Indicators of movie quality

An exploratory research into movie quality

Student name: Veronique Alida Maria Starmans

Student number: 386815

Supervisor: Dr. Christian Wolfgang Handke

Erasmus School of History, Culture and Communication

Erasmus University Rotterdam

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Abstract

The movie industry is constantly evolving, prompting production studios to rethink their movies in order to keep up with these changes. This thesis aims to find out how different indicators of movie quality are correlated and how these indicators can provide useful information to movie production studios before and after the production of a movie. This is done by answering the man research question: *How consistent are indicators of movie quality?* To make the concept of quality measurable, I use indicators of quality such as: box office revenue, production budget, award nominations, award wins, and review ratings, several other variables derived from literature. After analysing these variables I conclude that there is a consistent correlation between budget and box office revenue, which could provide information to producers before production starts, and there is a correlation between box office revenue and the review ratings, which could provide information after production ends. I conclude by discussing the difficulties in measuring the concept of quality and the other possible indicators of quality which are not included in this thesis.

Keywords: Movie industry, Cultural goods, Production studios, Quality, Indicators of quality, box office revenue, For-profit organisations, Consistency, Correlations

Contents

1. Introduction

What is a high quality movie? Your favourite movie is probably not your neighbours favourite movie, or your friends favourite movie. It is probably also not be the most expensive movie ever made, or the biggest movie at the box office. It might be an action movie, or a comedy. But for you it is the best movie of all time, for you this movie is of high quality. But what makes a movie high quality, and how is quality measured?

This thesis focusses on the concept of movie quality for for-profit movie production studios in the United States of America. Movie production studios aim to make the most high quality movies, but especially the most profitable ones. In an evolving industry, they have to try and keep up with changes in technology and shifts in market power. In order to do so, it is important for production studios to figure out how to make their movies successful.

The aim of this thesis is to find out how different indicators of movie quality are correlated and how these indicators can provide useful information to movie production studios before and after the production of a movie. To do this I will conduct a quantitative exploratory study aimed to answering three questions:

- Which indicator of movie quality correlates the most with box office revenue and production budget?
- Which indicator of movie quality is most useful for for-profit movie producers before the production of a movie?
- Which indicator of movie quality is most useful for for-profit movie producers after the production of a movie, during the promotion stage?

And one main research question:

- *How consistent are indicators of movie quality?*

The concept of quality is important in the cultural industry, because quality means success, it means that a product is worth experiencing or purchasing. But the concept of quality is subjective and therefore difficult to quantify. To be able to measure quality in this thesis, I use indicators of quality which are quantifiable and measurable. Among these indicators of movie quality are box office revenue, production budget, award nominations, award wins, and review ratings. All of these variables are related with the concept of quality, making them possible indicators of quality.

I use box office revenue as the most important indicator of quality for for-profit production studios, since acquiring box office revenue is the main objective for these organisations. Box office revenue is however not available before production or right after production of a movie. This is why other indicators of movie quality have to be explored. Indicators of movie quality that are most consistently correlated with box office revenue are therefore the indictors of quality which can provide the most information to production studios about the quality of movies. I use correlation tables and multiple regression analyses to find out which of the indicators of movie quality is most consistently correlated with box office revenue.

Chapter two consists of a literature review in which the changes in the movie industry are discussed. In chapter three I will explain my research design; my methods, the data collection process and my variables. I will also discuss the validity, reliability and the data limitations of this thesis. Chapter four captures the results of my research, with firstly the results from the correlation tables, than secondly the results from the regression analyses. I will answer my research questions and my main research question in chapter five, where I will discuss my conclusions based on the results in chapter four. Chapter six explores ideas for further research and discusses the limitations of this study.

2. Literature review

In this chapter I provide insight into the current state of the movie industry and the challenges it faces. My main focus in this thesis will be on movies from the U.S., which is why I will explore the state of the U.S. market, and its challenges of the U.S. market. Furthermore, I will define the indicators of movie quality as used in this thesis.

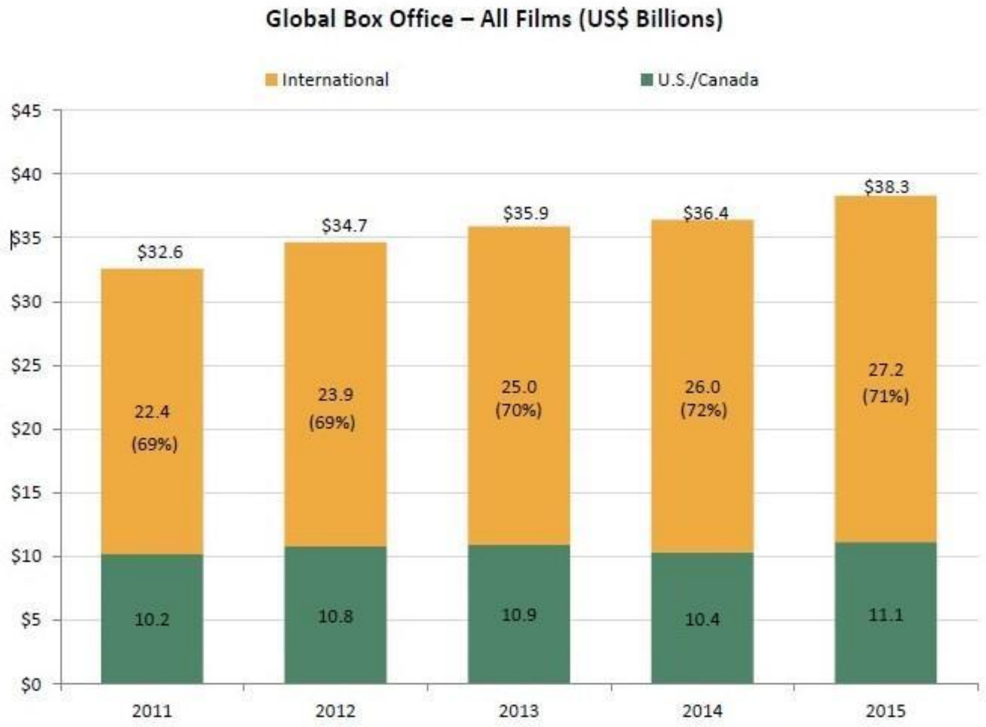
2.1 Changes and challenges in the movie industry

The movie industry is a multi-billion dollar industry, with large production studios in United States of America, India, Japan and China. Being a producer or actor within the movie industry can be very lucrative, but it is also a very uncertain industry because of the many factors which influence the success of a movie.

The Opinion Research Corporation (2015) released the Theatrical Market Statistics 2015 report, which was commissioned by the Motion Picture Association of America (MPAA). This report states that there is a steady increase in global box office revenue (figure 1 and table 1). The total global box office revenue grew from 32.6 billion U.S. dollars in 2011 to 38.4 billion U.S. dollars in 2015. This increase indicates that the movie industry has grown overall, but other results within this report suggest that there are shifts of power within the industry. Table 1 shows that the international movie industry grows faster, with 21% from 2011 to 2015, than the American movie industry, which grew 9% from 2011 to 2015.

According to Lorenzen (2007) India took over as the world's largest movie producer, in terms of quantity, in the second half of the twentieth century, mainly because of a large domestic interest in Bollywood movies. A similar trend can be seen in the Chinese market where, until 2017, Chinese movies have been mostly only successful in China itself. China has yet to bring a real worldwide blockbuster to the market (Stout, 2016), but there are signs of Chinese influence in U.S. blockbusters. One example given by Stout (2016) is the Vivo smartphone (only available in China) which is used in “Captain America: Civil War”, a Hollywood production.

Figure 1 and table 1: Global box office 2011-2015



	2011	2012	2013	2014	2015	% Change 15 vs. 14	% Change[2] 15 vs. 11
U.S./Canada[3]	$10.2	$10.8	$10.9	$10.4	$11.1	8%	9%
International[4]	$22.4	$23.9	$25.0	$26.0	$27.2	4%	21%
Total	**$32.6**	**$34.7**	**$35.9**	**$36.4**	**$38.3**	**5%**	**18%**

The MPAA report from 2015 also shows that the increase in box office revenue in the U.S. (5% domestically) was smaller than the increase in Asian countries. China's box office revenue increased 49% (to 6.8 billion U.S. dollars), which made up 50% of the Asia Pacific box office revenue. This increase is explained by the rapid growth in the amount of movies made in China (and India), as shown in table 2 (UNESCO Institute for Statistics, 2017). It is still rather remarkable and if this trend continues it could make China, or Asia as a whole, the new 'powerhouse' of the movie industry.

Table 2: Number of films produced per country 2011-2015

	2011	2012	2013	2014	2015
India	1255	1602	1724	1868	1907
U.S.A.	819	738	738	707	791
China	584	745	638	618	686
Japan	441	554	591	615	581
U.K.	299	326	241	339	298

2.2 New ways of watching movies

Another development in the global movie market is the shift in the way audiences access new movies. Technological developments such as the introduction of Internet, streaming media, encryption and digital file compression allows video files to be distributed online, legally and illegally. Going to the movie theatre is no longer the only way to enjoy recently released blockbusters, as there are online platforms such as Netflix, Hulu, HBO and many others on which the public can watch movies. These new platforms provided a new source of uncertainty for the movie industry, because the changes in consumption habits and the emergence of new virtual markets caused the industry to see their (mainly young) audience watch movies outside the theatre or online, rather than the traditional way (Pardo, 2013).These platforms provide consumers with a large variety of movies, which they can watch at any time and as many times as they want.

But quantity or variety is not the biggest threat coming from these new platforms. Netflix developed from a broadcaster to a producer of its own content (Jenner, 2016). Content on Netflix is increasingly produced by Netflix, lowering the interest in and availability of movies from other sources. Because of Netflix and other platforms such as HBO, Hulu and Amazon, the movie industry has to innovate to stay relevant.

Next to this legal way of accessing movies online, there is also an illegal way. Consumers can download their movies for free from the internet illegally. Although there are laws against this, often with high criminal penalties, 46% of U.S. citizens still pirate movies (Karaganis and Renkema, 2013). Many consumers pirate movies casually, only a few have an extensive collection with more than 1000 songs or 100 movies or tv shows. This points toward the notion that many consumers do not feel as though file sharing and downloading is illegal. Karaganis and Renkema (2013) point out that consumers who pirate a lot are also heavy legal media consumers. They buy more products legally than their counterparts who do not pirate, and also have a higher willingness to pay. These results show that heavy users of media like to try out more things before making decisions on buying products, but when they do buy them they are willing to pay more for them.

Piracy does not only have negative effects on movies, it also has a positive effect because it has a promotional function. This positive effect does however not outweigh the negative effects of piracy (Ma, Montgomery and Smith, 2016). It is however still interesting to look at this positive effect, because online attention is crucial in the age of the internet and social media; it extends further than any normal marketing campaign would (Kim, Park & Park, 2013). Online attention, organic or non-organic, can increase box office revenue by a significant amount (Duan, Gu & Whinston, 2008). Online marketing is different from offline marketing in the sense that it reaches further. Marketing on social networks travels much faster and reaches more people than an advertisement in a newspaper will (Duan et al., 2008) Advertisements from movies which are particularly good will be ‘liked’, ‘retweeted’ and ‘shared’ more on different platforms, organically increasing its reach. Not only online content such as review ratings are part of this digital word-of-mouth (WOM), but also Google searches instigated by other events are a form of digital WOM. If a movie wins an award, there will be an increase in digital WOM because consumers get curious about the movie. This does not only influence the rating of a movie, but also the volume of attention it gets online (Duan et al., 2008).

