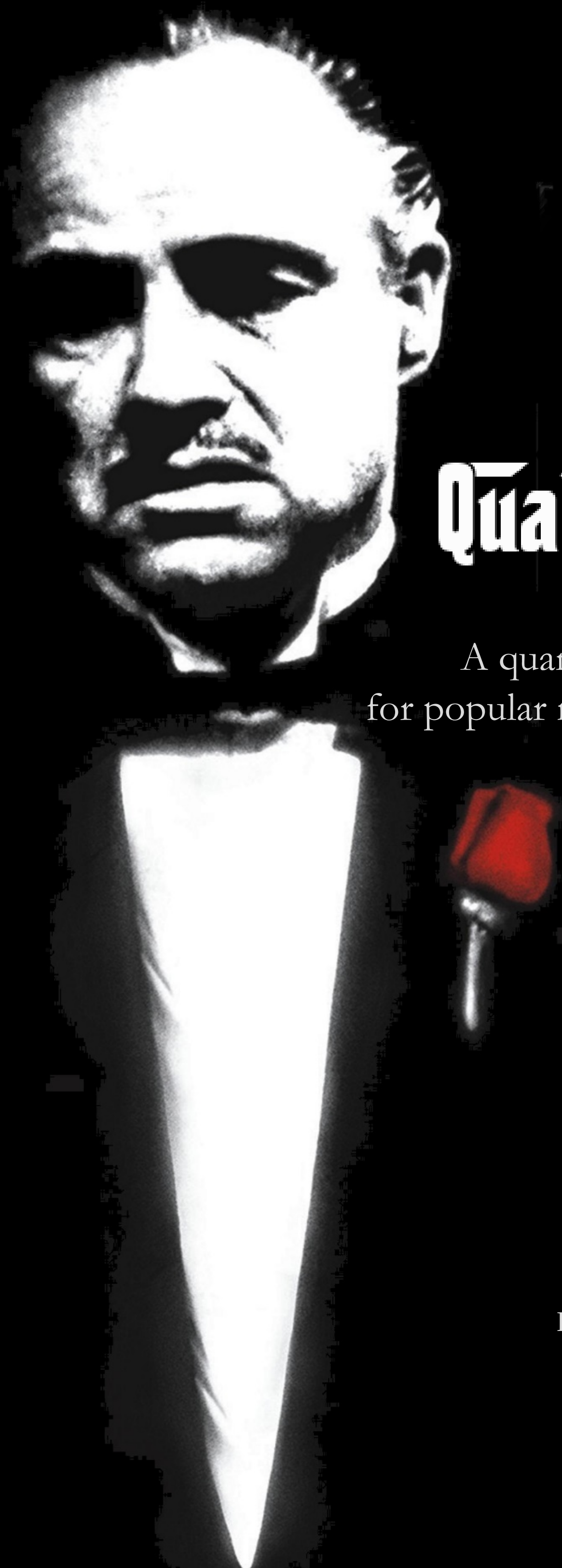

Quality time at the movies

A quantitative analysis of the perceived quality
for popular movies by consumers, experts and peers

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ABSTRACT

Academic research pertained to the marketing of motion pictures has identified the importance of quality on the commercial success of popular movies with indicators as consumer evaluations, expert ratings and peer-recognized awards as the Academy Awards. However, most researchers fail to analyze the quality of a movie as a measurement of performance of a movie. The current study extents previous research by aiming to measure the perceived quality of consumers, experts and peers for popular movies, based on the assumptions made on the success factors for commercial performance in previous marketing literature. Through a quantitative internet content analysis, data was gathered on the motion picture industry. The models were tested with a sample of 320 movies released between 2000-2015. Results show that the perceived quality of consumers overlap with the perceived quality of experts, which contradicts statements about the ‘little taste’ of consumers. Moreover, the data shows that there is a difference between the perceived quality of consumers and the commercial success of a movie, measured in box office revenue. However, for both commercial success and the perceived quality of consumers, popular appeal is still important for the satisfaction of the consumer. Managerial and theoretical implications, as well as limitations and directions for future research are offered.

Keywords: *perceived quality, popular movies, consumer evaluations, expert evaluation, peer-recognition*

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Preface

This research was the final stage of my time as a student. I started my time as a student at the University of Groningen, where I studied Arts, Culture and Media. During that time, I gained a lot of knowledge and experience in the field of arts and culture by doing an internship at the Holland Festival and joining the board of my study association. Furthermore, I studied a minor at the University of Amsterdam, which gave me insights in the world of marketing and management. I finalized by bachelor with these comments of my supervisor: “I think you will make a large difference in the cultural sector of the Netherlands”.

With these words in the back of my mind, I started the pre-master Cultural Economics and Entrepreneurship in Rotterdam, in which I discovered my interest for economics and doing research to the creative industries. Almost two years later, here I am, finishing my final academic research (for the time being) on the topic of marketing for the motion picture industry.

I wish to thank my thesis supervisor Pawan Bhansing. He was a valuable addition to my thinking process and the development of my research. When I had to switch to a different topic, he helped me to set up a new research in a relatively short time. Also, I want to thank all the other lecturers and professors from the Cultural Economics and Entrepreneurship masters. I have gained so much new knowledge which changed my perception on the cultural field.

Furthermore, I want to thank my mother and my two brothers, who always supported me in my decision of moving to Rotterdam and choosing to study the field of the arts and culture. Also, I would like to thank my friends Lysanne, Lonneke and Esker for the endless Polak sessions the last couple of months, but even more for the amazing things we did the last two years. Thank you for making me feel so at home in the favorite city I have ever lived in: Rotterdam.

As for the future, I hope to pursue a career in the creative sector where it will be my aim to make a difference in this world.

Introduction

Quality is an important influencer on purchase decisions of consumers. Especially in the case of creative goods as movies, quality is often the only reason why people consume a certain good (Ginsburgh & Weyers, 1999). Due to the fact that movies are experience goods, the quality cannot be assessed prior to consumption. This results into an extremely uncertain demand, which makes the motion picture industry one of the most unpredictable industries: nobody knows anything (a.o. Clement, Wu & Fisher, 2014; Eliashberg, Elberse & Leenders, Suárez-Vásquez, 2011; Gemser, Leenders & Wijnberg, 2008).

In order to reduce the quality uncertainty, consumers search for credible signs of information that could indicate the level of quality for the movie. Third party sources as expert evaluations, awards such as the Academy Awards, and the recommendations they get from their social network can help them determine which movie to watch. Motion picture companies try to influence this perception of quality by giving signs of information such as the genre, the hiring of superstars and the creation of buzz through a marketing campaign (Eliashberg et al., 2006; Hadida, 2009; Suárez-Vázquez, 2011).

The effectiveness for indicators of quality on the commercial success of a movie, measured in box office results, has been the subject of many researches in the past, such as the effect of online word of mouth from consumers, expert evaluations and awards, (a.o. Clement et al., 2014; Hennig-Thurau, Houston & Walsh, 2006; Elberse & Eliashberg, 2003). However, quality has only been used as an predictor on the (commercial) success of a movie, but rarely as a form of success. As quality is one of the most important outcomes of a product in the motion picture industry and in the creative industries in general, it can be seen as a form of success. Therefore, the aim of this research is to investigate to what extent there is a difference between the performance of a popular movie in terms of perceived quality, and the performance in terms of commercial success.

This research measures the performance of a movie in terms of perceived quality for consumers, experts and peers, in line with the selection system theory (Bhansing, Leenders & Wijnberg, 2012), instead of only through commercial performance, which has not yet been done in academic research to my knowledge. It is expected that there is a difference between perceived quality of consumers and the perceived quality of peers and experts, as consumer evaluations are often associated with popular appeal, whilst experts and peers have the knowledge and expertise to judge the quality of the movie (Bourdieu, 1984; Holbrook, 2005; Tsao, 2012). The theoretical and modeling framework of this study is based on previous marketing literature on the commercial performance of motion pictures (Clement et al., 2014; Elberse & Eliashberg, 2003; Hennig-Thurau et al., 2006). The results of this research will be compared to the assumptions made those previous studies.

Only popular movies were used for the analysis, as it is expected that the difference between popular appeal and the perceived quality of experts and peer is the largest for these movies: moviegoers that consumer less popular movies are often more knowledgeable about the quality of movies in general. Moreover, as many researchers have used popular movies for their analysis (a.o. Desai & Basuroy, 2005; Hennig-Thurau et al., 2006; Kim, Park & Park, 2013), these types of movies would be the most suitable for replicating the theoretical and modeling frameworks. Last, the data availability for popular movies is much larger than for small, low-budget movies.

This research contributes to the literature in several ways. First, it is interesting to see which factors influence the perceived quality performance for consumers, experts and peers, compared to the elements that affect box office revenue. To a large extent, econometric models were developed to measure the commercial success of a movie in terms of box office revenue or attendance numbers, but to my knowledge, these models were never used to measure the performance of a movie in terms of (perceived) quality. Studies have analyzed quality of movies in a quantitative analysis (Holbrook, 2005; Ginsburgh, 2003; Ginsburgh & Weyers, 1999), but not with use of those models which were extensively used in the marketing literature for prediction of commercial performance of movies (a.o. Clement, Wu & Fischer, 2014; Desai & Basuroy, 2005; Elberse & Eliashberg, 2003; Gemser, Leenders & Wijnberg, 2008). It is important for motion picture companies to know which elements actually influence the perceived quality of a popular movie, as quality is an important determinant of demand for movies (Ginsburgh & Weyers, 1999).

Second, it is relevant to compare the perceived quality by consumers with the perceived quality by experts and peers. Hundreds of years, the debate has been going on about whether consumers were able display ‘good taste’ in the appreciation of cultural goods. The French sociologist Pierre Bourdieu stated that only certain individuals that have a high amount of cultural capital, acquired through long training and demonstrated by acknowledged expertise, are able to judge what is ‘good taste’ (Bourdieu, 1984; Holbrook, 2005), which indicates that ordinary consumers are not able to judge quality. However, due to the online availability of movies, consumers have generated more experience in watching movies, which makes is possible that consumers have developed a ‘good taste’ for movies. Moreover, it has become easier to analyze the assessment of quality by consumers through online platforms as *IMDb* and social media. Therefore, it is possible that consumers do indeed show signs of ‘good taste’. Research to this phenomenon was done by Holbrook (2005), but he did not take into account other elements than reviews of consumers and critics. This research will add to that discussion by using models which analyze more than just those reviews.

Third, the comparison between experts and peers is intriguing. Often, these two selectors are used intertwiningly, as they are both important gatekeepers in the motion picture industry for assessing quality (Ginsburgh, 2003). However, according to Ginsburgh (2003), movies that won peer-recognized awards as the Academy Awards did not necessarily show signs of long-term quality, but are more focused on short-term commercial success. As experts are often seen as the only gatekeepers who actually can judge long-term quality of creative goods (Bourdieu, 1984; Ginsburg & Weyers, 1999), it is possible that there is a difference in the perception of quality by experts and peers.

Last, the comparison between box office revenue and the perceived quality of consumers is vital. It is often assumed box office revenue represents the demand for consumers (Clement et al., 2014; Desai & Basuroy, 2005; Elberse & Eliashberg, 2003; Litman, 1983; Liu, 2006), without taking into account the fact that the perceived quality of a movie can be completely different than the commercial success of a movie. This research compares the pre-assessment of quality for a movie, measured in box office revenue, and the post-assessment of quality, measured in consumer ratings. It is expected that there is a difference between these measurements.

This study will use the selection system theory (Bhansing et al., 2012) to analyze the perceived quality for the market, experts and peers. This theory describes three types of product selection: market, expert and peer selection (Bhansing et al., 2012; Gemser et al., 2008). In the decision process, consumers rely on these three types of selectors as they refer to the relative importance of different types of information sources (Gemser et al., 2008).

A quantitative content analysis was conducted to measure the performance of popular movies in terms of perceived quality. The sample consists of 320 movies, released between 2000 and 2015, which is a period of 16 years. Regressions analyses were conducted to analyze the results of the data collection.

This research is structured in the following way. The study will start with a theoretical framework, in which the motion picture industry in general will be discusses, as well as the perceived quality for movies and previous studies on the commercial success of a movie. Second, the method of the research will be explained, which included the method of data retrieval. Third, the results of the research will be analyzed, which is divided in descriptive statistics and the regression analyses. Fourth, the results of the regressions will be reviewed in the discussion. And last, concluding remarks will be made on the outcome of the research, as well as managerial implications, academic implications and limitations of the research.

1. Theoretical framework

In this section, the relevant theoretical concepts for this research will be discussed, based on previous research. First, an overview of the motion picture industry in general will be given. Second, literature about the perceived quality for movies by consumers, experts and peers will be discussed. And last, the variables that were the largest influencers on the commercial success of a movie in previous literature will be discussed.

1.1 General characteristics of the motion picture industry

The motion picture industry has been a popular topic for academic research, as the sector has a high global economic importance and there is a rich amount of data available, especially on the internet. The division of market share is highly skewed, for which Hollywood has a large share in the industry (a.o. Eliashberg et al., 2006; Fu, 2006; Hadida, 2009). Many researchers have stated that there is a one-way media flow in the global context. Producers from other countries than the U.S. can simply not compete against the budgets and the quality of the Hollywood movies. This results in the fact that American movies dominate the cinemas and other distribution platforms on a global scale (Fu, 2006; Lee, 2006).

The motion picture industry has been one of the largest creative industry for a long time, for which it received quite a lot of attention by the media through prestigious events as the Academy Awards and the private lives of superstar actors. This resulted in a high demand for movies for a large pool of interested people (Eliashberg et al., 2006). This is visible in the commercial success of the industry: the global box office revenue from 2015 was more than $11 billion dollars, and this amount will probably keep on increasing (Motion Picture Association, 2015; The Numbers, 2016). Moreover, the amount of people that watch movies from the comfort of their own homes has increased, which is visible in the amount of Netflix subscribers. Internationally, there are 81 million subscribers in April 2016, which was 'only' 65 million subscribers around the same time the year before (Roberts, July 2015; Smith, April 2016).

Beyond doubts, the motion picture industry is booming. However, even though movies are popular among a large group of people, the demand for movies is highly uncertain: there is hardly any product which is commercially more uncertain as movies (De Vany & Walls, 1999, 2002; Eliashberg et al., 2006; Hadida, 2009; Walls, 2005).

There are four characteristics of movies (McKensie, 2012). First, each motion picture is an experience good that is unique and cannot be duplicated. Therefore, the quality of the motion picture cannot be assess prior to consumption (Suárez-Vázquez, 2011). Second, the demand for a movie is unpredictable. Third, a film needs time on a screen to build an audience. And lastly, most of the costs of production and distribution that occur before the release of a movie are sunk, which means that the costs cannot be undone (McKensie, 2012). Because most costs are sunk, the risk of producing a movie is high: the production costs are already made but there is no guarantee for profit.

Movies are highly hedonic in nature. Hedonic goods are consumed for luxury purposes which gives the consumer the possibility to experience pleasure and enjoyment (Clement, Fabel & Schmidt-Stölting, 2006; Hirschman & Holbrook, 1982). The consumption of hedonic goods is accompanied by multisensory, fantasy and emotive aspects, in contrary to the consumption of utilitarian goods, which are consumed for practical reasons and primary needs (Hirschman & Holbrook, 1982). For utilitarian goods, the evaluation is more objective, tangible and functional, which means that it much more easy to assess the quality beforehand (Clement et al., 2006). For hedonic goods, the quality is harder to assess as each experience is different and the evaluation is subjective due to taste and emotions of the consumer. Therefore, hedonic goods have a high consumption risk that results from quality uncertainty and subjective evaluation of the goods (Clement et al., 2006).

Motion picture companies use many strategies to decrease the quality uncertainty for consumers by, for example, hiring star actors and directors, and launching large marketing campaigns to create buzz (Eliashberg et al., 2006; Hadida, 2009; Suárez-Vázquez, 2011). As movies have a relatively short lifecycle due to the fact that most of the profit is earned through theatrical revenue, it is important that much attention for the movie must be created prior to the release of the movie. This means that the promotion of a movie can only happen in a short time span: the success of a movie is dependent on the premiere and the early reception of movies by important stakeholders (Jedidi et al., 1999). This results in sky-high budgets by motion picture companies in an attempt to attract the attention of the consumer. However, the recruitment of stars and investments in large marketing campaigns are by no means a guarantee for success (Suárez-Vázquez, 2011).

Moreover, the cost for the first copy of a movies is often very high, which makes it a risky business. For example, *Transformers: Dark of the Moon* (2011) costed $195,000,000, while the potential of achieving a commercial success is always low (Clement et al., 2006). The potential is low because the production process of producing a movie is expensive, involves a large amount of sunk costs and takes a long time, while the time to earn theatrical revenue is short. To conclude, it is clear that the motion picture industry inhibits high risks as the production costs are large and mostly sunk, whilst demand for the movies is highly uncertain.

Much research in the marketing literature has been conducted to the factors that explain the success of a movie, but there is never one formula that works the best for generating a large audience (De Vany & Walls, 1999; Hadida, 2009). Especially because movies are often not functionally or technologically more advanced than the predecessors and because individuals all have a different taste that develops over the years, the demand of the audience always changes. Even though motion picture studios spent millions of dollars on investing in marketing campaigns and star actors, it is the audience that always determines the success of a movie, which makes the business so uncertain (De Vany & Walls, 1999; Hadida, 2009).

Various marketing studies have researched the potential success factors for movies in terms of box office revenue. Scholars have analyzed the effect of a variation of factors, such as *star power* (Desai & Basuroy, 2005; De Vany & Walls, 1999; De Vany & Walls, 2004; Elberse, 2007; Karniouchina, 2011; Liu, Liu & Mazumdar, 2014; Suárez-Vázquez, 2011; Wallace, Seigerman & Holbrook, 1993), *genre* (Desai & Basuroy, 2005; Litman, 1983; Perretti & Negro, 2007), *film critics* (Desai & Basuroy, 2005; Gemser, Leenders & Oostrum, 2007; King, 2007; Reinstein & Snyder, 2005; Suárez-Vázquez, 2011), *awards* (Deuchert, Adjamah & Pauly, 2005; Ginsburgh & Weyers, 1999; Ginsburgh, 2003) and *online word of mouth* (Gopinath, Chintagunta & Venkataraman, 2013; Kim, Park & Park, 2013; Liu, 2006; Riu, Liu & Whinston, 2013).

Movie studios try to attract these elements for their movies to reduce the risk of quality uncertainty for their consumers, as these factors can be an indication of quality or entertainment value for the movie. However, the findings are heterogeneous, which indicates it is still not clear which aspects have the largest influence on the commercial performance of a movie, measured in box office revenue (Clement et al., 2014; De Vany & Walls, 1999). But box office revenue is not the only way to measure the performance of a movie. This research focuses on the performance of a movie, measured in terms of perceived quality, as quality has always been one of the most important determinants of consumer demand (Ginsburgh & Weyers, 1999; Zhuang, Quan & Paul, 2014). In the next section, the perceived quality for movies will be discussed.

1.2 Perceived quality of a movie

In order to reduce the risk of consuming a good for which someone will not be satisfied with, consumers constantly look for signs of information when purchasing goods or services. Quality is one of the most important influencers of demand: it is often the reason why people decide on buying a certain good over another similar one (Ginsburgh & Weyers, 1999). Especially in the case of experience goods and luxury consumer goods, quality can be a more important indicator than price on the decisions of consumers.

According to Ginsburgh & Weyers (1999), there are three basic ideas with regard to the assessment of quality in cultural economics: “1. The assessment of quality should be left to specialists who are familiar with and have experience with works of art; 2. Some unanimous, even if subjective, judgement is necessary; and 3. Only time makes it possible to separate fashion from art” (p. 270). This indicates that quality is hard to measure and extremely complex (Gemser et al., 2008; Ginsburgh & Weyers, 1999; Zhuang et al., 2014).

Prior research suggest that consumers are influenced by information provided by the motion picture companies as well as by third-party sources. The information from the companies include signs as price and brand image, but third-party sources of information often have a stronger influence on consumer decisions, such as awards and the judgment of experts (Zhuang, Quan & Paul, 2013). However, the assessment of quality is often a sensitive topic, especially in the case of the cultural industries.

Taste formation and individual characteristics of a consumer are a large determinant in the judgement of quality. Bourdieu (1984) stated that only experts have the ability to judge quality, and can therefore display ‘good taste’. According to him, individuals who have acquired a large amount of cultural capital through long training and experience in a field of interest, can be recognized and legitimated as having ‘good taste’ in a particular field (Bourdieu, 1984). Also Ginsburgh & Weyers (1999) state that “the assessment of quality should be left to specialists who are familiar with and have experience with works of art” (p. 270). This indicates that consumers do not have the ability to judge if something is ‘good’, and therefore have ‘little taste’ (Holbrook, 2005).

A long debate has been going on about the ability of consumers to judge the quality of a cultural good, but to my knowledge, little quantitative academic research on the judgement of quality for the motion picture industry has been conducted. For consumer evaluations, Holbrook

(2005) made a distinction between ordinary consumer evaluations, which were consumer ratings on *IMDb*, and popular appeal, which were the amount of ratings given by consumers. He showed that the ordinary consumer evaluations showed signs of ‘good taste’, as they overlap with the evaluations of critics. Measurement of popular appeal showed a negative relation with critics. This indicates that consumers are able to show signs of ‘good taste’ thought the ordinary consumer evaluations.

The drawback of this research is that no other variables were taken into account when ‘measuring’ the taste of consumers. Moreover, only the assessment of quality by experts were taken into account, while peer recognition can also be an important sign of quality in the movie industry (Gemser et al., 2008; Ginsburgh, 2003). Moreover, in the research of Holbrook (2005), as well as in other researches, no models were constructed to measure the perceived quality by important stakeholders for movies.

For this research, the perceived quality by consumers, experts and peers will be measured as a proxy for the success of a movie. It is interesting to see if consumers are able to judge the quality of a certain movie (Holbrook, 2005), or that the assessment of quality should be left to the experts and peers (Bourdieu, 1984; Ginsburgh & Weyers, 1999). Moreover, it is important to compare the factors that influence the perceived quality of a movie and the factors that influence the box office results. In the end, will be interesting to see which of the selectors is most similar to the commercial success of a movie, measured in box office revenue.

1.2.1 Selection system theory.

When consuming a movie, the evaluations of certain important selectors weigh in the mind of the consumer. To determine how consumers select the movie they want to watch, the selection system theory was used for this research. In the selection system theory, it is assumed that in their decision process, consumers rely on three different types of information sources: the market, experts and peers (Bhansing et al., 2012; Gemser et al., 2008). The market represents the consumers, the experts provide evaluations based on expertise and experience, and peers are the industry players in the field. Based on this theory, the performance of a movie, commercial as well as in terms of perceived quality, can largely depend on the evaluation of each of these selectors as these actors can determine the value, quality and the outcome of the movie (Bhansing et al., 2012).

Expert selection has been one of the most critical determinants of the behavior of the film consumer, and are often assumed to be the only ones who are able to judge the quality of a movie (Eliashberg & Shugan, 1997; Gemser, Van Oostrum & Leenders, 2006). Peer selection in the form of awards can help consumers and other stakeholders in the field in their selection process, as they may function as a signal of quality (Gemser et al., 2008). In the motion picture industry, an important source of peer-recognition are awards as the Academy Awards. Also, consumer evaluations in the form of online word-of-mouth, which are evaluations of other consumers, has strongly influenced the selection process of the end-consumers. (Liu, 2006; Duan, Gu & Whinston, 2008). Consumers enjoy a larger utility when more people consume the same movie due to network effects, which means that the opinions of others, but also the volume of evaluations can be a large determinant of quality (Kats & Sharipo, 1994).

Often, it is expected that popular movies are more consumer-oriented than expert-oriented or peer-oriented. However, the demand of the consumer is mostly measured in box office revenue instead of the perceived quality, whilst the value of experts and peers are measured in terms of quality such as critics’ reviews and awards. Therefore, it is essential to apply this theory to the motion picture industry when taking into consideration the quality perceived by consumers.

