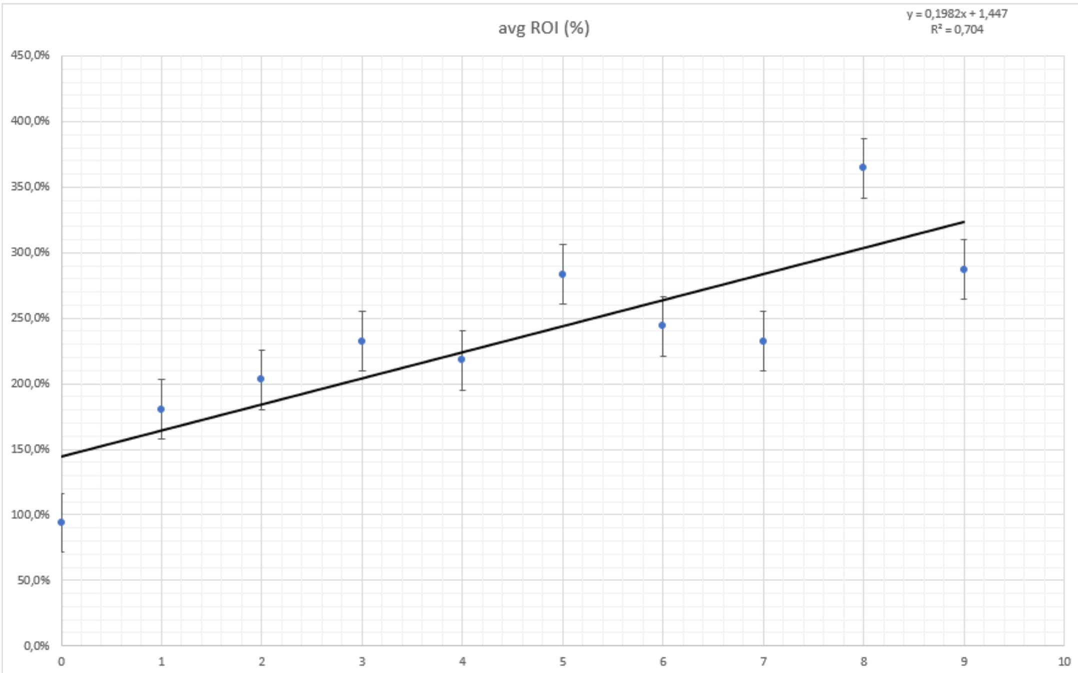
Table 9: Gap Polynomial Regression for ROI (%) for 9 days

Polynomial Regression			%roi					
			9days			*degree*	*R-square*	*p-value*
OVERALL FIT			polinomial			1	0,703953732	
Multiple R	0,839019506		AIC	-15,93200212		2	0,744160202	0,3291
R Square	0,703953732		AICc	-11,93200212		3	0,772911158	0,4169
Adjusted R Square	0,666947949		SBC	-15,32683193		4	0,805978746	0,3983
Standard Error	0,412702481							
Observations	10					opt deg	1	
ANOVA				Alpha	0,05			
	df	*SS*	*MS*	*F*	*p-value*	*sig*		
Regression	1	3,240027316	3,240027316	19,02280307	0,002407747	yes		
Residual	8	1,362586704	0,170323338					
Total	9	4,60261402						
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*		
Intercept	1,446951636	0,242567457	5,965151521	0,000336225	0,887590077	2,006313196		
Degree 1	0,198174313	0,045437048	4,361513851	0,002407747	0,093396293	0,302952333		

Source: Prepared by the Author

The R^2 is strong at 0,70 with and adjusted R^2 of 0,66. The p value is significant to a 0,05 Alpha. The curve in figure 22 describes the regression model.

Figure 22: Gap x Average ROI (%) curve for 9 days



Source: Prepared by the Author

For a regression of gap x TBO a linear regression was found to be the best fit for the data collected. It can be seen in table 10.

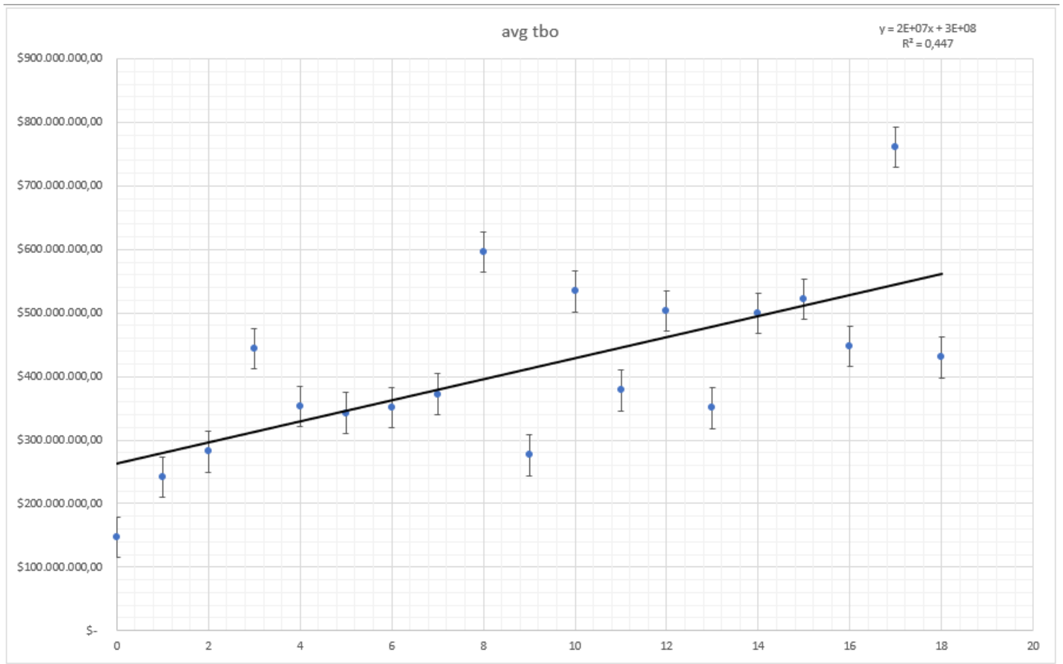
Table 10: Gap Polynomial Regression for TBO

Polynomial Regression			18 days				
			tbo				
OVERALL FIT					*degree*	*R-square*	*p-value*
Multiple R	0,668544796		AIC	704,5722	1	0,446952144	
R Square	0,446952144		AICc	706,1722	2	0,464862001	0,474893045
Adjusted R Sq	0,414419918		SBC	706,4611	3	0,495487902	0,355091844
Standard Erro	107362693				4	0,519631543	0,415653786
Observations	19						
					opt deg	1	
ANOVA				Alpha	0,05		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	1	1,58363E+17	1,58E+17	13,73875	0,001752605	yes	
Residual	17	1,95955E+17	1,15E+16				
Total	18	3,54318E+17					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	
Intercept	262051118,7	47378080,12	5,531062	3,66E-05	162092107,2	362010130,2	
Degree 1	16668233,88	4496928,357	3,706582	0,001753	7180544,382	26155923,38	

Source: Prepared by the Author

The R^2 is 0,44 with and adjusted R^2 of 0,41 which shows a weak correlation. The p value is significant to a 0,05 Alpha. The curve in figure 23 describes the regression model.

Figure 23: Gap x Average TBO curve



Source: Prepared by the Author

In order to find a curve that best fits for smaller numbers of gap, another linear regression was made up to 7 days of gap and the results are in table 11.

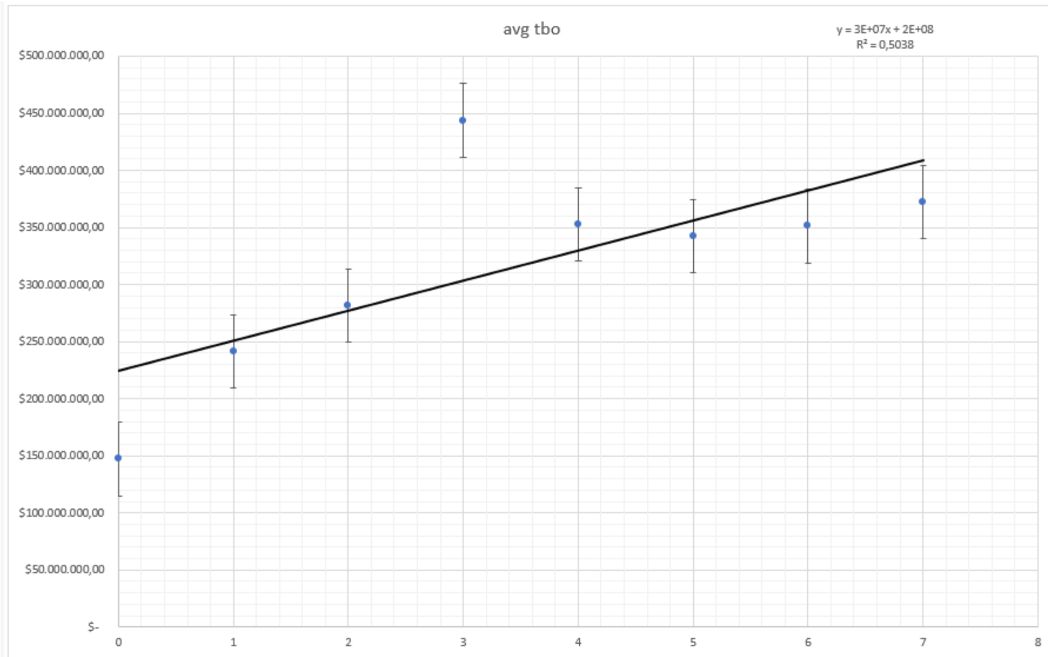
Table 11: Gap Polynomial Regression of TBO for 7 days

Polynomial Regression			7 days				
			tbo				
OVERALL FIT					*degree*	*R-square*	*p-value*
Multiple R	0,709797478		AIC	290,5505	1	0,503812459	
R Square	0,503812459		AICc	296,5505	2	0,774710675	0,057795172
Adjusted R Sq	0,421114536		SBC	290,7094	3	0,824786661	0,345207288
Standard Erro	69251111,88				4	0,866970304	0,401323061
Observations	8						
					opt deg	1	
ANOVA				Alpha	0,05		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	1	2,92165E+16	2,92E+16	6,092202	0,048573585	yes	
Residual	6	2,87743E+16	4,8E+15				
Total	7	5,79908E+16					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	
Intercept	224253649,2	44701400,5	5,016703	0,002412	114873262,6	333634035,9	
Degree 1	26374804,84	10685678,55	2,468239	0,048574	227891,355	52521718,33	

Source: Prepared by the Author

The R^2 is 0,50 with and adjusted R^2 of 0,42 which shows a weak correlation, however just a little better than the previous one. The p value is significant to a 0,05 Alpha. The curve in figure 24 describes the regression model.

Figure 24: Gap x Average TBO curve for 7 days



Source: Prepared by the Author

The last regression was a linear one for gap x budget. The R^2 is a little under moderate, with 0,46 and adjusted to 0,43. The p-value is significant to a 0,05 Alpha. As seen in table 12.

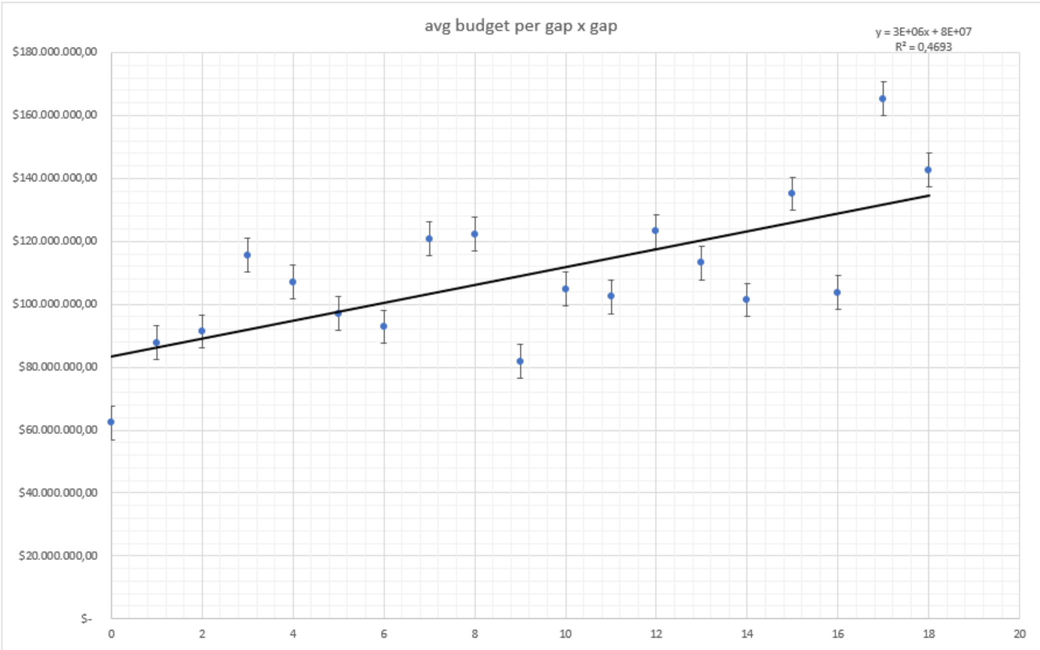
Table 12: Gap Polynomial Regression for Average Budget

OVERALL FIT								
Multiple R	0,685024		AIC	635,6213		*degree*	*R-square*	*p-value*
R Square	0,469257		AICc	637,2213		1	0,469257	
Adjusted R Square	0,438037		SBC	637,5102				
Standard Error	17491510					opt deg	1	
Observations	19							
ANOVA				Alpha	0,05			
	df	*SS*	*MS*	*F*	*p-value*	*sig*		
Regression	1	4,6E+15	4,6E+15	15,03058	0,001211	yes		
Residual	17	5,2E+15	3,06E+14					
Total	18	9,8E+15						
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*		
Intercept	83416832	7718828	10,80693	4,91E-09	67131529	99702136		
Degree 1	2840389	732638,7	3,87693	0,001211	1294656	4386121		

Source: Prepared by the Author

The curve in figure 25 describes the regression model. A regression model with gap ranging from 0 to 9 days was atempted, but the p-value was found no to be significative for a 0,05 Alpha.