2.3 Movies as cultural & experience goods

Most challenges faced by the movie industry exist because of the kind of product movies are. Movies are cultural goods, which makes them different from ‘ordinary’ goods. Cultural goods do not only have monetary or economic value, but also other values such as personal, social or artistic value attached to them (Klamer, 2016). These added values cause consumers to look at these goods differently. A movie does not only have to ‘work’ as a movie, it also has to be of good quality. It has to provide the consumer with something more than just a working product, which would suffice with a pen for example. A pen only has to write, nothing more. This notion of a cultural good as more than just a good, can be linked to the phenomenon of the 'experience good'. Products such as movies, but also other products such as restaurants and books, are called 'experience goods'. Nelson (1970) was the first scholar to mention the term 'experience goods' to give a name to goods of which the value can only be determined after the good is already purchased and consumed. There is not enough information available about the quality of the good before consumption. This means that an informed decision about the good cannot be made (Nelson, 1970). The consumer must buy and consume the good to know if he or she likes the good and to see if it is of high quality or not.

This is an example of information asymmetry, which means that the seller has more information about the good he or she is selling, than the buyer does (Trimarchi, 2011). Trimarchi (2011) determines that the value of a good is determined by a system of cross-valuation and assessment, in which an excess of information on the sellers side is most important. This indicates that the value of a good is not attributed to the characteristics of the good itself, but rather to the amount of money the seller deems the good is worth (Trimarchi, 2011). Movies are a special case however, because all movies have a homogenous price in theatres. This means that the choice between one movie or another is not a case of willingness to pay, but purely depends on the content of the movie, setting aside the problem of availability of movies in certain movie theatres.

There are two main sources of information to which a consumer can turn; review ratings, either from professionals or from peers, or awards. Review ratings from other consumers provide insight into the quality of the movie through the eyes of another consumer (Reinstein & Snyder, 2005). This knowledge can be helpful in making purchasing decisions, but it will however never be complete because consumers have different tastes and preferences. Review ratings from professionals and awards have a similar effect, although this information is often available earlier than consumer reviews.

Uncertainty concerning experience goods is not only a problem for consumers but also for producers. Although the movie producers have more information about the goods they are selling, there is no way of knowing the reaction of consumers on a certain product (Caves, 2000). This is called the 'nobody knows' principle by Caves (2000), who has defined seven economic properties which characterize the creative industries and therefore the movie industry as well. The basic notion of the ‘nobody knows’ principle is that there is uncertainty surrounding the reaction of consumers before and after production and distribution, which means that producers cannot apply knowledge gained by these reactions on future movies.

Caves (2000) also names this problem in his ‘infinite variety’ property, which explains that all products are an unique combination of infinite options and therefore also have a different level of quality. It is difficult to counteract this uncertainty because movies which are distributed have a homogenous price, which consequently means that movie producers cannot increase their demand by setting lower prices for certain movies.

2.4 Quality of movies

There are different reasons for making goods in the cultural industry. Some goods are produced according to the ‘art for art’s sake’ principle, in which case workers within the cultural industry care about originality, skills and harmony and therefore settle for lower wages so they can keep making art (Caves, 2000). This principle does however only partially apply to the movie industry. Independent movies, which are produced outside of the big production studios, are largely produced for the sake of making art (Valck, 2013). These movies are however increasingly commercialized because of the different stakeholders involved in production. Producers who produce movies for art’s sake are mainly focussed on creating added (non-monetary) value (Klamer, 2016). These producers create movies so they can show their creativity, or focus attention on an important political or societal issue. They will be more concerned with a good review than with a high box office revenue. Large production studios are for-profit organizations and therefore produce movies with the intent to make a profit from the movies they produce. They focus on making movies which earn a lot of box office revenue. Both the small independent movie producer, as the large production studio is concerned with the quality of their movies, but in two different ways.

Movies produced with the purpose of earning a lot of box office revenue are called “blockbusters” (Anderson, 2006). Within this thesis I will focus on American blockbuster movies and the best indicators of quality in the preproduction and marketing stages of movies. There are no clear rules or guidelines to follow while producing a blockbuster. There are blockbusters in every genre and there are no particular features to them other than the large amount of attention and box office revenue they acquire (Stringer, 2003). One unwritten rule is that blockbusters always start off with a high production budget, because it is believed that a big production gives a better performance at the box office (Cucco, 2009). Production studios use this bigger budget during production to differentiate their movies from others by using the most advanced technology and the best actors (Cucco, 2009). After production an increasingly important part of making a blockbuster is the promotion surrounding it. This can make up for the fact that a blockbuster is not necessarily of high quality, while a smaller production might be (Anderson, 2006).

2.5 Quality indicators

The quality of movies is difficult to quantify, meaning that it is difficult to measure (Ginsburgh and Weyers, 2005). The best way to measure quality is by using different indicators of quality such as awards (Ginsburgh, 2003; Gemser, Leenders & Wijnberg, 2008, Reinstein & Snyder, 2005), reviews (Boatwright, Basuroy & Kamakura, 2007; Escoffier & McKelvey, 2015), and box office revenue (Krauss, Nann, Simon, Fischbach & Gloor, 2008; Chang & Ki, 2005; Kim, Park & Park, 2013). For consumers quality can be aesthetic excellence, but a for-profit organisation such as movie producing studios will be more inclined to see a movie with a high box office revenue as a movie of high quality.

Therefore it can be concluded that box office revenue provides a way for for-profit production studios to quantify the success of a movie and is therefore a clear indicator of the quality of a movie. Box office revenue is however not a perfect indicator of movie quality, because it is an unavailable statistic before production, so it cannot be used by producers in order to make their movie successful. Other indicators of quality could be able to provide producers with the extra knowledge they need before production to make their movies a success.

2.5.1. Awards

An indicator of movie quality is the amount of awards a movie has won or was nominated for. Awards are found in almost every industry, so also in the movie industry. Awards can be seen as a signal of quality to consumers (Gemser et al., 2008), and therefore a movie with a lot of awards can be seen as a movie of high quality. Measuring the quality of a movie by looking at awards can however be problematic because the amount of awards a movie has won depends largely on the opinion of professional jury's, which is therefore not an objective representation the quality of a movie.

2.5.2. Consumer review ratings

Another indicator of movie quality are reviews, which are closely related to awards because both concepts make the opinion of viewers measurable, but in different ways. Where awards portray professional opinions, reviews show the opinion of the audiences and professionals depending on the source.

Both awards and reviews are used as signals of quality. As described above information asymmetry is a big problem for consumers of cultural goods, especially concerning experience goods. Determining the value of such a good is impossible without consuming the good first, which is why some potential consumers look at others' opinions to gain more information (Nelson, 1970). By informing themselves about the good, they can lessen the gap between themselves and the seller. The internet provides a pool of information for consumers provided by the sellers, but also by other consumers and professional reviewers. It is important to look closely at these reviews, because they become increasingly important in the decision making process of consumers (Verboord, 2014)

Reviews and therefore reviewers are very influential in many different industries. This is why reviewing has become have become a business; there are people who have made it their hobby to review certain products on YouTube or other platforms in order to not only give their opinion, but also influence people and earn money doing so (Gillin, 2007). These people are called 'influencers', because they have a big influence on the consumption behaviour of their many followers. The problem with these influencers from the industries' point of view is that it is not always clear if they belong to the company who sells the good or gets payed in any other way to give a positive review over a certain good. The line between a seller who provides information and a consumer who provides an honest opinion isn't very clear anymore (Gillin, 2007).

Reviews can make or break a product, as is shown in a study by Zhu and Zhang (2006), which focusses on the influence of online consumer reviews on the demand for experience goods. In this study, they look at consumer reviews and their effect on the sales of video games. They find that consumer reviews have a significant effect on the demand for games (p. 377). They also point out that negative reviews have a bigger influence than positive reviews, and the impact of the reviews is higher for less popular games than for popular games. These outcomes are interesting, because movies are similar to games in the sense that they are also experience goods, and they thus have to be played before an opinion about them can be formed. Games are also similar to movies in the sense that they have an homogenous price and are reproducible goods.

2.5.3. Professional review ratings

Other than reviews from consumers and influencers, there are also professional reviews. In the case of movies these reviews are traditionally from professional jury's or established reviewers who publish their opinions in newspapers. Although the opinions of professional and consumer reviews are often similar, they are not equal, as review ratings from websites such as rottentomatoes.com suggests. Similarities between reviews from different sources, consumer and professional, could be due to the notion that they influence each other (Verboord, 2014). Professional reviewers often get to make their judgement earlier than consumers because they get to see movies before they are shown in theatres. Differences between these reviews could be due to taste (Wanderer, 1970). Movies belonging to popular culture are often reviewed as lower quality by professional reviewers, while consumers are more likely to watch and like these kinds of movies. Movies with difficult complex stories are often more liked by professionals and less by consumers (Wanderer, 1970). Differences in taste should logically be reflected in the review ratings of different genres. But as Reinstein and Snyder (2005) discovered in their research; there is no difference in the opinions of consumers and professionals regarding genres.

I will thus use, box office revenue, consumer and professional review ratings, the amount of awards won by a movie and award nominations as indicators of movie quality. Other indicators of movie quality which I will use in this research are based on the decisions made by the production studios themselves. These indicators are production budget, the size of the production studio, the release date, and the genre of a movie.

3. Research design

In this chapter I will first explain which methods I will use in my research and the reasoning behind them. Secondly, I will describe my data collection process, my variables and preliminary statistics regarding them. Lastly I will address the validity, reliability and the limitations of this research.

For this research I will conduct quantitative analysis on secondary data. All of the data within the dataset is obtained from online sources such as IMDb.com and its subsidiary boxofficemojo.com, which are specialized in gathering data on movies.

3.1 Methods

This thesis is aimed at finding useful indicators of quality for producers to use in different stages of movie production and marketing. To do this I will focus on the research question: *How consistent are indicators of movie quality?*

Within this thesis I will focus on the American movie industry, since, as it is a large and globally well-known industry, there is a lot of information available on it. In the production process of a movie, a lot of decisions have to be made. Because of the uncertainty in the movie industry as explained in chapter 2, producing high quality movies is difficult. To research quality and to find out how to make a high quality movie, it is important to quantify the concept of quality. This is however difficult because the concept is subjective and cannot be objectively expressed in numbers. To make quality a measurable concept, indicators of quality which are measurable can be used such as reviews, awards, box office revenue, genre and budget.

For for-profit organisations with the objective to acquire as much box office revenue as possible, which is why I will use box office revenue as my main dependent variable. But what causes a movie to obtain a high box office revenue? To answer this question I turn back to my research question: *How consistent are indicators of movie quality?* By looking at the consistency between the different indicators of movie quality: reviews, awards, box office revenue, genre and budget, it will become clear which indicator explains the most variance in box office revenue and will therefore provide producers with more insight into box office revenue.

Because this study will be an exploratory and descriptive study, I will not state hypotheses to answer my research question. Instead I will explore the following questions:

1. Which indicator of movie quality correlates the most with box office revenue and production budget?
2. Which indicator of movie quality is most useful for for-profit movie producers before the production of a movie?
3. Which indicator of movie quality is most useful for for-profit movie producers after the production of a movie, during the promotion stage?

There are several methods available to determine correlations and relations between these different indicators of quality. I will use a two-step process in which I will start by analysing the correlations between different variables, so that I will get a preliminary indication of which independent variables are most closely associated. This will provide me with an indication of which variables to use in my further analyses. After this I will conduct multivariate regressions to review how the variables are related to each other when control variables are added in two stages: before production and after production (promotion stage). I use these two stages to determine which variables can provide movie producers with information about the quality of their movie before and after production. Important in these analyses is the R^2, which indicates how much of the variance in the dependent variable box office revenue is explained by one of the indicators of quality.

3.2 Data collection and sampling

In this part of my thesis I will explain the data gathering process and show the results of the preliminary descriptive statistics. This dataset is constructed using secondary data from different online sources which specialize in collecting data about movies: IMDb.com and boxofficemojo.com.