In this analysis, these three types of selectors will be used to create the statistical models to measure perceived quality. The perceived quality for the market will be measured by consumer ratings. Perceived quality by experts will be measured by expert ratings, and perceived quality by peers will be measured in Academy Awards and BAFTA Awards. In the following section, previous literature on factors that explain commercial success will be analyzed.

1.3 Factors that influence the commercial success of a movie

As stated before, it is almost impossible to attribute the success of a movie to individual factors. Many researchers in academia as well as in the motion picture industry search for risk reducing strategies by measuring which factors have the largest influence on the commercial success of a movie. In this section, an overview of the most discussed variables that could be of influence on the commercial performance of a movie will be given, based to previous written marketing literature on the motion industry.

In previous studies, commercial success of a movie is measured in terms of (domestic) theatrical box office, such as box office revenue and theatre attendance (a.o. Clement et al., 2014; Eliashberg et al., 2003; Litman, 1983). It is a large puzzle for researchers and even more for motion picture studios to discover why certain movies are successful and why certain movies flop. Producing a movie involves high sunk costs and, due to high demand uncertainty, large risks. Desai et al. (2002) describe three types of risks that occur the most when producing a movie: completion risk, performance risk and financial risk. The *completion risk* occurs because of the high financial investment and the changing motives of the involved people during the creative process. Due to the fact that each movie is unique and important factors as the popularity of star actors and directors change over time, the motion picture studio faces a *performance risk* as it is hard to predict the actual profit and revenues. This results in the *financial risk*, as the production of a movie involves high sunk costs and no guarantee on return on investment due to the demand uncertainty (Desai et al., 2002).

Many researchers have tried to analyze which factors have the largest impact on the final box office results. In line with previous research (Clement et al., 2014; Eliashberg et al., 2006; Hadida, 2009; McKenzie, 2012), the most researched elements will be discussed in this section. These variables will be used in the analysis for measuring success in terms of perceived quality of movies, instead of measuring the commercial success of the movie.

1.3.1 Consumer evaluations

Word of mouth is the “informal communication among consumers about products or services” (Liu, 2006 p. 74). It is often regarded as one of the most powerful and influential transmitters of information for consumers of goods and services, especially for experience goods (Duan, Gu & Whinston, 2008[1, 2]; Godes & Mayzlin, 2004; Liu, 2006). If the social network of consumers recommend a certain film, the consumer is more inclined to follow that advice than listen to other signs of information, such as the marketing campaigns or the star-actors (Duan et al., 2008[1, 2]). Moreover, network effects occur when there is a larger group of consumers that watched the movie: consumers generate a higher utility of consumption because they have the ability to talk about the movie with their friends (Kats & Sharipo, 1994). Also, when a large group of of friends tend to like a certain movie, the chances are high that the behavior of consumers is influenced by that, without thinking of their own opinion (Tsao, 2014).

However, word of mouth is limited to social contact boundaries and the influence diminishes quickly over time (Duan et al., 2008[1]). Information technology and digitization has given the consumers the opportunity to spread their opinion on certain goods much easier and for a broader audience via the internet, which led to a large base of reviews and recommendations from other consumers (Duan et al., 2008[1]). Therefore, in the literature on explaining the commercial success of a movie, (online) word of mouth is often used as a variable to predict box office sales (Duan et al., 2008[1,2]; Hennig-Thurau, Houston & Walsh, 2006; Holbrook, 2005; Liu, 2006).

In the movie industry, it is often believed that WOM strongly influences people’s selection of movies. Movies as *My Big Fat Greek Wedding* and *Zoolander* had to thank their commercial success to the buzz that was created around them (Liu, 2006). As the movie industry is such a popular cultural good, it often receives a great amount of attention and public interest due to secondary elements as the private life of actors and the Academy Awards (Karniouchina, 2011; Liu, 2006). For example, the fact that Leonardo DiCaprio did not receive an Academy Award until this year had increased his popularity and therefore the commercial success of the movies he played in.

As the life cycle of a movie is small because of the limited theatrical running time (Jedidi et al., 1999), it is essential for motion picture companies to create buzz around their movies. Karniouchina (2011) defines buzz as “consumer excitement, interest and communication around a project or a participating star that is capable of increasing their visibility with both moviegoers and movie industry participants” (p. 63). The most influential effect of buzz is created around the pre-release of the movie due to the short running time (Liu, 2006), for which the valence as well as the volume of WOM is important to stimulate box office results (Holbrook, 2005; Liu, 2006). People then speculate about the potential content and quality of the movie before it is shown in the cinemas.

Movies with big budgets often create more WOM than low budget movies, as the big budget movies can afford to have a larger marketing and advertising campaign, which results in a higher awareness (Karniouchina, 2011). However, buzz can also backlash if the quality of the movie was disappointing or if the private life of the large movie stars have influenced the perception of the viewers on the movie. Therefore, it is important to be aware of the role WOM can play in the commercial success of a movie, as it is an important source of information for people (Duan et al., 2008[1,2]; Karniouchina, 2011; Kim, Park & Park, 2013; Liu, 2006)

In most researches, online WOM is measured in user ratings (a.o. Duan et al., 2008[1,2]; Holbrook, 2005; Liu, 2006). However, the influence of social media has increased throughout the years, which makes it important to study it in the context of movies. Therefore, in this research, social media followers were also analyzed. For consumer evaluations, a distinction between popular appeal and ordinary consumer ratings will be used (Holbrook, 2005). Ordinary consumer evaluations will be measured in the ratings of consumers, and popular appeal will be measured in social media followers and the amount of ratings given by consumers.

1.3.1.1 Ordinary consumer evaluations: consumer ratings

Reviews from consumers online are often seen as the representation of mass taste and popular appeal (Tsao, 2014). Through web-based opinion platforms, such as *IMDb*, consumers have the ability to share their opinions about the experience goods they just consumed. Consumer ratings on the internet usually have a high volume. According to Liu (2006), when consumers see that a movie has been highly rated (valence) by lots of other people (volume), they are stimulated positively in their decision process due to network effects.

However, consumers are more and more able to judge the actual quality of a movie, rather than only the enjoyable aspects of it. Ordinary consumer evaluations are becoming more available online, in which non-expert consumers assess the excellence of the movie, rather than the entertainment value (Holbrook, 2005). According to Holbrook (2005), consumers did indeed showed signs of ‘good taste’ on platforms such as *IMDb*, which was in line with the taste of experts, rather than just popular appeal. In this research, the consumer ratings will be used as the ordinary consumer evaluations.

Also, consumer ratings can be more influential than the ratings from critics (Tsao, 2014), where the negative reviews have a stronger impact on the movie selection, and the positive reviews have a stronger impact on movie evaluation. As the online environment is anonymous, consumers are more inclined to share their real experience and opinion about goods, without considering the feelings of others (Tsao, 2014). Therefore, it can be expected that the reviews of consumers are actually accurate to what people really think.

It is expected that the consumer ratings have a positive impact on box office revenue, with a stronger effect than the ratings of experts, which is in line with the theory of Tsao (2014). Two theories will be tested to see which effect consumer ratings will have on experts and peers. First, the theory of Bourdieu (1984) suggests that consumers are not able to judge the quality of a movie, which indicates that there should be a negative relation between consumer ratings and the assessment of quality by experts and peers. Second, the theory of Holbrook (2005) states that consumers are able to judge quality, which means that there should be a positive relation between consumer ratings and the perceived quality of experts and peers.

1.4.1.2 Popular appeal: Social media mentions and the amount of consumer ratings

Social media has been an important topic of discussion in academia and in the business world. This type of online WOM enables people to share information with each other on a personal level, as it is linked to your social network. Moreover, through the online real-time interaction, it is possible to share information very quickly, instead waiting for information received only through physical contact (Riu, Liu & Whinston, 2013). But because social media is such a fast medium where posting information is so easy, the effect of it on consumer decisions is not clear.

Social media is largely used for marketing purposes by companies to communicate with customers. Branded social media campaigns are used to deepen the bond with the customer and discover certain themes in the behavior of consumers through online interaction (Ashley & Tuten, 2015). As movies are experience goods, it is important for motion picture companies to brand their movies to engage with the potential customers and stimulate buzz (Karniouchina, 2012). Therefore, social media has been a largely used marketing tool by the motion picture companies.

Social media platforms give consumers the ability to post microblogs in such a high speed, the assessment of quality of a just released product can be brought out in the world very quickly (Hennig-Thurau et al., 2015). Therefore, it is expected that social media could have a positive as well as a negative effect on consumer decisions.

As social media is such a young discipline in marketing and consumer psychology, there has not yet been a lot of academic research been done to the actual effects on the commercial success as well as on the perception of quality. One of the researches that investigated social media is that of Hennig-Thurau et al. (2015). They tested the effect of tweets on Twitter on consumer decisions. They found out that in the opening week, only the negative tweets had influence on the commercial performance of the movie. There was no effect for positive WOM, which means that positive tweets have less to no effect on consumer decisions in the opening week. However, Rui et al. (2013) found out that there are positive and negative effects of Twitter mentions for movies, for which their main outcome was that pre-consumption WOM is a larger predictor of the commercial success of a movie than post-consumption WOM. Moreover, the amount of followers also has a large influence on the persuasiveness of the posts on Twitter (Rui et al., 2013).

In this research, social media will be used as a form of popular appeal, which is the expressions of liking by non-expert consumers, rather than assessing the quality of the movie (Holbrook, 2005). Moreover, the amount of ratings given by consumers on IMDb will also be used as a popularity measurement, as it shows how much appreciation or enthusiasm it produces (Holbrook, 2005). For this research, the amount of Facebook likes, the amount of Twitter followers and the amount of Instagram followers will be used to assess the predictive effect of social media on the perceived quality of consumers, experts and peers, as well as on the box office revenue. It is expected that social media has a significant effect on the perceived quality of consumers and box office results, but no relation with the perceived quality of experts and peers.

1.3.2 Critics’ ratings

The opinion of critics are often regarded as powerful signs of quality (Ginsburgh & Weyers, 1999) as critics have a high volume of cultural capital and therefore a ‘good taste’ in cultural goods (Bourdieu, 1984). Consumers often consult the expertise of the critic in their decision process of watching a movie as the quality is uncertain (Holbrook & Hirschman, 1982). Therefore, it is believed that review and ratings of critics can shape the box office results (Elberse & Eliashberg, 2003; Eliashberg & Shugan, 1997; Suárez-Vázquez, 2011; Reinstein & Snyder, 2005).

Critics cannot only inform consumers about the artwork and give a ‘seal of approval’, but they also have the power to forge reputations and to promote a certain artwork (Cameron, 1995). According to Eliashberg & Shugan (1997), critics can take the role of two actors: influencer, which means that their reviews influence the decisions of consumers on seeing a particular movie, and predictor, where critics assess if the movie will appeal to the consumers.

There are several that studies that state that critics indeed have an influential power on the box office revenue. According to Suárez-Vázquez (2011), the critics can influence the pre-assessment of a movie by consumers, which means that a critic review can be a determinant of deciding to see a particular movie. Moreover, Desai & Basuroy (2005) state that when the genre of the movie is less familiar to consumers, they tend to look for other sources of information, such as the reviews of critics. When looking at the reviews of critics, risk of consuming something from little quality is lower (Desai & Basuroy, 2005).

Other studies state that critics have a predictive power on box office revenue, but are not largely influencing the profit of a movie (Eliashberg & Shugan, 1997; Gemser et al., 2007; King, 2007. Moreover, as was visible in previous research, reviews of critics do not often influence the commercial success on the short run, but have a larger impact on the long run: it takes some time for the reviews to get to the consumers (Collins et al., 2002). Also, negative reviews has more effect on the commercial performance of a movie than positive reviews (Litman & Kohl, 1989; Lampel & Shamsie, 2000).

In this research, it is expected that quality assessment by experts is influential on the perceived quality for movies for consumers, as experts are important gatekeepers for assessing quality. Moreover, there will be a positive relation between the ratings of critics and the quality perceived by peers, as they are both seen as important gatekeepers for assessing quality

(Ginsburgh, 2003). Moreover, it is expected that there is a significant effect from critics’ ratings on box office revenue, but because negative reviews are more harmful for the commercial success of a movie (Litman & Kohl, 1989; Lampel & Shamsie, 2000), it is expected that this relation is negative.

1.4.3 Awards

As stated before, awards can be an important indicator of quality for consumers (Gemser et al., 2008; Ginsburgh, 2003). When a movie has won an Academy Award, consumers often regard the movie as high quality (Ginsburgh & Weyers, 1999; Ginsburgh, 2003; Siminton, 2004). Moreover, award winning pictures are often ranked high in box office statistics (Ginsburgh & Weyers, 1999; Deuchert Adjamah & Pauly, 2005). This indicates that the commercial performance could possibly explained by awards as consumers think that movies with an award are high quality. However, the ability to judge quality by juries of awards such as the Academy Awards has often been questioned.

The effect of awards on the commercial performance, and to a lesser extent to the performance in terms of quality, has been analyzed in many researches, which resulted in mix outcomes. Some studies state that awards indeed have a significant effect on the box office results (Siminton, 2004; Desai & Basuroy, 2005; Nelson et al., 2001). However, other researchers found out that winning an award is less profitable than expected (Deuchert et al., 2005; Gemser et al., 2008).

In general, awards appear to be a form of short-term quality recognition. On the long run, movies that received awards did often not passed the test of time. This indicates that awards are not a good measure of long-term quality (Ginsburgh & Weyers, 1999; Ginsburgh, 2003). Moreover, the investment in Academy Awards was less profitable than expected by the motion picture companies (Deuchert et al., 2005), which indicates that awards do not have a large effect on the commercial success of a movie. Also, Gemser et al. (2008) found out that peer awards as the Academy Awards were not seen as awards of higher prestige than the other awards. It is therefore questionable to what extent awards do have an effect on the commercial performance of the movie, as well as on the perceived quality of consumers and experts.

For this research, it is expected that box office revenue and the perceived quality of consumers can positively be predicted by the fact if a movie has won an award. Moreover, it is expected that expert ratings positively influence the perception of quality by peers, but that experts are not influenced by peer awards, as they are not a good measurement of long-term quality (Ginsburgh & Weyers, 1999; Ginsburgh, 2003).

1.4.4 Genre

Genre is often seen as one of the most important determinant for consumers in deciding which movie to see, as the genre contains a recognizable sign of information (Austin & Gordon, 1987; De Silva, 1998 as cited by Desai & Basuroy, 2005). Familiarity by consumers with genre and plot lines influenced the box office revenue positively (Desai & Basuroy, 2005; Perreti & Negro, 2007). In general, the more familiar consumers are with the genre of the movie, the less dependent they are on other sources of information such as star power and reviews. This means that when the genre is less familiar, consumers depend more on other signs of information as critics’ judgement and advertisement (Desai & Basuroy, 2005). Therefore, making a movie with a familiar genre can be a tactical decision for reducing the quality uncertainty for consumers, and make in turn more profit for motion picture studios. In table 1, an overview of the highest grossing genres is displayed.

Table 1: Top grossing genres worldwide from 1995 to 2016 (Source: The Numbers).

	Movies	**Total Gross**	**Average Gross**	**Market Share**
1. Adventure	671	$41,934,347,718	$62,495,302	21.93%
2. Comedy	2,229	$41,822,891,293	$18,763,074	21.87%
3. Action	768	$34,467,216,240	$44,879,188	18.02%
4. Drama	4,216	$31,895,871,312	$7,565,434	16.68%
5. Thriller/Suspense	837	$16,440,270,144	$19,641,900	8.60%
6. Romantic Comedy	515	$9,323,915,261	$18,104,690	4.88%
7. Horror	449	$8,662,603,789	$19,293,104	4.53%
8. Musical	141	$2,074,621,700	$14,713,629	1.08%
9. Documentary	1,719	$1,905,995,811	$1,134,960	1.02%
10. Black Comedy	149	$1,224,906,088	$8,220,846	0.64%

In this research, the genres drama, comedy, action, horror, children and other were analyzed, in line with the research of Clement et al. (2014). Based on table 2, it is expected that comedy, action and drama will have the largest effect on the box office revenue. It will be interesting to see if these genres were also perceived as the highest quality by consumers, experts and peers. It is expected that the most familiar genres (action, comedy and drama) have a positive effect on the perceived quality of consumers. For experts and peers, it is expected that only drama will have a positive effect on perceived quality, as this is often regarded as the genre with the highest artistic value (Reinstein & Snyder, 2005).

1.4.5 Story adaptation

Another way to reduce the uncertainty of quality of movies for consumers is to base the storyline on a previously written or featured story, such as sequels remakes and the adaptation of a book. With these story adaptations, motion picture companies try to capitalize the success of the original written piece by presenting a movie that has the same storyline and characters (Sood & Dreze, 2006). Companies assume that making a sequel is a save investment because they can effectively reach the fan base of the original movie (Moon, Bergey & Iacobucci, 2010), which is visible in the movies produced in 2015. Universal Studios had its highest grossing year in terms of box office revenue in 2015: only in August 2015, they reached more than $5.5 billion in revenue, which was mostly due to the large amount of adapted screenplays. The highest grossing movies were *Jurrassic World* (sequel), *Fifty Shades of Grey* (adaptation of a book), *Minions* (sequel), and *Pitch Perfect 2* (sequel) (Busch, August 2015; Lesnik, 2015).

In this example, it was clear that on the short term, story adaptations can be successful in terms of box office revenue. However, this is often not the case for long-term commercial success. According to Dhar, Sun and Weinberg (2011), sequels have much less attendance than the parent movie on the long run. Also, Basuroy and Chatterjee (2008) found out that sequels almost never match the revenue of the parent movie. They do state that on the short-run, sequels are more commercially successful than non-sequel movies released at the same time on the short run, but they saw that the longer the movie is played in the theatres, the faster the revenue drops for sequels than for non-sequels (Basuroy & Chatterjee, 2008).

Moreover, in the research of Moon et al. (2010) and Sood & Dreze (2006), it was evident that the consumers of movies are in general less satisfied with sequels, which was visible in lower ratings (Moon et al., 2010; Sood & Dreze, 2006). This could be explained by the fact that sequels are usually an intensified and strengthened version of the framework and storyline of the original movie (e.g. more action and special effects), which did not suit the expectations of the spectators (Moon et al., 2010; Sood & Dreze, 2006). For sequels, consumers give higher ratings to sequels that look dissimilar to the original. Those sequels that are not numbered, but have a new name (Sood & Dreze, 2006).

However, not much research has been conducted to the effect of remakes and story adaptations from books on the perceived quality. Therefore, this research will also take these types of story adaptation into account. It is expected that story adaptations will have a positive effect on box office revenue, but a negative effect on the perceived quality of consumers, experts and peers, based on the research of Moon et al. (2010) and Sood & Dreze (2006).

1.4.5 Star power

The most well-known marketing technique for motion picture companies is recruitment of expensive star actors, on which a large proportion of the budget is spent. For example, Leonardo DiCaprio received $25 million for the movie *The Wolf of Wall Street*, and Jennifer Lawrence earned $10 million for one of the *Hunger Games* sequels (Galloway, 2015). These amounts are, of course, not representable for the whole motion picture industry, but it indicates that movie studios are willing to invest in big stars in order to increase their revenue. However, stars are by no mean a guarantee for success and the effect of stars on box office revenue is often overstated (Eliashberg et al., 2006; Hadida, 2009; McKenzie, 2012).

Movie stars are often used as a high-equity brand for a movie. They enjoy name recognition, a positive image and association with a particular kind of movie and storyline, which reduces the quality uncertainty for consumers (Desai & Basuroy, 2005). Companies use actors as key components that are responsible for attracting a large fan base (Wallace, Seigerman & Holbrook, 1993). This can result in a positive effect on box office revenue, especially when other variables such as genre and story are not familiar for the audience (Desai & Basuroy, 2005). Moreover, stars are an indication of quality, which reduces the risk for the consumer to watch a low-quality movie. Furthermore, stars are a general informational signal. Due to previous performance of the star, consumers can get an indication of the content of the movie due to the acting skills of the star (Suárez-Vázquez, 2011).

In academic research, many researchers have tried to predict the influence of star actors on the commercial success of a movie. This led to mixed results, where on the one hand, star actors had a (large) influence on box office results (Litman & Kohl, 1989; Wallace et al., 1993), especially due to the buzz that was created around them (Karniouchina, 2011), but on the other hand, the effect of star power was often overestimated as it seems that they did not account for the largest part of the success of a movie (De Vany & Walls, 1999; Hadida, 2009; Liu et al., 2014; Ravid, 1999; Suárez-Vázquez, 2011). Only for low to medium budget movies, star power had a significant positive influence on the box office results (Litman, 1983; Porkorny & Seth, 2011).

Suárez-Vázquez (2011) investigated that stars were actually not seen as a sign of quality by the consumers and therefore, the quality uncertainty of choosing a movie did not decline when a superstar appeared in movies. Also, when the genre of a movie is familiar to the audience, the effect of superstars is much lower (Desai & Basuroy, 2005). Lastly, stars fail to mitigate the negative reviews that are given about a movie, which means that negative reviews have a stronger force in consumer decision making (Suárez-Vázquez, 2011).

It is clear that the effect of stars on the commercial success of a movie cannot be guaranteed and it seems irrational to spend that much of the budget on stars. However, not much research has been conducted on the perceived quality of movies in which super stars appear. In this research, it is expected that star power has a positive effect on the box office revenue, but a negative effect on the perceived quality of consumers, as is in line with the research of Suárez-Vázquez (2011). For experts and peers, it is expected that star power has no effect on the perceived quality of movies.

1.4.6 MPAA ratings

Motion Picture Association of America (MPAA) is an institution that gives ratings to movies to inform parents about the expected content of the movie. Currently, there are five types of ratings: G (general audiences), PG (parental guidance suggested), PG-13 (parents strongly cautioned), R (restricted) and NC-17 (adults only). For this research, only G, PG, PG-13 and R-rated movies were used in the analysis as movies rated with NC-17 did not appear in the sample. Films that receive a G-rating or a PG-rating are often suitable for children and youngsters. PG-13, R and NC-17-rated movies are movies that contain adult themes such as sex, violence and abusive language, which are not suitable for every audience (Litman, 1983; *MPAA*, n.d.).

In previous research, some MPAA ratings were often positively related to the commercial performance of a movie. De Vany & Walls (2002) discovered that G and PG-ratings had a positive correlation with box office revenue, which meant that for movies with a G or a PG rating, the chances of having commercial success was higher. Movies rated with PG-13 or R-rating, however, led to less box office revenue. An interesting observation is that Hollywood studios produce much more PG-13 and R movies in comparison to the other categories (Ravid & Basuroy, 2004). Reasons that directors of movies choose to produce more PG-13 and R movies is that they do not solely focus on the demand for consumers, but also on generating of peer recognition and the achievement of prestige (De Vany & Walls, 2002). It can therefore be assumed that R and PG-13 rated movies are seen as more prestigious movies by peers and experts. Also, PG-rated and R-rated movies lose money less often and the variances are lower, which makes producing such a movie less ‘risky’ (Ravid & Basuroy, 2004).

Not much research has been conducted to the effect of MPAA ratings on the perceived quality for movies. For this research, it is expected that box office revenue and consumers are more likely to perceive G and PG-rated movies as higher quality, whilst experts and peers prefer the PG-13 and R-rated movies, as they display prestige (De Vany & Walls, 2002).

2. Method

In this section, the method of the research is explained. First, the research design is presented, which describes the main issues of the research, the methodology, the description of the sampling method. the research questions, the study type, the type of data gathering and the analyses for the study will be discussed. Second, the models for the statistical analysis are presented. Third, the statistical analyses for this research is explained. And last, the method of data collection and the description of the variables are described.

2.1 Research design

This study focuses on analysing which factors influence the perceived quality for popular movies by consumers, experts and peers, as well as on the difference between the successes of popular movies measured in perceived quality and the commercial success of popular movies. Expectations and assumptions about the variables that could influence the success of a movie were based on marketing literature, as was discussed in the literature review. For this study, a quantitative content analysis was conducted, for which popular movies were analysed. `

A quantitative content analysis was chosen for this research, as its purpose was to replicate previous marketing studies on the commercial success of movies, measured in box office revenue. This study differs from those analyses as it measures which elements affect the performance of popular movie in terms of perceived quality, instead of in terms of commercial performance. It is important to see to what extent there is a difference between the commercial success and the success in terms of quality, as commercial success is often intertwined with the perception of quality by consumers.