Figure 25: Gap x Average Budget curve



Source: Prepared by the Author

4 Final Considerations

4.1 What could be inferred

4.1.1 About How Variables Relate do TBO

One purpose of this research was to determine which factors, if any, contribute to the financial success of movies. Using stepwise multiple regression model, several variables tested. The model's coefficient of determination, R^2 was at 0,647, overall significant.

The most significant contributor to box office revenue was found to be budget. The model implied that higher budgets would lead to higher TBO. This result was consistent with three studies, (Litman B. , 1983),(Ravid 1999), (Terry, Butler, & De'Armond, 2005).

Only one study showed no evidence of a positive relationship between budget and TBO (De Vany & Walls,1999) As expected, there were certain anomalies though, since some low budget films performed very well at the box office. These movies are mainly represented as the ones with highest ROI (%) in the sample and are identifiable in the ROI boxplot.

Different from the results found by other authors, a release by a major studio had no relationship with revenue. Only one other study (Litman B. , 1983) focused on this variable and his conclusion was that they correlate positively. The reason why this did not happen with this sample might be related to the fact that the 20 million dollars budget lower limit prevented many smaller studios from entering the analysis, which would reinforce the financial difference between big and small studios.

Studios did not differ much from one another within this sample of higher than 20 million Dollars budget.

Sequel was found to be a positive significant variable to TBO. These findings were consistent with that of (Terry, Butler, & De’Armond, 2005) and (Somburanasin, 2010) who also found a similar result.

No significant relationship between a holiday release and revenue was found. This was contrary to the evidence presented by other researchers.

All the authors reported a positive relationship between critic reviews and revenue. The same happened on this research.

It was concluded that the factors that aggregate to box office success, are films with higher budgets, with positive critic rating, and a sequel to a prior success. These statistical findings have significance corroborated by the literature.

4.1.2 About How Gap Relates to Rating and TBO

In order to find out if gap could relate to rating, it was important to know if rating could be of statistical significance to TBO or ROI, and this proved to be true in this study and is consistent with the finding of previous authors.

Then a correlation matrix was made, and 0,353 Pearson correlation was found between gap and average critic rating. Given that, a detailed analysis was done with gap being independent variable relating to budget, TBO, ROI (%) and critic rating. Linear and polynomial regressions were conducted to verify the significance of this variables.

There was some correlation of gap and the financial variables, especially for smaller values of gap. But there was a remarkable high relation of gap and critic rating, especially for lower gap values.

That being said, there seems to be enough evidence to say that studios do force smaller gaps for movies with lower ratings, and since TBO also carries some significant correlation with rating, it is possible that this is performed so spectators are not able to know if a movie is good or bad before buying a ticket to watch on premiere date. And is interesting for the studio not to have a negative review on display for many days bringing bad publicity to its film.

4.2 Suggestion of Future Works

Could be interesting to get to know the actual budget of a movie including cost of marketing, advertising, etc. However complete production cost data is hard to obtain. This study could be redone using income data beyond ticket sales, (e.g. deriving from physical media such as DVD sales, Blu-Ray sales and rentals, digital downloads, cable and satellite television and merchandising). This supplementary data is also extremely hard to obtain. Finally, incorporating revenue that could not be earned because of piracy may add a further dimension to studies regarding film investment.

It would be noteworthy to see if there were more movies in the sample by lowering the minimum budget stablished it would result in much different results, especially for how gap correlates to the other variables. Other variables could be considered as well such as 3D vs 2D or runtime of a movie and it’s TBO or ROI (%), since a movie of longer runtime can be screened less times during a day, thus generating less revenue.

It is hard to know how the movie industry is going to generate revenue after the COVID-19 pandemic and how it affected streaming, V.O.D. and the movie theatres. It seems like the future for movies is in constant change and there is a lot to be observe right know so conclusions can be drawn and new researches can be proposed in the future.