For this research I constructed a dataset with 300 movies. In order to make my results useful in the production and marketing stages of blockbuster movies, I chose 300 recently released blockbusters; 100 from 2013, 100 from 2014 and 100 from 2015. A large box office revenue is the main objective for the for-profit production studios, which is why I limited myself to using these movies which are the top 100 regarding box office revenue in their year of release according to boxofficemojo.com. I chose these movies because they have been released relatively recently and were successful, which means that data on the indicators of quality is widely available. Appendix A shows an overview of the titles of the movies I have used in the dataset.

3.3 Variables

In the following paragraphs I will show which variables I will be using in this research, the method of collection, and some preliminary data analysis regarding these variables. An overview of all variables is also available in appendix B.

3.3.1. Box office revenue, production and marketing budget

Within this thesis I will only include box office revenue and production budget to measure the monetary success of a movie. I leave earnings from DVD sales, streaming rights, and merchandize out of this study because reliable and complete information to base variables for these concepts on is difficult to acquire. This is also the case with marketing budget, which is often not disclosed by production companies. Vogel (2001) argues that there is a rule of thumb used for marketing budget; spend an additional 50% of the production budget on marketing. So, for example, when the production of a movie costs 100 million U.S. dollars, an additional 50 million needs to be spend on marketing. This is a large amount of money spend on advertising every time a production studio makes a movie, especially taking into account that the overall budgets for movies are increasing to keep competition alive (Vogel, 2001). Even if adjusted for inflation, 12 out of the 15 most expensive movies to make were made between 2000 and 2017 (IMDb.com).

The first variables I will use are box office revenue and production budget, which are expressed in millions of U.S. dollars to make comparison with other variables easier. Table 3 shows an overview of these variables. The values for the variables box office revenue and budget are from boxofficemojo.com, the same sources as the titles of the movies used in the dataset. Box office mojo is a sister company of IMDb.com, an online database for movies. The data on these websites is collected from various sources in the industry, as well as from users from these websites (IMDb.com). This indicates that the information is not always reliable, but it forms one of the most complete sources available for financial information on movies.

Table 3: Descriptive statistics for box office revenue and production budget and profit

	Mean	Median	Mode	St. Dev.	Min	Max
Box office revenue[a]	99.55	64.50	26	100.408	16.	29,865
Production budget[a]	66.43	41.00	40	59.950	0.1	250
N = 300						

[a] *In millions of U.S. dollars*

3.3.2. Production studio and production studio size

The next variable I will use in this research is the production studio. This is a nominal variable consisting of the different production studios from the movies in the dataset. Table 4 shows an overview of these studios ordered by market share (boxofficemojo.com). This table shows that there are some production studios with only a few cases, which means that this variable will not be useful in my analysis. I therefore constructed a new variable; production studio size, in which the production studios are labelled as ‘major’ or ‘indie’. Studios with more than 1% market share are labelled as a major production studio and studios with less than 1% market share are labelled as indie production studios. It has to be noted that in the production of blockbusters, there are no actual indie production studios. The studios labelled as such in this research are still well known, but based on their market share they are relatively small compared to other studios. Table 5 shows the amount of box office revenue per movie production studio category; major or indie. The major studios make movies with a higher box office revenue on average, but there is a lot of variance among these movies.

Table 4: Production studios by market share 1995-2017

	Production studio	Market Share	Frequency	Size
1	**Walt Disney/Buena Vista**	15.44%	29	Major
2	**Warner Bros.**	15.05%	49	Major
3	**Sony/Columbia**	12.98%	49	Major
4	**20th Century Fox**	11.70%	40	Major
5	**Universal**	11.50%	41	Major
6	**Paramount**	11.04%	23	Major
7	**Lionsgate/Summit**	3.88%	13	Major
8	**Weinstein Company**	1.20%	2	Major
9	**Fox Searchlight**	1.15%	6	Major
10	**Focus Features**	0.89%	2	Indie
11	**Relativity**	0.46%	11	Indie
12	**Open Road Films**	0.37%	7	Indie
13	**IFC**	0.20%	12	Indie
14	**CBS**	0.19%	1	Indie
15	**STX Entertainment**	0.15%	1	Indie
16	**A24**	0.09%	1	Indie
17	**Freestyle Releasing**	0.06%	1	Indie
18	**Broad Green Pictures**	0.04%	1	Indie

Source: boxofficemojo.com

Table 5: Average box office revenue[a] for production studio size

	Frequency	Mean	Median	St. Dev.	Min	Max
Indie	37	$67.05	$39.00	$88.0145	$22.00	$425.00
Major	263	$104.12	$71.00	$101.3461	$16.00	$937.00
Total	300	$99.55	$64.50	$100.4081	$16.00	$937.00

N = 300

[a] *In millions of U.S. dollars*

3.3.3. Time of release

The next variables I will use regards the time of release. Because of the size of the dataset, it would not be reliable to use the months of release in the analysis. This is why I chose to compare the four seasons to each other so there were enough cases in each category to compare. I will use the four seasons as dummy variables: winter, spring, summer and autumn, in my analyses.

Table 6 shows how many movies were released in each season of the three years represented in the dataset. To make my analyses as representative as possible, I will be analysing just the years and the seasons, not the seasons per year because there aren't enough cases per season when the year is also taken into account. Most of the categories have less than 30 cases in them. Table 6 shows that the movies with the highest box office revenue are released in spring, and the movies with the lowest box office revenue are released in winter.

Table 6: Means Seasons and years regarding box office revenue[e]

Year	Season	Frequency	Mean	Median	St. Dev.	Min	Max
2013	**Winter[a]**	21	$73.62	$56.00	$54.775	$26	$235
	Spring[b]	21	$140.24	$108.00	$98.657	$32	$409
	Summer[c]	29	$82.55	$71.00	$67.657	$26	$368
	Autumn[d]	29	$107.48	$62.00	$107.371	$25	$425
	Total	100	$100.02	$69.50	$87.782	$25	$425
2014	**Winter**	19	$83.79	$61.00	$53.840	$31	$258
	Spring	23	$121.13	$100.00	$82.197	$26	$260
	Summer	26	$77.69	$52.00	$70.305	$16	$333
	Autumn	32	$98.69	$66.00	$85.420	$26	$350
	Total	100	$95.56	$64.50	$76.334	$16	$350
2015	**Winter**	23	$74.39	$47.00	$57.487	$22	$201
	Spring	22	$139.27	$61.50	$167.249	$21	$652
	Summer	29	$80.45	$59.00	$68.719	$22	$336
	Autumn	26	$123.04	$71.00	$179.620	$25	$937
	Total	100	$103.07	$58.00	$129.953	$21	$937
Total	**Winter**	63	$76.97	$59.00	$54.796	$22	$258
	Spring	66	$133.26	$94.00	$119.995	$21	$652

	Summer	84	$80.32	$59.00	$67.879	$16	$368
	Autumn	87	$108.90	$65.00	$125.946	$25	$937
	Total	300	$99.55	$64.50	$100.408	$16	$937
	N = 300						

[a] *Winter: January, February and March*

[b] *Spring: April, May and June*

[c] *Summer: July, August and September*

[d] *Autumn: October, November and December*

[e] *In millions of U.S. dollars*

Table 7 shows the average movie production budget per month and year. The movies with the highest production budgets are produced in spring, which is consistent with the highest box office revenue earned. One exception is 2015, where the production budget was the highest in autumn.

Table 7: Means Seasons and years regarding budget[e]

Year	**Season**	Frequency	Mean	Median	St. Dev.	Min	Max
2013	**Winter**[a]	21	$60.05	$35.00	$60.129	$3	$215
	Spring[b]	21	$104.14	$103.00	$71.040	$3	$225
	Summer[c]	29	$66.10	$50.00	$54.398	$3	$215
	Autumn[d]	29	$66.24	$40.00	$57.071	$5	$225
	Total	100	$72.86	$50.00	$61.455	$3	$225
2014	**Winter**	19	$56.95	$50.00	$41.007	$2	$145
	Spring	23	$82.43	$40.00	$76.743	$5	$210
	Summer	26	$51.15	$35.00	$46.288	$4	$170
	Autumn	32	$61.28	$46.00	$58.516	$5	$250
	Total	100	$62.69	$40.00	$57.968	$2	$250
2015	**Winter**	23	$51.96	$48.00	$45.616	$3	$176

	Spring	22	$75.45	$35.00	$74.036	$1	$250
	Summer	29	$46.83	$31.00	$45.253	$0.5	$155
	Autumn	26	$83.08	$56.50	$69.091	$11	$245
	Total	100	$63.73	$40.00	$60.452	$0.5	$250
Total	**Winter**	63	$56.16	$42.00	$49.038	$2	$215
	Spring	66	$87.02	$46.50	$73.923	$1	$250
	Summer	84	$54.82	$36.50	$49.046	$0	$215
	Autumn	87	$69.45	$50.00	$61.374	$5	$250
	Total	300	$66.43	$41.00	$59.950	$0	$250
	N = 300						

[a] *Winter: January, February and March*

[b] *Spring: April, May and June*

[c] *Summer: July, August and September*

[d] *Autumn: October, November and December*

[e] *In millions of U.S. dollars*

3.3.4. Award winnings and nominations

The next indicator of quality I will use is awards; nominations for awards as well as the amount of awards a movie has won. I looked at the amount of nominations and awards a movie has (IMDb.com) and counted them to construct two variables: Award wins and award nominations, and one variable which adds the two together: awards total. As shown in table 8, there are a total of 3568 awards won by all of the movies in the dataset combined, and 8341 nominations, which adds up to 11909 awards in total. There are six movies in the dataset with more than 100 awards. These movies are all Oscar winning movies: 12 Years a Slave (3 Oscars), Gravity (7 Oscars), Mad Max: Fury Road (6 Oscars), Birdman (4 Oscars), Boyhood (1 Oscar), and The Grand Budapest Hotel (4 Oscars), The 23 movies with more than 100 nominations, have all won or been nominated for an Oscar. There is a limited amount of Oscar winners every year, which means that winning an Oscar highly depends on the competition a movie has.

Both nominations and award winnings provide a signal of quality, but a nomination does not provide a movie with the same prestige as an award. They are however still interesting to study to capture the effect they have on the concept of quality. To do this I created a derived variable based on the variables: award wins and award nominations (table 8), named awards weighted. This variable is constructed by multiplying the amount of nominations (award nominations) by a reduction factor of 0.43, and adding this to the awards 565 which were won (award wins). This reduction factor is not arbitrary because it has been derived from the dataset itself; it is calculated by dividing award total by award nominations. The equation used can be found in table 8. It suggests that a movie needs an average of 2,34 nominations to win an award. This reduction factor is not generalizable to a different dataset, but the method of calculation can be used in different situations.

Table 8: Awards variables

	Mean	Median	Mode	St. Dev.	Min	Max	Sum
Award Wins	11.93	2.00	0	31.751	0	237	3568
Award Nominations	27.80	8.00	1	47.809	0	317	8341
Award Total	39.70	10.00	5	76.363	0	554	11909
Award Weighted[a]	23.79	5.28	0	50.102	0	373	7136

[a] *Awards weighted = award wins + (reduction factor *award nom)*

Reduction factor = award total / award nominations

3.3.5. Professional and consumer review ratings

The next indicators of quality I will use in my analysis are professional and consumer review ratings. I included ratings from different websites in order to provide the most representative image of the strength of review ratings as an indicator of quality (table 9), to be able to look at how professional and audience ratings differ. I included ratings from the IMDb website (IMDbScore), metacritic.com (Metascore), and the audience (RTAudience) and critic (RTCritics) rating from rottentomatoes.com. All review ratings were on a scale from 1 to 100, except for the ratings from the IMDb website, which was on a scale from 1 to 10. In order to make these different ratings comparable, I converted the ratings from the IMDb website to a scale of 1 through 100.