Moreover, for a long time, it was assumed that only experts could assess the quality of a cultural good (Bourdieu, 1984), but due to the large opportunities for consumers to watch movies online via distribution platforms or illegal downloading, it is possible that the experience and knowledge about movies has increased. Moreover, there are many online platforms where consumers can broadcast their evaluation of movies, such as consumer ratings on *IMDb*, which gives a better insight in the perception of consumers than before these platforms existed. Therefore, it is important to test whether the theory of Bourdieu (1984) will still maintain valid in the light of these developments. Do consumers indeed still show signs of ‘little taste’, compared to the ‘good taste’ of the experts and peers?

Another reason why a quantitative analysis was conducted to the motion picture industry is due to the large data availability on popular movies. An online content analysis is very suitable for the motion picture industry due to the large amount of websites that contains a high amount of useful sources of data, research on the motion picture industry, even for the quality of movies,

2.1.1 Methodology

The sample consists of 320 movies over a period of 16 years (2000 to 2015), which appeared in the list of most popular motion picture of that particular year on *IMDb*. For each year, every third movie was selected, which led to a total of 20 movies per year. To test which factors influence the perceived quality of consumers, experts and peers for popular movies, as well as the box office revenue, models were constructed based on previous marketing research to the effects of certain elements on the commercial success of a movie (Clement et al., 2014; Elberse & Eliashberg, 2003; Hennig-Thurau et al., 2006). Through logistic and linear regressions, these models were tested, which gave an insight in which factors had the highest influence on perceived quality on popular movies by consumers, experts and peers. After that, the outcomes of the regressions could be compared to each other, as well as to the model of box office revenue.

Moreover, due to the fact that the sample covered a time period of 16 years, a descriptive time analysis was conducted to the variables that were used in the analysis in order to discover possible trends.

2.1.2. Population

The units of analysis of the study were popular movies. The population of this research consists of all popular movies released between 2000 and 2015. The reason why only popular movies were used for the analysis is because it expected that the difference between popular appeal by consumers and the perceived quality of experts and peers is the largest for these movies. Consumers that like to see less popular movies are often already more knowledgeable on the content of movies.

Moreover, most marketing literature on the commercial performance was conducted for popular movies. As the aim of the research is to replicate similar models in order to analyze the perceived quality by consumers, experts and peers, popular movies were the most suitable units of analysis. Also, due to the large amount of theory on Hollywood movies and the large data availability on those type of movies, only popular movies were analyzed. This means that the outcome of this research could only be generalized for popular movies.

2.1.3 Sampling method

The sample was constructed out of lists of popular movies, available on the *Internet Movie Database* (IMDb). *IMDb* is the most popular online movie database which includes more than 3.5 million movies, TV, and entertainment programs, has 200 million unique visitors per month, and has more than 65 million registered users (‘About *IMDb*’). It is a common source of data collection in academic researches (e.g. Clement et al., 2014; Holbrook, 2005; Karniouchina, 2010), which made the website appropriate for the data collection of this study.

The sampling frame consisted of lists of the most popular movies released in that particular year, named ‘Most Popular Feature Films Released in [year]’. The lists of most popular feature films are created through the *MOVIEmeter* rank of *IMDb* (Dan Dassow - *IMDb*, personal communication, 7th of April 2016). The *MOVIEmeter* ranking is largely based on page views of paged related to a film. The meter is weekly updated, which means that the sampling frame for this research constantly changed over time. *IMDb* will not disclose how they specifically calculate this measure, but as it is largely calculated through page views, it can be assumed that the lists indicate the popularity of a movie and the public awareness of a movie through the behavior of millions of *IMDb*-users. In appendix 7.4, a table was included with the exact times of the data collection.

From those list of most popular movies, 20 movies per year were selected, which were every third movie from the list. Therefore, the sample was purposive, as from each year, the same position was measured. I have chosen this method as I wanted to have a representable sample which not only consisted the top most popular movies. Moreover, I wanted to have a sample in which the movies were be similar to each other. By measuring the same positions from each year, it can be assumed that movies are fairly similar.

It is clear that a random sample would give a more representable image of the motion picture industry as a whole. However, as it is my intention to measure the perceived quality only for popular movies, and because it was not possible to analyze all popular movies for each year due to time constraints, this sampling method was the most appropriate for this research.

2.2 Models

Five models were constructed to measure the perceived quality of movies for consumers, experts and peers, as well as for the commercial success of a movie measured in box office revenue. Through these models, significant influencers for the perceived quality of movies were found, which were compared to the outcome of the model on commercial success and to assumptions made in previously written theory.

Several considerations underlie the model specification. First, only popular movies were analyzed, which means that all conclusions in this study can only be drawn for popular movies. Second, the time of theatrical release of movies was not taken into account in this analysis. Third, even though the models were compared to each other, the models are not exactly the same, as the dependent variable for one model was a predictor for the other model.

2.2.1 Consumers

The perceived quality for popular movies by consumers was measured in consumer ratings, for which was collected from *IMDb*. Model 1 provides the measure for perceived quality of consumers (measured in consumer ratings) for movie *i*:

Model for the perceived quality of consumers (measured in consumer ratings) for movie *i*:

$$Rating\ consumers_{\mathrm{i}} =$$

$$\alpha \cdot \beta_1\text{year}_i \cdot \beta_2\text{amount of ratings consumers log}_i \cdot \beta_3\text{rating critics}_i \cdot \beta_4\text{amount of ratings critics}_i \cdot \beta_5\text{awards}_i \cdot \beta_6\text{amount of awards log}_i \cdot \beta_7\text{peer awards}_i \cdot \beta_8\text{amount of peer awards}_i \cdot \beta_9\text{nominations}_i \cdot \beta_{10}\text{amount of nominations log}_i \cdot \beta_{11}\text{nomination peer awards}_i \cdot \beta_{12}\text{amount of nominations peer awards}_i \cdot \beta_{13}\text{content awards}_i \cdot \beta_{14}\text{amount of content awards log}_i \cdot \beta_{15}\text{technical awards}_i \cdot \beta_{16}\text{amount of technical awards log}_i \cdot \beta_{17}\text{3D or IMAX}_i \cdot \beta_{18}\text{genre: drama, action, comedy, horror, children, other}_i \cdot \beta_{19}\text{sequel, remake, story adaptation}_i \cdot \beta_{20}\text{star power actors}_i \cdot \beta_{21}\text{star power directors}_i \cdot \beta_{23}\text{competition}_i \cdot \beta_{24}\text{box office revenue log}_i \cdot \beta_{25}\text{budget log}_i \cdot \beta_{26}\text{profit log}_i \cdot \beta_{27}\text{MPAA rating}_i \cdot \beta_{28}\text{distribution company}_i \cdot \beta_{29}\text{land of production}_i \cdot \beta_{30}\text{duration}_i \cdot \beta_{31}\text{Facebook likes log}_i \cdot \varepsilon_{Ri}$$

Consumer ratings were driven by a set of continuous variables (amount of ratings consumers, ratings critics, amount of awards, amount of peer awards, amount of nominations for awards, amount of nominations for peer awards, amount of content awards, amount of technical awards, box office revenue, budget, profit and duration) and categorical variables (awards, peer awards, nominations, peer nominations, 3D or IMAX, genre, story adaptation, star power, MPAA rating, distribution company, and land of production). The log-transformed variables are represented by *log*. Details on the measurement of the variables is presented in section 2.4. The error term for the consumer rating equation is denoted as ε_{Ri}.

2.2.2 Experts

The perceived quality for popular movies by experts was measured through critics' ratings, gathered from *Metacritic*. Model 1 provides the measure for perceived quality of experts (measured in critics' ratings) for movie *i*:

Model for the perceived quality of experts (measured in ratings of critics) for movie *i*:

$$Rating\ critics_i =$$

$\alpha \cdot \beta_1$year$_i$ · $\beta_2$rating consumers$_i$ · $\beta_3$amount of ratings consumers log$_i$ · $\beta_4$amount of ratings critics$_i$ · $\beta_5$awards$_i$ · $\beta_6$amount of awards log$_i$ · $\beta_7$peer awards$_i$ · $\beta_8$amount of peer awards$_i$ · $\beta_9$nominations$_i$ · β_{10}amount of nominations log$_i$ · β_{11}nomination peer awards$_i$ · β_{12}amount of nominations peer awards$_i$ · β_{13}content awards$_i$ · β_{14}amount of content awards log$_i$ · β_{15}technical awards$_i$ · β_{16}amount of technical awards log$_i$ · β_{17}3D or IMAX$_i$ · β_{18}genre: drama, action, comedy, horror, children, other$_i$ · β_{19}sequel, remake, story adaptation$_i$ · β_{20}star power actors$_i$ · β_{21}star power directors$_i$ · β_{22}competition$_i$ · β_{23}box office revenue log$_i$ · β_{24}budget log$_i$ · β_{25}profit log$_i$ · β_{26}MPAA rating$_i$ · β_{27}distribution company$_i$ · β_{28}land of production$_i$ · β_{29}duration$_i$ · β_{30}Facebook likes$_i$ · ε_{Ri}

Critics' ratings were influenced by a set of continuous variables (consumer ratings, amount of ratings consumers, amount of ratings critics, amount of awards, amount of peer awards, amount of nominations for awards, amount of nominations for peer awards, amount of content awards, amount of technical awards, box office revenue, budget, profit and duration) and categorical variables (awards, peer awards, nominations, peer nominations, 3D or IMAX, genre, story adaptation, star power, MPAA rating, distribution company, land of and production). The log-transformed variables are represented by *log*. Details on the measurement of the variables is presented in section 2.4. The error term for the consumer rating equation is denoted as ε_{Ri}.

2.2.3 Peers

Perceived quality for movies by peers was measured through awards based on peer recognition, which were the Academy Awards and the BAFTA Awards. These awards are rewarded to movies by industry players. Two models were constructed to measure the perceived quality by peers, namely the amount of peer awards and the dichotomous variable which measures the probability of winning a peer award.

Model for the perceived quality of peers (measured in the amount of peer awards) for movie *i*:

$$Amount\ of\ peer\ awards_i =$$

$\alpha \cdot \beta_1$year$_i$ · $\beta_2$rating consumers$_i$ · $\beta_3$amount of ratings consumers log$_i$ · $\beta_4$amount of ratings critics$_i$ · $\beta_5$awards$_i$ · $\beta_6$amount of awards log$_i$ · $\beta_7$peer awards$_i$ · $\beta_8$amount of peer awards$_i$ · $\beta_9$nominations$_i$ · β_{10}amount of nominations log$_i$ · β_{11}nomination peer awards$_i$ · β_{12}amount of nominations peer awards log$_i$ · β_{13}content awards$_i$ · β_{14}amount of content awards log$_i$ · β_{15}technical awards$_i$ · β_{16}amount of technical awards log$_i$ · β_{17}3D or IMAX$_i$ · β_{18}genre: drama, action, comedy, horror, children, other$_i$ · β_{19}sequel, remake, story adaptation$_i$ · β_{20}star power actors$_i$ · β_{21}star power directors$_i$ · β_{22}competition$_i$ · β_{23}box office revenue log$_i$ · β_{24}budget log$_i$ · β_{25}profit log$_i$ · β_{26}MPAA rating$_i$ · β_{27}distribution company$_i$ · β_{28}land of production$_i$ · β_{29}duration$_i$ · β_{30}Facebook likeslog$_i$ · ε_{Ri}

The amount of peer awards a movie received was driven by a set of continuous variables (consumer ratings, amount of ratings consumers, critics' ratings, amount of ratings critics, amount of awards, amount of nominations for awards, amount of nominations for peer awards, amount of content awards, amount of technical awards, box office revenue, budget, profit and duration) and categorical variables (awards, peer awards, nominations, peer nominations, 3D or IMAX, genre, story adaptation, star power, MPAA rating, distribution company, land of and production). The log-transformed variables are represented by *log*. Details on the measurement of the variables is presented in section 3. The error term for the equation for the amount of peer awards is denoted as ε_{Ri}.

Model for the perceived quality of peers (measured in peer awards) for movie *i*:

$$Peer\ awards\ (yes\ or\ no)_i =$$

α · $\beta_1$year$_i$ · $\beta_2$rating consumers$_i$ · $\beta_3$amount of ratings consumers$_i$ · $\beta_4$amount of ratings critics$_i$ · $\beta_5$awards$_i$ · $\beta_6$amount of awards log$_i$ · $\beta_7$peer awards$_i$ · $\beta_8$amount of peer awards$_i$ · $\beta_9$nominations$_i$ · β_{10}amount of nominations$_i$ · β_{11}nomination peer awards$_i$ · β_{12}amount of nominations peer awards$_i$ · β_{13}content awards$_i$ · β_{14}amount of content awards$_i$ · β_{15}technical awards$_i$ · β_{16}amount of technical awards$_i$ · β_{17}3D or IMAX$_i$ · β_{18}genre: drama, action, comedy, horror, children, other$_i$ · β_{19}sequel, remake, story adaptation$_i$ · β_{20}star power actors$_i$ · β_{21}star power directors$_i$ · β_{22}competition$_i$ · β_{23}box office revenue$_i$ · β_{24}budget$_i$ · β_{25}profit$_i$ · β_{26}MPAA rating$_i$ · β_{27}distribution company$_i$ · β_{28}land of production$_i$ · β_{29}duration$_i$ · β_{30}Facebook likes$_i$ · ε_{Ri}

The probability of winning a peer award for a movie was driven by a set of continuous variables (consumer ratings, amount of ratings consumers, critics' ratings, amount of ratings critics, amount of awards, amount of peer awards, amount of nominations for awards, amount of nominations for peer awards, amount of content awards, amount of technical awards, box office revenue, budget, profit and duration) and categorical variables (awards, nominations, peer nominations, 3D or IMAX, genre, story adaptation, star power, MPAA rating, distribution company, land of and production). Contrary to the other models, there were no log-transformed variables as variables do not need to be transformed for a logistic regression. Details on the measurement of the variables is presented in section 2.4. The error term for the equation for peer awards is denoted as ε_{Ri}.

2.3 Statistical analysis

A multiple regression analysis was conducted to analyze which elements could predict the perceived quality for consumers, expert, the amount of peer awards, and the box office revenue. In a regression, the coefficients represent the change in perceived quality resulting from a unit change in the corresponding explanatory variable (everything having been held constant). In the multiple variable regression, several indicators that could predict the dependent variable were analyzed, instead of only one (Field, 2013; Litman, 1983).

Conditions for a multiple regression are that the variables must be normally distributed, have no perfect multicollinearity, and the variables must not be auto-correlated (Field, 2013). For the variables that were not normally distributed, log transformed variables were created to make the variables suitable for the regression. Moreover, in the regression analyses, the test for Variance Inflation Factor (VIF) was conducted to check for multicollinearity. Variables that had high forms of multicollinearity (VIF > 5) were extracted from the regression. Lastly, to test for auto-correlation, a Durbin-Watson test was conducted for every regression to test for independent error, for which the value has to lie closely to 2 (Field, 2013).

There were missing values for a few of the variables, which is visible in appendix 7.2. For the variables that missed a low amount of values, the missing values were replaced by the mean in the regression. It is clear that the mean is not the perfect replacement for that missing value, but in order to get the most significant results in the regression, it was important that the highest amount of values could be taken into account. For the variables that measure the followers on Instagram and Twitter, there were too much missing values. To keep the results representable, it was decided to exclude these variables from the regressions.

A logistic regression was conducted to analyze which factors could predict the probability of a movie winning a peer award (Academy Award or BAFTA Award) or not. A logistic regression is an analysis where the dependent variable only has two values, which means is that only two values can be predicted. The regression measures the probability that the value is 1 for the dependent variable, rather than 0 (Field, 2013). As the variable that measured the probability of winning a peer award for a movie dichotomous, a logistic regression had to be conducted, for which the regression analyzed the probability of a movie winning a peer award as a proxy for perceived quality of peers (Field, 2013).

For the logistic regression, multicollinearity was tested by conducting the VIF test in a multivariate regression to see which variables had too much multicollinearity, as there is no VIF test in the logistic regression. Moreover, the variables do not need to be normally distributed in the logistic regression, which means that the transformed log variables were not used for this analysis (Field, 2013).

2.4 Data collection

In this section, the data collection is discussed. The sample consists of 320 movies from 2000 to 2015, out of a list of most popular movies created by the *Internet Movie Database (IMDb)*. For each variable, the mean (denoted as *M*) and the standard deviation were mentioned (denoted as *SD*). An overview of all variables can be found in appendix 7.1. Moreover, an overview of all the descriptive statistics can be found in appendix 7.2.

2.4.1 Consumers evaluation

2.4.1.1 Consumer ratings

Ratings consumers$_i$ was used to measure the perceived quality by consumers (M = 6.9, SD = 0.86). *Amount of ratings consumers*$_i$ represented the amount of votes that were given by consumers on the movies that were analyzed (M = 202146, SD = 151336), which was a measurement of popular appeal. Data on these two variables was gathered from *IMDb*. This online database was reliable for the collection of data of this research as it is the largest internet movie database with more than 65 million registered users. Moreover, as stated before, *IMDb* is often used in other academic research as a source of data collection, which also indicates that data from this website can be seen as reliable.

All consumers that have access to the internet have the ability to register their rating on a certain movie, but the precondition is that people need to register themselves to be able to vote. People are only allowed to vote once for every movie to keep the ratings representative (‘About *IMDb’).*

The obligatory registration for consumers can be a barrier for them to give their opinion about the quality of the movie on *IMDb*, which indicates that this measure of quality may not a perfect representation of the perceived quality by consumers. However, the amount of ratings given on *IMDb* were significantly higher than from comparable websites as *Metacritic* or *Rotten Tomatoes.* Therefore, these ratings were the best option for measuring the perceived quality by consumers via a quantitative online content analysis.

The ratings of consumers on *IMDb* can change every day, as there is no deadline for consumers to bring out their rating on the movie. Each day, more consumers bring out their vote on that particular movie, which means that the rating is constantly changing. Therefore, an overview of the actual dates of the data collection can be found in appendix 7.4.

2.4.1.2 Social media followers

In this analysis, a social media analysis was included to enrich the amount of data on popular appeal as a complement on the amount of ratings from consumers, and as an indicator of online word of mouth.

Instagram followers$_i$ (M = 124100, SD = 308706) was used to measure the amount of followers on Instagram on the accounts of the movies in the sample. These were only the followers from official Instagram accounts of the movie, or from reasonably large fan-accounts (more than 500 followers). Instagram provided an exact number of followers per account.

Twitter followers$_i$ (M = 181716, SD = 411255) measured the amount of followers on Twitter-accounts of the movies in the sample, which were also only the large fan-accounts or the official movie accounts. Twitter did not give an exact amount of followers per account, but rounded the number of followers to thousands. For Twitter as well as Instagram, data of the official movie accounts were used for the analysis in most cases.

Initially, data was collected for the amount of Instagram mentions. The amount of mentions on Instagram was measured through the hashtag of the movie. For example, #theperksofbeingawallflower has almost 236,000 Instagram mentions. However, as many movies have general titles, such as *Drive* or *Up,* much of the Instagram mentions were not about the film itself. Therefore, the decision has been made to exclude this variable from the analysis in order to keep the results more representative.

In many cases, especially in the starting years of this analysis, there is little social media data available on Twitter and Instagram. As Twitter was founded in 2006 (Twitter, n.d.) and Instagram in 2010 (Instagram, n.d.), the data in these years was little due to the fact that these platforms were not yet existing or they had to win more popularity from the users. Therefore, there is a lot of missing data within these variables. This resulted in the fact that *Instagram followers*$_i$ and *Twitter followers*$_i$ could only be analyzed in separate analyses, instead of adding the variables to the regression models.

For the variable *Facebook likes*$_i$, the amount of likes on the official Facebook pages of the films were gathered, which were exact numbers (M = 1848703, SD = 411255). Facebook was founded in 2004 (Facebook, n.d.), which means that there was much more data available followers on Facebook than for Instagram and Twitter. This resulted in the fact that for almost every unit of analysis, data could be gathered. Therefore, *Facebook likes*$_i$ could be used in the regression analyses.

There were some flaws in the collection of data for social media followers. First, as many sequels used official movie accounts for the whole series of the movies, there were accounts that had a significantly higher amount of followers than regular movies, such as the *Harry Potter* or the *Twilight* movies. Therefore, some values significantly larger than other amounts of followers on a social media account, which may not be representable for the popular appeal of each separate movie. Second, there are many paid programs that could analyze social media attention much more sophisticated. Social media platforms make use of these programs by making information on the amount of attention exclusive for those programs. As this research did not have the means to make use of these programs, it is possible that the data on this variable may not be as accurate as on these programs. However, as social media is such an important form of communications and a source of attention for movies, it still felt important to add the variables to the analysis.

2.4.2 Critic ratings

Critic rating$_i$ represented the perceived quality by experts, measured in the ratings from critics (*M* = 6.0, *SD* = 1.67). *Amount critics rating$_i$* measures the amount of reviews from critics that were assessed before determining a rating (*M* = 34.55, *SD* = 7.33). This data is not used as a measurement of popular appeal.

The data for this variable was collected via *Metacritic*. *Metacritic* is a website which displays aggregate reviews from critics on movies, games, television shows, and music. The ratings from *Metacritic* are constructed by the team of *Metacritic*. They curate a large amount of reviews from respected critics, assign scores to the reviews of those critics, and apply a weighted average to summarize the range of their opinions. One single number is the result of this process, which captures the essence of the critics on a certain creative score. This is called the ‘Metascore’. Users from the website are not allowed to enter their votes and the score only includes published critical reports about the creative goods they measure (Metacritic, n.d.).

Metacritic is one of the most used website to assess ratings from critics as it collects published ratings from all over the world. There are some downsides to this website, as the organization of *Metacritic* does not disclose how they assess the weights to the critics and how they select the most prestigious reviews from critics. Moreover, there are many other websites that also displayed ratings from critics such as *Rotten Tomatoes*. However, as *Metacritic* combines several sources of reviews from critics, is one of the largest websites for the assessment of quality by critics and because *Metacritics* is a cooperating partner with *IMDb*, the decision has been made to use *Metacritic* as a reliable website for the ratings of critics.

2.4.3 Peer recognition

2.4.3.1 Peer awards

Peer recognition is measured through the Academy Awards and BAFTA Awards that were received by the movies. These types of awards are assigned by industry players in the field of the motion picture industry. Therefore, these awards were suitable for this online content analysis to measure the perceived quality by peers.

The variables *peer awards*$_i$ (15% of the movies in the sample received an Academy Award or a BAFTA Award) and *amount peer awards*$_i$ (M = 0.51, SD = 1.586) were used to measure the perceived quality of peers. Data on these variables was gathered via *IMDb*. *IMDb* suggests that the Academy Awards, Golden Globes and the BAFTA Awards are the most prestigious awards in the motion picture industry. In this research, this selection of most prestigious awards was followed. The Golden Globes were excluded as they are not peer reviewed. Therefore, the variable *peer awards*$_i$ and *amount peer awards*$_i$ measures only the most prestigious peer awards.

Limitations to this type of data gathering is that the research is bounded to only Academy Awards and BAFTA Awards, while there are many more peer reviewed awards, such as the *Directors Guild Awards*. As winning an Oscar is often regarded as the most desirable and prestigious awards for movies (Deuchert et al., 2006), and due to the fact that *IMDb* selected the Academy Awards and BAFTA Awards as one of the top three most prestigious awards, these two types of peer awards were used for this study.

2.4.3.1 Awards

There were 10 types of variables that collected information on awards, which is visible in the variable overview. All information about awards was gathered via *IMDb*, as they have an overview of all awards and nominations for movies. The first variables *awards*$_i$ (82% of the movies received an award) and *amount of awards*$_i$ (M = 14.43, SD = 25.979) measures if a movie has won an award and how many awards it has won. This variable measures all awards that movies could possibly win, with the exception of awards based on bad quality of a movie, such as the award for the worst movie of the year. However, as almost every movie in the sample had won an award, this variable does not represent the quality of the movie.