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Appendix

Appendix A: Movies Released in 2014

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$)	US box office	International box o	total box office	Profit/loss	ROI(%)
Legend of Hercules	lionsgate	0	PG-13	10/01/2014	10/01/2014	0	0	3,7	22	2,36	27,5	$ 70.000.000,00	$ 18.848.538,00	$ 42.430.914,00	$ 61.279.452,00	$ -8.720.548,00	-12%
The Nut Job	open road	0	PG	17/01/2014	11/01/2014	1	6	5,3	37	4	43,3	$ 42.000.000,00	$ 64.251.541,00	$ 56.633.986,00	$ 120.885.527,00	$ 78.885.527,00	188%
Jack Ryan Shadow Recruit	paramount	0	PG-13	17/01/2014	06/01/2014	1	11	5,8	57	5,65	57,2	$ 60.000.000,00	$ 50.577.412,00	$ 84.926.336,00	$ 135.503.748,00	$ 75.503.748,00	126%
I, Frankenstein	lionsgate	0	PG-13	24/01/2014	24/01/2014	0	0	4,7	30	3,24	36,5	$ 65.000.000,00	$ 19.075.290,00	$ 57.725.889,00	$ 76.801.179,00	$ 11.801.179,00	18%
Vampire Academy	weinstein	0	PG-13	07/02/2014	07/02/2014	0	0	4,4	31	3,4	36,3	$ 30.000.000,00	$ 7.791.979,00	$ 7.850.367,00	$ 15.642.346,00	$ -14.357.654,00	-48%
The Monuments Men	sony	0	PG-13	07/02/2014	29/01/2014	0	9	5,9	52	5,2	54,3	$ 70.000.000,00	$ 78.031.620,00	$ 77.610.030,00	$ 155.641.650,00	$ 85.641.650,00	122%
The lego movie	warner	0	PG	07/02/2014	02/02/2014	0	5	7,2	83	8,15	78,8	$ 60.000.000,00	$ 257.760.692,00	$ 210.300.000,00	$ 468.060.692,00	$ 408.060.692,00	680%
Robocop	sony	0	PG-13	12/02/2014	05/02/2014	1	7	5,9	52	5,62	55,7	$ 100.000.000,00	$ 58.607.007,00	$ 184.081.958,00	$ 242.688.965,00	$ 142.688.965,00	143%
Winter's Tale	warner	0	PG-13	14/02/2014	11/02/2014	1	3	5,2	31	3,55	39,5	$ 60.000.000,00	$ 12.600.231,00	$ 18.200.000,00	$ 30.800.231,00	$ -29.199.769,00	-49%
Pompeii	tristar	0	PG-13	21/02/2014	19/02/2014	1	2	5,3	39	4,38	45,3	$ 100.000.000,00	$ 23.219.748,00	$ 94.611.883,00	$ 117.831.631,00	$ 17.831.631,00	18%
Non-Stop	universal	0	PG-13	28/02/2014	26/02/2014	0	2	6,6	56	5,83	60,1	$ 50.000.000,00	$ 92.168.600,00	$ 130.641.000,00	$ 222.809.600,00	$ 172.809.600,00	346%
300: Rise of na Empire	warner	1	R	07/03/2014	03/03/2014	0	4	5,8	48	4,98	51,9	$ 110.000.000,00	$ 106.580.051,00	$ 231.000.000,00	$ 337.580.051,00	$ 227.580.051,00	207%
Mr Peabody & Sherman	fox	0	PG	07/03/2014	02/02/2014	0	33	6,2	59	6,66	62,5	$ 145.000.000,00	$ 111.506.430,00	$ 164.191.609,00	$ 275.698.039,00	$ 130.698.039,00	90%
Need for speed	disney	0	PG-13	14/03/2014	11/03/2014	0	3	5,6	39	4,31	46,0	$ 66.000.000,00	$ 43.577.636,00	$ 159.700.000,00	$ 203.277.636,00	$ 137.277.636,00	208%
Divergent	lionsgate	0	PG-13	21/03/2014	16/03/2014	0	5	5,9	48	5,42	53,7	$ 85.000.000,00	$ 150.947.895,00	$ 137.937.923,00	$ 288.885.818,00	$ 203.885.818,00	240%
Muppets Most Wanted	disney	1	PG	21/03/2014	11/03/2014	0	10	5,9	61	6,72	62,4	$ 50.000.000,00	$ 51.183.113,00	$ 29.200.000,00	$ 80.383.113,00	$ 30.383.113,00	61%
Sabotage	open road	0	R	28/03/2014	27/03/2014	0	1	5,5	41	4,31	46,4	$ 35.000.000,00	$ 10.508.518,00	$ 11.618.324,00	$ 22.126.842,00	$ -12.873.158,00	-37%
Noah	paramount	0	PG-13	28/03/2014	20/03/2014	0	8	5,6	68	6,66	63,5	$ 125.000.000,00	$ 101.200.044,00	$ 258.000.000,00	$ 359.200.044,00	$ 234.200.044,00	187%
Captain America: The Winter Soldier	disney	1	PG-13	04/04/2014	20/03/2014	0	15	7,5	70	7,62	73,7	$ 170.000.000,00	$ 259.766.572,00	$ 454.654.931,00	$ 714.421.503,00	$ 544.421.503,00	320%
Rio 2	fox	1	G	11/04/2014	26/03/2014	0	16	5,7	49	5,43	53,4	$ 103.000.000,00	$ 131.538.435,00	$ 367.242.682,00	$ 498.781.117,00	$ 395.781.117,00	384%
Draft Day	lionsgate	0	PG-13	11/04/2014	10/04/2014	0	1	6,3	54	5,85	58,5	$ 25.000.000,00	$ 28.842.237,00	$ 981.962,00	$ 29.824.199,00	$ 4.824.199,00	19%
Transcendence	warner	0	PG-13	18/04/2014	15/04/2014	0	3	5,6	42	4,61	48,0	$ 100.000.000,00	$ 23.022.309,00	$ 80.016.949,00	$ 103.039.258,00	$ 3.039.258,00	3%
The Other Woman	fox	0	PG-13	25/04/2014	22/04/2014	0	3	5,2	39	4,24	44,5	$ 40.000.000,00	$ 83.911.193,00	$ 112.799.203,00	$ 196.710.396,00	$ 156.710.396,00	392%
The Amazing Spider-man 2	sony	1	PG-13	02/05/2014	08/04/2014	0	24	6,1	53	5,78	57,3	$ 200.000.000,00	$ 202.853.933,00	$ 506.128.390,00	$ 708.982.323,00	$ 508.982.323,00	254%
Legends of Oz: Dorothy's Return	clarius	0	PG	09/05/2014	07/05/2014	0	2	4,6	25	3,47	35,2	$ 70.000.000,00	$ 8.462.347,00	$ 13.293.071,00	$ 21.755.418,00	$ -48.244.582,00	-69%
Million Dollar Arm	disney	0	PG	16/05/2014	30/04/2014	0	16	6,3	56	6,02	59,7	$ 25.000.000,00	$ 36.457.627,00	$ 2.025.828,00	$ 38.483.455,00	$ 13.483.455,00	54%
Godzilla	warner	0	PG-13	16/05/2014	10/05/2014	0	6	6,2	62	6,63	63,4	$ 160.000.000,00	$ 200.676.069,00	$ 324.300.000,00	$ 524.976.069,00	$ 364.976.069,00	228%
X-Men: Days of Future Past	fox	1	PG-13	23/05/2014	12/05/2014	1	11	7,6	75	7,53	75,4	$ 200.000.000,00	$ 233.921.534,00	$ 512.124.166,00	$ 746.045.700,00	$ 546.045.700,00	273%
Maleficent	disney	0	PG	30/05/2014	28/05/2014	1	2	6,5	56	5,72	59,4	$ 180.000.000,00	$ 241.410.378,00	$ 517.000.000,00	$ 758.410.378,00	$ 578.410.378,00	321%
Edge of Tomorrow	warner	0	PG-13	06/06/2014	22/05/2014	0	15	7,5	71	7,49	73,6	$ 178.000.000,00	$ 100.206.256,00	$ 270.335.000,00	$ 370.541.256,00	$ 192.541.256,00	108%
22 Jump Street	sony	1	R	13/06/2014	02/06/2014	0	11	6,4	71	6,97	68,2	$ 50.000.000,00	$ 191.719.337,00	$ 139.614.539,00	$ 331.333.876,00	$ 281.333.876,00	563%
How to Train Your Dragon 2	fox	1	PG	13/06/2014	16/05/2014	0	28	7,2	76	7,74	75,1	$ 145.000.000,00	$ 177.002.924,00	$ 444.534.595,00	$ 621.537.519,00	$ 476.537.519,00	329%
Jersey Boys	warner	0	R	20/06/2014	15/06/2014	0	5	6,3	54	5,9	58,7	$ 40.000.000,00	$ 47.047.013,00	$ 20.600.000,00	$ 67.647.013,00	$ 27.647.013,00	69%
transformers: Age of Extinction	paramount	1	PG-13	27/06/2014	22/05/2014	0	36	5,3	32	3,96	41,5	$ 210.000.000,00	$ 245.439.076,00	$ 858.614.996,00	$ 1.104.054.072,00	$ 894.054.072,00	426%
Dawn of the Planet of the Apes	fox	1	PG-13	11/07/2014	28/06/2014	0	13	7,4	79	7,91	77,4	$ 170.000.000,00	$ 208.545.589,00	$ 502.098.977,00	$ 710.644.566,00	$ 540.644.566,00	318%
Hercules	paramount	0	PG-13	25/07/2014	23/07/2014	0	2	5,8	47	5,37	52,9	$ 100.000.000,00	$ 72.688.614,00	$ 172.131.248,00	$ 244.819.862,00	$ 144.819.862,00	145%
Lucy	universal	0	R	25/07/2014	23/07/2014	0	2	6,3	61	6,06	61,5	$ 40.000.000,00	$ 126.663.600,00	$ 332.200.000,00	$ 458.863.600,00	$ 418.863.600,00	1047%
Get On Up	universal	0	PG-13	01/08/2014	28/07/2014	0	4	5,9	71	6,88	66,3	$ 30.000.000,00	$ 30.703.100,00	$ 2.745.871,00	$ 33.448.971,00	$ 3.448.971,00	11%
Guardians of the Galaxy	disney	0	PG-13	01/08/2014	24/07/2014	0	8	7,7	76	7,81	77,0	$ 170.000.000,00	$ 333.176.600,00	$ 439.600.000,00	$ 772.776.600,00	$ 602.776.600,00	355%
Teenage mutant Ninja Turtles	paramount	0	PG-13	08/08/2014	03/08/2014	0	5	5,3	31	4,16	41,9	$ 125.000.000,00	$ 191.204.754,00	$ 293.800.000,00	$ 485.004.754,00	$ 360.004.754,00	288%
Expendables 3	lionsgate	1	PG-13	15/08/2014	04/08/2014	0	11	5,8	35	4,86	47,2	$ 90.000.000,00	$ 39.322.544,00	$ 175.335.033,00	$ 214.657.577,00	$ 124.657.577,00	139%
Sin City: A Dame to Kill For	dimension	1	R	22/08/2014	20/08/2014	0	2	6,3	46	5,31	54,0	$ 65.000.000,00	$ 13.757.804,00	$ 25.649.812,00	$ 39.407.616,00	$ -25.592.384,00	-39%
Dolphin Tale 2	warner	1	PG	12/09/2014	10/09/2014	0	2	5,6	58	5,88	57,6	$ 36.000.000,00	$ 42.024.533,00	$ 15.800.000,00	$ 57.824.533,00	$ 21.824.533,00	61%
The Maze Runner	fox	0	PG-13	19/09/2014	09/09/2014	0	10	6,2	57	5,9	59,3	$ 34.000.000,00	$ 102.427.862,00	$ 245.891.999,00	$ 348.319.861,00	$ 314.319.861,00	924%
The Equalizer	sony	0	R	26/09/2014	07/09/2014	0	19	6,9	57	5,69	61,0	$ 55.000.000,00	$ 101.530.738,00	$ 90.800.000,00	$ 192.330.738,00	$ 137.330.738,00	250%
The Boxtrolls	focus	0	PG	26/09/2014	30/08/2014	0	27	6,2	61	7,12	64,7	$ 60.000.000,00	$ 50.837.305,00	$ 57.418.465,00	$ 108.255.770,00	$ 48.255.770,00	80%
Gone Girl	fox	0	R	03/10/2014	21/09/2014	0	12	7,7	79	8,01	78,7	$ 61.000.000,00	$ 167.767.189,00	$ 201.563.174,00	$ 369.330.363,00	$ 308.330.363,00	505%
Dracula Untold	universal	0	PG-13	10/10/2014	30/09/2014	1	10	5,7	40	4,46	47,2	$ 70.000.000,00	$ 56.280.355,00	$ 160.843.925,00	$ 217.124.280,00	$ 147.124.280,00	210%
The Judge	warner	0	R	10/10/2014	04/09/2014	1	36	6,9	48	5,59	57,6	$ 50.000.000,00	$ 47.119.388,00	$ 37.300.000,00	$ 84.419.388,00	$ 34.419.388,00	69%
Fury	sony	0	R	17/10/2014	10/10/2014	1	7	6,9	64	6,92	67,4	$ 68.000.000,00	$ 85.817.906,00	$ 126.000.000,00	$ 211.817.906,00	$ 143.817.906,00	211%
John Wick	lionsgate	0	R	24/10/2014	16/10/2014	0	8	7,1	68	6,94	69,5	$ 20.000.000,00	$ 43.037.835,00	$ 42.975.221,00	$ 86.013.056,00	$ 66.013.056,00	330%
Interstellar	paramount	0	PG-13	05/11/2014	27/10/2014	0	9	8	74	7,07	74,9	$ 165.000.000,00	$ 188.020.017,00	$ 489.443.796,00	$ 677.463.813,00	$ 512.463.813,00	311%
Big Hero 6	disney	0	PG	07/11/2014	23/10/2014	0	15	7,3	74	7,35	73,5	$ 165.000.000,00	$ 222.527.828,00	$ 435.300.000,00	$ 657.827.828,00	$ 492.827.828,00	299%
Dumb and Dumber to	universal	1	PG-13	14/11/2014	13/11/2014	1	1	5,2	36	4,32	43,7	$ 40.000.000,00	$ 86.208.010,00	$ 83.629.000,00	$ 169.837.010,00	$ 129.837.010,00	325%
Foxcatcher	sony	0	R	14/11/2014	19/05/2014	1	179	6,7	81	7,89	75,6	$ 24.000.000,00	$ 12.096.300,00	$ 7.110.213,00	$ 19.206.513,00	$ -4.793.487,00	-20%
The Hunger Games: Mockingjay - Part 1	lionsgate	1	PG-13	21/11/2014	10/11/2014	1	11	6,1	64	6,31	62,7	$ 125.000.000,00	$ 337.135.885,00	$ 418.220.826,00	$ 755.356.711,00	$ 630.356.711,00	504%
Penguins of Madagascar	fox	1	PG	26/11/2014	12/11/2014	1	14	6,3	53	6,24	59,5	$ 132.000.000,00	$ 83.850.911,00	$ 289.664.710,00	$ 373.515.621,00	$ 241.515.621,00	183%
Exodus	fox	0	PG-13	12/12/2014	29/11/2014	0	13	5,7	52	4,98	52,9	$ 140.000.000,00	$ 65.014.513,00	$ 203.161.118,00	$ 268.175.631,00	$ 128.175.631,00	92%
The Hobbit: The Battle of the Five Armies	warner	1	PG-13	17/12/2014	01/12/2014	0	16	7,3	59	6,29	65,0	$ 250.000.000,00	$ 255.119.788,00	$ 700.900.000,00	$ 956.019.788,00	$ 706.019.788,00	282%
Seventh son	Universal	0	PG-13	19/12/2014	17/12/2014	0	2	5,1	30	3,73	39,4	$ 95.000.000,00	$ 17.223.265,00	$ 96.955.348,00	$ 114.178.613,00	$ 19.178.613,00	20%
Annie	sony	0	PG	19/12/2014	14/12/2014	0	5	4,1	33	4,47	39,6	$ 65.000.000,00	$ 85.911.262,00	$ 50.942.244,00	$ 136.853.506,00	$ 71.853.506,00	111%
night at the museum 3	fox	1	PG	19/12/2014	12/12/2014	0	7	5,8	47	4,94	51,5	$ 127.000.000,00	$ 113.746.621,00	$ 249.458.014,00	$ 363.204.635,00	$ 236.204.635,00	186%
Into the woods	disney	0	PG	25/12/2014	17/12/2014	1	8	5,5	69	6,55	63,2	$ 50.000.000,00	$ 128.002.372,00	$ 84.900.000,00	$ 212.902.372,00	$ 162.902.372,00	326%
American sniper	warner	0	R	25/12/2014	11/11/2014	1	44	6,9	72	6,88	69,9	$ 58.000.000,00	$ 350.126.372,00	$ 197.300.000,00	$ 547.426.372,00	$ 489.426.372,00	844%