Table 9: Descriptive statistics different review rating sources

	Mean	Median	Mode	St. Dev.	Min	Max
IMDbScore	65.97	66.00	67	8.861	35	86
Metascore	53.52	54.00	55	17.515	2	100
RTCritics	54.38	58.50	60	26.806	4	99
RTAudience	63.10	63.00	57	17.234	19	93

N = 300

The IMDb ratings come from IMDb users and does not use the arithmetic mean but a weighted average based on the profile of users, which can be professionals or consumers. Although the exact method is not disclosed, the IMDb website does mention that they base it on the previous review ratings that are given by the user (IMDb.com). Using a weighted average could explain the low standard deviation of the ratings on IMDb.com (table 9).

The review ratings on Metacritic.com are also a weighted average. They do not look at the profile of users, but rather select a group of respected critics whose review they give a weight which together makes out the rating. A review rating is only put on the website when they have collected at least four critic's reviews (Metacritic.com).

I have collected data from two different review ratings on rottentomatoes.com: the critic's score and the audience score. The critic's score is a review rating based on the published opinions of hundreds of critics and is expressed using the arithmetic mean of all of the reviews. The audience review ratings from rottentomatoes.com is calculated using the arithmetic mean from all of the scores given by the users from rottentomatoes.com and flixter.com. Rottentomatoes.com also expresses a rating in the form of a 'tomato meter', but this only expresses the percentage of professional critics who are positive about the movie (rottentomatoes.com). There is however no indication of when a review is considered positive. I decided to leave this index out because it is not comparable to any of the other review indexes and could therefore provide a skewed image.

3.3.6. Genre

The last indicator of quality I will use in this thesis is genre. I gathered data on the genres of the movies in my dataset from boxofficemojo.com. By doing so I noticed that there are seven major genres: drama, comedy, action, adventure, thriller, documentaries and biographies. Because I only have 300 movies in my database, I decided to combine some of the similar genres, or genres with very few cases, in order to have enough movies in each category. I combined actions and adventures, because there were many movies which were named an action movie on boxofficemojo.com, but an adventure on imdb.com. And I combined documentaries and biographies because these two genres are very different from the others, and very similar to each other, and only make up a small part of the total dataset (table 10).

To be able to make the most use out of this variable, I will include the different genres as dummy variables; drama, comedy, action and adventure, thriller, and documentary and biography. I chose to do this because some of the genres have very little observations and the dummy variables make it easier to see what their relation is to the other indicators of quality.

Table 10: Frequencies of genre

Genre	Frequency	Percent
Drama	76	25.3
Comedy	95	31.7
Action Adventure	78	26.0
Thriller	34	11.3
Documentary Biography	17	5.7
Total	300	100.0

3.4 Validity, reliability and data limitations

In this paragraph I will explain the validity, reliability and the data limitations of my research.

3.4.1 Validity and reliability

In this paragraph, I will explain what I have done to ensure the validity of my research

To ensure the construct or measurement validity of my research I have used reliable literature and data sources to construct my variables. I have included as many available indicators of quality in order to measure quality itself. The measurement of these variables are discussed in chapter 3.

To ensure the internal validity of my research, I have separated my variables in dependent and independent variables. I can however not say that the relationships I find between variables are causal relationships. In order to not report false causalities, I will only report on correlations.

External validity is ensured by using a research design which can also be used with other datasets, and in studies about other cultural goods such as festivals, books or music. Results from this research can only partially be generalized to the movie industry, because I do limit my research to successful movies from the United States of America. Therefore, results might differ in other markets and with less successful movies.

Statistical validity will be ensured using a VIF-test, or variance inflation test, in every regression analysis. This VIF test will show any cases of multicollinearity in the regression analyses, which means that two variables measure the essentially the same variance in a dependent variable. A VIF score below 5 indicates that there are multicollinearity is unlikely, a score between 5 and 10 indicates that there is possibly multicollinearity, and a score above 10 indicates that there multicollinearity is very likely. It is important to ensure that there is no multicollinearity in this research because this could provide false insights into the consistency of the correlations between the different indicators of movie quality.

To ensure reliability in this thesis, I have made the measurements of the different variables for the same concepts comparable. An example of this are the variables for review ratings which I normalized so that they are all on a scale from 0 to 100 and therefore comparable.

3.4.2 Data limitations

One of the main limitations of this dataset is the small sample size. This dataset is relatively small compared to datasets from some other quantitative studies, because it only has 300 cases. This is mainly due to the fact that many of the variables and values had to be inserted by hand because they were gathered from many different online sources and sometimes even read from graphs.

Another limitation of this data is that there is no variable describing the actual quality of a movie, because this is subjective and not quantifiable. The quality of a movie might have a very big influence on box office success and could therefore outweigh the other variables used in this research (Terry, Butler & De'Armond, 2011). There is also a chance that there are variables missing in this research which explain the variance in box office revenue better than the variables used in this research. These intervening variables might therefore cause the correlations in this research to give a wrong representation of reality. I will explore this idea further in chapter 5 and 6.

4. Results

In this chapter I will analyse my variables according to the methods discussed in chapter 3. To answer my research questions and my main research question: *How consistent are different indicators of movie quality?*, I will first look at the correlations between my variables to see which independent variables are most closely associated. After this I will conduct multivariate regressions to see how these correlations are influenced when control variables are introduced.

4.1 Correlations

I will first look at the correlations between the variables to see which correlations are interesting to look further into. I am particularly interested in the correlations between my dependent variables, box office revenue and production budget, and the other indicators of quality.

Before I start analysing the correlations regarding the independent variables, I will look at how box office revenue and production budget are correlated, because the variable production budget measures the amount of trust which is put into a movie, or the expected quality of the movie, while the variable box office revenue measures the success of a move, which is high quality for a for-profit producer. Production budget and box office revenue are positively and highly correlated as shown in table 11, which indicates that a movie with a higher budget generates a higher box office revenue.

In the following paragraphs I will look at how the other indicators of quality are related to box office revenue and production budget.

Table 11: Correlation table dependent variables

	Production budget
Box office revenue	0.626****
	(0.000)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

4.1.1. Review ratings

I previously noted (paragraph 3.3.5) that I will be using review ratings from different sources: the IMDb website (IMDbScore), Metacritic.com (Metascore), and the audience (RTAudience) and critic (RTCritics) rating from rottentomatoes.com. Although how these review ratings are calculated is different on each website, they explain the same variance in box office revenue and production budget. Table 12 shows that the correlation between all review variables is very strong, which supports the suspicion that these variables measure the same variance and therefore could indicate multicollinearity. This is why I will not use these variables in the same regression analyses. Instead I will look at the difference the variables make when used as independent variables in separate regression analyses, and decide which variable is the most suitable to use in further analyses.

Table 12 : Correlation table different review rating sources

	Review ratings			
	IMDbScore	Metascore	RTCritics	RTAudience
Review ratings				
IMDbScore		0.750**** (0.000)	0.780**** (0.000)	0.841**** (0.000)
Metascore	0.750**** (0.000)		0.916**** (0.000)	0.692**** (0.000)
RTCritics	0.780**** (0.000)	0.916**** (0.000)		0.773**** (0.000)
RTAudience	0.841**** (0.000)	0.692**** (0.000)	0.773**** (0.000)	
Box office revenue	0.323**** (0.000)	0.289**** (0.000)	0.326**** (0.000)	0.380**** (0.000)
Production budget	0.214**** (0.000)	0.111* (0.056)	0.570** (0.011)	0.181*** (0.002)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

Table 12 also shows that the correlation coefficients from all review ratings are significant (p<0.1). It is interesting to note that the correlations regarding production budget are lower than the correlations regarding box office revenue. This indicates that review ratings explain box office better than they do production budget. This is to be expected because box office revenue relies on ticket sales from the consumers and producers who review the movies. When a movie is given a high review rating, the ticket sales will go up. On the other hand, production budget is determined before production and can therefore not increase or decrease from good or bad review ratings. The Rotten Tomatoes critic rating is however stronger correlated with budget than with box office revenue. This indicates that movies with higher budgets get better reviews from critics.

4.1.2. Awards

I explained in paragraph 3.3.4 that I will use the variable award weighted to incorporate both nominations and wins of award in one variable. Table 13 shows that the strongest correlation is between box office revenue and award nominations ($r(298)=0.250$, $p<0.001$), and the weakest correlation is between production budget and award weighted. All correlations regarding box office revenue are significant, which indicates that awards in general are correlated with box office revenue. Using the constructed variable instead of only the wins or nominations does therefore not influence if awards are significant of not. To include the influence of both award wins and nominations in further analyses, I will use the awards weighted variable as the main variable for awards in my regression analyses.

The correlations between the award variables and production budget are very weak, and the only significant correlation is between production budget and award nominations, but this is at a high significance level ($p=0.052$).

Table 13: Correlation table awards

	Awards		
	Award Wins	**Award Nominations**	**Award Weighted**
Box office revenue	0.167***	0.250****	0.208***
	(0.004)	(0.000)	(0.000)

Production budget	0.227	0.112*	0.064
	(0.636)	(0.052)	(0.270)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

Table 14 shows the correlations between the review rating variables and the award variables. All correlations are positive, high, strong and significant, which indicates that awards and reviews are consistent in indicating movie quality. Although the correlation coefficients are very high, I do not expect a problem with multicollinearity in this table. This is because the variables measure a different concept and come from different sources. To make sure there is no multicollinearity between these variables, I will use a VIF-test during my regression analyses.

Table 14 Correlation table review ratings and awards

	Review Ratings			
Awards	IMDbScore	Metascore	RTCritics	RTAudience
Award wins	0.452****	0.569****	0.439****	0.400****
	(0.000)	(0.000)	(0.000)	(0.000)
Award nominations	0.585****	0.668****	0.569****	0.537****
	(0.000)	(0.000)	(0.000)	(0.000)
Award weighted	0.525****	0.633****	0.511****	0.473****
	(0.000)	(0.000)	(0.000)	(0.000)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

4.1.3. Genre

I use dummy variables to analyse genre as an indicator of movie quality, as mentioned in chapter 3. Table 15 shows the correlation coefficients between box office revenue, production budget and the dummy variables for genre. There, there are multiple dummy variables significantly correlated with box office revenue and production budget. I will use these dummy variables in further analyses as the variables for the concept of genre, to analyse the relationship between genre and box office revenue, and between genre and production budget.

Interestingly, this correlation table displays the first negative correlations in this chapter; all significant genre dummies are negatively correlated with box office revenue and production budget, except for the dummy representing action and adventure movies. From this table it becomes clear that action and adventure movies earn the most box office revenue, followed by comedies, thrillers and lastly dramas. Documentaries and biographies are left out of this list because this correlation is not significant. Action and adventure movies also get the highest production budget from the production studios, followed by comedies, documentaries and biographies, dramas, and lastly thrillers. The similarities between these lists can be explained by the high correlation between production budget and box office revenue (table 11).

Table 15: Correlation table box office revenue, production budget, and genre dummies.

	Genre Dummies				
	Drama	Comedy	Action Adventure	Thriller	Documentary Biography
Box office revenue	-0.188**** (0.001)	-0.029 (0.622)	0.315**** (0.000)	-0.109* (0.058)	-0.035 (0.548)
Production budget	-0.213**** (0.000)	-0.097* (0.092)	0.570**** (0.000)	-0.266**** (0.000)	-0.120** (0.038)

$*p<0.1$

$**p<0.05$

$***p<0.01$

$**** p<0.001$

Table 16 shows the correlations between the award variables and the genre dummies. It becomes clear that the genre dummy representing drama is positively correlated with all award variables, while the genre dummy representing comedy is negatively correlated with all award variables. This indicates that winning or being nominated for an award happens more often for movies which are dramas than movies which are not. The opposite is true for comedies. The genre dummy representing documentaries and biographies is positively correlated with award nominations and award weighted, not with award wins. This indicates that movies from these genres are more inclined to be nominated for an award than movies which are not from this category. The dummy variable for thrillers is only significantly correlated with award nominations, this indicates that there is a higher chance of getting a nomination for a thriller than for a movie which is not a thriller. The dummy variable for action and adventure movies is not significantly related to any of the award variables.