Nominations for awards also had been included in the research, as they also give a sign of perceived quality, but to a lesser extent. The variables *nomination*$_i$ (nomination for any award; 96.9% of the sample), *nomination peer award*$_i$ (32% of the sample), *amount of nominations*$_i$ (amount of nominations for any award; M = 30.26, SD = 38.341), and *amount of nominations for peer awards*$_i$ (M = 1.72, SD = 3.660) were also gathered from *IMDb* through counting the amount of total award nominations and the amount of peer-recognized award nominations.

For the variables *content awards*$_i$ (80% of the sample), *amount of content awards*$_i$ (M = 12.65, SD = 22.486), *technical awards*$_i$ (27% of the sample), *amount technical awards*$_i$ (M = 1.59, SD = 5.721), a distinction has been made between awards that are based on the content of the movie, such as the storyline and the actors, and the technical aspects of a movie, such as editing and cinematography. Technical awards are an indication of the advanced techniques used in the movie. It was interesting to see if those technical aspects have an effect on the perceived quality of movies, as watching a movie in the cinema has become a larger experience than just watching the storyline of the movie. Therefore, a distinction between technical awards and awards based on the content of the movie was made in order to see if the quality is mostly influenced by the content of the movie or by the technical aspects.

IMDb provides a list of awards for each movie. In each list, the amount of technical awards and content awards were counted. Technical awards were awards based on the best editing skills, best cinematography, best sound, best visual effect, best production design, best special effects, best sound design and best lighting (including variations on these awards). Content awards were all the other awards.

2.4.4 Genre

Data on genre was collected via *IMDb* and *Box Office Mojo*. Two websites were used to assess the genre as *IMDb* categorizes its genres on alphabetical order instead of on which genre is the most accurate. Therefore, the genre of the movie was double-checked via *Box Office Mojo*, where they often only mention one or two genres. In general, the first genre that was mentioned on *IMDb* which overlapped with the genre mentioned on *Box Office Mojo*, was used for the analysis.

The genres *drama*$_i$ (32% of the sample), *action*$_i$ (29% of the sample), *comedy*$_i$ (26% of the sample), *horror*$_i$ (7% of the sample), *children*$_i$ (7% of the sample), and *other genres*$_i$ (3% of the sample) were used for the analysis, based on the division made by Clement et al. (2014). For the movies that received the genre ‘children’, another genre was added to give clearer image of the genre.

2.4.5 Story adaptation

In this research, story adaptation is divided in three variables: *sequel*$_i$, *remake*$_i$ and *story adaptation*$_i$. First, it was assessed if a movie was a *sequel*$_i$ (25% of the sample), which were movie that were part of a series, which were released chronological and have same storylines. For sequels, the parent movie was also coded as part of a sequel. Second, the variable *remake*$_i$ (8% of the sample) measured if the movie was a remake of an older movie. Third, *story adaptation*$_i$ (34% of the sample) measured if a movie was based on existing written stories from books, comics or theatre plays. The movies in the sample could be more than one type of story adaptation.

Data on these variables were gathered via *IMDb* and *Wikipedia. Wikipedia* is a user-based online encyclopedia which also provides short descriptions and summaries of movies (Wikipedia, n.d.). Even though this website is not useful theoretical academic research, for the purpose of finding out if a movie is a story adaptation or not, *Wikipedia* was reliable. Because *IMDb* did not provide full information on story adaptation, additional information from *Wikipedia* was gathered.

2.4.6 Star power

For this influencer, several variables were used to get the most representative measurement of star power. For the first variable *current star power actors*$_i$ and *star power director*$_i$, the STARmeter of *IMDb* was used which the current ranking of the star on *IMDb,* based on popularity measurements as page clicks. These variables were divided in four categories: 0 = no star power; 1 = top 5000; 2 = top 500; 3 = top 100 (27% of the actors had high star power; 2% of the directors had high star power). However, as many actors in the early years of the sample are currently not that popular anymore (for example, Orlando Bloom and Ben Stiller are only in the top 5000), a second measurement of star power was added.

The variable *all-time star power actors*$_i$ (54% of the actors in the sample are all time stars)$_i$ measures the star power of actors based on two lists of the top 100 most popular actors of all time. The first list, which was gathered from *The Numbers*, a website with statistics and information on the motion picture industry, was constructed on the base of the earnings of the actors. However, this list is not comprehensive enough as only a small amount of actors in the list were female. The general fact that women earn less salary than men could explain the large absence of females in this list based on salary. Therefore, another popularity list of *IMDb* has been added in order to fill this gap. Due to a lack of comprehensive lists on popular actors of all time, I have used a list that was created by a user of *IMDb.* Although I am aware of the flaws of this measurement of star power, this was the best measure I could find for this type of analysis.

2.4.7 MPAA rating

Information on the MPAA rating of the movie was gathered via *IMDb.* Four categories have been made: 1 = G, which means that the movie is suitable for all audiences (3% of the sample); 2= PG, which means that parental guidance is suggested (9% of the sample; 3 = PG-13 which means that the movie is not suitable for children under 13 (45% of the sample; 4 = R which are the R-rated movies that are not suitable for children under 17 (41% of the sample). This measurement is determined by American authorities. There are different rules per country, but for this research, the American regulations were used.

2.4.8 3D or IMAX

As technical features of a movie may increase the perceived quality by consumers, experts and peers, another technical variable was added, which measured if a movie was featured in 3D or IMAX (21% of the sample from 2008). For this sample, movies featured in 3D and IMAX were only released from 2008, which means that the variable could only be analyzed from this year. Data on the variable was gathered by *IMDb* and *Wikipedia*, as *IMDb* did not always have the complete information on the technical aspects of the movie.

2.4.9 Competition and seasonality

Amount of movies released in the same period$_i$ was the variable that measures the competition for attention of the consumers, consisting of the amount of movies released in the same season of that particular year. On *IMDb*, information on the date of release and the season of the movie was gathered. After that, the amount of movies that were released in the same season were counted minus one, as that was the movie being analyzed. After that, the level of competition was categorized in three categories: low competition (between 1 and 3 movies released in the same season; 27% of the sample), medium competition (between 4 and 6 movies released in the same season; 54% of the sample) and high competition (more than 7 movies released in the same season; 19% of the sample).

Season$_i$ was also divided into four categories: winter (18% of the sample), spring (31% of the sample), summer (23% of the sample), and autumn (28% of the sample)

2.4.10 Box office revenue, budget and profit

Data on *box office revenue$_i$* (*M* = $218,893,874, *SD* = $252,762,727) was gathered by *Box Office Mojo*, a website which collects data on the financial facts of the movie industry (Box Office Mojo, n.d.). The website is a partner from *IMDb*. Data on the *budget$_i$* (*M* = $63,442,668, *SD* = $57,612,744) of the movie was gathered via *IMDb*. The *profit$_i$* (*M* = $159,561,527, *SD* = $215,913,756) of the movie was calculated by subtracting the budget from the box office revenue. Even though this may not be the actual profit of the movie, as there could be more expenses and incomes that were not calculated in the budget revenue, for this research, this calculation will be used to get an indication of the surplus or the loss of a movie. The financial value is documented in US dollars $.

2.4.11 Distributors and land of production

In this research, a distinction between the major distributors and the other (independent) distributors has been made in order to research to what extent the type of distributor had an influence on the perceived quality of movies. A dummy variable is created where the movie gets a 1 when the distributor is one majors, which are : Universal Pictures, Sony Pictures, Disney, Warner Bros, Paramount Pictures, Lionsgate, Focus Features, Touchstone, 20th Century Fox, Columbia Pictures, and New Line Cinema. The movie gets the value 0 when another distributor distributed the movie. 71% of the movies in the sample were produced by major distribution companies.

As most popular movies are U.S. produced, it is important to analyze is the land of production is a determinant of perceived quality in this population. The variable *land of production$_i$* is divided in three categories: 1 = produced in the USA only (55% of the sample); 2 = produced in cooperation with the USA (36% of the sample); and 3 = produced in other countries than the USA (9% of the sample. Data on these variables were collected from *IMDb* and *Box Office Mojo*.

2.4.12 Duration of the movie

The variable $duration_i$ measured the length of the movie in minutes (M = 115.063, SD = 19.0219). Data on the variable was gathered from *IMDb.*

3. Results

In this section, the results of the research are analyzed. First, the descriptive statistics are presented, for which the developments of the variables over time are the most important aspects. After that, the presentation of the statistical analyses is presented. In this section, the results of the regressions, based on the models, are discussed.

3.1 Descriptive statistics

3.1.1 Consumer evaluations

3.1.1.1 Consumer ratings

The lowest rating for a movie by consumers was a 2.4 (*Gigli* in 2003) and the highest was a 8.7 (*City of God* in 2002 and *Lord of the Rings: The Two Towers* in 2002). As the standard deviation of the variable is low and the distribution of the variable seems normal in figure 1, it is assumed that this variable is normally distributed.

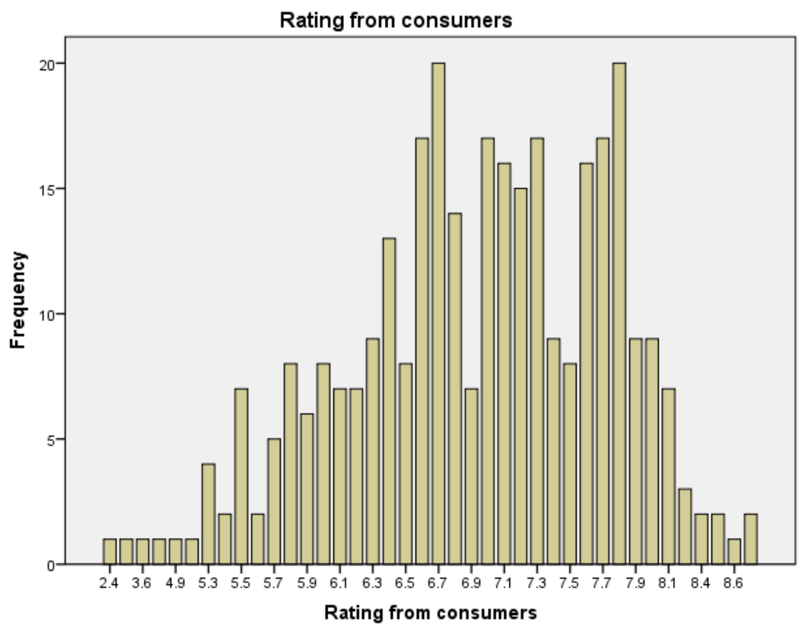


Figure 1: Distribution of the ratings from consumers

In general, around 202,147 votes per movies are given by registered users on *IMDb* (SD = 151.335), which means that the ratings on movies can be regarded as representative through the large amount of votes. This variable was positively skewed and therefore not normally distributed as was tested with the Sharipo-Wilk's test ($p < .05$). Therefore, the variable was transformed into a log variable, as a highly skewed distribution cannot be used for multiple regression analysis.

In figure 2, the development of the consumer ratings from 2000 until 2015 is visible. From 2000 to 2015, there was an upward trend where the ratings of consumers got higher throughout the years. This could be explained by the fact that movies which were released in 2015 had a significant smaller amount of votes, which is visible in figure 3. If a movie has a smaller amount of votes, the rating will be more sensitive for outliers, which means that the ratings deviate more from the mean. To get the most representable results in the regression, data from 2015 was excluded from the analysis. When 2015 is not taken into account, there is still an upward trend in the ratings of consumers, which starts at around 2009. This indicates that in general, the perceived quality for consumers is increasing. However, as only 20 movies per year were analyzed, bold conclusions cannot be made about this trend.

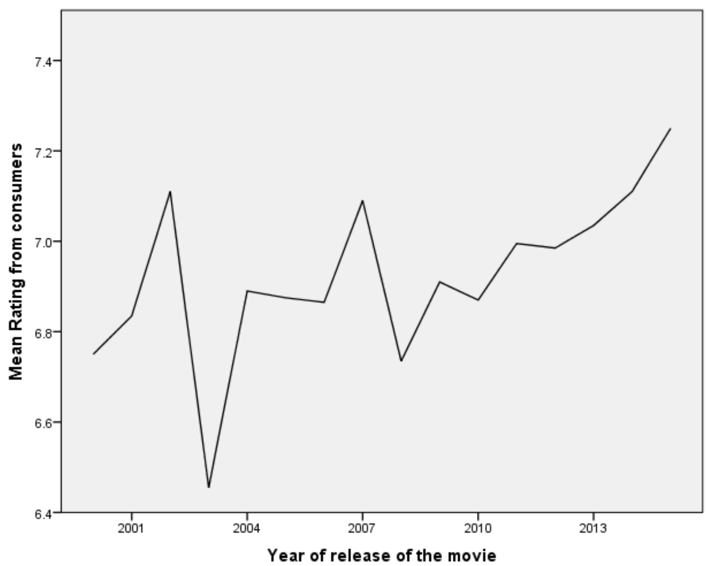


Figure 2: Development of consumer ratings from 2000 – 2015

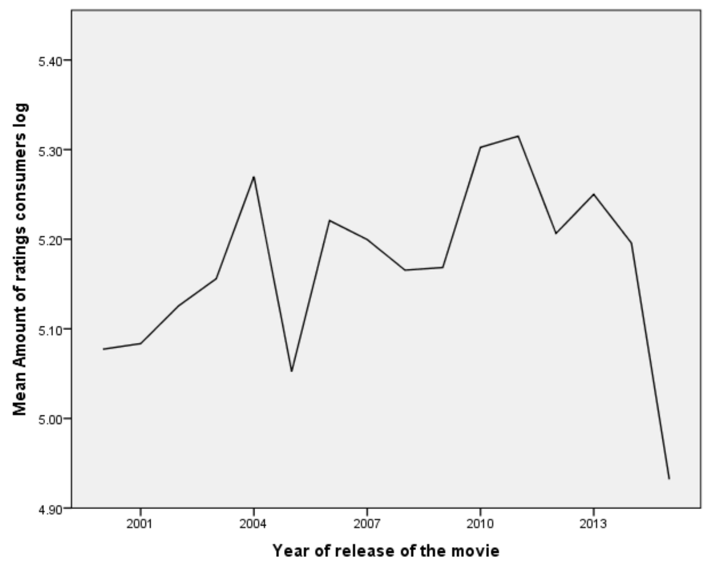


Figure 3: Development of the amount of consumer ratings from 2000 - 2015

3.1.1.2 Social media mentions

As stated before, as followers on Instagram and followers on Twitter had a low amount of cases, these were excluded from the regression analyses.

In the sample, movies have around 124,000 followers on their official Instagram accounts or on their most popular fan accounts. The most popular account of Instagram is for the *Harry Potter* movies, with 1.6 million followers. As is indicated by the high standard deviation, the distribution of the variable is highly skewed. This is confirmed by the Shapiro-Wilk test ($p < .05$). Therefore, a log variable was created for the multiple regression analysis.

The time development for the amount of followers on Instagram accounts of movies is visible in figure 4, which shows that there is not a clear trend. The expectation would be that the amount of accounts for movies and the followers for those accounts would have increased throughout time as the popularity of the platform increased, but this is not the case. There are also still a lot of missing variables in the sample (n = 68) which makes it difficult to discover a trend. For future research, it will be interesting to research the amount of Twitter and Instagram accounts over time, but this is only possible in a few years.

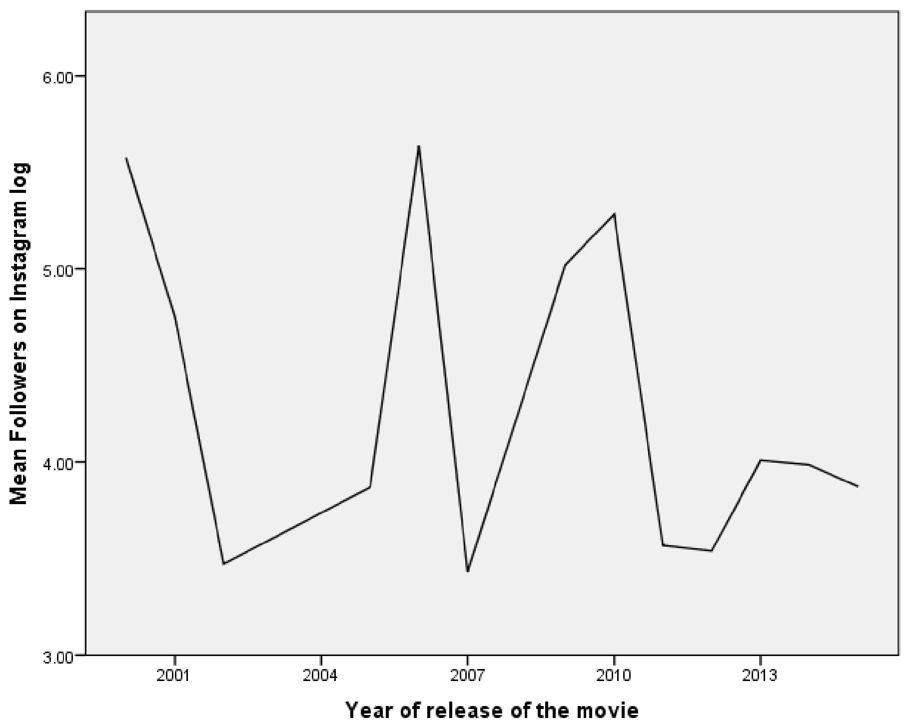


Figure 4: Development of the amount of followers on the Instagram account of movies (Log) from 2000 to 2015

In the sample, the general movie account on Twitter has around 182,000 followers. As was also the case for Instagram, the most popular Twitter account is for the *Harry Potter* movies with 1.9 million followers. The standard deviation is high which indicates that the distribution of the values is not normal. This also visible in the Sharipo-Wilk test ($p < .05$). Therefore, a log variable is created for the amount of followers on Twitter accounts for movies for the multiple regression analysis.

In figure 5, the development of the amount of followers on Twitter accounts is visible. Also for the time analysis of the Twitter followers, a clear trend cannot be defines, especially due to the low amount of values in this sample. However, in the last few years (2008-2015) there is a decrease in the amount of followers on the movie accounts on Twitter, which indicates that Twitter has become less popular. This statement can definitely not be generalized for the whole population, as there were too little units analyzed in this research (*n* = 84).

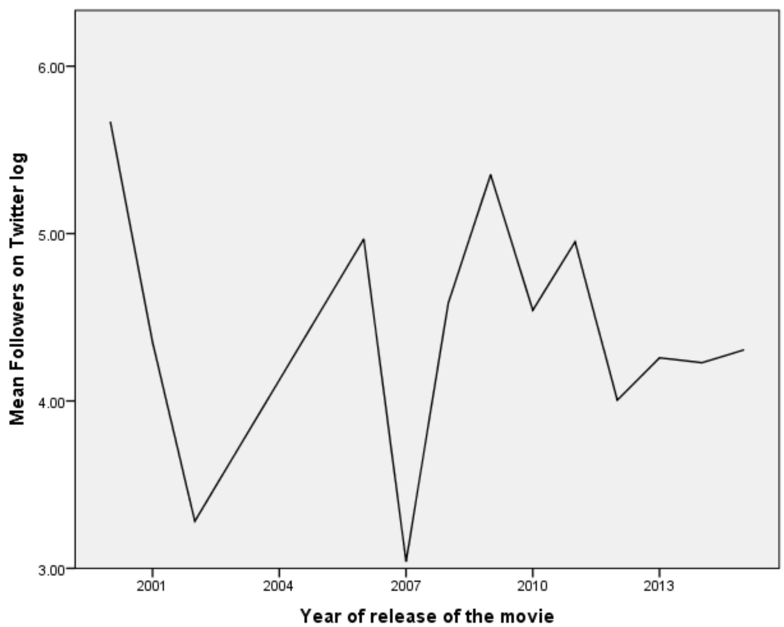


Figure 5: Development of the amount of followers on the Twitter accounts of movies (log) from 2000 to 2015

In comparison to the availability of data on Twitter and Instagram accounts, there were much more values in the sample for the followers on movie accounts on Facebook (*n* = 319), which indicates that Facebook is a social network platform that has been used extensively throughout the last 16 years and has been more popular than Instagram and Twitter for movies. Facebook is also the platform that exists the longest, as it was founded in 2004 (Facebook, n.d.).

In this sample, a movie received in general around 1,85 million followers on the Facebook account, which is much higher than for the accounts on Instagram and Twitter. The most popular movies in terms of Facebook likes are the *Transformer*-movies (2009) with over 32 million likes. The standard deviation for this variable is high, which indicates that the distribution of the variable is not normal. The Sharipo-Wilk test confirms this ($p < .05$). Therefore, a log variable is created for the multiple regression analyses.

The development over time on the amount of Facebook likes on movies is visible in figure 6. As there is a much higher value for followers on Facebook accounts of movies in this sample, compared to Instagram and Twitter, it is possible to say something more about the time development. There was a peak around 2010, which indicates that movies in the sample for 2010 were popular. After 2010, there was a decrease in the amount of Facebook likes, which could mean several things. First, the decrease could be caused by the fact that motion picture companies had less time to develop a fan base for their movies. Second, Facebook was a less popular medium for consumers to express in which elements they are interested in, for movies as well as for general aspects in life. However, definite conclusions cannot be drawn based on this time development. Further research must point out if this process of declining amount of Facebook likes is structural.

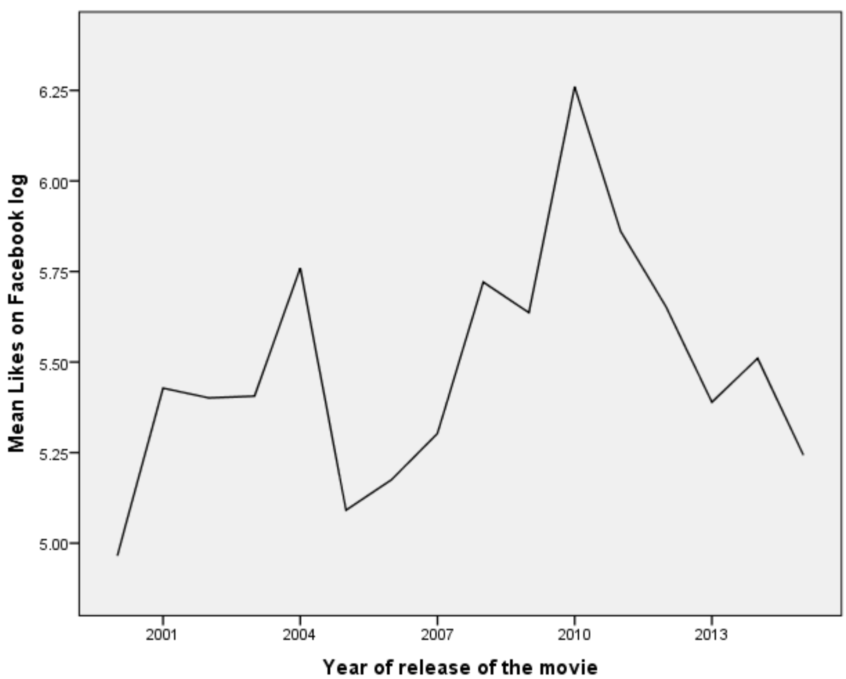


Figure 6: Development of the amount of Facebook likes for movies (Log) from 2000 to 2015

3.1.2 Expert evaluation: Ratings from critics

Due to the low standard deviations (*ratings from critics$_i$: SD* = 1.67; *amount of ratings from critics$_i$*: 7.326), it can be assumed that the distributions of these variables are normal. The distribution of the ratings of consumers is visible in figure 7. In general, critics gave a lower rating to the movies than consumers, for which the mean was approximately a 6. The lowest rating from critics was a 1.8 (*Gigli*, 2003) and the highest rating was a 9.5 (*The Social Network*, 2010). In the sample, approximately 35 reviews of critics were used to create the rating per movie.

As is visible in figure 9, there is an upward trend in the rating of the critics from 2009, which indicates that the perceived quality of movies in this sample has increased in the last few years. This development was also visible in the consumer ratings. However, as only 20 movies per year were analyzed, this statement cannot be generalized for the whole population.