Appendix B: Movies Released in 2015

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$)	US box office	International box o	total box office	Profit/loss	ROI(%)
Taken 3	fox	1	PG-13	09/01/2015	31/12/2014	0	9	5,7	26	3,61	39,7	$ 48.000.000,00	$ 89.256.424,00	$ 237.222.717,00	$ 326.479.141,00	$ 278.479.141,00	580%
Blackhat	universal	0	R	16/01/2015	13/01/2015	1	3	5	51	4,79	49,6	$ 70.000.000,00	$ 8.005.980,00	$ 11.646.077,00	$ 19.652.057,00	$ -50.347.943,00	-72%
Paddington	dimension	0	PG	16/01/2015	19/11/2014	1	58	6,7	77	7,88	74,3	$ 55.000.000,00	$ 76.271.832,00	$ 206.098.303,00	$ 282.370.135,00	$ 227.370.135,00	413%
Mortdecai	lionsgate	0	R	23/01/2015	22/01/2015	1	1	4,7	27	3,43	36,1	$ 60.000.000,00	$ 7.696.134,00	$ 96.955.348,00	$ 104.651.482,00	$ 44.651.482,00	74%
jupiter ascending	warner	0	PG-13	06/02/2015	03/02/2015	0	3	5	40	4,41	44,7	$ 176.000.000,00	$ 47.387.723,00	$ 96.955.348,00	$ 144.343.071,00	$ -31.656.929,00	-18%
Fifty shades of grey	universal	0	R	13/02/2015	11/02/2015	1	2	3,7	46	4,16	41,5	$ 40.000.000,00	$ 166.167.230,00	$ 403.484.237,00	$ 569.651.467,00	$ 529.651.467,00	1324%
Chappie	sony	0	R	06/03/2015	04/03/2015	0	2	6,2	41	4,9	50,7	$ 49.000.000,00	$ 31.569.268,00	$ 71.242.621,00	$ 102.811.889,00	$ 53.811.889,00	110%
Cinderella	disney	0	PG	13/03/2015	13/02/2015	0	28	6,3	67	7,16	67,2	$ 95.000.000,00	$ 201.151.353,00	$ 341.200.000,00	$ 542.351.353,00	$ 447.351.353,00	471%
Insurgent	lionsgate	1	PG-13	20/03/2015	11/03/2015	0	9	5,5	42	5,01	49,0	$ 110.000.000,00	$ 130.179.072,00	$ 166.823.455,00	$ 297.002.527,00	$ 187.002.527,00	170%
Home	fox	0	PG	27/03/2015	07/03/2015	0	20	5,8	55	5,43	55,8	$ 135.000.000,00	$ 177.397.510,00	$ 208.644.097,00	$ 386.041.607,00	$ 251.041.607,00	186%
Furious 7	universal	1	PG-13	03/04/2015	23/03/2015	0	11	6,3	67	6,7	65,7	$ 190.000.000,00	$ 353.007.020,00	$ 1.162.040.651,00	$ 1.515.047.671,00	$ 1.325.047.671,00	697%
the longest ride	fox	0	PG-13	10/04/2015	06/04/2015	0	4	5,8	33	4,37	44,9	$ 34.000.000,00	$ 37.446.117,00	$ 25.498.698,00	$ 62.944.815,00	$ 28.944.815,00	85%
the age of adaline	lionsgate	0	PG-13	24/04/2015	21/04/2015	0	3	6,4	51	5,52	56,7	$ 25.000.000,00	$ 42.629.776,00	$ 23.033.500,00	$ 65.663.276,00	$ 40.663.276,00	163%
Avengers: Age of Ultron	disney	1	PG-13	01/05/2015	21/04/2015	0	10	7	66	6,75	67,8	$ 250.000.000,00	$ 459.005.868,00	$ 943.800.000,00	$ 1.402.805.868,00	$ 1.152.805.868,00	461%
Hot pursuit	warner	0	PG-13	08/05/2015	05/05/2015	0	3	4,6	31	3,17	36,2	$ 35.000.000,00	$ 34.580.201,00	$ 16.800.000,00	$ 51.380.201,00	$ 16.380.201,00	47%
pitch perfect 2	universal	1	PG-13	15/05/2015	04/05/2015	0	11	5,5	63	6,02	59,4	$ 29.000.000,00	$ 184.296.230,00	$ 102.847.849,00	$ 287.144.079,00	$ 258.144.079,00	890%
mad max:fury road	warner	1	R	15/05/2015	11/05/2015	0	4	7,9	90	8,59	85,0	$ 150.000.000,00	$ 153.636.354,00	$ 221.100.000,00	$ 374.736.354,00	$ 224.736.354,00	150%
Poltergeist	fox	0	PG-13	22/05/2015	19/05/2015	1	3	4,8	47	4,81	47,7	$ 35.000.000,00	$ 47.425.135,00	$ 48.012.869,00	$ 95.438.004,00	$ 60.438.004,00	173%
Tomorrowland	disney	0	PG	22/05/2015	17/05/2015	1	5	6	60	5,9	59,7	$ 190.000.000,00	$ 93.436.322,00	$ 96.955.348,00	$ 190.391.670,00	$ 391.670,00	0%
san andreas	warner	0	PG-13	29/05/2015	26/05/2015	1	3	5,8	43	5,24	51,1	$ 110.000.000,00	$ 155.190.832,00	$ 318.800.000,00	$ 473.990.832,00	$ 363.990.832,00	331%
Spy!	fox	0	R	05/06/2015	16/03/2015	0	81	6,4	75	7,27	70,6	$ 65.000.000,00	$ 110.825.712,00	$ 124.840.507,00	$ 235.666.219,00	$ 170.666.219,00	263%
Jurassic World	universal	1	PG-13	12/06/2015	10/06/2015	0	2	6,8	59	6,65	64,5	$ 150.000.000,00	$ 652.270.625,00	$ 96.955.348,00	$ 749.225.973,00	$ 599.225.973,00	399%
Inside Out	pixar	0	PG	19/06/2015	18/05/2015	0	32	7,6	94	8,93	86,4	$ 175.000.000,00	$ 356.461.711,00	$ 501.149.463,00	$ 857.611.174,00	$ 682.611.174,00	390%
Ted 2	universal	1	R	26/06/2015	24/06/2015	0	2	5,9	48	5,26	53,2	$ 68.000.000,00	$ 81.476.385,00	$ 134.387.221,00	$ 215.863.606,00	$ 147.863.606,00	217%
terminator genisys	paramount	1	PG-13	01/07/2015	24/06/2015	1	7	6	38	4,74	48,5	$ 155.000.000,00	$ 89.760.956,00	$ 350.842.581,00	$ 440.603.537,00	$ 285.603.537,00	184%
Minions	universal	1	PG	10/07/2015	18/06/2015	0	22	6,2	56	5,74	58,5	$ 74.000.000,00	$ 336.045.770,00	$ 96.955.348,00	$ 433.001.118,00	$ 359.001.118,00	485%
ant-man	disney	1	PG-13	17/07/2015	08/07/2015	0	9	7,1	64	6,9	68,0	$ 130.000.000,00	$ 180.202.163,00	$ 339.109.802,00	$ 519.311.965,00	$ 389.311.965,00	299%
Pixels	sony	0	PG-13	24/07/2015	22/07/2015	0	2	5,3	27	3,85	39,5	$ 88.000.000,00	$ 78.747.585,00	$ 166.127.224,00	$ 244.874.809,00	$ 156.874.809,00	178%
southpaw	weinstein	0	R	24/07/2015	17/06/2015	0	37	6,6	57	6,02	61,1	$ 30.000.000,00	$ 52.421.953,00	$ 39.548.874,00	$ 91.970.827,00	$ 61.970.827,00	207%
Mission: Impossible - Rogue Nation	paramount	1	PG-13	31/07/2015	24/07/2015	0	7	7,2	75	7,48	73,9	$ 150.000.000,00	$ 195.042.377,00	$ 487.671.890,00	$ 682.714.267,00	$ 532.714.267,00	355%
fantastic four	fox	0	PG-13	07/08/2015	04/08/2015	0	3	4,3	27	3,46	34,9	$ 120.000.000,00	$ 56.117.548,00	$ 96.955.348,00	$ 153.072.896,00	$ 33.072.896,00	28%
The man from uncle	warner	0	PG-13	14/08/2015	10/08/2015	0	4	6,6	56	6,17	61,2	$ 75.000.000,00	$ 45.445.109,00	$ 61.600.000,00	$ 107.045.109,00	$ 32.045.109,00	43%
Maze runner scorch trials	fox	1	PG-13	18/09/2015	07/09/2015	0	11	5,6	43	5,41	51,0	$ 61.000.000,00	$ 81.697.192,00	$ 230.598.864,00	$ 312.296.056,00	$ 251.296.056,00	412%
Everest	universal	0	PG-13	18/09/2015	02/09/2015	0	16	6,6	64	6,68	65,6	$ 55.000.000,00	$ 43.482.270,00	$ 159.945.314,00	$ 203.427.584,00	$ 148.427.584,00	270%
Black mass	warner	0	R	18/09/2015	04/09/2015	0	14	6,6	68	6,69	67,0	$ 53.000.000,00	$ 62.575.678,00	$ 37.200.000,00	$ 99.775.678,00	$ 46.775.678,00	88%
sicario	lionsgate	0	R	18/09/2015	19/05/2015	0	122	7,3	82	8,07	78,6	$ 30.000.000,00	$ 46.889.293,00	$ 37.983.151,00	$ 84.872.444,00	$ 54.872.444,00	183%
Hotel transylvania 2	sony	1	PG	25/09/2015	22/09/2015	0	3	6,2	44	5,24	52,8	$ 80.000.000,00	$ 169.700.110,00	$ 305.099.890,00	$ 474.800.000,00	$ 394.800.000,00	494%
The intern	warner	0	PG-13	25/09/2015	21/09/2015	0	4	6,5	51	5,76	57,9	$ 35.000.000,00	$ 75.764.672,00	$ 118.800.000,00	$ 194.564.672,00	$ 159.564.672,00	456%
the martian	fox	0	PG-13	02/10/2015	22/09/2015	0	10	7,8	80	7,85	78,8	$ 108.000.000,00	$ 228.433.663,00	$ 401.728.227,00	$ 630.161.890,00	$ 522.161.890,00	483%
pan	warner	0	PG	09/10/2015	05/10/2015	1	4	5,1	36	4,56	44,2	$ 150.000.000,00	$ 35.088.320,00	$ 96.955.348,00	$ 132.043.668,00	$ -17.956.332,00	-12%
Goosebumps	sony	0	PG	16/10/2015	05/10/2015	1	11	6	60	6,39	61,3	$ 58.000.000,00	$ 80.080.379,00	$ 78.180.573,00	$ 158.260.952,00	$ 100.260.952,00	173%
Bridge of spies	disney	0	PG-13	16/10/2015	04/10/2015	1	12	7,4	81	7,68	77,3	$ 40.000.000,00	$ 72.313.754,00	$ 96.955.348,00	$ 169.269.102,00	$ 129.269.102,00	323%
the last witch hunter	lionsgate	0	PG-13	23/10/2015	19/10/2015	0	4	5,4	34	3,82	42,1	$ 90.000.000,00	$ 27.367.660,00	$ 96.955.348,00	$ 124.323.008,00	$ 34.323.008,00	38%
Spectre	sony	1	PG-13	06/11/2015	21/10/2015	0	16	6,7	60	6,42	63,7	$ 245.000.000,00	$ 200.074.609,00	$ 680.600.000,00	$ 880.674.609,00	$ 635.674.609,00	259%
Peanuts movie	fox	0	G	06/11/2015	02/11/2015	0	4	6,6	67	7,06	67,9	$ 99.000.000,00	$ 130.178.411,00	$ 116.054.702,00	$ 246.233.113,00	$ 147.233.113,00	149%
The Hunger Games: Mockingjay - Part 2	lionsgate	1	PG-13	20/11/2015	18/11/2015	0	2	6	65	6,5	63,3	$ 160.000.000,00	$ 281.723.902,00	$ 376.620.235,00	$ 658.344.137,00	$ 498.344.137,00	311%
The Good Dinosaur	pixar	0	PG	25/11/2015	13/11/2015	0	12	6,2	66	6,59	64,6	$ 175.000.000,00	$ 123.087.120,00	$ 209.120.551,00	$ 332.207.671,00	$ 157.207.671,00	90%
Victor Frankenstein	fox	0	PG-13	27/11/2015	24/11/2015	0	3	5,6	36	4,68	46,3	$ 40.000.000,00	$ 5.775.076,00	$ 28.452.222,00	$ 34.227.298,00	$ -5.772.702,00	-14%
Creed	warner	1	PG-13	27/11/2015	18/11/2015	0	9	7,1	82	7,97	77,6	$ 37.000.000,00	$ 109.767.581,00	$ 63.800.000,00	$ 173.567.581,00	$ 136.567.581,00	369%
In The Heart Of The Sea	warner	0	PG-13	11/12/2015	02/12/2015	0	9	6,4	47	5,5	55,3	$ 100.000.000,00	$ 25.020.758,00	$ 68.900.000,00	$ 93.920.758,00	$ -6.079.242,00	-6%
Macbeth	weinstein	0	PG-13	11/12/2015	23/05/2015	0	202	6	71	7,2	67,7	$ 20.000.000,00	$ 1.110.707,00	$ 15.211.360,00	$ 16.322.067,00	$ -3.677.933,00	-18%
Alvin and the Chipmunks: The Road Chip	fox	1	PG	18/12/2015	16/12/2015	0	2	4,3	33	3,42	36,7	$ 90.000.000,00	$ 85.886.987,00	$ 148.911.649,00	$ 234.798.636,00	$ 144.798.636,00	161%
sisters	universal	0	R	18/12/2015	10/12/2015	0	8	5,4	58	5,9	57,0	$ 30.000.000,00	$ 87.044.645,00	$ 17.966.408,00	$ 105.011.053,00	$ 75.011.053,00	250%
Star Wars: The Force Awakens	disney	1	PG-13	18/12/2015	16/12/2015	0	2	7,5	80	8,27	79,2	$ 245.000.000,00	$ 936.662.225,00	$ 1.131.561.399,00	$ 2.068.223.624,00	$ 1.823.223.624,00	744%
point break	warner	0	PG-13	25/12/2015	03/12/2015	1	22	4,7	34	3,64	39,1	$ 105.000.000,00	$ 28.782.481,00	$ 104.936.230,00	$ 133.718.711,00	$ 28.718.711,00	27%
Daddy's Home	paramount	0	PG-13	25/12/2015	22/12/2015	1	3	5,7	42	4,88	49,3	$ 50.000.000,00	$ 150.357.137,00	$ 92.429.000,00	$ 242.786.137,00	$ 192.786.137,00	386%
The hateful 8	weinstein	0	R	25/12/2015	15/12/2015	1	10	7,5	68	7,33	72,1	$ 44.000.000,00	$ 54.117.416,00	$ 101.642.701,00	$ 155.760.117,00	$ 111.760.117,00	254%