Comparing the correlations from table 16 with table 15, it becomes clear that dramas have a higher chance of getting awards or being nominated for one (table 16), but they do not acquire a higher box office revenue than movies which are not drama's. This is an interesting result since awards and box office revenue are positively correlated (table 13), so it would be expected that movie which are likely to win or be nominated for awards also earn more box office revenue. I will analyse these results further using regression analyses in order to find out how these variables, awards, drama and box office revenue, are actually related.

Table 16 : Correlation table award variables & genre dummies

	Genre Dummies				
	Drama	Comedy	Action Adventure	Thriller	Documentary Biography
Awards					
Award wins	0.253****	-0.171***	-0.054	-0.078	0.077
	(0.000)	(0.003)	(0.348)	(0.177)	(0.184)
Award nominations	0.280****	-0.213****	-0.063	-0.101*	0.161***
	(0.000)	(0.000)	(0.276)	(0.079)	(0.005)
Award weighted	0.275****	-0.194****	-0.061	-0.091	0.115**
	(0.000)	(0.001)	(0.289)	(0.117)	(0.047)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

It is interesting to see the relationship between review ratings (professional and consumer) and the genre dummies, because it provides an insight into the review behaviour of different reviewers regarding genres. It becomes clear from table 17 that the review ratings are quite consistent in their rating of different genres; the ratings for documentaries and biographies is the highest, followed by dramas, action and adventures, comedies and lastly thrillers. There is however a lot of difference in the variance between the review rating websites. The overall standard deviation of the IMDbScore is relatively small (st. dev=8.466), compared to the Metascore (st. dev=15.550), RTCritics (st. dev=15.097) and RTAudience (st. dev=23.642). Which indicates that there is a big difference in opinion among the users of Rotten Tomatoes, and less so among the users of IMDb. Another explanation for this difference in variance is the way in which these variables are constructed: IMDbScore is a weighted average while the RTAudience is an the arithmetic mean of all of the review ratings for a particular movie.

Table 17 Means review ratings per genre

	Review ratings							
	IMDbScore		Metascore		RTCritics		RTAudience	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Genre								
Drama	70.07	7.881	60.47	18.511	62.59	25.302	62.59	25.302
Comedy	63.40	7.366	48.63	16.482	49.28	26.438	49.28	26.438
Action Adventure	66.44	7.779	52.04	15.615	52.99	25.773	52.99	25.773
Thriller	59.32	10.224	46.97	15.156	41.50	26.824	41.50	26.824
Documentary Biography	73.12	9.082	69.29	11.988	78.74	13.874	78.74	13.874

**All review ratings are normalized to a scale from 1 to 100.*

4.1.4. Time of release

To get insight into the correlations regarding the time of release, I have chosen to use the seasons of release as explained in chapter 3. Table 18 shows the average box office revenue and production budget for every season. In becomes clear that movies with the highest production budget and box office revenue are released in the spring. The lowest box office revenue is earned in the winter, while the lowest production budget is given to movies in the summer. These outcomes are not surprising because the winter months January and February, are seen as ‘dump months’, which are months in which movies are released that are produced but not expected to do well (Burr, 2013). While spring has become the new ‘blockbuster season’, surpassing summer with the biggest productions (Sims, 2017).

Table 18: Means seasons regarding box office revenue and production budget[e]

	Frequency	Mean	Median	St. Dev.	Min	Max
Box office revenue[e]						
Winter[a]	63	$76.97	$59.00	$54.796	$22	$258
Spring[b]	66	$133.26	$94.00	$119.995	$21	$652
Summer[c]	84	$80.32	$59.00	$67.879	$16	$368
Autumn[d]	87	$108.90	$65.00	$125.946	$25	$937
Total	300	$99.55	$64.50	$100.408	$16	$937
Production budget[e]						
Winter	63	$56.16	$42.00	$49.038	$2	$215
Spring	66	$87.02	$46.50	$73.923	$1	$250
Summer	84	$54.82	$36.50	$49.046	$0	$215
Autumn	87	$69.45	$50.00	$61.374	$5	$250
Total	300	$66.43	$41.00	$59.950	$0	$250
N = 300						

[a] *Winter: January, February and March*

[b] *Spring: April, May and June*

[c] *Summer: July, August and September*

[d] *Autumn: October, November and December*

[e] *In millions of U.S. dollars*

There are significant correlations between box office revenue, or production budget, and the dummy variables of season of release, as is shown in table 19. Winter is negatively and significantly correlated with box office revenue, spring is positively and significantly correlated with box office revenue and production budget, and summer is negatively and significantly correlated with box office revenue and production budget. This indicates that movies released in the summer earn more box office revenue than movies which are released in other seasons, and movies in the winter and summer earn less box office revenue than movies which are released in other seasons. Movies in the spring get higher production budgets than movies in other seasons, while movies in the winter get lower production budgets than movies which are not released in the winter. The directions of the correlations regarding box office revenue and production budget are the same in all seasons, which is to be expected because of the high correlation between these two variables (table 11).

Table 19: Correlation table dependent variables and seasons

	Dependent variables	
	Box office revenue	**Production budget**
Winter	-0.116**	-0.088
	(0.044)	(0.126)
Spring	0.179***	0.183***
	(0.002)	(0.001)
Summer	-0.120**	-0.121**
	(0.038)	(0.036)
Autumn	0.060	0.032
	(0.304)	(0.578)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

4.1.5. Production studio size

As explained in chapter 3, I decided to use a categorical variable called production studio size to measure the correlation between the size of the production studio and my dependent variables. Table 20 shows the average box office revenue and production budget per category. It becomes clear that the highest average box office revenue is earned by the major production studios, who also spend the most production budget on their movies. These statistics do however not include all costs and earnings, such as earnings from rentals and merchandise, or marketing costs (paragraph 3.3.1).

Table 20: Means production studio size regarding box office revenue and production budget *[a]*

	Frequency	Mean	Median	St. Dev.	Min	Max
Box office revenue[a]						
Major	263	$104.12	$71.00	$101.346	$16	$937
Indie	37	$67.05	$39.00	$88.015	$22	$425
Total	300	$99.55	$64.50	$100.408	$16	$937
Production budget[a]						
Major	263	$71.32	$50.00	$60.947	$0	$250
Indie	37	$31.65	$20.00	$37.395	$2	$160
Total	300	$66.43	$41.00	$59.950	$0	$250
N = 300						

[a]*In millions of U.S. dollars*

Table 21 shows the correlations between the dependent variables and production studio size. It becomes clear that box office revenue and production budget are significantly and positively correlated with production studio size. This indicates that major production studios spend more production budget on their movies and also earn more box office revenue than indie studios. This is not surprising since major studios have a larger market share and therefore more money to spend, and, as established earlier, a higher budget is positively correlated with a higher box office revenue (table 11). These correlations are very strong, so I will use this variable in my further regression analyses.

Table 21: Correlation table dependent variables and production studio size

	Dependent variables	
	Box office revenue	**Production budget**
Production studio size	0.122**** (0.000)	0.218**** (0.000)

**p<0.1*

***p<0.05*

****p<0.01*

***** p<0.001*

4.1.6. Preliminary conclusions

From these correlation tables, it has become clear which variables are usable for further analysis during this research and which are not.

The first interesting indicator of movie quality is review ratings. The correlations between production budget or box office revenue and the review ratings are very strong and very similar. The similarities between these regression is to be expected because these variables measure the opinion of the same groups of people; professionals and consumers. These variables partially measure the same variance in box office revenue. I will therefore decide, using regression analyses, which review rating variable I will use in my further research.

Secondly, I will use award weighted as the variable to measure the relationship between award wins and nominations and the dependent variables. From now on I will not include award wins or nominations separately, because this could cause multicollinearity in my regression analyses.

Thirdly, I will use the genre dummies as I have explained in this chapter, to see how box office revenue, production budget and genre are correlated. Fourthly, I will use dummy variables for seasons to see how much of the variance in the dependent variables is explained by the time of release.

And lastly, I will control for production studio size, since a production studio cannot work with this variable to increase the quality of their movies. A production studio can grow over time by producing high quality movies, but it cannot increase its size beforehand.

4.2 Regressions

In the following paragraphs I will conduct my regression analyses and work towards answering my research questions. In these regressions I will use box office revenue and production budget as dependent variables, and the other indicators of movie quality as my independent variables.

I will first conduct several regression analyses to find out which of the review rating variables I can use best for my further regressions; IMDbscore, Metascore, the Rotten Tomatoes audience rating, or the Rotten Tomatoes critic rating. Table 22 shows an overview of the regression models with either box office revenue or production budget as the dependent variable and the different review ratings as one of the independent variables. The other independent variables are consistent among all regressions: the dummy variables for season of release, production studio size, awards weighted, and the dummy variables for genre. In the regressions with box office revenue as the dependent variable, production budget is added as an independent variable. In the regressions with production budget as the dependent variable, box office revenue is added as an independent variable. The complete tables of these regression models can be found in appendix C.

From table 22 it can be concluded that the regression which includes the audience review rating from rottentomatoes.com explains the most variance in box office revenue, while the review ratings from metacritic.com, and the consumer and professional review ratings from rottentomatoes.com all explain the most variance in production budget. To be able to make comparisons between the regressions with budget and the regressions with box office revenue as the dependent variable, I will only chose one of these review variables, which will be the Rotten Tomatoes audience rating since the model using this explains the most variance in both box office revenue and production budget.

Table 22 Summary regression models dependent variables and review ratings

Dependent variable: Box office revenue			
	F	**p**	***R²***
Independent variables			
IMDbscore	23.229	0.000	0.470
Metascore	23.275	0.000	0.471
RTAudience	27.284	0.000	0.510
RTCritics	24.197	0.000	0.480
Dependent variable: Production Budget			
	F	**p**	***R²***
Independent variables			
IMDbscore	38.140	0.000	0.593
Metascore	37.761	0.000	0.591
RTAudience	37.886	0.000	0.591
RTCritics	37.905	0.000	0.591

Appendix C contains the complete tables of the regression models used in this table.

The following first two paragraphs will discuss the regression models using box office revenue or production budget as the dependent variable and the indicators of quality which are known before production as the independent variables. The next two paragraphs will discuss the indicators of movie quality which are known after production, in the promotion stage.

4.2.1. Indicators of movie quality before production

Table 23 and 24 show two regression models used with the indicators of movie quality which are available before the actual production of a movie starts. These indicators are; the dummy variables for season of release, production budget, production studio size, and the dummy variables for genre.

Both regressions explain a large amount of the variance in the dependent variables which are used. The model used in table 23 explains 41.2% of the variance in box office revenue, while the model used in table 24 explains 59.1% of the variance in budget. Since the same independent variables are used in both models, it can be concluded that budget is more consistent with the variables which are known before production than box office is.

Table 23 shows that from these variables, only budget is significantly correlated with box office revenue (β= 0.647, $p < 0.001$). This correlation is very strong and consistent with the correlation in table 11 (β= 0.626, $p < 0.001$). A higher budget thus indicates a higher box office revenue.

Table 24 indicates that all of the independent variables used in this regression are significantly correlated with production budget, except for two of the dummy variables for the season of release: winter and spring. Interestingly, the correlation coefficient between box office revenue and production budget is lower (β= 0.450, $p < 0.001$), than in table 23 (β= 0.647, $p < 0.001$). This indicates that the variance in box office revenue which is explained by production budget in table 23, is actually partially explained by the correlations between budget and other indicators of movie quality used in table 24: the production studio size, the season of release dummy of summer, and the genre dummies.