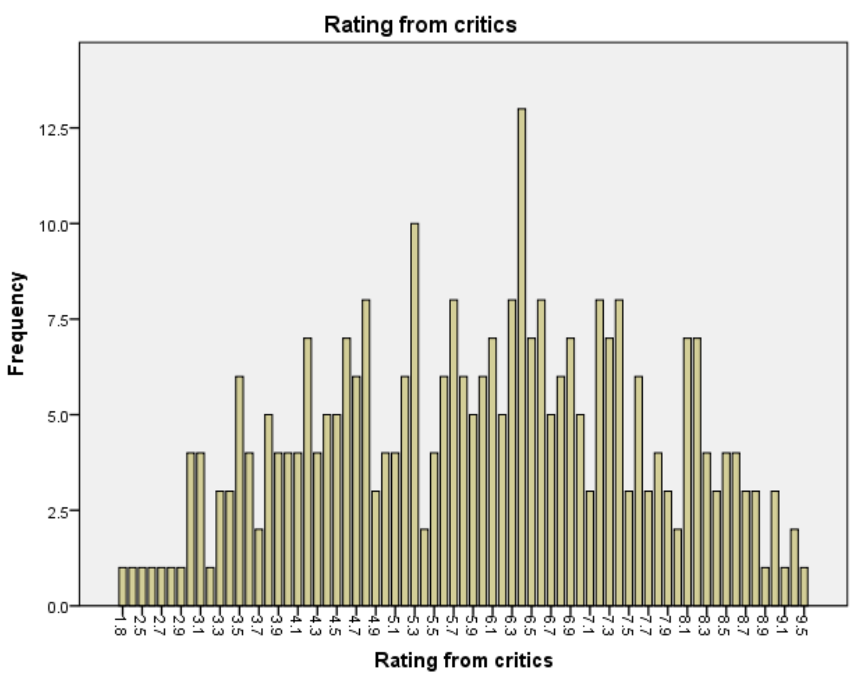


Figure 7: Distribution of the ratings from critics

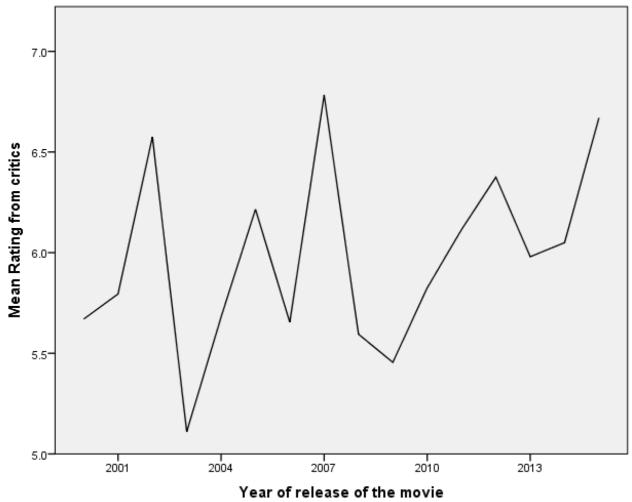


Figure 8: Development of ratings from critics from 2000 to 2015

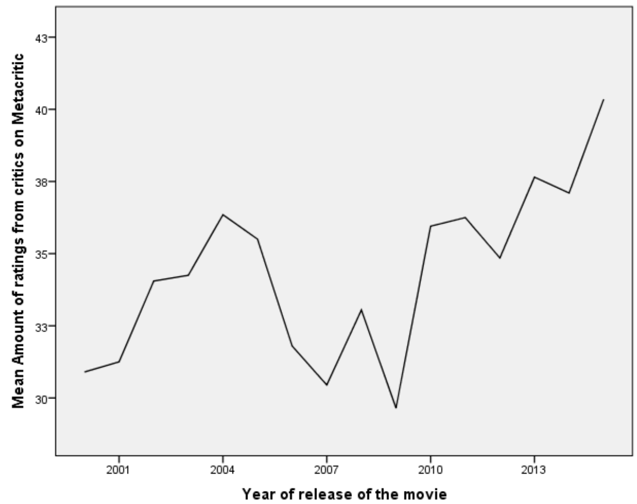


Figure 9: Development of amount of ratings from critics from 2000 to 2015

3.1.3 Peer recognition: Awards

In this sample, 82% of the films had received an award, which is a total of 263 movies. However, when you look at the amount of peer awards (*Academy Awards* and *BAFTA Awards*) that were received by movies, it is clear that only 16% of the movies got those awards. This indicates that the quality of movies that won a peer award is higher, as it is much more difficult to earn such an award. Moreover, most of the awards in the sample were based on the content of the movie (81%), while only 28% were based on the technical qualities of the movie.

3.1.3.1 General awards

In this sample, a movie received around 14 awards. The distribution of the sample is positively skewed (Sharipo-Wilk: $p < .05$), which means that a log variable was created for the parametrical tests. The movie with the highest amount of award was *Mad Max: Fury Road* (2015), with 192 awards in total. But as is visible in the following graph, this is an exception as most movies receive between 0 and 20 awards. As is visible in figure 10, the amount of awards received over time is quite stable in this sample. Only for the last few years, there is an upward trend. This could indicate that the quality of the movies, perceived by peers, has increased the throughout the last years. Another explanation could be that there are more awards in general, which means that there are more awards to be received by movies. A longer period of time and a larger sample need to be research in order to confirm these indications.

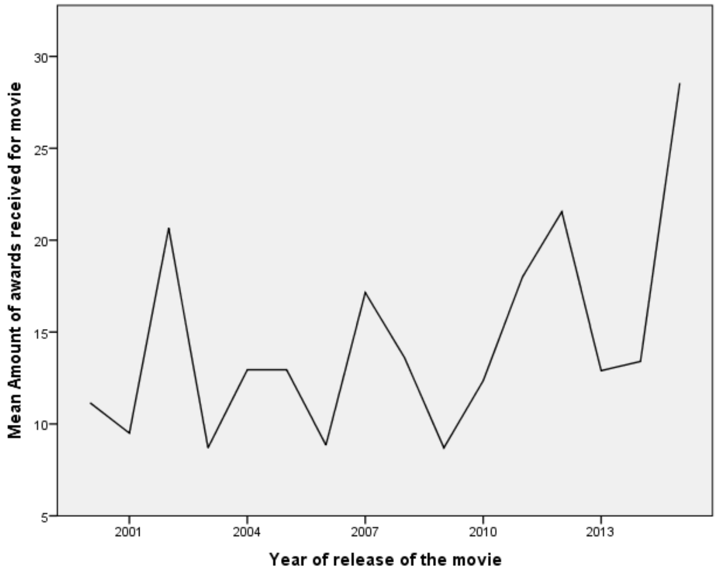


Figure 10: Development of the amount of awards for movies from 2000 to 2015

The amount of movies that receive a nomination for an award is 97% in the population, which indicates that receiving a nomination for a movie is no indicator of quality. The variable was positively skewed (Shapiro-Wilk: $p < .05$), which means that the variable was transformed to a log variable for the parametrical tests. In general, a film received 30 nominations for awards. The movie with the highest amount of nominations is *American Hustle* (2013) with 209 nominations. As is visible in figure 11, there is a clear upward trend from 2010 onwards in the nominations for movies, even more than for the actual awards. Again, this could be explained by the fact that the quality of the movies is going up. However, the possibility that more awards are being brought out from 2010 can also explain the extensive growth in the amount of nominations. As stated before, bold generalizations cannot be made on the basis of these results, as the sample is too small.

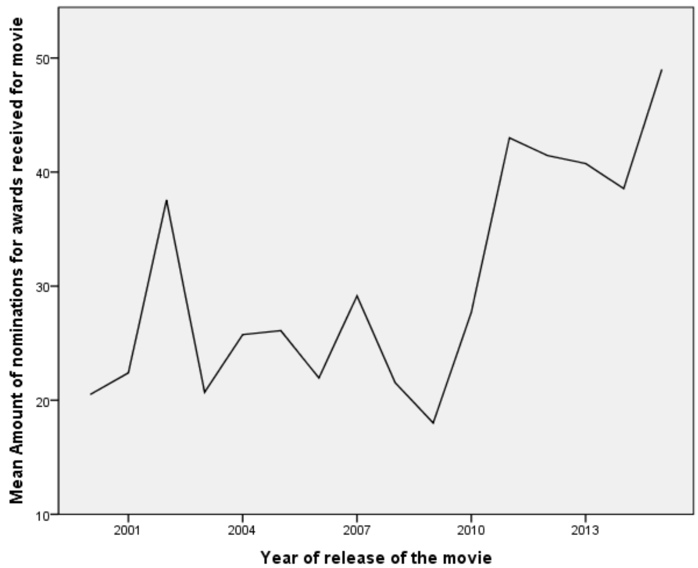


Figure 11: Development of the amount of nominations for movies from 2000 to 2015

3.1.3.2 Peer awards

As stated before, only 16% of the movies in the population received a peer-based award in the form of an Oscar or a BAFTA Award. The movie with the highest amount of peer-awards is *The Hurt Locker* (2008) with a total of 12 peer awards. In general, a movie received 0.5 peer award, but the median (0.000) showed that a large amount of the movies did not even win a peer award. This indicates that it was quite an accomplishment for a movie to win a peer award.

Contrary to awards in general, there is a downward trend in amount of peer awards received by the movies in the sample, which is visible in figure 12. For movies, it became more difficult to win an Oscar or a BAFTA Award, which makes peer awards even more prestigious for movies to receive. This also indicates that the jury of these awards are becoming more selective, which increases the reliability of the level of perceived quality by peers. Another explanation could be that the quality of movies has become lower throughout the years, which contradicts the development in awards in general, but also in the development of the ratings of consumers and critics. However, no clear-cut conclusions can be drawn from this time analysis.

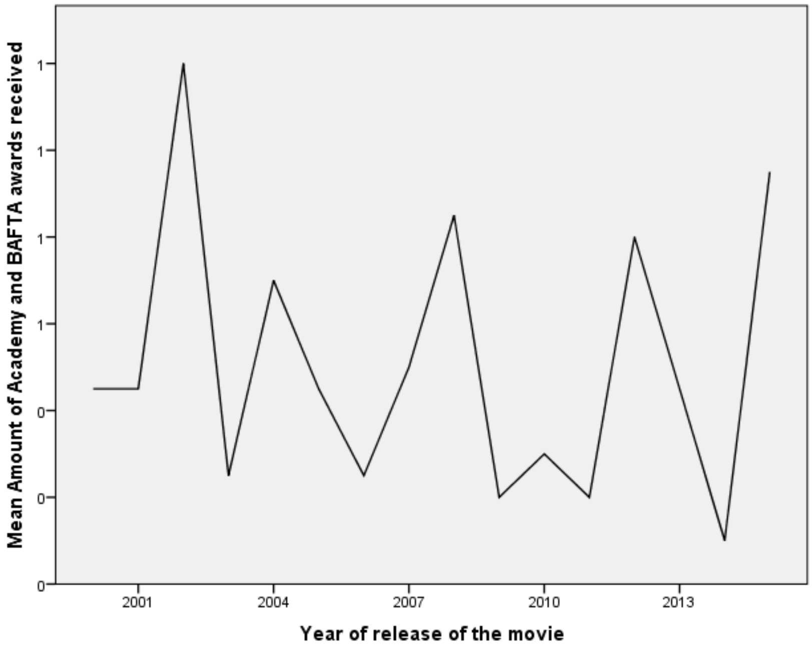


Figure 12: Development of the amount of peer awards for movies from 2000 to 2015

Also with regard to the nominations of the peer awards, there are only 32% of the movies nominated for a peer. This indicates that a nomination for a peer award can even have a prestigious status for movies. The movie with the highest amount of peer award nominations was *American Hustle* (2013) with 17 nominations in total.

There is no clear trend in the time analysis of the nominations for Academy Awards and BAFTA Awards, which is visible in figure 13. The conjectural development of the peer award nominations indicates that the quality of the movies was changing per year. Again, no definite conclusions can be drawn from these figures.

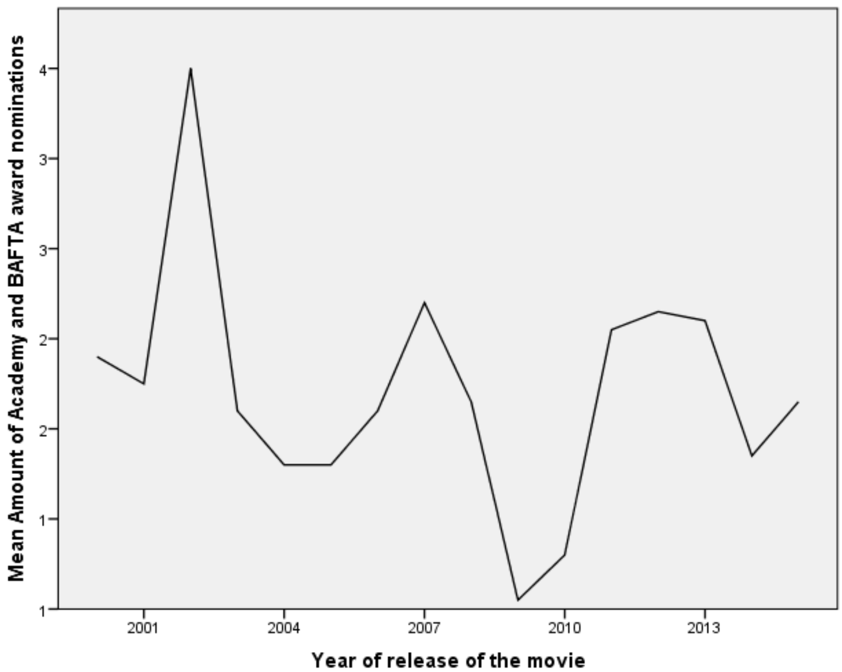


Figure 13: Development of the amount of nominations for peer awards for movies from 2000 to 2015

3.1.3.3 Content awards and technical awards

Most of the awards were based on the content of the movie, which related to the story line, the acting skills of the star actor or the music that was composed for the movie. From all awards won by movies, 81% is based on content. On average, a movie received around 13 content awards. The distribution was positively skewed (Sharipo-Wilk: $p < .05$), which means that the variable was transformed into a log variable for the parametrical tests.

Another type of awards measured in this research were the technical awards, which are rewarded on the base of the technical aspects of the movie such as the editing skills, the cinematography and the mixing of the sound. In the population, only 28% of the movies receive such a technical award. This indicates that there are much less technical awards than awards based on content. On average, a movie received around 2 technical awards. Also for this variable, the distribution is positively skewed (Sharipo-Wilk: $p < .05$), which means that a log variable was created for the multiple regression analyses.

When looking at the time analysis of these two types of awards, it is clear that throughout time, movies receive more awards, which is in line with the other analyses of the awards.

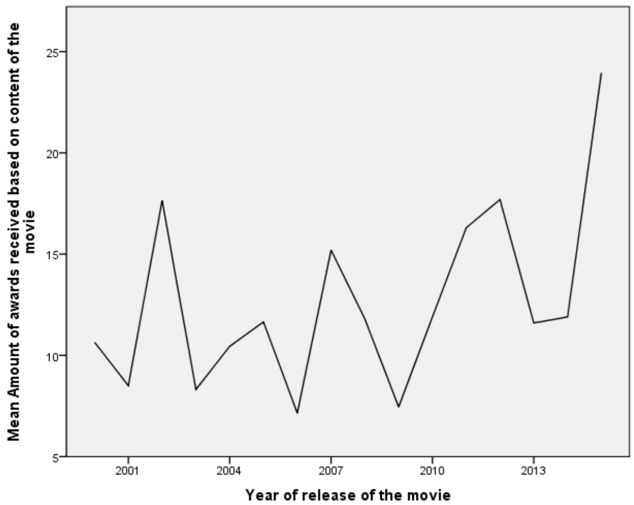


Figure : 14 Development of the amount of awards received for the content of the movie from 2000 to 2015

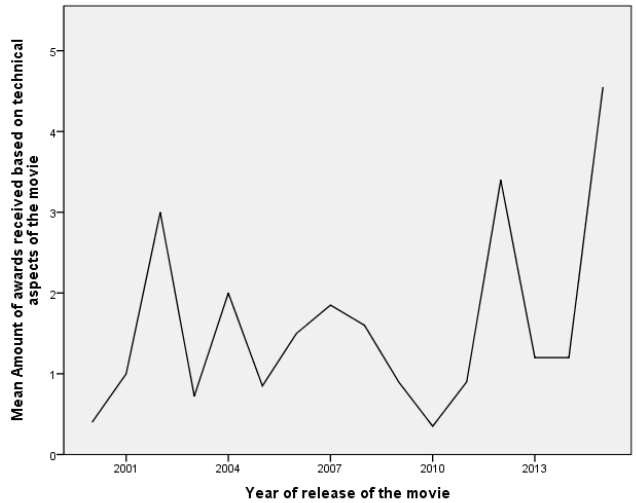


Figure 15: Development of the amount of awards received for the technical aspects of the movie from 2000 to 2015

3.1.4 Genre and story adaptation

The most popular genre in the sample was drama, which were 32% of the movies. 29% of the movies in the population were action movies, 26% were comedy movies, 7% were horror movies, 7% were children's movies and 3% were other genres of movies.

3.1.4.1 Drama, action and comedy

The development of drama, action and comedy is visible in figure. Throughout the years, drama has in general always been the most popular genre for movies in this sample, with the exception of some years. The amount of action movies has been fluctuating the most and the amount of comedy movies is pretty stable in this sample.

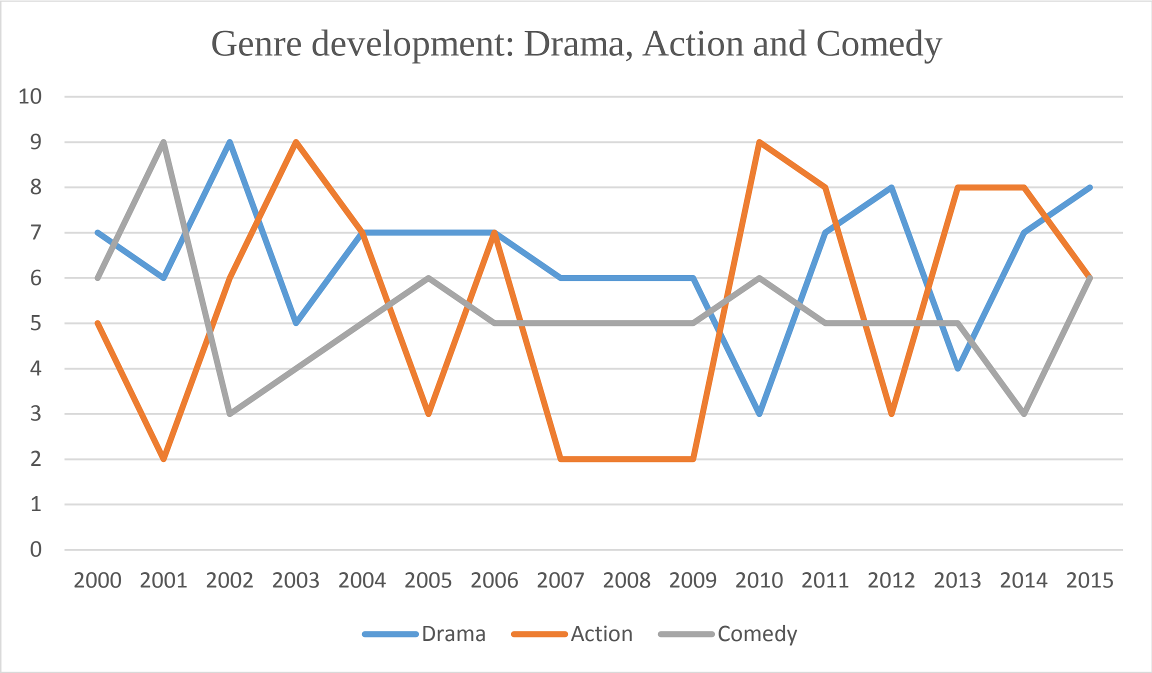


Figure 15: Development of the three most popular genres: drama, action and comedy from 2000 to 2015

3.1.4.2 Horror, children and other genres

The development of horror films, children’s films and other genres is visible in figure 16. In 2000 and 2001, horror movies were a popular genre to be produced by motion picture companies, but after those years, the popularity decreased. For children’s movies, there were some peaks in popularity from 2006 until 2009, further than that, the development has been quite stable. The popularity of other genres has always been moderately stable.

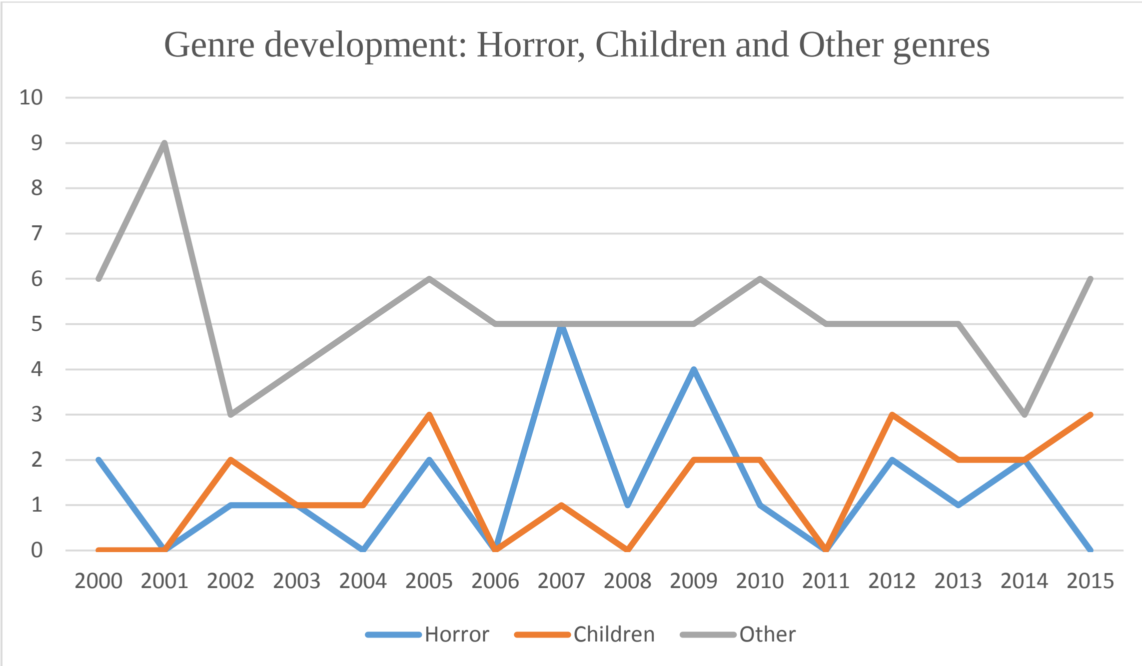


Figure 16: Development of the genres horror, children and other genres from 2000 to 2015

3.1.4.3 Story adaptation

24.7% of the movies in the sample were sequels, 8% were remakes and 34% were story adaptations from written stories. In total, 213 movies were a form of story adaptation, which is 67% of the whole sample.