Appendix C: Movies Released in 2016

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$)	US box office	International box o	total box office	Profit/loss	ROI(%)
the revenant	fox	0	R	08/01/2016	04/12/2015	0	35	7,7	76	7,85	77,2	$ 135.000.000,00	$ 183.637.894,00	$ 349.312.609,00	$ 532.950.503,00	$ 397.950.503,00	295%
13 Hours: The Secret Soldiers Of Benghazi	paramount	0	R	15/01/2016	13/01/2016	1	2	6,6	48	5,5	56,3	$ 50.000.000,00	$ 52.853.219,00	$ 16.558.151,00	$ 69.411.370,00	$ 19.411.370,00	39%
the finest hours	disney	0	PG-13	29/01/2016	18/01/2016	0	11	6,2	58	6	60,0	$ 80.000.000,00	$ 27.569.558,00	$ 24.529.532,00	$ 52.099.090,00	$ -27.900.910,00	-35%
kung fu panda 3	fox	1	PG	29/01/2016	16/01/2016	0	13	6,6	66	6,92	67,1	$ 145.000.000,00	$ 143.528.619,00	$ 377.642.206,00	$ 521.170.825,00	$ 376.170.825,00	259%
How to be single	warner	0	R	12/02/2016	10/02/2016	1	2	5,1	51	5,23	51,4	$ 38.000.000,00	$ 46.843.513,00	$ 65.600.000,00	$ 112.443.513,00	$ 74.443.513,00	196%
Deadpool	fox	0	R	12/02/2016	07/02/2016	1	5	7,4	65	7,03	69,8	$ 58.000.000,00	$ 363.070.709,00	$ 419.541.446,00	$ 782.612.155,00	$ 724.612.155,00	1249%
gods of egypt	lionsgate	0	PG-13	26/02/2016	25/02/2016	0	1	5	25	3,4	36,3	$ 140.000.000,00	$ 31.153.464,00	$ 119.527.400,00	$ 150.680.864,00	$ 10.680.864,00	8%
London has fallen	focus	1	R	04/03/2016	02/03/2016	0	2	5,7	28	3,98	41,6	$ 60.000.000,00	$ 62.524.260,00	$ 143.230.187,00	$ 205.754.447,00	$ 145.754.447,00	243%
Zootopia	disney	0	PG	04/03/2016	12/02/2016	0	21	7,7	78	8,08	78,6	$ 150.000.000,00	$ 341.268.248,00	$ 682.515.947,00	$ 1.023.784.195,00	$ 873.784.195,00	583%
Allegiant	lionsgate	1	PG-13	18/03/2016	07/03/2016	0	11	5	33	4,09	41,3	$ 110.000.000,00	$ 66.184.051,00	$ 113.062.817,00	$ 179.246.868,00	$ 69.246.868,00	63%
Batman v Superman: Dawn of Justice	warner	1	PG-13	25/03/2016	22/03/2016	0	3	6	44	4,94	51,1	$ 250.000.000,00	$ 330.360.194,00	$ 543.274.725,00	$ 873.634.919,00	$ 623.634.919,00	249%
The Jungle Book	disney	0	PG	15/04/2016	03/04/2016	0	12	7,1	77	7,73	75,1	$ 175.000.000,00	$ 364.001.123,00	$ 602.549.477,00	$ 966.550.600,00	$ 791.550.600,00	452%
The Huntsman: Winter's War	universal	1	PG-13	22/04/2016	04/04/2016	0	18	5,5	35	4,26	44,2	$ 115.000.000,00	$ 48.390.190,00	$ 116.599.148,00	$ 164.989.338,00	$ 49.989.338,00	43%
Captain America: Civil War	disney	1	PG-13	06/05/2016	13/04/2016	0	23	7,5	75	7,72	75,7	$ 250.000.000,00	$ 408.084.349,00	$ 745.211.944,00	$ 1.153.296.293,00	$ 903.296.293,00	361%
Angry birds	sony	0	PG	20/05/2016	07/05/2016	0	13	5,6	43	4,94	49,5	$ 73.000.000,00	$ 107.509.366,00	$ 244.824.563,00	$ 352.333.929,00	$ 279.333.929,00	383%
Neighbors 2: Sorority Rising	universal	1	R	20/05/2016	04/05/2016	0	16	5,1	58	5,74	55,5	$ 35.000.000,00	$ 55.455.765,00	$ 52.551.344,00	$ 108.007.109,00	$ 73.007.109,00	209%
The nice guys	warner	0	R	20/05/2016	15/05/2016	0	5	7	70	7,59	72,0	$ 50.000.000,00	$ 36.261.763,00	$ 26.526.455,00	$ 62.788.218,00	$ 12.788.218,00	26%
warcraft	universal	0	PG-13	27/05/2016	24/05/2016	1	3	5,9	32	4,23	44,4	$ 160.000.000,00	$ 47.365.290,00	$ 391.683.624,00	$ 439.048.914,00	$ 279.048.914,00	174%
Alice Through The Looking Glass	disney	1	PG	27/05/2016	10/05/2016	1	17	5,6	34	4,56	45,2	$ 170.000.000,00	$ 77.041.381,00	$ 222.415.643,00	$ 299.457.024,00	$ 129.457.024,00	76%
x-men: apocalypse	fox	1	PG-13	27/05/2016	09/05/2016	1	18	6,6	52	5,65	58,2	$ 178.000.000,00	$ 155.442.489,00	$ 388.491.616,00	$ 543.934.105,00	$ 365.934.105,00	206%
Teenage Mutant Ninja Turtles: Out of the Shadows	paramount	1	PG-13	03/06/2016	02/06/2016	0	1	5,4	40	4,7	47,0	$ 135.000.000,00	$ 82.051.601,00	$ 163.572.247,00	$ 245.623.848,00	$ 110.623.848,00	82%
Now You See Me 2	lionsgate	1	PG-13	10/06/2016	01/06/2016	0	9	5,9	46	4,85	51,2	$ 75.000.000,00	$ 65.075.540,00	$ 269.822.066,00	$ 334.897.606,00	$ 259.897.606,00	347%
Central intelligence	warner	0	PG-13	17/06/2016	15/06/2016	0	2	5,9	52	5,76	56,2	$ 50.000.000,00	$ 127.440.871,00	$ 89.531.672,00	$ 216.972.543,00	$ 166.972.543,00	334%
Finding Dory	pixar	1	PG	17/06/2016	10/06/2016	0	7	6,9	77	7,65	74,2	$ 200.000.000,00	$ 486.295.561,00	$ 542.275.328,00	$ 1.028.570.889,00	$ 828.570.889,00	414%
independence day resurgence	fox	1	PG-13	28/06/2016	21/06/2016	0	7	4,9	32	4,26	41,2	$ 165.000.000,00	$ 103.144.286,00	$ 286.537.649,00	$ 389.681.935,00	$ 224.681.935,00	136%
the legend of tarzan	lionsgate	0	PG-13	01/07/2016	29/06/2016	1	2	5,7	44	5,07	50,6	$ 180.000.000,00	$ 126.643.061,00	$ 230.057.296,00	$ 356.700.357,00	$ 176.700.357,00	98%
the bfg	disney	0	PG	01/07/2016	15/05/2016	1	47	6	66	6,78	64,6	$ 140.000.000,00	$ 55.483.770,00	$ 139.759.641,00	$ 195.243.411,00	$ 55.243.411,00	39%
The Secret Life of Pets	universal	0	PG	08/07/2016	16/06/2016	0	22	6,3	61	6,27	62,2	$ 75.000.000,00	$ 368.384.330,00	$ 507.073.607,00	$ 875.457.937,00	$ 800.457.937,00	1067%
Ghostbusters	sony	0	PG-13	15/07/2016	10/07/2016	0	5	4,9	60	6,49	58,0	$ 144.000.000,00	$ 128.350.574,00	$ 100.796.935,00	$ 229.147.509,00	$ 85.147.509,00	59%
star trek beyond	paramount	1	PG-13	22/07/2016	15/07/2016	0	7	6,7	68	7,03	68,4	$ 185.000.000,00	$ 158.848.340,00	$ 184.623.476,00	$ 343.471.816,00	$ 158.471.816,00	86%
jason bourne	universal	1	PG-13	29/07/2016	25/07/2016	0	4	6,3	58	5,83	59,8	$ 120.000.000,00	$ 162.434.410,00	$ 253.050.504,00	$ 415.484.914,00	$ 295.484.914,00	246%
Suicide Squad	warner	0	PG-13	05/08/2016	02/08/2016	0	3	5,7	40	4,8	48,3	$ 175.000.000,00	$ 325.100.054,00	$ 421.746.840,00	$ 746.846.894,00	$ 571.846.894,00	327%
Ben-Hur	paramount	0	PG-13	19/08/2016	17/08/2016	0	2	4,9	38	4,57	44,2	$ 100.000.000,00	$ 26.410.477,00	$ 67.650.834,00	$ 94.061.311,00	$ -5.938.689,00	-6%
Wardogs	warner	0	R	19/08/2016	16/08/2016	0	3	6,5	57	6,06	60,9	$ 50.000.000,00	$ 43.034.523,00	$ 43.200.000,00	$ 86.234.523,00	$ 36.234.523,00	72%
Kubo and the two strings	focus	0	PG	19/08/2016	09/08/2016	0	10	7	84	8,4	79,3	$ 60.000.000,00	$ 48.023.088,00	$ 28.226.350,00	$ 76.249.438,00	$ 16.249.438,00	27%
Sully	warner	0	PG-13	09/09/2016	02/09/2016	1	7	7,2	74	7,22	72,7	$ 60.000.000,00	$ 125.070.033,00	$ 115.727.590,00	$ 240.797.623,00	$ 180.797.623,00	301%
Bridget Jones's Baby	universal	1	R	16/09/2016	05/09/2016	0	11	5,5	59	6,33	59,1	$ 35.000.000,00	$ 24.252.420,00	$ 187.700.000,00	$ 211.952.420,00	$ 176.952.420,00	506%
the Magnificent seven	sony	0	PG-13	23/09/2016	08/09/2016	0	15	6,5	54	6,03	59,8	$ 90.000.000,00	$ 93.432.655,00	$ 68.927.981,00	$ 162.360.636,00	$ 72.360.636,00	80%
deepwater horizon	lionsgate	0	PG-13	30/09/2016	13/09/2016	0	17	6,9	68	6,97	68,9	$ 156.000.000,00	$ 614.333.527,00	$ 60.356.846,00	$ 674.690.373,00	$ 518.690.373,00	332%
The girl on the train	universal	0	R	07/10/2016	03/10/2016	1	4	5,9	48	5,3	53,3	$ 45.000.000,00	$ 75.395.035,00	$ 97.790.824,00	$ 173.185.859,00	$ 128.185.859,00	285%
Jack Reacher: Never Go Back	paramount	1	PG-13	21/10/2016	19/10/2016	0	2	5,9	47	5,14	52,5	$ 60.000.000,00	$ 58.697.076,00	$ 103.449.000,00	$ 162.146.076,00	$ 102.146.076,00	170%
Trolls	fox	0	PG	04/11/2016	08/10/2016	0	27	5,6	55	6,28	57,9	$ 125.000.000,00	$ 153.707.064,00	$ 193.157.398,00	$ 346.864.462,00	$ 221.864.462,00	177%
doctor strange	disney	0	PG-13	04/11/2016	23/10/2016	0	12	7,1	72	7,3	72,0	$ 165.000.000,00	$ 232.641.920,00	$ 445.076.475,00	$ 677.718.395,00	$ 512.718.395,00	311%
Hacksaw ridge	lionsgate	0	R	04/11/2016	04/09/2016	0	61	7,7	71	7,25	73,5	$ 40.000.000,00	$ 67.209.615,00	$ 113.241.303,00	$ 180.450.918,00	$ 140.450.918,00	351%
Arrival	paramount	0	PG-13	11/11/2016	04/09/2016	1	68	7,3	81	8,41	79,4	$ 47.000.000,00	$ 100.546.139,00	$ 102.842.047,00	$ 203.388.186,00	$ 156.388.186,00	333%
Fantastic Beasts and Where to Find Them	warner	1	PG-13	18/11/2016	12/11/2016	0	6	6,8	66	6,82	67,4	$ 180.000.000,00	$ 234.037.575,00	$ 580.000.000,00	$ 814.037.575,00	$ 634.037.575,00	352%
Allied	paramount	0	R	23/11/2016	21/11/2016	1	2	6,3	60	6,17	61,6	$ 85.000.000,00	$ 40.098.064,00	$ 79.421.959,00	$ 119.520.023,00	$ 34.520.023,00	41%
moana	disney	0	PG	23/11/2016	07/11/2016	1	16	7,1	81	7,88	76,9	$ 150.000.000,00	$ 248.757.044,00	$ 394.574.067,00	$ 643.331.111,00	$ 493.331.111,00	329%
Office Christmas Party	paramount	0	R	09/12/2016	07/12/2016	0	2	5,3	42	4,85	47,8	$ 45.000.000,00	$ 54.767.494,00	$ 59.733.805,00	$ 114.501.299,00	$ 69.501.299,00	154%
passengers	columbia	0	PG-13	16/12/2016	15/12/2016	0	1	6,6	41	4,95	52,2	$ 110.000.000,00	$ 100.014.699,00	$ 203.129.453,00	$ 303.144.152,00	$ 193.144.152,00	176%
Rogue One: A Star Wars Story	disney	1	PG-13	16/12/2016	13/12/2016	0	3	7,5	65	7,49	71,6	$ 200.000.000,00	$ 532.177.324,00	$ 523.879.949,00	$ 1.056.057.273,00	$ 856.057.273,00	428%
Assassin's Creed	fox	0	PG-13	23/12/2016	19/12/2016	1	4	5	36	3,96	41,9	$ 125.000.000,00	$ 54.647.948,00	$ 186.049.908,00	$ 240.697.856,00	$ 115.697.856,00	93%
Sing	universal	0	PG	23/12/2016	11/09/2016	1	103	6,5	59	6,5	63,0	$ 75.000.000,00	$ 270.395.425,00	$ 363.756.254,00	$ 634.151.679,00	$ 559.151.679,00	746%