The significant and positive correlation between production studio size and budget (table 24: β= 0.119, $p < 0.01$), indicates that a bigger production studio, or major studio, spends more production budget on their movies than a smaller, or indie studio. This is however not surprising since a major studio has a larger market share and therefore more budget available (chapter 3).

All dummy variables for genre are significant in table 24. This indicates that genre and budget are highly correlated. From these correlation coefficients it can be concluded that action and adventure movies get the largest amount of production budget, followed by documentaries and biographies, comedies, thrillers, and lastly dramas. These strong correlations between production budget and the genre dummy variables do not translate to the regression with box office revenue as the dependent variable (table 23). This indicates that the difference in production budget per genre is not related to the box office revenue earned by a movie.

The only significant correlation regarding season of release is between budget and the dummy variable for summer (table 24: β= -0.094, $p < 0.05$), which indicates that less production budget is spend on movies which will be released in summer than movies which will be released other seasons. Movies which are released in autumn, the reference category in this regression, get the most production budget.

Table 23: Regression before production with Box office revenue

Model	**F**	**p**	***R^2***	
	22.534	0.000	0.412	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	1.084	0.647****	10.923	0.000
Production studio size	-8.789	-0.029	-0.607	0.544
Season of release				
Winter	-19.817	-0.081	-1.458	0.146
Spring	5.491	0.023	-1.286	0.675
Summer	-14.285	-0.064	-1.148	0.252
Genre				
Drama	-15.755	-0.068	-1.286	0.199
Action Adventure	-13.541	-0.059	-0.989	0.323
Thriller	13.937	0.044	0.865	0.388
Documentary Biography	10.103	0.023	0.479	0.632
Reference categories: Comedy and Autumn				
N=300				
VIF-test < 1.9				
**p<0.1* ****p<0.01*				
p<0.05* * *p<0.001*				

Table 24: Regression before production with Production budget

Model	**F**	**p**	***R²***	
	46.477	0.000	0.591	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.269	0.450****	10.923	0.000
Production studio size	21.712	0.119***	3.057	0.002
Season of release				
Winter	-9.718	-0.066	-1.436	0.152
Spring	0.838	0.006	0.129	0.898
Summer	-12.594	-0.094**	-2.043	0.042
Genre				
Drama	-56.354	-0.410****	-8.316	0.000
Comedy	-50.722	-0.394****	-8.254	0.000
Thriller	-74.469	-0.394****	-8.956	0.000
Documentary Biography	-72.953	-0.282****	-6.736	0.000

Reference categories: Action and Adventure, and Autumn

N=300

VIF-test < 1.8

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*

4.2.2. Indicators of movie quality after production

Table 25 and 26 show regressions with all indicators of movie quality of which information is available after production; the dummy variables for the season of release, production budget, production studio size, awards, review ratings, and the dummy variables for genre. The correlations between the dependent variables and the award and review ratings variables are interesting since these variables were not included in the regressions in the previous paragraph.

The variable for awards, awards weighted, is not significantly related to box office revenue or production budget in these regression models. Table C4 in appendix C show that awards weighted is significantly related at a high significance level ($p<0.1$), when the Rotten Tomatoes critic rating are included among the independent variables. But in these regressions the correlations suggest that there is no significant relation between winning or being nominated for an award and the production budget or box office revenue of a movie.

The Rotten Tomatoes audience rating is only significant in table 25, where box office revenue is the dependent variable. This correlation is very strong; $\beta= 0.227$, $p < 0.001$, which indicates that a high review rating correlates with a higher box office revenue. Appendix C shows that all correlations regarding box office revenue and review ratings are positive and significant, while none of the correlations between budget and review ratings are significant. This indicates that there is no consistency regarding the correlations between box office revenue, production budget and awards.

As discussed in paragraph 4.2.1., from the dummy variable for season of release only summer is significantly correlated to production budget. This does not provide enough information to make conclusions about the relation between budget and season of release. It can only be concluded that there is less budget for movies which are released in the summer, than for movies which are released in another season.

Table 25: Regression after production variables with box office revenue

Model	F	p	R^2	
	24.197	0.000	0.480	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	0.984	0.588****	10.363	0.000
Production studio size	-12.473	-0.041	-0.920	0.358
Season of release				
Winter	-3.083	-0.013	-0.235	0.815
Spring	13.667	0.056	1.095	0.275
Summer	-4.236	-0.019	-0.354	0.723
Awards				
Awards weighted	0.199	0.099*	1.913	0.057
Review ratings				
RTCritics	0.868	0.232****	4.454	0.000
Genre				
Drama	-34.793	-0.151***	-2.880	0.004
Action Adventure	-13.053	-0.057	-1.010	0.313
Thriller	14.038	0.044	0.921	0.358
Documentary Biography	-20.393	-0.047	-0.994	0.321

Reference categories: Comedy and Autumn

N=300

VIF-test < 1.8

*p<0.1 ***p<0.01

**p<0.05 **** p<0.001

Table 26: Regression after production with production budget

Model	**F**	**p**	***R²***	
	37.886	0.000	0.591	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.274	0.459	9.848	0.000
Production studio size	21.828	0.120	3.058	0.002
Season of release				
Winter	-10.647	-0.072	-1.543	0.124
Spring	0.032	0.000	0.005	0.996
Summer	-13.422	-0.101	-2.129	0.034
Awards				
Awards weighted	-0.037	-0.031	-0.691	0.490
Review ratings				
RTAudience	-0.002	-0.001	-0.010	0.992
Genre				
Drama	-55.035	-0.400	-7.616	0.000
Comedy	-50.853	-0.395	-8.247	0.000
Thriller	-74.298	-0.394	-8.821	0.000
Documentary Biography	-71.877	-0.278	-6.224	0.000

Reference category: Action and Adventure, and Autumn

N=300

VIF-test < 2.0

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*

5. Conclusion and discussion

In this chapter I will discuss the conclusions of this study and answer my research questions, using the results of these regressions regarding my dependent variables; box office revenue and production budget.

5.1 Answering the research questions

My first research question is:

Which indicator of movie quality correlates the most with the dependent variables; box office revenue and production budget?

In the regression analysis with box office revenue as the dependent variable and all of the indicators of quality (table 24), there were three independent variables significantly correlated: production budget, review ratings, and the dummy variable for drama. Production budget and the review ratings were very strongly and positively correlated, while the dummy variable for drama was negatively correlated. From this it can be concluded that a movie with a high production budget will earn more in terms of box office revenue.

The direction of this relation is clear, since the production budget is decided before the box office revenue is known. This is not the case regarding the correlation between box office revenue and the review ratings. A high review rating can motivate consumers to go and see the movie for themselves. This creates more box office revenue. But a movie which is watched by a lot of people could also foster more reviews. In this last instance the reviews do not automatically have to be positive however. A movie which is watched by more people does not necessarily get a higher review rating than a movie which is watched less. It would be expected that a movie which is watched by more people would get a lot of different review ratings, low and high, which would make its overall review rating closer to the average review rating. The only way to achieve a high review rating and have a high box office revenue, is when a movie is of such quality that opinions on it are generally positive. A review rating would in this instance stay above the average and stimulate more and more consumers to go and see the movie, steadily increasing its box office revenue.

Review ratings are not significantly related to production budget (table 25). This is interesting to see, because this indicates that movies with a high production budget, even though they earn a lot of box office revenue, are not necessarily seen as high quality movies by reviewers. These correlations show that movie producers cannot ensure a high review rating by spending a lot of production budget.

The dummy variables for genre are strongly correlated with budget, indicating that there is a significant relation between the kind of genre and the amount of production budget which is spend on the movie. It is not surprising that action and adventure movies get the highest production budgets, since these movies require more budget for special effects. This higher production budget is however not translated in a significantly higher box office revenue. It is therefore unclear if action and adventures also earn more box office revenue than movies from other genres, because only the genre dummy for drama is significantly correlated with box office revenue.

Lastly, there is a significant correlation between production budget and the size of the production studio. This is not very surprising since the variable for the size of the production studio is calculated using the market share of production studios. A studio which is categorized as a major production studio has a higher market share and therefore more money to spend on production than a studio which is categorized as an indie studio. But, similarly to the review ratings, there is no significant correlation between box office revenue and the production studio size. From this it can be concluded that the size of a company does not matter for the overall result of a movie, since it does not significantly increase or diminish the amount of box office revenue.

To summarize; budget and box office revenue correlate most with each other. The second strongest correlations are box office revenue and review ratings, and budget and genre.

My second research question is:

Which indicator of movie quality is most useful for for-profit movie producers before the production of a movie?

This question specifies that it is about the indicators of movie quality which are available before production, indicating that some of the information regarding the indicators of quality used in the previous question are not available before production. From table 23 and 24 it can be concluded that production budget is most correlated with box office revenue. Interestingly, it is the only variable which is correlated with box office revenue in table 23. This correlation is positive and very strong and therefore indicates that a movie with an increased production budget is correlated with this movie earning more box office revenue.

A logical course of action for movie production studios would be to increase their production budget, and by doing so, increase their box office revenue. Production budget is however difficult to alter because it the amount of production budget depends on a lot of different factors, such as the size of the production studio and its reputation, and the sources of income. It is therefore interesting to look at the indicators of movie quality which are significantly correlated with production budget, since this information can change the production budget and therefore increase the probability of earning more box office revenue.

There are several strong correlations between production budget and the indicators of movie quality which are available before production, such as the production studio size and the dummy variables for genre. The correlation between production budget and production studio size is arbitrary, as concluded before. The correlations between production budget and the dummy variables for genre can however provide producers with some information. Production studios spend significantly more production budget on certain genres, but there are no genres with significantly more box office revenue than other genres. These correlations can be interpreted in two ways; either the production studios have to use more production budget for movies in a certain genre in order to make them a success than they have to with other genres, because they require more workers or special equipment. Or there is a notion that movies from a certain genre get more box office revenue, which is why the producers put more money in these genres. This research shows that the second interpretation has to be let go, because there are no signs that some genres earn more box office revenues than other genres based on their production budget. It does however hold up that a higher production budget increases the chance of a higher box office revenue, but it is not related to genre. The first interpretation is most likely the case; some movies require a bigger budget. It does have to be noted, again, that this increase in production budget does not equal a higher box office revenue. Genre is therefore also not an indicator of quality which is very useful for producers to look at in the production stage, since it does not increase the chance of a higher box office revenue.

To summarize; production budget and box office revenue are significantly and highly correlated. It is, however, not a very interesting indicator of movie quality to look at, since budget is dependent on a lot of other variables, such as the size of the production studio and the genre of the movie.

My third research question is:

Which indicator of movie quality is most useful for for-profit movie producers after the production of a movie, during the promotion stage?

This question can be answered using the same tables as the first question (table 25 and 26). As discussed in the answer of that first question, the highest correlation is between production budget and box office revenue. This is, as established in the answer of the second question, a variable which is difficult to manipulate by production studios. Production budget is also not relevant in answering this questions since it is impossible to change the production budget after the production of the movie is already finished. It is therefore interesting to look at the other significantly correlated indicators of movie quality.

The second highest correlations are box office revenue and review ratings, and production budget and genre. The correlation between production budget and genre has been discussed in the answer of question one; a production studio could chose a different genre for its movie, but this does not necessarily mean that the movie will earn more box office revenue. Genre is also not a variable which can be changed after production, so it is not a useful indicator regarding this question. The correlation between box office revenue and review ratings has also been discussed in the answer of question one. The problem of not knowing the direction of the correlation makes this a difficult variable for production studios to use. The review rating for a movie is out of the hands of the production studio, but it can be influenced by the production studio. A production studio could use a high review rating as an indicator of movie quality, and spend more marketing budget on these movies to increase the box office revenue.