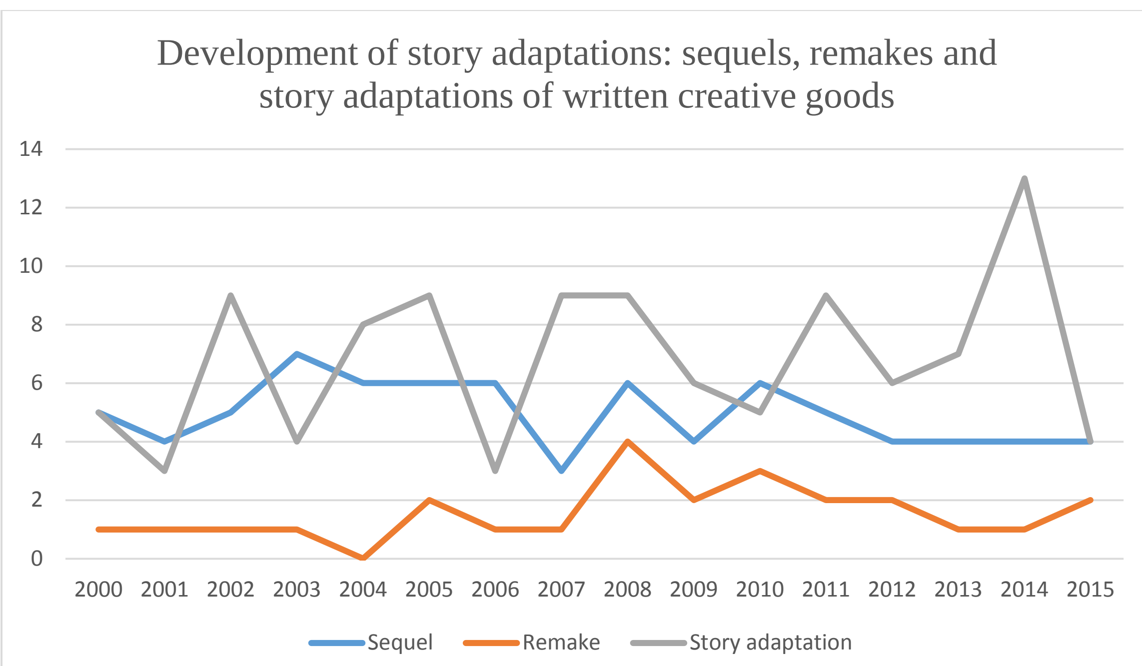


Figure 17: Development of story adaptations of movies from 2000 to 2015

The time analysis showed that the development of these types of story adaptations are fairly stable throughout time, for which popularity of producing written story adaptations fluctuated the most. From 2008, there is a small downward trend visible in the amount of remakes in this sample. The production of sequels has been quite stable throughout time.

The development of the production of story adaptations indicates that the amount of story adaptations did not increase over the last years, which contradicts with the image of the motion picture given by Busch (2015) and Lesnik (2015). But as this research did not analyze every story adaptation produced in every year, it is not possible to make definite conclusions about this development.

3.1.5 Star power

For most movies in the sample, the actors had a form of star power: 52% of the actors have all time star power, 27% of the actors have high current star power, 48% of the actors have medium current star power, 22% of the actors have low current star power and only 3% of the sample has no current star power.

The star power of directors was less present in this sample: 2% of the actors had high star power, 4% of the directors had medium star power, 40% of the star directors had low star power, and 54% of the directors had no star power.

3.1.6 MPAA rating

In this sample, it is clear that most of the movies are PG-13 rated (45%) or R-rated (41%), which is in line with the theory of Ravid & Basuroy (2004).

3.1.7 3D or IMAX

Another variable that could indicate the development of technical aspects of movies is the 3D or IMAX features of movies. In this sample, the first movie that was revealed in 3D or IMAX was in 2008, which was the movie *Journey to the Center of the Earth*. Therefore, this variable could only be analyzed from 2008.

From 2008, 21% of the movies in the population were shown in 3D or IMAX, which means that there are still a lot of movies that do not show their movies in 3D or IMAX. In the following table, the development of the amount of movies in 3D or IMAX is shown. It is clear that the amount of movies has increased using these techniques. The amount of years analyzed for this variable was too small in this sample to generalize about a certain trend, but for now, it is clear that an increasing amount of motion picture companies use the techniques to attract a larger audience.

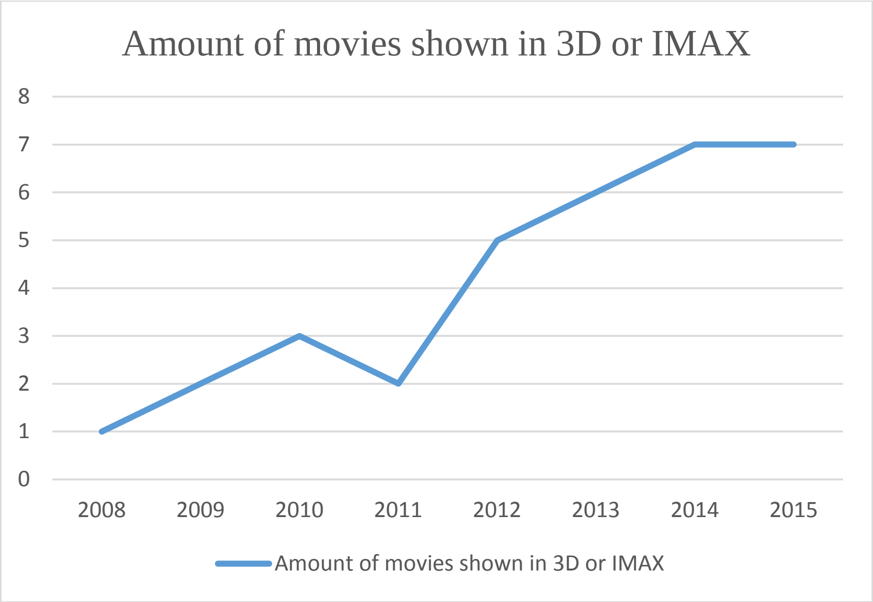


Figure 18: Development of the movies that are shown in 3D or IMAX from 2000 to 2015

3.1.8 Competition and seasonality.

In this sample, there were approximately 5 movies released around the same time. Most movies were released in a level of medium competition, which is between 4 and 6 movies released in the same season (54%). The lowest amount of movies were released in low competition, which was between 1 and 3 movies released in the same season (19%), followed by high competition, which were more than 7 movies released in the same season (27%). Moreover, in this sample, most movies were released in spring (31%), followed by autumn (28%), summer (24%) and winter (18%).

It is difficult to make conclusions based on these variables as there were only 20 movies analyzed per year, while much more movies are actually released per year. Moreover, in order to get a more thorough understanding of competition for movies, one must look at the movies released at the same time per week. Therefore, generalizations could not be made about the level of competition through the data of this sample. This is also visible in the correlations: there is no dependent variable that correlates with these variables.

3.1.9 Box office revenue, budget and profit

In the sample, the movie with the largest box office revenue was *Furious 7* (2015) with more than $1.5 billion revenue. This variable was highly skewed (Sharipo-Wilk: $p < .05$), which means that for the multiple regressions, the variable will be transformed into a log variable.

In the time analysis, it is clear that the box office revenue has drastically increased throughout the years.

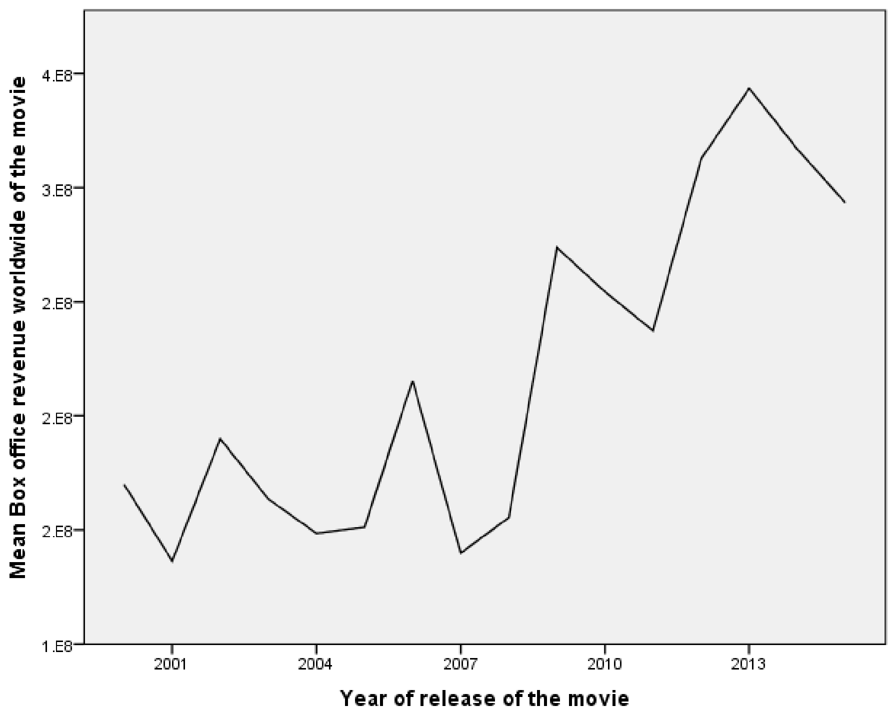


Figure 19: Development of the box office revenue (in US $) for movies from 2000 to 2015

The movie with the highest budget in this sample was Disney’s *Tangled* with a budget of $260 million. Also, this distribution is highly positively skewed (Sharipo-Wilk: $p < .05$), which means that for the parametrical tests, a log variable is created.

The same trend for the budget of the movie is visible, compared to box office revenue, which is visible in figure 20. There is an increase in the amount of money spent on the movies throughout the years, with the exception of 2012.

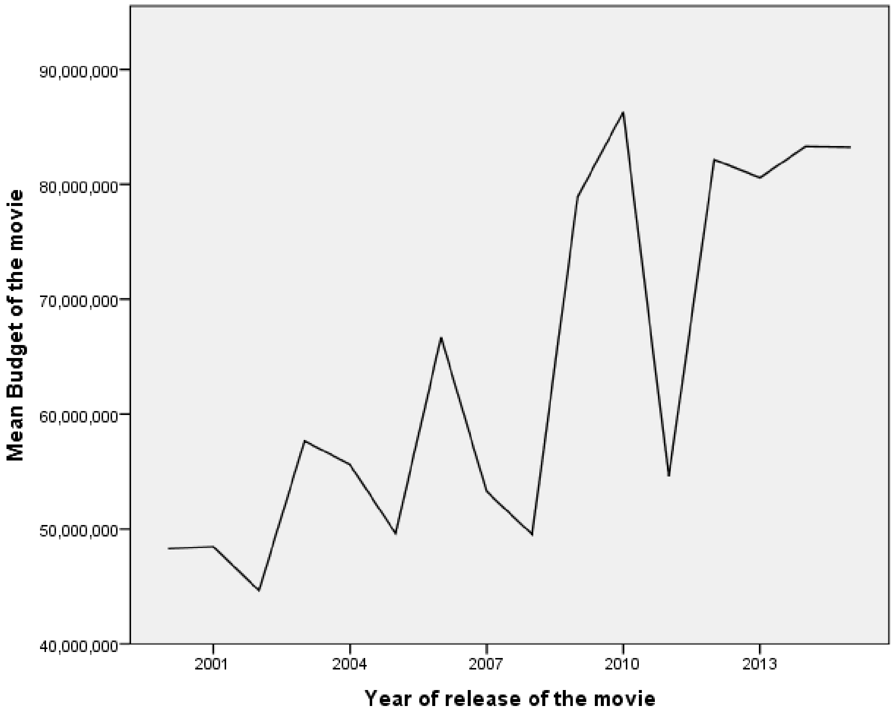


Figure 19: The development of the budget (in US $) for movies from 2000 to 2015

The distribution for profit was also positively skewed with negative values, so the variable will be transformed into a log variables. The movie with the highest profit in this sample was *Furious 7* (2015) with a profit of more than $1.3 billion. The film in this sample with the highest loss was *Sweeney Todd: The Demon Barber of Fleet Street* (2007) with a deficit of more than $200 million.

Also for the profit of movie, there was a similar trend as with the box office revenue and the budget, which is that there was a large increase in the profit throughout the years. This is visible in figure 20.

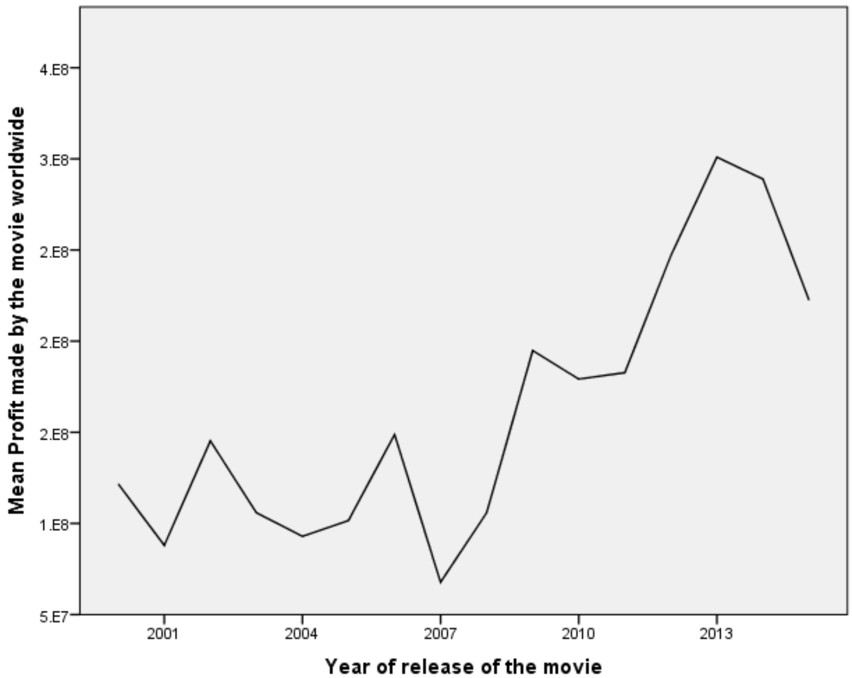


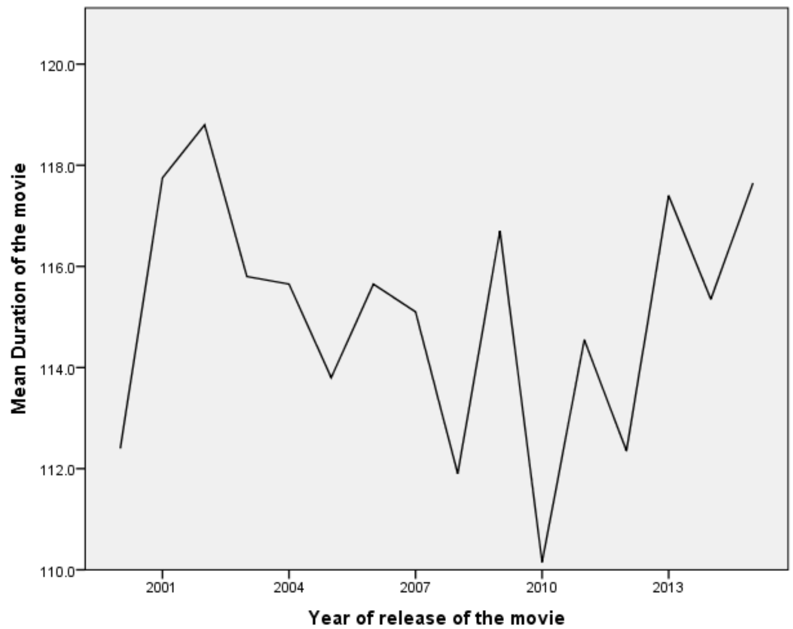
Figure 20: Development of the profit (in US $) of movies from 2000 to 2015

3.1.10 Distribution company and land of production

In the sample, 71% of the films were produced by a major distribution company. As the sample consisted of a selection of the most popular movies released in a year, this result could be expected as most popular movies are produced in Hollywood. 55% of the movies in the sample were solely produced in the USA. Moreover, 36% of the movies in the sample were produced by countries in cooperation with the USA. Only 9% of the sample consisted of movies that were produces completely outside of the USA.

3.1.11 Duration of the movie

In this sample, the duration of the movies were in general 115 minutes. The longest movie in the sample took 191 minutes, which was *Grindhouse* (2007). The shortest movie took 77 minutes, which was *Primer* (2004). In the development over time, it was clear that there was an increase in the duration of the movies. However, from 2000 until 2004, the movies were even longer.



Graph 20: Development of the duration of the movie (in minutes) from 2000 to 2015

3.2 Inferential statistics

In this section, the regression results and the interesting correlations are presented. For the regressions, data from 2015 was extracted were a significant lower amount of ratings from consumers and ratings from critics in the data, due to the fact that there has been too little time for the movies to generate the same amount of votes than the other years (see figure 3 and 6). Therefore, the amount of movies that were analyzed in the regression analyses were 300. In appendix 7.3, an overview of all correlations can be found. The results of the regressions are visualized in table 2 and 3.

4.2.1 The market

4.2.1.1 Correlations

Some significant correlations showed interesting results. There was a significant strong positive correlation between consumer ratings and critics’ ratings, r = .693, p < .05, which indicates that perceived quality by consumers was positively associated with the ratings of critics. There is a significant moderate association between consumer ratings, peer awards and the amount of peer, respectively r = .367, p < .05; r = .302, p < .05, which means that quality perceived by consumers was positively influenced by peer recognition.

Consumer ratings had a significant moderate positive correlation with the genre drama, r = .369, p < .05, which indicates that consumers perceived drama films as high quality movies. An interesting observation is that there was a significant negative very weak correlation between consumer ratings and action films, r = -.148, p < .05, horror films, r = -.128, p < .05 and comedy films r = -.176, p < .05. This indicates that in this sample, popular genres as action, horror and comedy were perceived as lower quality than the others. Moreover, there was a negative significant correlation between consumer ratings and the remakes of movies, r = -.279, p < .05. For story adaptations from written creative works, there was a very weak positive significant correlation, r = .192, p < .05.

There was no significant correlation between the consumer ratings and the star power of the actors, however, there was a positive significant correlation between star power of directors and consumer ratings, r = .204, p < .05. This indicates that star power of directors increased the chances for a movie of being perceived as high quality by consumers.

There was no significant correlation between consumer ratings and box office revenue, r = .100, p > .05, which is interesting as both perceived quality as box office revenue were used as a form of demand for consumers. Also, there was no significant correlation between consumer ratings and the budget of the movie, $r = -.094$, $p > .05$. There was, however, a significant weak association for the profit of the movie, $r = .133$, $p < .05$. A table of all correlations can be found in appendix 7.4.

4.2.1.2 Regression

A multiple regression analysis was conducted to test which factors could predict the perceived quality by consumers, measured in consumer ratings.

The prediction model contained most of the predictors that were included in the data collection. There were, however, a few variables removed from the analysis due to multicollinearity, which are *amount of nominations*$_i$, *content awards*$_i$, *amount of content awards*$_i$, *level of competition*$_i$, and *drama*$_i$ (*VIF* > 5). Moreover, *Instagram followers*$_i$ and *Twitter followers*$_i$ were excluded from the model as they have too little units of analysis. The missing variables were replaced by the mean. The regression analysis is presented in table 2.

The regression model of the perceived quality by consumers (measured in consumer ratings) as dependent variable is statistically significant, $F(16.759)$, $p < .05$. The model is thus useful for predicting the perceived quality of consumers (measured in consumer ratings) with relatively high predictive power. The results of the linear regression model indicates that in the population, the predictors explained 68.1% of the variance in perceived quality, $R^2 = .681$. The data met the assumption of independent errors (Durbin-Watson value = 2.068). In this section, *perceived quality by consumers, measured in consumer ratings* will be referred to as *perceived quality by consumers* or *ordinary consumer evaluations.*

Ordinary consumer evaluations were predicted by the amount of ratings for consumers, $\beta = .467$, $t(8.944)$, $p < .05$, and amount of Facebook likes, $\beta = 2.160$, $t(2.137)$, $p < .05$, which corresponded with the expectations. Interestingly, it was expected that budget would significantly predict online WOM positively, but in these results, the consumer ratings had a significant negative relation with the budget of the movie, $\beta = -.178$, $t(-3.123)$, $p < .05$.

Ratings from critics positively predicted the perceived quality of consumers, $\beta = .563$, $t(10.293)$, $p < .05$, which was in line with the expectations. There was no relation between perceived quality of consumers and awards based on peer recognition (amount of peer awards as well as the probability of receiving a peer award by a popular movie), which indicates that peer awards are not seen as a sign of quality by consumers. This contradicted the expectations.

Contrary to the expectations, the most popular genres had a negative effect on the perceived quality of consumers, which were *action*, β = -.198, t(-3.774), $p < .05$, *comedy*, β = -.155, t(-3.439), $p < .05$, and *horror*, β = -.138, t(-3.496), $p < .05$. There was, however, a positive relation between children's movies and perceived quality by consumers, β = .095, t(2.001), $p < .05$, which indicates that the for popular movies, children's movies were perceived as highest quality.

The perceived quality of actors was not affected by the star power of actors or directors. Moreover, the MPAA ratings did not affect the ordinary consumer evaluations on popular movies.

There were some other interesting results in the regression analysis. First, there was a positive predictive power of whether the movie was featured in 3D or IMAX on the perceived quality of consumers, β = .080, t(1.762), $p < .10$. Even though this effect is very weak, which could be attributed to the fact that the units of analysis for this variable was low, it indicates that these techniques had a positive impact on the perception of quality by consumers. Second, there was a positive association between perceived quality of consumers and the land of production, β = .061, t(1.663), $p < .10$, which means that for this sample, movies that were produced outside of the US were perceived as higher quality than US produced movies. Last, popular movies that were longer in duration scored higher in ordinary consumer evaluations, β = .166, t(2.137), $p < .05$, than shorter movies.

4.2.2 Experts

4.2.2.1 Correlations

There is a strong positive correlation between the ratings of critics and the ratings of consumers, $r = .691$, $p < .05$. Also, critics’ ratings quite significantly correlate with awards and peer awards, such as the amount of peer awards, $r = .427$, $p < .05$, and the amount of general award nominations received for a movie, $r = .648$, $p < .05$.

Drama films had a positive association with the ratings of critics, $r = .330$, $p < .05$, but there is a negative relationship for action films, $r = -.213$, $p < .05$ and remakes, $r = -.236$, $p < .05$, which seems to confirm the expectation that critics like more complex movies. Also, star power of directors had a positive association with the ratings from critics, $r = .238$, $p < .05$. Lastly, a negative correlation between the budget and the critics’ ratings was found, $r = -.166$, $p < .05$, which again indicates that critics do not tend to like the high budget, easy movies. A table of all correlations can be found in appendix 7.4.

4.2.2.2 Regression

A multiple regression analysis was conducted to test which factors could predict the perceived quality by experts, measured in the ratings of critics.

In the regression, the variables *Instagram followers*$_i$ and *Twitter followers*$_i$ were not included in the analysis due to low units of analysis (n = 59). Moreover, multicollinearity was found for the following variables: *amount of nominations*$_i$, *content awards*$_i$, *amount of content awards*$_i$, *genre: drama*$_i$, *and level competition*$_i$ (*VIF* > 5). Therefore, these variables were also excluded to the regression model. The missing variables for the values in the regression were replaced by the mean. The regression table can be found in table 2.

The regression model of the perceived quality by experts (measured in critics’ ratings) as dependent variable was statistically significant, $F(22.129)$, $p < .05$. The model was thus useful for predicting the perceived quality of experts (measured in critics’ ratings) with relatively high predictive power. The results of the regression indicated that the predictors explained 74.6% of the variance, $R^2 = .746$. The data met the assumption of independent errors (Durbin-Watson value = 1.942). In this section, the *perceived quality by experts, measured in critics’ ratings* will be referred to as *perceived quality by experts* or *expert evaluations*.

It was found that consumer ratings significantly predict the critics’ ratings, $\beta = .444$, $t(9.541)$, $p < .05$, which means that perceived quality by consumers and experts showed similarities, which contradicts the expectations. Perceived quality by experts did have a negative relation with the amount of Facebook likes, β = -.068, t (-1.841), $p < .10$ and the amount of ratings given by consumers, β = -.160, t(-2.811), $p < .05$, which confirmed the expectation about the negative relation between expert judgement and popular appeal.

The amount of peer awards that a popular movie received positively predicted the perceived quality of experts, β = .150, t(2.676), $p < .05$, which indicates that experts and peers have the same valuation of quality for movies. This contradicts the expectations.

In line with the theory, genres and story adaptations could not predict the perceived quality of experts in this sample. Expert evaluation were, however, positively influenced by the star power of directors, β = .064, t(1.787), $p < .10$. Interestingly, there was a significant negative association between the expert evaluation and the MPAA ratings, β = -.069, t(-1.851), $p < .10$, which contradicts the expectations as was expected that high MPAA ratings (R and PG-13) would have more prestige and recognition from peers.

Another interesting result was that box office revenue negatively predicts the perceived quality of experts, β = -.196, t(-2.687), $p < .05$, which means that there was a difference between the demand of consumers (measured in box office revenue) and the judgement of critics in this sample. Lastly, experts tend to perceive shorter movies as high quality, β = -.090, t(-2.102), $p < .05$, which was different from the perception of quality by consumers.