Appendix D: Movies Released in 2017

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$)	US box office	International box o	total box office	Profit/loss	ROI(%)
monster trucks	paramount	0	PG	13/01/2017	09/01/2017	1	4	5	41	4,48	45,3	$ 125.000.000,00	$ 33.370.166,00	$ 31.123.749,00	$ 64.493.915,00	$ -60.506.085,00	-48%
Silence	paramount	0	R	13/01/2017	10/12/2016	1	34	6,6	79	7,5	73,3	$ 40.000.000,00	$ 7.100.177,00	$ 16.734.632,00	$ 23.834.809,00	$ -16.165.191,00	-40%
xXx: Return of Xander Cage	paramount	1	PG-13	20/01/2017	18/01/2017	1	2	5	42	4,83	46,8	$ 85.000.000,00	$ 44.898.413,00	$ 301.219.864,00	$ 346.118.277,00	$ 261.118.277,00	307%
Resident evil the final chapter	sony	1	R	27/01/2017	26/01/2017	0	1	5,4	49	4,47	49,2	$ 40.000.000,00	$ 26.830.068,00	$ 285.412.558,00	$ 312.242.626,00	$ 272.242.626,00	681%
Fifty shades darker	universal	1	R	10/02/2017	09/02/2017	0	1	3,5	33	3,23	33,4	$ 55.000.000,00	$ 114.581.250,00	$ 266.964.596,00	$ 381.545.846,00	$ 326.545.846,00	594%
Lego batman movie	warner	0	PG	10/02/2017	04/02/2017	0	6	6,9	75	7,53	73,1	$ 80.000.000,00	$ 175.750.384,00	$ 136.200.000,00	$ 311.950.384,00	$ 231.950.384,00	290%
John wick 2	lionsgate	1	R	10/02/2017	06/02/2017	0	4	7,2	75	7,32	73,4	$ 40.000.000,00	$ 92.029.184,00	$ 79.510.703,00	$ 171.539.887,00	$ 131.539.887,00	329%
the great wall	universal	0	PG-13	17/02/2017	15/12/2016	1	64	5,6	42	4,91	49,0	$ 150.000.000,00	$ 45.540.830,00	$ 289.393.001,00	$ 334.933.831,00	$ 184.933.831,00	123%
Logan	fox	1	R	03/03/2017	17/02/2017	0	14	7,6	77	7,93	77,4	$ 97.000.000,00	$ 226.277.068,00	$ 392.744.368,00	$ 619.021.436,00	$ 522.021.436,00	538%
kong skull island	warner	0	PG-13	10/03/2017	02/03/2017	0	8	6,6	62	6,53	64,4	$ 185.000.000,00	$ 168.052.812,00	$ 398.600.000,00	$ 566.652.812,00	$ 381.652.812,00	206%
Beauty and the Beast	disney	0	PG	17/03/2017	03/03/2017	0	14	6,4	65	6,69	65,3	$ 160.000.000,00	$ 504.014.165,00	$ 759.506.961,00	$ 1.263.521.126,00	$ 1.103.521.126,00	690%
Power rangers	lionsgate	0	PG-13	24/03/2017	19/03/2017	0	5	5,4	44	5,27	50,2	$ 100.000.000,00	$ 85.364.450,00	$ 56.972.790,00	$ 142.337.240,00	$ 42.337.240,00	42%
Life	sony	0	R	24/03/2017	18/03/2017	0	6	6,3	54	5,97	58,9	$ 58.000.000,00	$ 30.234.022,00	$ 70.307.784,00	$ 100.541.806,00	$ 42.541.806,00	73%
ghost in the shell	paramount	0	PG-13	31/03/2017	28/03/2017	0	3	5,8	52	5,47	54,9	$ 110.000.000,00	$ 40.563.557,00	$ 129.238.364,00	$ 169.801.921,00	$ 59.801.921,00	54%
The Fate of the Furious	universal	1	PG-13	14/04/2017	09/04/2017	0	5	6,1	56	6,14	59,5	$ 250.000.000,00	$ 226.008.385,00	$ 1.009.996.733,00	$ 1.236.005.118,00	$ 986.005.118,00	394%
the promise	open road	0	PG-13	21/04/2017	19/04/2017	0	2	5,4	49	5,66	53,2	$ 90.000.000,00	$ 8.224.288,00	$ 4.224.388,00	$ 12.448.676,00	$ -77.551.324,00	-86%
the lost city of z	bleecker st	0	PG-13	21/04/2017	13/03/2017	0	39	6,3	78	7,35	71,5	$ 30.000.000,00	$ 8.580.410,00	$ 10.683.528,00	$ 19.263.938,00	$ -10.736.062,00	-36%
Guardians of the Galaxy Vol. 2	disney	1	PG-13	05/05/2017	24/04/2017	0	11	7,4	67	7,26	71,2	$ 200.000.000,00	$ 389.813.101,00	$ 473.942.950,00	$ 863.756.051,00	$ 663.756.051,00	332%
King Arthur: Legend of the Sword	warner	0	PG-13	12/05/2017	09/05/2017	0	3	5,8	41	4,69	48,6	$ 175.000.000,00	$ 39.175.066,00	$ 109.500.000,00	$ 148.675.066,00	$ -26.324.934,00	-15%
Alien Covenant	fox	1	R	19/05/2017	06/05/2017	0	13	6,3	65	6,3	63,7	$ 97.000.000,00	$ 74.262.031,00	$ 166.629.732,00	$ 240.891.763,00	$ 143.891.763,00	148%
Baywatch	paramount	0	R	26/05/2017	23/05/2017	1	3	4,9	37	3,95	41,8	$ 69.000.000,00	$ 58.060.186,00	$ 119.796.565,00	$ 177.856.751,00	$ 108.856.751,00	158%
Pirates of the Caribbean: Dead Men Tell No Tales	disney	1	PG-13	26/05/2017	22/05/2017	1	4	6,2	39	4,66	49,2	$ 230.000.000,00	$ 172.558.876,00	$ 622.302.918,00	$ 794.861.794,00	$ 564.861.794,00	246%
Wonder Woman	warner	0	PG-13	02/06/2017	29/05/2017	0	4	7	76	7,65	74,2	$ 149.000.000,00	$ 412.563.408,00	$ 409.283.604,00	$ 821.847.012,00	$ 672.847.012,00	452%
the mummy	universal	0	PG-13	09/06/2017	07/06/2017	0	2	5	34	4,19	42,0	$ 125.000.000,00	$ 80.227.895,00	$ 329.003.712,00	$ 409.231.607,00	$ 284.231.607,00	227%
cars 3	pixar	1	G	16/06/2017	12/06/2017	0	4	6,2	59	6,12	60,7	$ 175.000.000,00	$ 152.901.115,00	$ 231.029.541,00	$ 383.930.656,00	$ 208.930.656,00	119%
transformers the last knight	paramount	1	PG-13	21/06/2017	20/06/2017	0	1	4,7	27	3,2	35,3	$ 217.000.000,00	$ 130.168.683,00	$ 475.256.474,00	$ 605.425.157,00	$ 388.425.157,00	179%
Despicable Me 3	universal	1	PG	30/06/2017	14/06/2017	1	16	6	49	5,69	55,3	$ 80.000.000,00	$ 264.624.300,00	$ 770.175.109,00	$ 1.034.799.409,00	$ 954.799.409,00	1193%
baby driver	tristar	0	R	30/06/2017	05/06/2017	1	25	7,3	86	8,03	79,8	$ 34.000.000,00	$ 107.825.862,00	$ 119.119.225,00	$ 226.945.087,00	$ 192.945.087,00	567%
Spider-Man: Homecoming	sony	1	PG-13	07/07/2017	29/06/2017	1	8	7	73	7,67	73,2	$ 175.000.000,00	$ 334.201.140,00	$ 545.965.784,00	$ 880.166.924,00	$ 705.166.924,00	403%
war for the planet of the apes	fox	1	PG-13	14/07/2017	26/06/2017	0	18	7,2	82	8,18	78,6	$ 150.000.000,00	$ 146.880.162,00	$ 343.839.601,00	$ 490.719.763,00	$ 340.719.763,00	227%
Valerian and the City of a Thousand Planets	stx	0	PG-13	21/07/2017	10/07/2017	0	11	6,1	51	5,52	55,7	$ 177.200.000,00	$ 41.189.488,00	$ 184.648.740,00	$ 225.838.228,00	$ 48.638.228,00	27%
Dunkirk	warner	0	PG-13	21/07/2017	17/07/2017	0	4	7,5	94	8,67	85,2	$ 100.000.000,00	$ 189.740.665,00	$ 337.200.000,00	$ 526.940.665,00	$ 426.940.665,00	427%
Emoji	warner	0	PG	28/07/2017	27/07/2017	0	1	3,1	12	2,67	23,2	$ 50.000.000,00	$ 86.089.513,00	$ 131.687.133,00	$ 217.776.646,00	$ 167.776.646,00	336%
atomic blonde	focus	0	R	28/07/2017	17/07/2017	0	11	6,3	63	6,56	63,9	$ 30.000.000,00	$ 51.687.870,00	$ 48.326.155,00	$ 100.014.025,00	$ 70.014.025,00	233%
Dark tower	sony	0	PG-13	06/08/2017	02/08/2017	0	4	5,1	34	4,13	42,1	$ 60.000.000,00	$ 50.701.325,00	$ 62.529.753,00	$ 113.231.078,00	$ 53.231.078,00	89%
It	warner	0	R	08/09/2017	29/08/2017	1	10	6,9	69	7,24	70,1	$ 35.000.000,00	$ 328.828.874,00	$ 372.967.570,00	$ 701.796.444,00	$ 666.796.444,00	1905%
mother	paramount	0	R	15/09/2017	05/09/2017	0	10	5,8	75	6,83	67,1	$ 30.000.000,00	$ 17.800.004,00	$ 26.716.995,00	$ 44.516.999,00	$ 14.516.999,00	48%
Kingsman: The Golden Circle	fox	1	R	22/09/2017	18/09/2017	0	4	6,4	44	5,36	53,9	$ 104.000.000,00	$ 100.234.838,00	$ 310.667.824,00	$ 410.902.662,00	$ 306.902.662,00	295%
American made	universal	0	R	29/09/2017	17/08/2017	0	43	6,7	65	6,95	67,2	$ 50.000.000,00	$ 51.342.000,00	$ 83.524.593,00	$ 134.866.593,00	$ 84.866.593,00	170%
Blade Runner 2049	warner	1	R	06/10/2017	29/09/2017	0	7	7,4	81	8,24	79,1	$ 150.000.000,00	$ 92.054.159,00	$ 167.185.499,00	$ 259.239.658,00	$ 109.239.658,00	73%
geostorm	sony	0	PG-13	20/10/2017	19/10/2017	0	1	4,8	21	3,62	35,1	$ 120.000.000,00	$ 33.700.160,00	$ 187.900.000,00	$ 221.600.160,00	$ 101.600.160,00	85%
Thor: Ragnarok	disney	1	PG-13	03/11/2017	19/10/2017	0	15	7,4	74	7,58	74,6	$ 180.000.000,00	$ 315.058.289,00	$ 538.918.837,00	$ 853.977.126,00	$ 673.977.126,00	374%
Daddy's Home 2	paramount	1	PG-13	10/11/2017	09/11/2017	1	1	5,4	30	3,93	41,1	$ 70.000.000,00	$ 104.029.443,00	$ 76.583.737,00	$ 180.613.180,00	$ 110.613.180,00	158%
Murder on the orient express	fox	0	PG-13	10/11/2017	02/11/2017	1	8	7,2	52	6,11	61,7	$ 55.000.000,00	$ 102.826.543,00	$ 249.963.268,00	$ 352.789.811,00	$ 297.789.811,00	541%
Justice League	warner	1	PG-13	17/11/2017	15/11/2017	0	2	6	45	5,26	52,5	$ 300.000.000,00	$ 229.024.295,00	$ 428.900.000,00	$ 657.924.295,00	$ 357.924.295,00	119%
coco	pixar	0	PG	22/11/2017	20/10/2017	1	33	7,5	81	8,3	79,7	$ 175.000.000,00	$ 209.726.015,00	$ 597.356.181,00	$ 807.082.196,00	$ 632.082.196,00	361%
the shape of water	fox	0	R	01/12/2017	31/08/2017	0	92	7	87	8,39	80,3	$ 20.000.000,00	$ 63.859.435,00	$ 131.473.877,00	$ 195.333.312,00	$ 175.333.312,00	877%
Star Wars: The Last Jedi	disney	1	PG-13	15/12/2017	12/12/2017	0	3	6,8	85	8,1	78,0	$ 200.000.000,00	$ 620.181.382,00	$ 712.358.507,00	$ 1.332.539.889,00	$ 1.132.539.889,00	566%
the greatest showman	fox	0	PG	20/12/2017	20/12/2017	1	0	6,6	48	6	58,0	$ 84.000.000,00	$ 174.340.174,00	$ 260.653.009,00	$ 434.993.183,00	$ 350.993.183,00	418%
Pitch perfect 3	universal	1	PG-13	22/12/2017	19/12/2017	1	3	4,8	40	4,61	44,7	$ 45.000.000,00	$ 104.897.530,00	$ 80.502.815,00	$ 185.400.345,00	$ 140.400.345,00	312%
Jumanji welcome to the jungle	sony	1	PG-13	22/12/2017	08/12/2017	1	14	6,6	58	6,19	62,0	$ 90.000.000,00	$ 404.540.171,00	$ 557.562.066,00	$ 962.102.237,00	$ 872.102.237,00	969%
All the Money in the World	tristar	0	R	25/12/2017	19/12/2017	1	6	6,5	72	6,96	68,9	$ 50.000.000,00	$ 25.113.707,00	$ 31.882.597,00	$ 56.996.304,00	$ 6.996.304,00	14%