To summarize; the best indicator of movie quality to look at after production are the review ratings. They give the best indication of where a production studio should spend their marketing budget.

5.2 Consistency and discussion

In this part of my thesis I will answer my main research question: *How consistent are indicators of movie quality?* And discuss the overall conclusions and results of this thesis. As discussed in paragraph 5.1, there are some strong correlations between the different indicators of movie quality. But the only real consistent correlation which could be found was the correlation between box office revenue and the production budget. As discussed in this thesis, this is not enough to provide production studios with the information they need to improve their chances of earning more box office revenue.

Information about the quality of a movie before the production of a movie has started, can best be gained by looking at the production budget of a movie. Surprisingly, genre, as well as the season of release, do not provide information about the quality of the movie in these early stages. During the promotion stage, after production, information can best be gained from the review ratings of movies. These review ratings provide insight into the quality as it is perceived by consumers and professional reviewers. Movies with high review ratings might benefit from a higher marketing budget, which increases the box office revenue. Including variables such as marketing budget, earnings from rentals, and other sources of profit, could have provided more insight into the quality of a movie.

Marketing budget for movies is kept secret for most movies. This is a statistic with which production studios differentiate themselves from others. According to Vogel (2001), the marketing budget should be equal to 50% of the production budget. Table 27 shows the descriptive statistics of this theoretic marketing budget in millions of U.S. dollars for this dataset, and the theoretic profit if this marketing budget is deducted from the overall profit. From all 300 movies, 141 movies did not make a profit according to these statistics. Again it should be noted that income other than box office revenue has not been taken into account.

Table 27: Descriptive statistics for marketing budget

	Mean	Median	Mode	St. Dev.	Min	Max
Marketing budget[a]	33.21	20.50	20	29.975	0.05	125
Gross profit after marketing expenses[ab]	-0.09	3.50	-49	82.817	-265.5	569.5
N = 300						

[a] *In millions of U.S. dollars*

[b] *Gross profit after marketing expenses = box office revenue – (budget + marketing budget)*

If, for academic purposes, this marketing budget would be available, it would provide more insight into the dynamics of the movie industry. Marketing budget could be a very important indicator of movie quality, because a marketing budget which is spend the right way, could initiate a lot of attention for a movie. This, in turn, influences the amount of tickets sold, the general opinion about the movie, and therefore the review ratings.

This research has dealt with only a small list of indicators of movie quality. After analysing these variables, it has become clear that there is no actual consistency between these variables. This indicates there are other variables, which have not been used in this thesis, which are important as indicators of movie quality. As discussed in chapter 3, there could be a confounding, or third variable which explains some or most of the variance of the indicators of quality used in this research. These confounding variables could be variables such as rentals, marketing budget, actors, directors, reputation of the production studio, or other measurable variables which were excluded in this research. But the main indicator of movie quality could also be the script, the way in which the movie is shot, aesthetics, or another variable which is difficult to quantify such as luck.

Movies are cultural goods, which means that they have more than just economic value (Klamer, 2016). Movies are also experience goods, which means that it is impossible to know the value of the product before consumption (Nelson, 1970). The combination of these theories makes it so movie quality is not measurable, and the indicators of movie quality are seemingly endless.

6. Further research and limitations

This chapter discusses possibilities of further research in relation to the limitations of this research in terms of method and sampling.

Further research into the indicators of movie quality can be done in number of ways. As concluded in chapter 5, there are seemingly endless indicators of movie quality which can be explored in further research.

Further research could start with gathering data on different variables regarding revenue and costs, other than box office revenue and production budget. I have chosen not to use profit as one of my variables because I did not have enough information about costs and revenues surrounding the production to make sure this variable gave an accurate representation of the movies in the dataset. A start could be made with the marketing budget and the influence of this marketing budget on the attention a movie receives in terms of box office revenue, review ratings and award nominations or wins. Other interesting revenues and costs are rentals, merchandise and sponsoring deals.

Further research could also focus on making this dataset a lot larger, by including more movies. This research only included data on 300 movies, from three different years (2013, 2014 and 2015). Further research could either include more movies per year, or go further back in time. By going back in time, the researcher could also research the evolution of the correlations between the different indicators of movie quality. This would provide insight into which direction the movie industry is headed and give the production studios an advantage by knowing what is coming in the future.

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Appendix A: The movies in the dataset

Movies 2013			
Rank	Title	Rank	Title
1	The Hunger Games: Catching Fire	51	Percy Jackson: Sea of Monsters
2	Iron Man 3	52	A Good Day to Die Hard
3	Frozen	53	Warm Bodies
4	Despicable Me 2	54	Jack the Giant Slayer
5	Man of Steel	55	The Purge
6	Gravity	56	Last Vegas
7	Monsters University	57	Ender's Game
8	The Hobbit: The Desolation of Smaug	58	Prisoners
9	Fast & Furious 6	59	After Earth
10	Oz The Great and Powerful	60	The Secret Life of Walter Mitty
11	Star Trek Into Darkness	61	Escape From Planet Earth
12	Thor: The Dark World	62	12 Years a Slave
13	World War Z	63	Free Birds
14	The Croods	64	Hansel and Gretel: Witch Hunters
15	The Heat	65	Evil Dead (2013)
16	We're the Millers	66	Red 2
17	American Hustle	67	Tyler Perry's A Madea Christmas
18	The Great Gatsby	68	Tyler Perry's Temptation: Confessions of a Marriage Counselor
19	The Conjuring	69	The Call
20	Identity Thief	70	Pain and Gain
21	Grown Ups 2	71	Gangster Squad
22	The Wolverine	72	The Internship
23	Anchorman 2: The Legend Continues	73	Instructions Not Included
24	Lone Survivor	74	Snitch
25	G.I. Joe: Retaliation	75	Riddick
26	Cloudy with a Chance of Meatballs 2	76	A Haunted House
27	Now You See Me	77	47 Ronin
28	The Wolf of Wall Street	78	August: Osage County
29	Lee Daniels' The Butler	79	Philomena
30	The Hangover Part III	80	The Family (2013)
31	Epic	81	Walking with Dinosaurs
32	Captain Phillips	82	Carrie (2013)
33	Jackass Presents: Bad Grandpa	83	Texas Chainsaw 3D
34	Pacific Rim	84	R.I.P.D.
35	This is the End	85	Blue Jasmine
36	Olympus Has Fallen	86	Kevin Hart: Let Me Explain

37	42.	87	Side Effects (2013)
38	Elysium	88	Scary Movie 5
39	Planes	89	The Mortal Instruments: City of Bones
40	The Lone Ranger	90	Delivery Man
41	Oblivion	91	Grudge Match
42	Insidious Chapter 2	92	One Direction: This is Us
43	Saving Mr. Banks	93	Kick-Ass 2
44	Turbo	94	Dallas Buyers Club
45	2 Guns	95	Rush (2013)
46	White House Down	96	The Host (2013)
47	Mama	97	The World's End
48	Safe Haven	98	21 and Over
49	The Smurfs 2	99	Her (2013)
50	The Best Man Holiday	100	Escape Plan

Movies 2014			
Rank	Title	Rank	Title
1	American Sniper	51	The Nut Job
2	The Hunger Games: Mockingjay - Part 1	52	God's Not Dead
3	Guardians of the Galaxy	53	Son of God
4	Captain America: The Winter Soldier	54	The Grand Budapest Hotel
5	The LEGO Movie	55	Planes: Fire & Rescue
6	The Hobbit: The Battle of the Five Armies	56	RoboCop (2014)
7	Transformers: Age of Extinction	57	Dracula Untold
8	Maleficent	58	Horrible Bosses 2
9	X-Men: Days of Future Past	59	The Hundred-Foot Journey
10	Big Hero 6	60	No Good Deed (2014)
11	Dawn of the Planet of the Apes	61	Selma
12	The Amazing Spider-Man 2	62	Muppets Most Wanted
13	Godzilla (2014)	63	Ouija
14	22 Jump Street	64	The Boxtrolls
15	Teenage Mutant Ninja Turtles (2014)	65	Jack Ryan: Shadow Recruit
16	Interstellar	66	If I Stay
17	How to Train Your Dragon 2	67	The Book of Life (2014)
18	Gone Girl	68	About Last Night (2014)
19	Divergent	69	Into The Storm
20	Neighbors	70	The Judge
21	Ride Along	71	Jersey Boys
22	Rio 2	72	Blended
23	Into the Woods	73	The Giver
24	Lucy	74	St. Vincent
25	The Fault in our Stars	75	Need for Speed

26	Unbroken	76	A Million Ways to Die in the West
27	Night at the Museum: Secret of the Tomb	77	John Wick
28	Mr. Peabody & Sherman	78	Birdman
29	300: Rise of An Empire	79	Dolphin Tale 2
30	The Maze Runner	80	The Expendables 3
31	The Equalizer	81	Earth to Echo
32	Noah	82	Sex Tape
33	Edge of Tomorrow	83	Wild (2014)
34	Non-Stop	84	Million Dollar Arm
35	Heaven is for Real	85	The Theory of Everything
36	The Imitation Game	86	This is Where I Leave You
37	Dumb and Dumber To	87	The Gambler
38	Annie (2014)	88	Paranormal Activity: The Marked Ones
39	Fury (2014)	89	Nightcrawler
40	Tammy	90	Chef
41	Annabelle	91	Get On Up
42	The Other Woman (2014)	92	3 Days to Kill
43	Penguins of Madagascar	93	Deliver Us From Evil
44	Let's Be Cops	94	When the Game Stands Tall
45	The Monuments Men	95	Draft Day
46	Hercules (2014)	96	Oculus
47	The Purge: Anarchy	97	The Best of Me
48	Alexander and the Terrible, Horrible, No Good, Very Bad Day	98	A Walk Among the Tombstones
49	Think Like a Man Too	99	That Awkward Moment
50	Exodus: Gods and Kings	100	Boyhood

Movies 2015			
1	Star Wars: The Force Awakens	51	The Perfect Guy
2	Jurassic World	52	Joy
3	Avengers: Age of Ultron	53	Fantastic Four
4	Inside Out	54	The Hateful Eight
5	Furious 7	55	Focus (2015)
6	Minions	56	Southpaw
7	The Hunger Games: Mockingjay - Part 2	57	Insidious Chapter 3
8	The Martian	58	Poltergeist (2015)
9	Cinderella (2015)	59	Jupiter Ascending
10	Spectre	60	Sicario
11	Mission: Impossible - Rogue Nation	61	The Man From U.N.C.L.E.
12	Pitch Perfect 2	62	Spotlight
13	The Revenant	63	McFarland, USA
14	Ant-Man	64	The Gift (2015)
15	Home (2015)	65	Everest (2015)

16	Hotel Transylvania 2	66	The Night Before
17	Fifty Shades of Grey	67	Krampus
18	The SpongeBob Movie: Sponge Out of Water	68	Max (2015)
19	Straight Outta Compton	69	The Age of Adaline
20	San Andreas	70	Brooklyn
21	Mad Max: Fury Road	71	The Longest Ride
22	Daddy's Home	72	The Boy Next Door
23	The Divergent Series: Insurgent	73	Pan
24	The Peanuts Movie	74	Hot Pursuit
25	Kingsman: The Secret Service	75	Concussion (2015)
26	The Good Dinosaur	76	The DUFF
27	Spy	77	Woman in Gold
28	Trainwreck	78	The Second Best Exotic Marigold Hotel
29	Creed	79	Unfriended
30	Tomorrowland	80	Entourage
31	Get Hard	81	Paper Towns
32	Terminator: Genisys	82	Chappie
33	Taken 3	83	Crimson Peak
34	Sisters	84	A Walk in the Woods
35	Alvin and the Chipmunks: The Road Chip	85	Point Break (2015)
36	Maze Runner: The Scorch Trials	86	Sinister 2
37	Ted 2	87	The Last Witch Hunter
38	Goosebumps	88	No Escape
39	Pixels	89	Ricki and the Flash
40	Paddington	90	The Woman in Black 2: Angel of Death
41	The Intern	91	Run All Night
42	Bridge of Spies	92	Love the Coopers
43	Paul Blart: Mall Cop 2	93	The Lazarus Effect
44	The Big Short	94	Ex Machina
45	War Room	95	In the Heart of the Sea
46	Magic Mike XXL	96	The Gallows
47	The Visit	97	Hitman: Agent 47
48	The Wedding Ringer	98	Project Almanac
49	Black Mass	99	Black or White
50	Vacation	100	Aloha