4.2.3 Peer recognition

4.2.3.1 Correlations

Some interesting significant correlations were between the amount of peer awards and the ratings of consumers, r = .302, $p < .05$ and the rating of critics, r = .436, $p < .05$, which indicates that in this sample consumers and critics are influenced by peer awards in their judgment of quality.

Moreover, drama movies had a positive correlation with the amount of peer awards, r = .240, $p < .05$, which was the only genre with a significant correlation. Interestingly, there were positive significant correlations between box office revenue, r = .129, $p < .05$, and profit, r = .135, $p < .05$, which means that in this sample, it is possible peer awards stimulated the commercial success of a movie. A table of all correlations can be found in appendix 7.4.

4.2.3.2 Regressions

Two regressions were conducted to measure the perceived quality by peers, measured through the Academy Awards and the BAFTA Awards: a multiple regression for which the dependent variable was the amount of peer awards that a movie had received, and a logistic regression for which the dependent variable was the probability of receiving a peer award.

In the regression, the variables *Instagram followers*$_i$ and *Twitter followers*$_i$ were not included in the analysis due to low units of analysis (n = 59). Moreover, multicollinearity was found for the following variables: *amount of nominations*$_i$, *content awards*$_i$, *amount of content awards*$_i$, *genre: drama*$_i$, *and level competition*$_i$ (*VIF* > 5). Therefore, these variables were also excluded to the regression model. The missing variables for the values in the regression were replaced by the mean.

The multiple regression model of the perceived quality by peers (measured in the amount of peer awards) as dependent variable was statistically significant, F(18.890) , $p < .05$. The model was thus useful for predicting the perceived quality of peers (measured in the amount of peer awards) with relatively high predictive power. The results of the multiple regression model indicates that the predictors explained 71.6% of the variance, R^2 = .716. The data met the assumption of independent errors (Durbin-Watson value = 1.943).

For the logistic regression, a test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between the receiving of a peer award or not receiving a peer award (χ^2 = 226.869, $p < .05$ with df = 36). *Nagelkerke’s* R^2 of .878 indicated a strong relationship between prediction and grouping.

Prediction success overall was 97.2% (98.9 % for not winning a peer award and 88.0% for winning a peer award).

Interestingly, consumer ratings significantly negatively predict the amount of peer awards, $\beta = -.155$, $t(-1.837)$, $p < .10$, but positively predict the chances of a popular movie winning a peer award, as was visible in the Wald-criterion, $\beta = 2.779$, $p < .05$, with an Exp(B) value of .658. There was no relation between perceived quality by peers and popular appeal.

Ratings from critics positively influence the amount of peer awards popular movies receive, $\beta = .176$, $t(2.676)$, $p < .05$, but the probability of winning a peer award was not predicted by critics' ratings, $\beta = -.301$, $p > .05$.

There are less action movies that win a high amount of award in this sample, $\beta = -.097$, $t(-1.768)$, $p < .10$. Interestingly, the Wald criterion showed that the probability of winning a peer award is higher for children's movies, $\beta = 8.474$, $p < .10$ with an Exp(B) value of 4788.663, which is the strongest effect in this logistic regression. In general, remakes received a higher amount of peer awards, $\beta = .079$, $t(2.048)$, $p < .05$, which is not in line with the expectations. However, sequels, $\beta = -4.641$, $p < .05$, Exp(B) = .010, and written story adaptations $\beta = -4.249$, $p < .05$, Exp(B) = .014 have a lower chance of winning a peer award, as was visible in the Wald criterion.

The amount of peer awards could not be predicted by star power of actors and directors. However, the probability of winning a peer award was positively influenced by the current star power of actors, $\beta = 1.883$, $p < .10$, with an Exp(B) value of 6.750. There was no effect of the MPAA rating on the chances of winning a peer award or on the amount of peer award a movie received.

Other significant results showed that movies that won a technical award had an increased chance of winning a high amount of peer awards, $\beta = .164$, $t(3.359)$, $p < .05$; $\beta = .329$, $t(8.199)$, $p < .05$. However, as the awards based on the content of the movie were not taken into account in this regression due to multicollinearity, it is not possible to make generalizable conclusions.

It was interesting to notice that box office revenue negatively predicted the amount of peer awards for a movie, $\beta = -.074$, $t(-2.038)$, $p < .05$, but that the budget of the movie positively influenced the amount of peer awards for a movie, $\beta = .180$, $t(2.272)$, $p < .05$. This suggests that movies with a high budget were perceived as high quality by peers, but that movies with received a large commercial success did not appeal to the taste of the peers.

The probability of winning a peer award was negatively predicted by the distribution company, which was visible in the Wald criterion, $\beta = -3.319$, $p < .05$, with an Exp(B) value of .036. This means that in the sample, the minor distribution companies produced movies that were perceived as high quality by peers. Moreover, according to the Wald criterion, there was a positive association between the land of production and the probability of winning a peer award, $\beta = 1.939$, $p < .10$, with an Exp(B) value of 6.953. This indicates that movies produced outside of the US were perceived as high quality by peers in this research.

Table 2

Linear Regression Results – Commercial Success & Perceived Quality for Consumers, Experts and Peers

	Commercial success of the movie		*Success of the movie in terms of perceived quality*					
	Model 1: Box office revenue		Model 2: Consumer ratings		Model 3: Critics' ratings		Model 4: Amount of peer awards	
Independent variables	β	*t*	β	*t*	β	*t*	β	*t*
Constant		4.221**		-.876		-.500		.184
Year	-.158	-4.989**	.039	.936	-.012	-.292	-.006	-.144
Ratings consumers	-.019	-.395	-	-	.508	10.293**	-.115	-1.837*
In(Amount of ratings consumers) $_{t-2}$	.149	3.158**	.476	8.944**	..160	-2.811**	.014	.231
Ratings critics'	-.136	-2.687**	.563	10.293**	-	-	.176	2.676**
Amount of ratings critics'	.322	7.894**	-.191	-3.338**	.311	6.092**	-.119	-2.034**
Awards	.057	1.674*	-.049	-1.131	.187	4.718**	.022	.488
In(Amount of awards) $_{t-2}$	-.086	-1.181*	-.122	-2.039**	.278	5.082**	.185	3.043**
Peer awards	-.001	-.016	.053	1.001	-.031	-.623	-	-
Amount of peer awards	.107	2.272*	-.109	-1.837	.150	2.676**	.280	5.452**
Nominations	.067	2.327**	-.016	-.441	.082	2.367**	-.056	-1.479
In(Amount of nominations) $_{t-2}$	-	-	-	-	-	-	-	-
Nomination peer awards	.052	1.282	.018	.359	.045	.923	-.240	-4.743**
Amount of nominations peer awards	.046	1.020	.037	.656	.016	.294	.270	4.835**
Content awards	-	-	-	-	-	-	-	-
In(Amount of content awards) $_{t-2}$	-	-	-	-	-	-	-	-
Technical awards	-.100	-2.656**	-.043	-.899	.030	.663	.164	3.359**
In(Amount of technical awards) $_{t-2}$	-.086	-2.512**	.027	-.899	-.067	-1.617	.329	8.199**
3D or IMAX	-.016	-.448	.080	1.762*	.002	.048	.034	.732
Genre: Drama	-	-	-	-	-	-		
Genre: Action	.036	.855	-.198	-3.774**	.042	.818	-.097	-1.768*
Genre: Comedy	.001	.027	-.155	-3.439**	.060	1.365	-.012	-.250
Genre: Horror	.084	2.678**	-.138	-3.496**	.054	1.405	-.047	-1.150

Genre: Children	.056	1.489	.095	2.001**	-.021	-.455	.000	.000
Genre: Other	.004	.127	-.053	-1.426	.050	1.420	-.039	-1.022
Sequels	-.009	-.278	-.022	-.535	.056	1.439	-.027	-.637
Remakes	.012	.413	-.105	-2.796**	.030	.830	.079	2.048**
Story adaptations	.024	.792	.040	1.061	.007	.197	-.006	-.163
Current star power actors	-.020	-.631	-.052	-1.271	-.019	-.499	-.031	-.732
All-time star power actors	.006	.173	-.014	-.355	.002	.040	-.008	-.191
Star power directors	.006	.198	.003	.074	.064	1.787*	.030	.769
Released in the same period	.029	1.050	.039	1.114	-.030	-.890	.013	.362
Level of competition	-	-						
Season	.063	2.270**	-.030	-.830	.047	1.402	-.074	-2.038**
In(Box office revenue) $_{t-2}$	-	-	-.031	-.395	-.196	-2.687**	.180	2.272**
In(Budget) $_{t-2}$	.274	6.414**	-.178	-3.123**	.001	.020	-.024	-.403
In(Profit) $_{t-2}$	.369	8.505**	-.004	-.069	-.029	-.498	-.050	-.780
Rating MPAA	-.019	-.607**	.050	1.281	-.069	-1.851*	-.008	-.200
Distribution company	.051	1.606	.014	.347	-.001	-.037	.043	1.031
Land of production	.000	.005	.061	1.663*	-.013	-.375	-.035	-.930
Duration	-.028	-.769	.166	3.747**	-.090	-2.102**	.052	1.123
In(Facebook likes) $_{t-2}$	.068	2.160**	.085	2.137**	-.059	-1.567	-.021	-.505
R^2	.824		.718		.746		.716	
F	35.410		19.225		22.129		18.890	
p	.000**		.000**		.000**		.000**	
Durbin-Watson	1.980		2.107		1.942		1.970	
N	300		300		300		300	
df	35		35		35		35	

Note: In(x) = log (x)
* p < .10. ** p < .05

Table 3

Logistic Regression Result – Dependent Variable: Perceived Quality by Peers

	Success of the movie measured in perceived quality by peers		
	Model 1: Peer awards		
Independent variables	β	*Wald-test*	*Exp(B)*
Year	-.378	7.322**	.685
Ratings consumers	2.779	5.280**	16.108
Amount of ratings consumers	.000	1.240	1.000
Ratings critics’	-.301	.401	.740
Amount of ratings critics’	.327	5.679**	1.386
Awards	15.279	.000	4319179.202
Amount of awards	.040	3.249*	1.041
Peer awards	-	-	-
Amount of peer awards	1.900	7.196**	6.688
Nominations	10.464	.000	35040.204
Amount of nominations	.002	.026	1.002
Nomination peer awards	-.058	.104	.9.43
Amount of nominations peer awards	6.698	8.584**	811.047
Content awards	-	-	
Amount of content awards	-	-	
Technical awards	.762	.378	2.142
Amount of technical awards	-.027	.041	.973
3D or IMAX	-2.587	.538	.075
Genre: Drama	-	-	
Genre: Action	1.392	.610	4.022
Genre: Comedy	1.269	.548	3.557
Genre: Horror	-10.256	1.384	.000
Genre: Children	8.474	3.439*	4788.663
Genre: Other	-14.614	.000	.000
Sequels	-4.641	2.911*	.010
Remakes	-6.566	.696	.001
Story adaptations	-4.249	5.522**	.014
Current star power actors	1.883	3.810*	6.570

All-time star power actors	2.245	2.105	9.439
Star power directors	-1.459	2.650	.232
Released in the same period	-.747	3.254*	.474
Level of competition	-	-	
Season	.273	.368	1.314
Box office revenue	.000	2.482	1.000
Budget	.000	2.438	1.000
Profit	.000	2.093	1.000
Rating MPAA	.011	.000	1.011
Distribution company	-3.319	4.066**	.036
Land of production	1.939	3.103*	6.953
Duration	.007	.021	1.007
Facebook likes	.000	.328	1.000
R^2	202.260		
df	36		
p	.000**		
-2 Log likelihood	47.233		
Nagelkerke	.869		
N	298		

* p < .10. ** p < .05

4. Discussion

In this section, the results of the statistical analysis will be discussed, linked to the theoretical expectations.

4.1 Major findings

4.1.1 Factors that influence the perceived quality for popular movies by consumers, experts and peers

The perceived quality of consumers for popular movies was positively influenced by the amount of ratings given by consumers, the ratings of critics, 3D or IMAX movies, if a movie was a children’s movie or not, the land of production, the duration of the movie and the amount of Facebook likes. The perceived quality by consumers for popular movies was decreased when the movie was an action, comedy or horror movie as well as if it was a remake. Moreover, high budget movies had a negative effect on consumer ratings, as well as the amount of awards and the amount of ratings from critics.

The perceived quality by experts could positively be predicted by the ratings of consumers, the amount of ratings from critics, awards, the amount of awards, the amount of peer awards and nominations for an award, as well as the star power from the directors. There was a negative influence on the perception of quality of experts from the amount of ratings from consumers, the box office revenue of the movie, the rating from the MPAA and the duration of the movie.

The perceived quality by peers, measured in the amount of peer awards, could positively be explained by the ratings from critics, the amount of awards, the amount of peer awards, the amount of nominations for peer awards, if a movie had won a technical award and the amount of technical awards, the fact if a movie was a remake or not, and the budget of the movie. A movie got less peer awards when ratings from consumers were higher, the amount of ratings from critics were higher, the movie was nominated for a peer award, if the movie was an action movie, and if the box office revenue was high.

Box office results were positively influenced by the amount of ratings from consumers, if the movie had won an award, the amount of peer awards, if a movie was nominated for an award, if the movie was a horror movie, the season, the budget of the movie, and the amount of Facebook likes. There were negative associations between the year, the ratings from critics, the amount of awards, the technical awards, and the rating of the MPAA.

4.1.2 Differences and similarities between perceived quality for popular movies by consumers, experts and peers

The perceived quality by consumers overlapped the most with the expert ratings. For consumer ratings, the strongest predictor were the expert ratings, and the expert ratings could also be explained the strongest through consumer ratings. As the judgement of quality showed similarities between consumers and experts, it can thus be expected that consumers are indeed able to judge the quality of a popular movie, based on the results of this research. This contradicts the theory of Bourdieu (1984), and confirms the theory of Holbrook (2005). Interestingly, the perceived quality by consumers was not influenced by peer awards and in turn, peer awards were negatively predicted by consumer ratings. This indicates that there is a difference in the perception of quality between peers and consumers.

The perceived quality of consumers differed to some extent from the expected outcomes, based on previous discussed theory on commercial success of movies. First, familiar genres had a negative effect on the perception of quality by consumers, as there was a negative relation between consumer ratings and action, comedy and horror movies, which contradicts the theory of Desai & Basuroy (2005).

Moreover, high budgets negatively influenced the perception of quality by consumers, which meant that in this research, consumers were less satisfied with the outcome of high budget movies. Also, quality perceived by consumers was higher when the movie was produced in countries outside the U.S.A. Furthermore, there was no association between box office results and consumer ratings.

In line with the expectations, sequels and written story adaptation had no effect on the perception of quality, whilst remakes even had a negative association with consumer ratings. This confirms the theory of Moon et al., 2010 and Sood & Dreze, 2006, which stated that consumers are in general less satisfied with movies that are sequels. The results of this research indicate that consumers were less satisfied with movies that were remakes.

Star power did not have any influence on the perception of quality for consumers, which was in line with the theory of Suárez-Vázquez (2011). Moreover, it also had no effect on the box office results of the popular movies in this sample, which confirms the results of Litman (1983) Porkorny & Seth (2011), who state that star power only has a significant effect on medium to low budget movies, rather than on high budget movies. This indicates that star power is indeed not a profitable investment by motion picture companies.

Even though there is a positive association between consumer ratings and popular appeal (measured in the amount of ratings and the likes on Facebook), the rest of the results suggest that there is a large difference between the perceived quality of consumers and the elements for which motion picture companies assume that they will influence the commercial success of a popular movie. Most techniques that tend to reduce the quality uncertainty for consumers, such as genre and star power, had a negative or no effect on the perception of quality by consumers. Moreover, the strongest relation was between expert ratings and consumer ratings, which means that their opinions on the quality of movies overlapped.

The amount of peer awards positively influenced the perceived quality of experts, which indicates that their perception of quality was approximately the same in this research. This contradicts the theory of Ginsburgh & Weyers (1999) who state that awards are not a good proxy of long term quality. This is, however, only the case for the amount of peer awards: there was no significant relation between the probability of winning an award and the expert ratings.

The perceived quality of experts was negatively predicted by box office revenue, which meant that the commercially successful and most popular movies were not perceived as high quality by experts, which is in line with the expectations. Also, the evaluations of experts was positively influenced by the star reputation of the directors. This is also in line with the expectations.

Experts did not perceive the high rated movies (PG-13 and R-rated movies) as high quality, which contradicts the theory of De Vany & Walls (2002). This means that in this research, critics perceive the lower rated movies as higher quality instead of seeing this as high-prestige movies. Therefore, motion picture companies should be cautious about producing high rated movies. Also, box office results show that consumers are less inclined to buy tickets for high rated movies.

As expected, most of the other factors did not have a significant effect on the ratings of critics, which indicates that critics were in general not largely influenced by elements that could decrease the quality uncertainty of the consumers, such as the star power of actors and the story adaptations. Therefore, this research argues that critics are independent judgers of quality.

For the perceived quality of peers, there is a difference between the probability of winning an award and the amount of awards a movie has won. It can be assumed that movies with a higher amount of awards can be perceived as higher quality than chance of winning a peer award. One of the largest difference is that the amount of peer awards were negatively predicted by consumer ratings, but that the probability of winning a peer award was positively associated with consumer ratings. This suggests that the perceived quality of consumers can increase the chances of winning a peer award, but that in the end, the popular movies, perceived as high quality by consumers, were not regarded as quality by peers.

There is a positive association between expert ratings and the amount of peer awards, which, again, indicates that peers have a similar perception of quality for popular movies as experts. Interestingly, the probability of winning an award is the highest for children’s movies, which is the strongest effect in the equation. This indicates that in this sample, children’s movies were the most likely to be perceived as high quality by peers.

Sequels and written story adaptations were not perceived as high quality by peers, as the probability of winning a peer award for these movies was low. Remakes, however, were perceived as high quality by peers, as there was a positive relations between remakes and the amount of peer awards.

The probability of winning a peer award was positively influenced by the star power of actors, but it had a negative correlation for the amount of peer awards. The influence of star power on peer evaluations contradicts the expectations. However, it indicates that star actors are more likely to win a peer award than other actors, but that this does not indicate that the quality of the movie is better due to the fact that movies with stars did not influence the amount of awards.

Interestingly, box office results negatively predict the perceived quality of peers, measured in the amount of peer awards, which means that the most popular movies in terms of consumer demand were not perceived as high quality by peers. However, the budget positively influences the amount of peer award. This can also be explained by the fact that stars have a higher probability of winning a peer award. Hiring star actors is a large proportion of the budget. Therefore, it can be concluded that the perception of quality by peers differed from the commercial success of a movie.

To conclude, the major influencer on the perceived quality of consumers were the ratings of critics, which indicates that consumers are able to detect which movie are of high quality, contrary to what Bourdieu (1984) suggest. The perception of quality for experts was not largely influenced by elements which motion picture companies use to reduce the quality uncertainty for consumers, which indicates that their judgment of quality is relatively independent of other factors. The perception of quality from experts and peers were largely overlapping for which the main difference was that the perception of quality from peers were explained by elements of popular appeal, such as star power and budget, but this can be explained by the fact that star actors are more likely to win peer awards than other actors. This is not per se an indication of quality for the movie by peers.

4.1.3 Difference between the commercial success of a movie and the perception of quality by consumers

Based on the results of this research, there was a large difference between the commercial performance of a movie and the perception of quality by consumers. The fact that consumers buy a ticket to see a movie does not say anything about how satisfied they were about the movie. This is important for motion picture companies to be aware of.

There is no relation between box office results and consumer ratings. Moreover, even though a higher budget leads to a higher box office revenue, consumers do not perceive the high budget movies as high quality. Therefore, the satisfaction of consumers for the large blockbuster movies is much lower than for other movies, which could lead to a decrease in visitor numbers on the long run. This contradicts the theory of Karniouchina (2011), Liu (2006) and Tsao (2014).

Box office results were negatively predicted by critics' ratings, whilst the perception of consumers were positively explained by the ratings of critics. This indicates that negative ratings from critics hurt the commercial success of a movie more than positive ratings, which is in line with the research of Litman & Kohl (1989) and Lampel & Shamsie (2000).

Box office results could be explained by the amount of peer awards, but the perception of quality by consumers were not affected by this. This indicates that consumers were influenced by peer awards in deciding to buy a ticket for a particular movie, but that the quality of that movie was not always as expected. Also, box office results were lower for movies that had won many technical awards, which indicates that special effects and good editing techniques were not convincing for consumers to buy tickets. However, quality perceived by consumers was positively affected by the fact that a movie was a 3D or IMAX movie.

The differences between perception of quality by consumers and the box office revenue was especially visible in genres. Consumers did not perceive the popular genres as high quality, but box office results could positively be predicted when a movie was a horror movie. However, the effects of genre on popular movies was not that large, which indicates that genre is not the most important determinant of demand. This contradicts with the theory of Desai & Basuroy (2005).

Similarities between box office revenue and the perceived quality of consumers for movies was the positive effect of popular appeal, measured in the amount of ratings by consumers and the amount of Facebook likes. This indicates that consumers are still more sensitive to the amount of people that consume the popular movies, which could be explained by network effects and herd behavior: the utility of consuming a movie is higher when more people have consumed the movie (Kats & Sharipo, 1994). These factors are not of influence on quality perceived by experts and peers, as their intention of watching a movie is different from consumers.

5.2 Minor findings

In this section, the findings which were not discussed in the theoretical framework will be analyzed.

In the time development, it is clear that there was an increase in the ratings from consumers as well in the ratings from critics. This could be an indication of an increase in quality throughout the years. However, as the sample size is only 320 movies, this is only an indication. For the amount of likes on Facebook and the amount of followers on Twitter and Instagram, there are, however, a lower amount of people that have followed the account for the last few year.

For the social media platforms, it was visible that Facebook had the highest amount of followers for movie accounts. This is possible as Facebook was founded earlier than Instagram and Twitter, and therefore has much more followers. For future research, it would be interesting to do a more thorough analysis of Instagram and Twitter accounts for movies, as it could be possible to see a different effect on the success of a movie, commercial as well as in terms of perceived quality.

Interestingly, in the descriptive results, it was evident that there was a large increase in box office revenue, budget and profit for the last 5 years. However, in the regression results, there was a negative relation between box office revenue and the year when the movie was released, which indicates that the earlier years had a larger commercial success.

In general, critics give lower ratings to the movies in the sample than consumers. As the sample consists of only popular movies, it could be expected that experts are more critical on these movies than consumers. An interesting finding is that consumers perceive longer movies as higher quality, whilst experts think that shorter movies are higher quality.

5. Conclusion

A substantial amount of studies have research the commercial success of movies in the marketing literature. Many researchers have tried to explain which factors play an important role in achieving the highest amount of box office revenue and visitor numbers. In general, these studies only measure the success of a movie in terms of box office revenue, but forget one of the most important issues in the motion picture industry: quality.

Quality is an important outcome of a creative good as a movie (Ginsburgh & Weyers, 1999), which means that quality can also be seen as a measurement of success. Factors that indicate quality, such as expert ratings and awards, have been taken into account in explaining the commercial success of a movie, but quality has not been used as a proxy for the success of a movie, to my knowledge. This research added to the discussion by measuring the perceived quality of consumers, experts and peers as a measurement of performance for popular movies, instead of focusing on the box office results. It is important to be aware of the fact that all conclusions can only be generalized for popular movies.

Central in this research was the comparison between the perceived quality by consumers, experts and peers for popular movies, following the contention of the selection system theory. One of the most important issues was the comparison between the judgement of quality for popular movies between consumers and experts (and peers). This research suggests that consumers are able to judge the quality of a movie, as it overlaps with the quality assessment of critics. This contradicts the theory of Bourdieu (1984), but confirms the research of Holbrook (2005) who states that there is a difference between ordinary consumer evaluations and popular appeal. The increasing ability for consumers to judge movies could be explained by the fact that consumers have gathered more experience in watching movies due to the low costs of watching a movie through online downloading and streaming. Also, consumers have more possibilities to share their opinions on movies online, which means that a better assessment of the difference between consumers and critics could be made than in the past.