Appendix E: Movies Released in 2018

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$)	US box office	International box o	total box office	Profit/loss	ROI(%)
The commuter	lionsgate	0	PG-13	12/01/2018	29/12/2017	1	14	6,1	56	5,4	57,0	$ 40.000.000,00	$ 36.343.858,00	$ 83.598.529,00	$ 119.942.387,00	$ 79.942.387,00	200%
Paddington 2	warner	1	PG	12/01/2018	26/10/2017	1	78	7,1	88	8,77	82,2	$ 40.000.000,00	$ 40.891.591,00	$ 187.086.932,00	$ 227.978.523,00	$ 187.978.523,00	470%
Maze runner the death cure	fox	1	PG-13	26/01/2018	17/01/2018	0	9	5,5	50	5,09	52,0	$ 62.000.000,00	$ 58.032.443,00	$ 230.142.892,00	$ 288.175.335,00	$ 226.175.335,00	365%
Fifty shades freed	universal	1	R	09/02/2018	07/02/2018	0	2	3,4	31	3,08	31,9	$ 55.000.000,00	$ 100.407.760,00	$ 271.577.258,00	$ 371.985.018,00	$ 316.985.018,00	576%
Peter rabbit	sony	0	PG	09/02/2018	04/02/2018	0	5	5,8	51	5,77	55,6	$ 50.000.000,00	$ 115.253.424,00	$ 236.013.009,00	$ 351.266.433,00	$ 301.266.433,00	603%
Early man	lionsgate	0	PG	16/02/2018	14/01/2018	1	33	5,6	68	6,65	63,5	$ 50.000.000,00	$ 8.267.544,00	$ 46.355.270,00	$ 54.622.814,00	$ 4.622.814,00	9%
Black Panther	disney	1	PG-13	16/02/2018	06/02/2018	1	10	6,8	88	8,28	79,6	$ 200.000.000,00	$ 700.059.566,00	$ 646.853.595,00	$ 1.346.913.161,00	$ 1.146.913.161,00	573%
death wish	mgm	0	R	02/03/2018	01/03/2018	0	1	5,9	31	3,88	42,9	$ 30.000.000,00	$ 34.017.028,00	$ 15.545.682,00	$ 49.562.710,00	$ 19.562.710,00	65%
Red sparrow	fox	0	R	02/03/2018	16/02/2018	0	14	6	53	5,51	56,0	$ 69.000.000,00	$ 46.874.505,00	$ 104.698.129,00	$ 151.572.634,00	$ 82.572.634,00	120%
A Wrinkle In Time	disney	0	PG	09/03/2018	07/03/2018	0	2	3,6	53	5,27	47,2	$ 103.000.000,00	$ 100.478.608,00	$ 32.197.256,00	$ 132.675.864,00	$ 29.675.864,00	29%
Tomb raider	warner	0	PG-13	16/03/2018	14/03/2018	0	2	6	48	5,47	54,2	$ 94.000.000,00	$ 58.250.803,00	$ 216.400.000,00	$ 274.650.803,00	$ 180.650.803,00	192%
Sherlock gnomes	paramount	0	PG	23/03/2018	22/03/2018	0	1	4,4	36	4,4	41,3	$ 59.000.000,00	$ 43.242.871,00	$ 47.254.907,00	$ 90.497.778,00	$ 31.497.778,00	53%
pacific rim uprising	universal	1	PG-13	23/03/2018	20/03/2018	0	3	5,2	44	5,01	48,7	$ 150.000.000,00	$ 59.874.525,00	$ 231.055.623,00	$ 290.930.148,00	$ 140.930.148,00	94%
Ready Player One	warner	0	PG-13	30/03/2018	12/03/2018	0	18	7	64	6,84	67,5	$ 175.000.000,00	$ 137.690.172,00	$ 445.200.000,00	$ 582.890.172,00	$ 407.890.172,00	233%
rampage	warner	0	PG-13	13/04/2018	11/04/2018	0	2	5,8	45	5,29	52,0	$ 120.000.000,00	$ 101.028.233,00	$ 327.000.000,00	$ 428.028.233,00	$ 308.028.233,00	257%
Avengers: Infinity War	disney	1	PG-13	27/04/2018	24/04/2018	0	3	7,7	68	7,63	73,8	$ 321.000.000,00	$ 678.815.482,00	$ 1.369.544.272,00	$ 2.048.359.754,00	$ 1.727.359.754,00	538%
Deadpool 2	fox	1	R	18/05/2018	14/05/2018	0	4	7,5	66	7,08	70,6	$ 110.000.000,00	$ 324.591.735,00	$ 461.202.444,00	$ 785.794.179,00	$ 675.794.179,00	614%
Solo: A Star Wars Story	disney	1	PG-13	25/05/2018	15/05/2018	1	10	6,6	62	6,42	64,1	$ 275.000.000,00	$ 213.767.512,00	$ 179.157.295,00	$ 392.924.807,00	$ 117.924.807,00	43%
Oceans 8	warner	1	PG-13	08/06/2018	05/06/2018	0	3	5,7	61	6,27	60,2	$ 70.000.000,00	$ 140.218.711,00	$ 157.500.000,00	$ 297.718.711,00	$ 227.718.711,00	325%
Incredibles 2	pixar	1	PG	15/06/2018	11/06/2018	0	4	7,3	80	7,85	77,2	$ 200.000.000,00	$ 608.581.744,00	$ 634.223.615,00	$ 1.242.805.359,00	$ 1.042.805.359,00	521%
Jurassic World: Fallen Kingdom	universal	1	PG-13	22/06/2018	05/06/2018	0	17	5,9	51	5,45	54,8	$ 170.000.000,00	$ 417.719.760,00	$ 890.748.184,00	$ 1.308.467.944,00	$ 1.138.467.944,00	670%
Sicario: Day of the Soldado	sony	1	R	29/06/2018	20/06/2018	0	9	6,6	61	6,31	63,4	$ 35.000.000,00	$ 50.072.235,00	$ 25.765.508,00	$ 75.837.743,00	$ 40.837.743,00	117%
Ant man and the wasp	disney	1	PG-13	06/07/2018	27/06/2018	1	9	6,9	70	6,99	69,6	$ 130.000.000,00	$ 216.648.740,00	$ 406.025.399,00	$ 622.674.139,00	$ 492.674.139,00	379%
skyscraper	universal	0	PG-13	13/07/2018	10/07/2018	0	3	5,4	51	5,15	52,2	$ 125.000.000,00	$ 68.420.120,00	$ 236.448.841,00	$ 304.868.961,00	$ 179.868.961,00	144%
Hotel transylvania 3	sony	1	PG	13/07/2018	07/07/2018	0	6	5,7	54	5,45	55,2	$ 80.000.000,00	$ 167.510.016,00	$ 361.073.758,00	$ 528.583.774,00	$ 448.583.774,00	561%
The equalizer 2	sony	1	R	20/07/2018	17/07/2018	0	3	6,3	50	5,63	56,4	$ 62.000.000,00	$ 102.084.362,00	$ 88.315.795,00	$ 190.400.157,00	$ 128.400.157,00	207%
Mamma Mia! Here We Go Again	universal	1	PG-13	20/07/2018	17/07/2018	0	3	5,4	60	6,31	59,0	$ 75.000.000,00	$ 120.634.935,00	$ 274.409.771,00	$ 395.044.706,00	$ 320.044.706,00	427%
Mission: Impossible—Fallout	paramount	1	PG-13	27/07/2018	12/07/2018	0	15	7,4	86	8,36	81,2	$ 178.000.000,00	$ 220.159.104,00	$ 570.956.000,00	$ 791.115.104,00	$ 613.115.104,00	344%
The spy who dumped me	lionsgate	0	R	03/08/2018	26/07/2018	0	8	5,4	52	5,32	53,1	$ 40.000.000,00	$ 33.562.069,00	$ 41.758.611,00	$ 75.320.680,00	$ 35.320.680,00	88%
Christopher Robin	disney	0	PG	03/08/2018	01/08/2018	0	2	6,6	60	6,21	62,7	$ 75.000.000,00	$ 99.215.042,00	$ 98.529.335,00	$ 197.744.377,00	$ 122.744.377,00	164%
the meg	warner	0	PG-13	10/08/2018	02/08/2018	0	8	5,6	46	5,31	51,7	$ 130.000.000,00	$ 145.443.742,00	$ 384.800.000,00	$ 530.243.742,00	$ 400.243.742,00	308%
The Predator	fox	1	R	14/09/2018	07/09/2018	0	7	5,4	48	4,88	50,3	$ 88.000.000,00	$ 51.024.708,00	$ 109.517.426,00	$ 160.542.134,00	$ 72.542.134,00	82%
The House with a Clock in its Walls	universal	0	PG	21/09/2018	18/09/2018	0	3	5,5	57	5,94	57,1	$ 42.000.000,00	$ 68.549.695,00	$ 62.907.452,00	$ 131.457.147,00	$ 89.457.147,00	213%
Venom	sony	0	PG-13	05/10/2018	02/10/2018	0	3	6,3	35	4,42	47,4	$ 100.000.000,00	$ 213.515.506,00	$ 642.569.645,00	$ 856.085.151,00	$ 756.085.151,00	756%
Goosebumps 2	sony	1	PG	12/10/2018	09/10/2018	1	3	5,4	53	5,4	53,7	$ 35.000.000,00	$ 46.700.633,00	$ 46.619.747,00	$ 93.320.380,00	$ 58.320.380,00	167%
First man	universal	0	PG-13	12/10/2018	29/08/2018	1	44	6,6	84	8,05	76,8	$ 59.000.000,00	$ 44.936.545,00	$ 60.760.870,00	$ 105.697.415,00	$ 46.697.415,00	79%
The Nutcracker and the Four Realms	disney	0	PG	02/11/2018	31/10/2018	0	2	5	39	5,16	46,9	$ 120.000.000,00	$ 54.858.851,00	$ 119.102.218,00	$ 173.961.069,00	$ 53.961.069,00	45%
Bohemian Rhapsody	fox	0	PG-13	02/11/2018	23/10/2018	0	10	7,2	49	6,11	60,7	$ 52.000.000,00	$ 216.428.042,00	$ 687.227.217,00	$ 903.655.259,00	$ 851.655.259,00	1638%
The girl in the spiders web	sony	1	R	09/11/2018	24/10/2018	1	16	5,5	43	5,06	49,5	$ 43.000.000,00	$ 14.841.338,00	$ 20.323.582,00	$ 35.164.920,00	$ -7.835.080,00	-18%
The grinch	universal	0	PG	09/11/2018	07/11/2018	1	2	5,4	51	5,97	54,9	$ 75.000.000,00	$ 270.620.950,00	$ 240.975.007,00	$ 511.595.957,00	$ 436.595.957,00	582%
Fantastic Beasts: The Crimes of Grindelwald	warner	1	PG-13	16/11/2018	08/11/2018	0	8	6	52	5,27	54,9	$ 200.000.000,00	$ 159.555.901,00	$ 495.300.000,00	$ 654.855.901,00	$ 454.855.901,00	227%
Widows	fox	0	R	16/11/2018	09/09/2018	0	68	6,4	84	8,11	76,4	$ 42.000.000,00	$ 42.402.632,00	$ 33.582.068,00	$ 75.984.700,00	$ 33.984.700,00	81%
Ralph Breaks the Internet	disney	1	PG	21/11/2018	14/11/2018	1	7	6,8	71	7,33	70,8	$ 175.000.000,00	$ 201.091.711,00	$ 328.232.251,00	$ 529.323.962,00	$ 354.323.962,00	202%
Robin Hood	lionsgate	0	PG-13	23/11/2018	20/11/2018	1	3	4,5	32	3,68	37,9	$ 100.000.000,00	$ 30.824.628,00	$ 55.664.403,00	$ 86.489.031,00	$ -13.510.969,00	-14%
Creed II	mgm	1	PG-13	23/11/2018	16/11/2018	1	7	6,5	66	6,88	66,6	$ 50.000.000,00	$ 157.115.889,00	$ 98.500.000,00	$ 255.615.889,00	$ 205.615.889,00	411%
Mortal Engines	universal	0	PG-13	14/12/2018	05/12/2018	0	9	5,8	44	4,89	50,3	$ 100.000.000,00	$ 15.951.040,00	$ 67.721.633,00	$ 83.672.673,00	$ -16.327.327,00	-16%
The mule	warner	0	R	14/12/2018	12/12/2018	0	2	7	58	6,13	63,1	$ 50.000.000,00	$ 103.804.407,00	$ 71.000.000,00	$ 174.804.407,00	$ 124.804.407,00	250%
spiderman into the spiderverse	sony	0	PG	14/12/2018	28/11/2018	0	16	7,6	87	8,77	83,6	$ 90.000.000,00	$ 190.241.310,00	$ 185.299.521,00	$ 375.540.831,00	$ 285.540.831,00	317%
mary poppins returns	disney	1	PG	19/12/2018	12/12/2018	0	7	6,1	66	7,27	66,6	$ 130.000.000,00	$ 171.958.438,00	$ 177.579.056,00	$ 349.537.494,00	$ 219.537.494,00	169%
Welcome to Marwen	universal	0	PG-13	21/12/2018	19/12/2018	1	2	5,5	40	4,92	48,1	$ 39.000.000,00	$ 10.763.520,00	$ 2.297.971,00	$ 13.061.491,00	$ -25.938.509,00	-67%
Aquaman	warner	0	PG-13	21/12/2018	11/12/2018	1	10	6,6	55	6,04	60,5	$ 160.000.000,00	$ 335.061.807,00	$ 813.400.000,00	$ 1.148.461.807,00	$ 988.461.807,00	618%
bumblebee	paramount	1	PG-13	21/12/2018	08/12/2018	1	13	6,5	66	6,97	66,9	$ 135.000.000,00	$ 127.195.589,00	$ 340.794.056,00	$ 467.989.645,00	$ 332.989.645,00	247%
Vice	annapurna	0	R	25/12/2018	17/12/2018	1	8	6,6	61	6,67	64,6	$ 60.000.000,00	$ 47.836.282,00	$ 28.237.206,00	$ 76.073.488,00	$ 16.073.488,00	27%