Appendix B: Variables in the dataset

Concept and source	**Operationalization**	**Variable**	**Measurement**
Title (boxofficemojo.com)	The film title	Title	String nominal
Production Studio Size (boxofficemojo.com)	Big or small production company	Production StudioSize	Categorical: 1. Indie 2. Major
Release date (IMDb.com)	Date of release in the US	ReleaseDate	Date scale; month
Release date (IMDb.com)	Season of release: In winter or not?	SeasonWinter	Dummy Categorical 0. No 1. Yes
Release date (IMDb.com)	Season of release: In spring or not?	SeasonSpring	Dummy Categorical 0. No 1. Yes
Release date (IMDb.com)	Season of release: In summer or not?	SeasonSummer	Dummy Categorical 0. No 1. Yes
Release date (IMDb.com)	Season of release: In autumn or not?	SeasonAutumn	Dummy Categorical 0. No 1. Yes
Release date (IMDb.com)	Year of release in the US	Year	Numeric scale 1. 2013 2. 2014 3. 2015
Review rating (IMDb.com)	IMDb score from IMDb users.	IMDbScore	Numeric scale 0-10, normalized to 0-100
Review rating (Metascore.com)	Metascore from metascore.com users.	Metascore	Numeric scale 0-100
Review rating (Rottentomatoes.com)	Rotten Tomatoes critic rating from 'professional critics'.	RTCritics	Numeric scale Percentage 0-100%
Review rating (Rottentomatoes.com)	Rotten Tomatoes Audience rating from moviegoers.	RTAudience	Numeric scale Percentage 0-100%
Genre (IMDb.com)	Is the movie a Drama or not?	Drama	Dummy Categorical 2. No

			3. Yes
Genre (IMDb.com)	Is the movie a Comedy or not?	Comedy	Dummy Categorical 0. No 1. Yes
Genre (IMDb.com)	Is the movie an Action or Adventure or not?	ActionAdventure	Dummy Categorical 0. No 1. Yes
Genre (IMDb.com)	Is the movie a Thriller or not?	Thriller	0. No 1. Yes
Genre (IMDb.com)	Is the movie a Documentary or Biography or not?	DucoBio	Dummy Categorical 0. No 1. Yes
Genre (IMDb.com)	The main genre of the movie.	Genre	Numeric Categorical 1. Drama 2. Comedy 3. ActionAdventure 4. Thriller 5. DocumentaryBiography
Awards (IMDb.com)	Amount of awards won by the movie	AwardWin	Numeric scale
Awards (IMDb.com)	Amount of times a movie was nominated for an award	AwardNom	Numeric scale
Awards (IMDb.com)	Total amount of nominations and wins of awards.	AwardTotal	Numeric scale Calculation: AwardWin + AwardNom
Awards (IMDb.com)	Total amount of awards weighted	Award Weighted	Numeric scale Calculation: (AwardWin)+((3568/8341)*AwardNom) AwardWin total = 3568 AwardNom total = 8341
Box office revenue (boxofficemojo.com)	Total box office income in the USA in millions of dollars	BoxOffice Revenue	Dollar scale
Production budget (boxofficemojo.com)	Total budget of the movie in millions of dollars	Production Budget	Dollar scale

Appendix C: Regression tables

Table C1: Regression Box office revenue and IMDbscore

Model	**F**	**p**	***R²***	
	23.229	0.000	0.470	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	0.969	0.579****	9.991	0.000
Production studio size	-8.683	-0.028	-0.629	0.530
Season of release				
Winter	-4.039	-0.016	-0.304	0.761
Spring	13.300	0.055	1.055	0.292
Summer	-5.003	-0.022	-0.414	0.679
Awards				
Awards weighted	0.228	0.114**	2.173	0.031
Review ratings				
IMDbscore	-2.348	0.207****	3.732	0.000
Genre				
Drama	-40.067	-0.174***	-3.220	0.001
Action Adventure	-16.211	-0.071	-1.243	0.215
Thriller	17.049	0.054	1.101	0.272
Documentary Biography	-19.989	-0.046	-0.959	0.338

Reference categories: Comedy and Autumn

N=300

VIF-test < 1.9

**p<0.1*	****p<0.01*
***p<0.05*	***** p<0.001*

Table C2: Regression Box office revenue and Metascore

Model	F	p	R^2	
	23.275	0.000	0.471	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	1.002	0.598****	10.478	0.000
Production studio size	-13.880	-0.045	-0.997	0.319
Season of release				
Winter	-3.658	-0.015	-0.275	0.783
Spring	15.195	0.063	1.205	0.229
Summer	-3.669	-0.016	-0.304	0.761
Awards				
Awards weighted	0.151	0.075	1.317	0.189
Review ratings				
Metascore	1.286	0.224****	3.861	0.000
Genre				
Drama	-36.384	-0.158***	-2.968	0.003
Action Adventure	-14.949	-0.065	-1.146	0.253
Thriller	11.170	0.035	0.721	0.472
Documentary Biography	-19.288	-0.045	-0.929	0.354

Reference categories: Comedy and Autumn

N=300

VIF-test < 1.9

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*

Table C3: Regression Box office revenue and Rotten Tomatoes audience rating

Model	**F**	**p**	***R²***	
	27.284	0.000	0.510	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	0.920	0.549****	9.848	0.000
Production studio size	-3.566	-0.012	-0.268	0.789
Season of release				
Winter	-6.505	-0.026	-0.512	0.609
Spring	8.650	0.036	0.712	0.477
Summer	-9.294	-0.042	-0.799	0.425
Awards				
Awards weighted	0.157	0.078	1.588	0.113
Review ratings				
RTAudience	1.878	0.322****	6.221	0.000
Genre				
Drama	-42.479	-0.186****	-3.609	0.000
Action Adventure	-11.349	-0.050	-0.904	0.367
Thriller	23.760	0.075	1.291	0.113
Documentary Biography	-39.473	-0.091*	-1.935	0.054

Reference categories: Comedy and Autumn

N=300

VIF-test < 1.9

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*

Table C4: Regression Box office revenue and Rotten Tomatoes critics rating

Model	**F**	**p**	***R²***	
	24.197	0.000	0.480	
	Dependent variable			
	Box office revenue			
Independent variables	**B**	**β**	**t**	**p**
Budget	0.984	0.588****	10.363	0.000
Production studio size	-12.473	-0.041	-0.920	0.358
Season of release				
Winter	-3.083	-0.013	-0.235	0.815
Spring	13.667	0.056	1.095	0.275
Summer	-4.236	-0.019	-0.354	0.723
Awards				
Awards weighted	0.199	0.099*	1.913	0.057
Review ratings				
RTCritics	0.868	0.232****	4.454	0.000
Genre				
Drama	-34.793	-0.151***	-2.880	0.004
Action Adventure	-13.053	-0.057	-1.010	0.313
Thriller	14.038	0.044	0.921	0.358
Documentary Biography	-20.393	-0.047	-0.994	0.321

Reference categories: Comedy and Autumn

N=300

VIF-test < 1.8

**p<0.1*　　****p<0.01*

***p<0.05*　　***** p<0.001*

Table C5: Regression Production budget and IMDbscore

Model	**F**	**p**	***R^2***	
	38.140	0.000	0.593	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.265	0.445****	9.991	0.000
Production studio size	21.880	0.120***	3.079	0.002
Season of release				
Winter	-9.961	-0.068	-1.440	0.151
Spring	0.051	0.000	0.008	0.994
Summer	-13.504	-0.101**	-2.153	0.032
Awards				
Awards weighted	-0.061	-0.051	-1.101	0.272
Review ratings				
Metascore	0.360	0.053	1.070	0.285
Genre				
Drama	-26.327	-0.409****	-7.927	0.000
Comedy	-50.393	-0.392****	-8.172	0.000
Thriller	-72.617	-0.385****	8.576	0.000
Documentary Biography	-74.074	-0.286****	-6.667	0.000

Reference category: Action and Adventure, and Autumn

N=300

VIF-test < 1.9

**p<0.1*   ****p<0.01*

***p<0.05*   ***** p<0.001*

Table C6: Regression Production budget and Metascore

Model	**F**	**p**	R^2	
	37.761	0.000	0.591	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.276	0.463****	10.478	0.000
Production studio size	22.598	0.123***	3.142	0.002
Season of release				
Winter	-11.154	-0.076	-1.606	0.109
Spring	-0.087	-0.001	-0.013	0.990
Summer	-13.415	-0.101**	-2.133	0.034
Awards				
Awards weighted	-0.026	-0.022	-0.436	0.663
Review ratings				
Metascore	-0.065	-0.019	-0.362	0.718
Genre				
Drama	-54.625	-0.397****	-7.683	0.000
Comedy	-50.869	-0.395****	-8.248	0.000
Thriller	-74.996	-0.392****	-8.922	0.000
Documentary Biography	-71.142	-0.275****	-6.341	0.000

Reference category: Action and Adventure, and Autumn

N=300

VIF-test < 2.0

*p<0.1 ***p<0.01

**p<0.05 **** p<0.001

Table C7: Regression Production budget and RTAudience

Model	F	p	R^2	
	37.886	0.000	0.591	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.274	0.459****	9.848	0.000
Production studio size	21.828	0.120***	3.058	0.002
Season of release				
Winter	-10.647	-0.072	-1.543	0.124
Spring	0.032	0.000	0.005	0.996
Summer	-13.422	-0.101**	-2.129	0.034
Awards				
Awards weighted	-0.037	-0.031	-0.691	0.490
Review ratings				
RTAudience	-0.002	-0.001	-0.010	0.992
Genre				
Drama	-55.035	-0.400****	-7.616	0.000
Comedy	-50.853	-0.395****	-8.247	0.000
Thriller	-74.298	-0.394****	-8.821	0.000
Documentary Biography	-71.877	-0.278****	-6.224	0.000

Reference category: Action and Adventure, and Autumn

N=300

VIF-test < 2.0

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*

Table C8: Regression Production budget and RTCritics

Model	**F**	**p**	***R²***	
	37.905	0.000	0.591	
	Dependent variable			
	Production budget			
Independent variables	**B**	**β**	**t**	**p**
Box office revenue	0.274	0.459****	9.848	0.000
Production studio size	21.828	0.120***	3.058	0.002
Season of release				
Winter	-10.647	-0.072	-1.543	0.124
Spring	0.032	0.000	0.005	0.996
Summer	-13.422	-0.101**	-2.129	0.034
Awards				
Awards weighted	-0.037	-0.031	-0.691	0.490
Review ratings				
RTCritics	-0.002	-0.001	-0.010	0.992
Genre				
Drama	-55.035	-0.400****	-7.616	0.000
Comedy	-50.853	-0.395****	-8.247	0.000
Thriller	-74.298	-0.394****	-8.821	0.000
Documentary Biography	71.877	-0.278****	-6.224	0.000

Reference category: Action and Adventure, and Autumn

N=300

VIF-test < 2.0

**p<0.1* ****p<0.01*

***p<0.05* ***** p<0.001*