Appendix F: Movies Released in 2019

movie	studio	sequel	MPAA Rating	Premiere date	1st review date	Holiday	gap	Imdb rating	metacritic rating	RT rating	average rating	budget (>=20mi U$	US box office	International box o	total box office	Profit/loss	ROI(%)
glass	universal	1	PG-13	18/01/2019	09/01/2019	1	9	6,3	43	5,12	52,4	$ 20.000.000,00	$ 111.048.468,00	$ 135.950.571,00	$ 246.999.039,00	$ 226.999.039,00	1135%
The kid who would be king	fox	0	PG	25/01/2019	12/01/2019	0	13	5,2	66	6,85	62,2	$ 59.000.000,00	$ 16.790.790,00	$ 15.350.180,00	$ 32.140.970,00	$ -26.859.030,00	-46%
Cold pursuit	lionsgate	0	R	08/02/2019	28/01/2019	0	11	6	57	6,21	59,7	$ 60.000.000,00	$ 32.138.862,00	$ 44.280.893,00	$ 76.419.755,00	$ 16.419.755,00	27%
Lego movie 2	warner	1	PG	08/02/2019	26/01/2019	0	13	6,1	65	6,98	65,3	$ 99.000.000,00	$ 105.806.508,00	$ 86.500.000,00	$ 192.306.508,00	$ 93.306.508,00	94%
alita battle angel	fox	0	PG-13	14/02/2019	31/01/2019	1	14	6,8	53	6,01	60,4	$ 170.000.000,00	$ 85.710.210,00	$ 319.142.333,00	$ 404.852.543,00	$ 234.852.543,00	138%
How to train Your Dragon 3	universal	1	PG	22/02/2019	04/01/2019	1	49	6,8	71	7,25	70,5	$ 129.000.000,00	$ 160.799.505,00	$ 361.000.000,00	$ 521.799.505,00	$ 392.799.505,00	304%
Captain Marvel	disney	1	PG-13	08/03/2019	05/03/2019	0	3	6,6	64	6,8	66,0	$ 160.000.000,00	$ 426.829.839,00	$ 701.444.955,00	$ 1.128.274.794,00	$ 968.274.794,00	605%
Wonder park	paramount	0	PG	15/03/2019	14/03/2019	0	1	5,1	45	4,79	48,0	$ 90.000.000,00	$ 45.216.793,00	$ 74.342.317,00	$ 119.559.110,00	$ 29.559.110,00	33%
Dumbo	disney	0	PG	29/03/2019	26/03/2019	0	3	5,8	51	5,55	54,8	$ 170.000.000,00	$ 114.766.307,00	$ 238.518.314,00	$ 353.284.621,00	$ 183.284.621,00	108%
shazam!	warner	0	PG-13	05/04/2019	23/03/2019	0	13	6,8	71	7,27	70,6	$ 100.000.000,00	$ 140.371.656,00	$ 225.600.000,00	$ 365.971.656,00	$ 265.971.656,00	266%
Hellboy	lionsgate	0	R	12/04/2019	10/04/2019	0	2	4,9	31	3,68	38,9	$ 50.000.000,00	$ 21.903.748,00	$ 22.760.942,00	$ 44.664.690,00	$ -5.335.310,00	-11%
the missing link	United Artists	0	PG	12/04/2019	02/04/2019	0	10	6,2	68	7,18	67,3	$ 100.000.000,00	$ 16.649.539,00	$ 9.599.930,00	$ 26.249.469,00	$ -73.750.531,00	-74%
Avengers: Endgame	disney	1	PG-13	26/04/2019	23/04/2019	0	3	7,7	78	8,24	79,1	$ 356.000.000,00	$ 858.373.000,00	$ 1.939.427.564,00	$ 2.797.800.564,00	$ 2.441.800.564,00	686%
Longshot	lionsgate	0	R	03/05/2019	10/03/2019	0	54	6,2	67	7,08	66,6	$ 40.000.000,00	$ 30.316.271,00	$ 23.557.538,00	$ 53.873.809,00	$ 13.873.809,00	35%
detective pikachu	warner	0	PG	10/05/2019	02/05/2019	0	8	6	53	6,02	57,7	$ 150.000.000,00	$ 144.105.346,00	$ 288.990.000,00	$ 433.095.346,00	$ 283.095.346,00	189%
John wick 3	lionsgate	1	R	17/05/2019	10/05/2019	0	7	7,2	73	7,47	73,2	$ 40.000.000,00	$ 171.015.687,00	$ 155.694.040,00	$ 326.709.727,00	$ 286.709.727,00	717%
Aladdin	disney	0	PG	24/05/2019	21/05/2019	1	3	6,2	53	5,88	57,9	$ 183.000.000,00	$ 355.559.216,00	$ 695.134.737,00	$ 1.050.693.953,00	$ 867.693.953,00	474%
godzilla king of monsters	warner	1	PG-13	31/05/2019	28/05/2019	1	3	5,8	48	5,17	52,6	$ 170.000.000,00	$ 110.500.138,00	$ 276.100.000,00	$ 386.600.138,00	$ 216.600.138,00	127%
Rocketman	paramount	0	R	31/05/2019	16/05/2019	1	15	6,6	69	7,63	70,4	$ 40.000.000,00	$ 96.368.160,00	$ 98.811.139,00	$ 195.179.299,00	$ 155.179.299,00	388%
dark phoenix	fox	1	PG-13	07/06/2019	05/06/2019	0	2	5,4	43	4,63	47,8	$ 200.000.000,00	$ 65.845.974,00	$ 186.597.000,00	$ 252.442.974,00	$ 52.442.974,00	26%
The Secret life of pets 2	universal	1	PG	07/06/2019	23/05/2019	0	15	5,9	55	5,74	57,1	$ 80.000.000,00	$ 158.874.395,00	$ 271.176.898,00	$ 430.051.293,00	$ 350.051.293,00	438%
mib international	sony	1	PG-13	14/06/2019	12/06/2019	0	2	5,2	38	4,47	44,9	$ 110.000.000,00	$ 80.001.807,00	$ 173.888.894,00	$ 253.890.701,00	$ 143.890.701,00	131%
Toy Story 4	pixar	1	G	21/06/2019	13/06/2019	0	8	7,5	84	8,37	80,9	$ 200.000.000,00	$ 434.038.008,00	$ 639.356.585,00	$ 1.073.394.593,00	$ 873.394.593,00	437%
Spider-Man: Far From Home	sony	1	PG-13	05/07/2019	27/06/2019	1	8	7,1	69	7,45	71,5	$ 160.000.000,00	$ 390.532.085,00	$ 741.395.911,00	$ 1.131.927.996,00	$ 971.927.996,00	607%
The Lion King	disney	0	PG	19/07/2019	11/07/2019	0	8	6,2	55	6	59,0	$ 260.000.000,00	$ 543.638.043,00	$ 1.113.305.351,00	$ 1.656.943.394,00	$ 1.396.943.394,00	537%
Once upon a time in hollywood	sony	0	R	26/07/2019	21/05/2019	0	66	7,4	83	7,82	78,4	$ 90.000.000,00	$ 142.502.728,00	$ 231.840.989,00	$ 374.343.717,00	$ 284.343.717,00	316%
Fast & Furious Presents: Hobbs & Shaw	universal	1	PG-13	02/08/2019	31/07/2019	0	2	6,1	60	6,1	60,7	$ 200.000.000,00	$ 173.956.935,00	$ 585.100.000,00	$ 759.056.935,00	$ 559.056.935,00	280%
The kitchen	warner	0	R	09/08/2019	07/08/2019	0	2	4,7	35	4,45	42,2	$ 38.000.000,00	$ 12.180.032,00	$ 3.800.000,00	$ 15.980.032,00	$ -22.019.968,00	-58%
Angry birds 2	sony	1	PG	13/08/2019	28/07/2019	0	16	5,7	60	5,7	58,0	$ 65.000.000,00	$ 41.667.116,00	$ 106.124.931,00	$ 147.792.047,00	$ 82.792.047,00	127%
Angel has fallen	lionsgate	1	R	23/08/2019	21/08/2019	0	2	6	45	5,02	51,7	$ 40.000.000,00	$ 69.030.436,00	$ 78.471.554,00	$ 147.501.990,00	$ 107.501.990,00	269%
It 2	warner	1	R	06/09/2019	03/09/2019	1	3	6,2	58	6,11	60,4	$ 79.000.000,00	$ 211.593.228,00	$ 261.500.000,00	$ 473.093.228,00	$ 394.093.228,00	499%
The goldfinch	warner	0	R	13/09/2019	08/09/2019	0	5	5	40	4,49	45,0	$ 45.000.000,00	$ 5.332.621,00	$ 4.600.000,00	$ 9.932.621,00	$ -35.067.379,00	-78%
Rambo last blood	lionsgate	1	R	20/09/2019	18/09/2019	0	2	6	26	4,01	42,0	$ 50.000.000,00	$ 44.819.352,00	$ 46.671.001,00	$ 91.490.353,00	$ 41.490.353,00	83%
Ad astra	fox	0	PG-13	20/09/2019	13/09/2019	0	7	6,2	80	7,54	72,5	$ 90.000.000,00	$ 50.188.370,00	$ 82.619.057,00	$ 132.807.427,00	$ 42.807.427,00	48%
lucy in the sky	fox	0	R	04/10/2019	02/10/2019	0	2	4,1	36	4,38	40,3	$ 27.000.000,00	$ 319.976,00	$ 5.974,00	$ 325.950,00	$ -26.674.050,00	-99%
Joker	warner	0	R	04/10/2019	31/08/2019	0	34	7,8	59	7,2	69,7	$ 55.000.000,00	$ 335.451.311,00	$ 738.800.000,00	$ 1.074.251.311,00	$ 1.019.251.311,00	1853%
gemini man	paramount	0	PG-13	11/10/2019	21/09/2019	1	20	5,2	38	4,69	45,6	$ 138.000.000,00	$ 48.546.770,00	$ 124.922.746,00	$ 173.469.516,00	$ 35.469.516,00	26%
Maleficent: Mistress of Evil	disney	1	PG	18/10/2019	15/10/2019	0	3	5,8	43	5,09	50,6	$ 185.000.000,00	$ 113.929.605,00	$ 377.800.484,00	$ 491.730.089,00	$ 306.730.089,00	166%
Zombieland double tap	sony	1	R	18/10/2019	16/10/2019	0	2	6,4	55	6,2	60,3	$ 42.000.000,00	$ 73.123.082,00	$ 49.687.317,00	$ 122.810.399,00	$ 80.810.399,00	192%
terminator dark fate	paramount	1	R	01/11/2019	21/10/2019	0	11	5,9	54	6,22	58,4	$ 185.000.000,00	$ 62.253.077,00	$ 198.866.215,00	$ 261.119.292,00	$ 76.119.292,00	41%
playing with fire	paramount	0	PG	08/11/2019	07/11/2019	1	1	4	24	3,96	34,5	$ 29.900.000,00	$ 44.451.847,00	$ 24.179.822,00	$ 68.631.669,00	$ 38.731.669,00	130%
Midway	lionsgate	0	PG-13	08/11/2019	05/11/2019	1	3	6,1	47	5,22	53,4	$ 100.000.000,00	$ 56.846.802,00	$ 68.561.447,00	$ 125.408.249,00	$ 25.408.249,00	25%
Doctor sleep	warner	1	R	08/11/2019	30/10/2019	1	9	6,8	59	7,05	65,8	$ 45.000.000,00	$ 31.581.712,00	$ 40.800.000,00	$ 72.381.712,00	$ 27.381.712,00	61%
Charlies angels	sony	0	PG-13	15/11/2019	12/11/2019	0	3	4,1	52	5,36	48,9	$ 48.000.000,00	$ 17.803.077,00	$ 55.476.811,00	$ 73.279.888,00	$ 25.279.888,00	53%
Ford v ferrari	fox	0	PG-13	15/11/2019	10/09/2019	0	66	7,5	81	7,77	77,9	$ 97.600.000,00	$ 117.624.357,00	$ 107.883.853,00	$ 225.508.210,00	$ 127.908.210,00	131%
Frozen II	disney	1	PG	22/11/2019	14/11/2019	1	8	6,2	64	6,72	64,4	$ 150.000.000,00	$ 477.373.578,00	$ 972.653.355,00	$ 1.450.026.933,00	$ 1.300.026.933,00	867%
Knives out	lionsgate	0	PG-13	29/11/2019	21/11/2019	1	8	7,5	82	8,3	80,0	$ 40.000.000,00	$ 165.363.234,00	$ 143.869.563,00	$ 309.232.797,00	$ 269.232.797,00	673%
Jumanji: The Next Level	sony	1	PG-13	13/12/2019	22/11/2019	0	21	6,4	58	6,04	60,8	$ 125.000.000,00	$ 316.831.246,00	$ 479.744.747,00	$ 796.575.993,00	$ 671.575.993,00	537%
cats	universal	0	PG	20/12/2019	18/12/2019	0	2	2,8	32	3,69	32,3	$ 95.000.000,00	$ 27.166.770,00	$ 46.529.215,00	$ 73.695.985,00	$ -21.304.015,00	-22%
Star Wars: The Rise of Skywalker	disney	1	PG-13	20/12/2019	19/12/2019	0	1	6,3	53	6,15	59,2	$ 275.000.000,00	$ 515.202.542,00	$ 558.941.706,00	$ 1.074.144.248,00	$ 799.144.248,00	291%
spies in disguise	fox	0	PG	25/12/2019	16/12/2019	1	9	6	54	6,47	59,6	$ 100.000.000,00	$ 66.757.013,00	$ 104.859.751,00	$ 171.616.764,00	$ 71.616.764,00	72%
1917.	universal	0	R	10/01/2020	23/12/2019	0	18	7,9	78	8,37	80,2	$ 95.000.000,00	$ 159.227.644,00	$ 208.800.000,00	$ 368.027.644,00	$ 273.027.644,00	287%