Similarities were found between the perceived quality of movies by peers and experts. Ginsburg & Weyers (1999) stated that awards, especially the Academy Awards, are not a good indication of long-term quality, which would indicate that experts have a different perception of quality than peers. However, experts and peers both positively influence each other, which indicates that they do have similarities in their perception of quality. This means that, according to these results, the notion from Ginsburgh & Weyers (1999) was rejected, or that the ability of peers to judge quality has increased throughout the years.

Interestingly, consumers are not influenced by the quality assessment of peers, which indicates that awards are not perceived as prestigious and high qualitative as expected by motion picture companies. However, the similarities between the perception of quality by peers and that of experts do suggest that peers have the ability to judge quality of movies, which contradicts with the notion of Ginsburgh (2003) and Ginsburg & Weyers (1999) who stated that awards do not signal long-term quality.

Another central issue was the comparison between the perceived quality of consumers and the demand for consumers for popular movies, measured in box office revenue. There was a large difference between the perception of quality from consumers and their decision on buying tickets for a movie. This indicates that consumers are influenced by the marketing techniques by motion picture companies in their purchase decisions, but that the satisfaction of seeing those movie is actually disappointing. However, perception of quality by consumers is still influenced by popular appeal, which indicates that the utility of consuming a movie is larger when more people have seen the movie. For experts and peers, the motive of watching a movie is different as it is their job to judge the quality of a movie, which could explain the fact that they are not influenced by popular appeal.

There is a difference in the probability of winning a peer award and the amount of peer award. Winning an Academy Award or BAFTA Award is easier than receiving multiple awards. This could be explained by the fact that super star actors regularly receive a peer award, but that those movies do often not win more peer awards, based on other aspects of the movie. Therefore, when assessing the quality of a movie from the peer perspective, it is important to look at both results in order to get the complete image.

For the box office results, there are less elements that contribute the commercial success of a movie in this research than was expected from previous theory. Signs of quality did not largely affect the revenue: only the amount of peer awards, the budget and measurement of popular appeal significantly positively increased the box office revenue. Critics' ratings negatively affected the box office revenue. However, the storylines, such as genre and story adaptation, did not largely influence the box office results, just as the expensive super stars.

To conclude, based on the results of this research, it can be expected that consumers are able to judge quality of popular movies, which challenges the notion of Bourdieu. Moreover, the judgement of quality by experts and peers overlap, which counters the theory of Ginsburgh and Weyers. And lastly, there is indeed a difference in the performance of a movie in terms of perceived quality and the commercial performance of a movie in case of popular films. The factors that influence the purchase decisions of consumers did, in general, not overlap with the box office results.

5.1 Managerial implications

In this section, the relevance of this research for motion picture studios and distributors will be discussed. The study offers insights in the relation between quality and commercial performance of a movie. As there is a large difference between perceived quality and the commercial performance of a popular movies, it is suggested that the quality of a movie should be taken into account when producing a movie, instead of only looking at the short-term box office results. Moreover, it is important to be aware of the fact that a high profitable movie does not necessarily means that the quality of the movie is good.

According to these results, consumers are more and more able to judge quality by themselves, as their judgement overlaps with the quality perception of experts. This has a large effect on the post-assessment and the satisfaction on the movie, which is important for the future decision process of the consumer. Even though quality assessment does not have a large impact on the commercial success of a movie yet, it is possible that consumers demand higher qualitative movies in the future, more than only depending on story adaptations or familiar genres.

Another opportunity for distributors of movies, such as cinemas, is to assume that the consumers know more about movies than is expected. Therefore, it is possible to attract more consumers to the cinema by offering interesting side programs where consumers have the ability to discuss with the creators of the movie or to stimulate conversations about the experience they just had.

Furthermore, in this research, the large difference between consumers, peers and experts is that consumers were sensitive for measurement of popular appeal. This indicates a movie becomes more valuable for consumers if more people have also seen it. For experts and peers, this is not applicable as they do not watch movies for the sake of having a conversation with their friends. This outcome is essential for motion picture companies, as the stimulation of buzz for popular movies can lead to a higher satisfaction of the consumers, as well as a higher commercial success.

5.2 Academic implications

This research aims to measure the performance of a movie in terms of quality, rather than in terms of commercial success. It has been shown that it is possible to measure quality through quantitative, econometric models.

Moreover, this research demonstrates that the role of the consumer with regard to the assessment of quality has changed. The old-fashion dichotomy between experts and consumers is fading away. Consumers have a larger ability in identifying which movies are of high quality, instead of being the inexperienced spectator that can only assess the popular appeal.

Also, in academic research, the performance of a movie is often assigned to the commercial success of a movie, while that is not the only form of performance. This research shows that quality can also be an indicator of performance, which differs from the commercial performance. Therefore, academic research should consider to use the quality as a dependent variable, rather than only an influencer on the performance of a movie.

To conclude, this research included an analysis of social media followers, for which the amount of likes on Facebook had significant results for some of the dependent variables. This indicates that it is important for researchers to be aware of the importance of social media in research to the motion picture industry, which has not been done very often yet.

5.3 Limitations and future research

As in every research, there were limitations bound to this research. First, the sample of the research consisted of only 320 popular movies for a time span of 11 years, for which only 300 movies could be used for the regression analysis. Also, the selection of the sample was not random. Moreover, even though it was aimed to collect most data on an international level, most data sources on Hollywood movies are based on U.S. data. This means that the research is not fully representable for the whole population of popular movies that were released in this time period. Due to time constraints, it was not possible to increase the size of the sample. Thus, for future research, it is recommended to research a larger amount of movies per year, or to reduce the time span in order to analyze a larger amount of movies per year.

Also, this study only analyzed popular movies that were released between 2000 and 2015, which was retrieved from a list on *IMDb*. Therefore, the perception of quality by consumers, experts and peers was not analyzed for low budget movies or movies produced outside of Hollywood, with a few exceptions. The reason why these movies were not added to the sample was due to lack of data availability. Moreover, the intention of the research was to look at how the Hollywood industry could be analyzed on the hand of perceived quality, as most marketing research was conducted to this market. To get a broader image of the motion picture industry as a whole and the factors that influence the quality of movies, it is recommended for future research to not only research popular movies, but select a sample that represents a larger scope of movies, which includes other lists of movies for the selection of the sample.

Moreover, for some variables, it was not possible to collect the data in a representable and sophisticated way. First, the analysis of social media followers and mentions could be done more effectively by using programs that can analyze the social media attention online. Due to time and financial restraints, there was no alternative in measuring social media attention for this study, but it is recommended to search for more sophisticated manners of social media data collection, as this variable is interesting for the motion picture industry. Second, due to the fact that the time period of the analysis was 11 years, there was no comprehensive list of star actors and directors for each year. Therefore, only the current star power and all time star power could be analyzed in this research. For further research, the star power should be analyzed per year, as the popularity of actors and directors differ per time period.

There were some variables that showed multicollinearity with the other variables, which made them unsuitable for the regression analyses, such as the genre 'drama' which did have significant correlations with the dependent variables. In a new analysis to the perceived quality of movies, this multicollinearity should be avoided, as it is important to investigate what the effect of drama would have on the perception of quality.

It is increasingly important to measure the performance of movies in terms of (perceived) quality, rather than sticking to the commercial performance. This study is relevant because it shows that there is a large difference between the pre-assessment of quality (the willingness to buy tickets for the cinema, which is visible in the box office revenue) and the post-assessment (which is visible in the perceived quality by consumers, experts and peers). Moreover, it is important to compare the perceived quality between experts, peers and consumers, as these all have different intentions in seeing a movie. Therefore, this research lays a foundation for further research in the perception of quality as a measurement of performance of movies.

6. List of references

Ashley, C., & Tuten, T. (2015). Creative Strategies in Social Media Marketing: An Exploratory Study of Branded Social Content and Consumer Engagement. *Psychology & Marketing*, *32*(1), 15. DOI: 10.1002/mar.20761

Basuroy, S., & Chatterjee, S. (2008). Fast and frequent: Investigating box office revenues of motion picture sequels. *Journal Of Business Research, 61*(7), 798-803. doi:10.1016/j.jbusres.2007.07.030

Bhansing, P. V., Leenders, M. A., & Wijnberg, N. M. (2012). Performance effects of cognitive heterogeneity in dual leadership structures in the arts: The role of selection system orientations. *European Management Journal*, *30*(6), 523. doi:10.1016/j.emj.2012.04.002

Bourdieu, P. (1984). Distinction : A social critique of the judgement of taste. Cambridge, Mass.: Harvard University Press.

Box Office Mojo (n.d.). About Box Office Mojo. Retrieved from http://www.boxofficemojo.com/about/?ref=ft

Box Office Mojo. (2016). Studio Market Share. Retrieved from http://www.boxofficemojo.com/studio/

Busch, A. (August 2015). Universal Pictures has highest grossing box office in industry history [blogpost]. Retrieved from http://deadline.com/2015/08/universal-pictures-highest-grossing-box-office-year-in-industry-history-1201492365/

Cameron, S. (1995). On the role of critics in the culture industry. *Journal Of Cultural Economics* : *Published In Cooperation With The Association For Cultural Economics International*, *19*(4), 321-331. doi:10.1007/BF01073994

Clement, M., Fabel, S., & Schmidt-Stolting, C. (2006). Diffusion of Hedonic Goods: A Literature Review. *International Journal On Media Management, 8*(4), 155-163. doi: 10.1207/s14241250ijmm0804_1

Clement, M., Wu, S., & Fischer, M. (2014). Empirical generalizations of demand and supply dynamics for movies. *International Journal Of Research In Marketing*, *31*(2), 207. doi:10.1016/j.ijresmar.2013.10.007

Collins, A., Hand, C., & Snell, M. C. (2002). What makes a blockbuster? Economic analysis of film success in the United Kingdom. *Managerial And Decision Economics, 23*(6), 343-354. doi:10.1002/mde. 1069

De Vany, A. S., & Walls, W. D. (2004). Motion picture profit, the stable Paretian hypothesis, and the curse of the superstar. *Journal Of Economic Dynamics & Control, 28*(6), 1035-1057.

De Vany, A., & Walls, W. D. (1999). Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office? *Journal Of Cultural Economics, 23*(4), 285-318.doi 10.1023/A:1007608125988

De Vany, A., & Walls, W. D. (2002). Does Hollywood make too many R-rated movies? Risk, stochastic dominance, and the illusion of expectation. *The Journal Of Business*, *75*(3), 425-451. DOI: 10.1086/339890

Desai, K. K., & Basuroy, S. (2005). Interactive influence of genre familiarity, star power, and critics' reviews in the cultural goods industry: The case of motion pictures. *Psychology & Marketing*, *22*(3), 203-223. doi:10.1002/mar.20055

Desai, M. A., G. J. Loeb, M. F. Veblen. (2002). The strategy and sources of motion picture finance. *Harvard Business School Note* 9-203-007, Harvard Business School, Cambridge, MA.

Deuchert, E., Adjamah, K., & Pauly, F. (2005). For Oscar Glory Or Oscar Money? Journal Of Cultural Economics, 29(3), 159-176. doi:10.1007/s10824-005-3338-6

Duan, W., Gu, B., & Whinston, A. B. (2008)[1]. Do online reviews matter? - An empirical investigation of panel data. *Decision Support Systems*, *45*(4), 1007. doi:10.1016/j.dss.2008.04.001

Duan, W., Gu, B., & Whinston, A. B. (2008)[2]. The dynamics of online word-of-mouth and product sales--An empirical investigation of the movie industry. *Journal Of Retailing*, *84*(2), 233-242. doi:10.1016/j.jretai.2008.04.005

Elberse, A., & Eliashberg, J. (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science*, *22*(3), 329-354. doi:10.1287/mksc.22.3.329.17740

Elberse, A. (2007). The Power of Stars: Do Star Actors Drive the Success of Movies? *Journal Of Marketing*, *71*(4), 102. doi**:** http://dx.doi.org/10.1509/jmkg.71.4.102

Eliashberg, J., & Shugan, S. M. (1997). Film critics: Influencers or predictors? *Journal Of Marketing*, 61(2), 68-78. doi: 10.2307/1251831

Eliashberg, J., Elberse, A., & Leenders, M. A. A. M. (2006). The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions. *Marketing Science, 25*(6), 638-661. doi:10.1287/mksc.1050.0177

Fu, W. W. (2006). Concentration and Homogenization of International Movie Sources: Examining Foreign Film Import Profiles. Journal Of Communication, 56(4), 813-835. doi: 10.1111/j.1460-2466.2006.00321.x

Gemser, G. (2007). The impact of film reviews on the box office performance of art house versus mainstream motion pictures. *Journal Of Cultural Economics, 31*(1), 43. doi:10.1007/s10824-006-9025-4

Gemser, G., Leenders, M. A. A. M., & Wijnberg, N. M. (2008). Why Some Awards Are More Effective Signals of Quality Than Others: A Study of Movie Awards. *Journal Of Management*, *34*(1), 25. doi: 10.1177/0149206307309258

Ginsburgh, V. (2003). Awards, success and aesthetic quality in the arts. *The Journal Of Economic Perspectives*, *17*(2), 99-111. doi: 10.1257/089533003765888458

Ginsburgh, V., & Weyers, S. (1999). On the Perceived Quality of Movies. *Journal Of Cultural Economics*, *23*(4), 269-283. doi: 10.1023/A:1007596132711

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545-560. doi:10.1287/mksc.1040.0071

Hadida, A. L. (2009). Motion picture performance: A review and research agenda. *International Journal Of Management Reviews*, *11*(3), 297-335. doi:10.1111/j.1468-2370.2008.00240.x

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does twitter matter? The impact of microblogging word of mouth on consumers’ adoption of new movies. *Journal of The Academy Of Marketing Science: Official Publication Of The Academy Of Marketing Science*, *43*(3), 375-394. doi:10.1007/s11747-014-0388-3

Hennig-Thurau, T., Houston, B., & Walsh, G. (2006). The differing roles of success drivers across sequential channels: an application to the motion picture industry. *Journal of the Academy of Marketing Science*, *34*(4), 559-575. doi:10.1177/009207030628935

Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic Consumption: Emerging Concepts, Methods and Propositions. *Journal Of Marketing*, *46*(3), 92. doi: 10.2307/1251707

Holbrook, M. B. (2005). The Role of Ordinary Evaluations in the Market for Popular Culture: Do Consumers Have "Good Taste"? *Marketing Letters*, *16*(2), 75-86. doi:10.1007/s11002-005-2774-6

IMDb (n.d.). About IMDb [company website]. Retrieved from http://www.imdb.com/pressroom/about/

Instagram (n.d.). About Instagram [company website]. Retrieved from https://www.instagram.com/about/us/

Jarzabkowski, P., & Fenton, E. (2006). Strategizing and Organizing in Pluralistic Contexts. *Long Range Planning*, *39*(6), 631. doi:10.1016/j.lrp.2006.11.002

Jean-Louis, D., Langley, A., & Rouleau, L. (2007). Strategizing in pluralistic contexts: Rethinking theoretical frames. *Human Relations*, *60*(1), 179-215. doi: 10.1177/0018726707075288

Jedidi, K., Krider, R., & Weinberg, C. (1998). Clustering at the Movies. Marketing Letters : A *Journal Of Research In Marketing*, *9*(4), 393-405. doi:10.1023/A:1008097702571

Karniouchina, E. V. (2011). Impact of star and movie buzz on motion picture distribution and box office revenue. *International Journal Of Research In Marketing*, *28*(1), 62. doi:10.1016/j.ijresmar.2010.10.001

Katz, M.L., & Sharipo, C. (1994). System competition and network effects. *The Journal of Economic Perspectives*, *8*(2), 93-115. Retrieved from: http://www.jstor.org/stable/2138538

Kim, S. H., Park, N., & Park, S. H. (2013). Exploring the Effects of Online Word of Mouth and Expert Reviews on Theatrical Movies' Box Office Success. *Journal Of Media Economics*, *26*(2), 98.

King, T. (2007). Does film criticism affect box office earnings? Evidence from movies released in the U.S. in 2003. *Journal Of Cultural Economics, 31*(3), 171-186. doi:10.1007/s10824-007-9041-z

Lampel, J. and Shamsie, J. (2000). Critical push: strategies for creating momentum in the motion picture industry. *Journal of Management, 26*, 233–257.

Lee, F. L. F. (2006). Cultural Discount and Cross-Culture Predictability: Examining the Box Office Performance of American Movies in Hong Kong. Journal Of Media Economics, 19(4), 259. doi:10.1207/s15327736me1904_3

Lesnick, S. (2015, August 5). Universal Pictures has had an incredible 2015, setting records left and right with five months still to go [News article]. *Coming Soon.* Retrieved from: http://www.comingsoon.net/movies/news/468753-universal-pictures-sets- industry-box-office- record

Litman, B. R. (1983). Predicting Success of Theatrical Movies: An Empirical Study. *The Journal Of Popular Culture*, *16*(4), 159-175. doi:10.1111/j.0022-3840.1983.1604_159.x

Litman, B.R. & Kohl, A. (1989). Predicting Financial Success of Motion Pictures: The 80's Experience. *The Journal of Media Economics, 2* (1), 35-50.

Liu, A., Liu, Y., & Mazumdar, T. (2014). Star power in the eye of the beholder: A study of the influence of stars in the movie industry. *Marketing Letters : A Journal Of Research In Marketing*, *25*(4), 385-396. doi:10.1007/s11002-013-9258-x

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal Of Marketing*, *70*(3), 74-89.

Luo, X., Zhang, J., & Duan, W. (2013). Social Media and Firm Equity Value. *Information Systems Research*, *24*(1), 146-163. doi:10.1287/isre.1120.0462

McKenzie, J. (2012). The economics of movies: A literature survey. *Journal Of Economic Surveys*, *26*(1), 42-70. doi:10.1111/j.1467- 6419.2010.00626.x

Metacritic (n.d.). About Metascores [company website]. http://www.metacritic.com/about-metascores

Moon, S., Bergey, P. K., & Iacobucci, D. (2010). Dynamic Effects Among Movie Ratings, Movie Revenues, and Viewer Satisfaction. *Journal Of Marketing, 74*(1), 108. doi: http://dx.doi.org/10.1509/jmkg.74.1.108

Motion Picture Association America. (n.d.). Film ratings [company website]. Retrieved from http://www.mpaa.org/film-ratings/

Motion Picture Association America. (2015). *MPAA Theatrical Market Statistics 2015* [online report]. Retrieved from http://www.mpaa.org/wp-content/uploads/2016/04/MPAA-Theatrical-Market-Statistics- 2015_Final.pdf

Oscars (n.d.). Voting [company website]. Retrieved from http://www.oscars.org/oscars/voting

Perretti, F., & Negro, G. (2007). Mixing Genres and Matching People: A Study in Innovation and Team Composition in Hollywood. *Journal Of Organizational Behavior, 28*(5), 563-586. doi: 10.1002/job.464

Ravid, S. A. (1999). Information, Blockbusters, and Stars: A Study of the Film Industry. *The Journal Of Business*, *72*(4), 463-492. doi:10.1086/209624

Ravid, S. A., & Basuroy, S. (2004). Managerial Objectives, the R-Rating Puzzle, and the Production of Violent Films. *The Journal Of Business*, *77*(S2), S155-S192. doi: 10.1086/381638

Reinstein, D. A., & Snyder, C. M. (2005). The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *The Journal Of Industrial Economics, 53*(1), 27-51. doi:10.1111/j.0022-1821.2005.00244.x015-9156-z

Roberts, J.J. (July 2015). Netflix streams its way to another blockbuster quarter, share price soars [blogpost]. Retrieved from: http://fortune.com/2015/07/15/netflix-q2-earnings-2015/

Rui H., Liu Y., & Whinston A. (2013). Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems, 55*(4), 863-870. doi:10.1016/j.dss.2012.12.022

Simonton, D. K. (2004). Film Awards as Indicators of Cinematic Creativity and Achievement: A Quantitative Comparison of the Oscars and Six Alternatives. Creativity Research Journal, 16(2 & 3), 163-172. doi: 10.1080/10400419.2004.9651450

Sood, S., & Dreze, X. (2006). Brand Extensions of Experiential Goods: Movie Sequel Evaluations. *Journal Of Consumer Research, 33*(3), 352-360. doi: 10.1086/508520

Suárez-Vázquez, A. (2011). Critic power or star power? The influence of hallmarks of quality of motion pictures: an experimental approach. *Journal Of Cultural Economics, 35*(2), 119-135. doi:10.1007/s10824-011-9140-8

The Numbers (2016). Market [company website]. Retrieved from http://www.the-numbers.com/market/

The Numbers (n.d.). About [company website]. Retrieved from http://www.the-numbers.com/about.php

Tsao, W.-c. (2014). Which type of online review is more persuasive? The influence of consumer reviews and critic ratings on moviegoers. *Electronic Commerce Research*, *14*(4), 559-583. doi:10.1007/s10660-014-9160-5

Twitter (n.d.). About Twitter [company website]. Retrieved from https://about.twitter.com/company

Wallace, T.W., Seigerman, A., & Holbrook, M.B. (1993). The role of actors and actresses in the success of films: How much is a movie star worth? *Journal of Cultural Economics, 17*(1), 1-27.

Walls, W. D. (2005). Modelling heavy tails and skewness in film returns. *Applied Financial Economics, 15*(17), 1181-1188. Doi 10.1080/09603100500391040

Wikipedia (n.d.). Wikipedia: about [company website]. Retrieved from https://en.wikipedia.org/wiki/Wikipedia:About

Zhuang, W., Babin, B., Xiao, Q., & Paun, M. (2014). The influence of movie's quality on its performance: evidence based on Oscar Awards. *Managing Service Quality: An International Journal*, *24*(2), 122-138. doi:10.1108/MSQ-11-2012-0162

7. Appendix

7.1 Variable description

Variable	*Variable description*	*Measure data*	*Source*
Year	Year the movie was released	-	IMDb
Movie	Name of the movie	-	IMDb
Consumer ratings	Ratings of consumers	Rating given by registered *IMDb*- users	IMDb
Amount of consumer ratings	Amount of ratings given by users	Amount of ratings given by registered *IMDb*-users	IMDb
Critics’ ratings	Critic rating	Rating given by critics, which are assessed and weighted by *Metacritic*	Metacritic
Amount of critics’ ratings	Amount of ratings given by critics	Amount of ratings given by critics on *Metacritic*	Metacritic
3D or IMAX	If the movie was featured in 3D movie or IMAX	1 = 3D or IMAX movie; 0 = no 3D or IMAX movie	IMDb/Wikipedia
Awards	Awards received by a movie	Analyzing if the movie received an award, excluding the awards for ‘worst movie’. 1 = won an award; 0 = no awards	IMDb
Amount of awards	Amount of awards won	Counting the awards that are received by a movie, excluding the awards for ‘worst movie’	IMDb
Peer awards	Awards peer recognition: *Academy Awards* and *BAFTA*	Analyzing if the movie received an *Academy Award* or a *BAFTA Award.* 1 = won a peer award; 0 = no peer award	IMDb
Amount of peer awards	Amount of peer recognized awards: *Academy Awards* and/or *BAFTA Awards*	Counting the amount of *Academy Awards* and/or *BAFTA Awards* a movie received	IMDb
Nomination	Nominations for awards	1 = nominated for award; 0 = no nomination award	IMDb
Amount of nomination	Amount of nominations for awards	Counting the amount of award nominations that movies received	IMDb
Peer nomination	Nomination peer recognized awards: *Academy Award* and/or *BAFTA Award*	1 = nominated for peer award; 0 = no nomination for peer award	IMDb
Amount of peer nominations	Amount of nomination for peer recognized awards	Counting the amount of *Academy Award* and/or *BAFTA Award* nominations	IMDb
Content awards	Award won based on the content of the movie	These are all the awards excluding: editing, cinematography, best sound, visual effect, production design, special effects, sound mixing and best lighting (and variations on those) 1 = won an award based on content; 0 = no award won based on content	IMDb
Amount of content awards	Amount of awards won based on the content of the movie	These are all the awards excluding: editing, cinematography, best sound, visual effect, production design, special effects, sound	IMDb

		mixing and best lighting (and variations on those)	
Technical awards	Awards won based on the technical aspects of the movie	These include the following categories: editing, cinematography, best sound, visual effect, production design, sound mixing and best lighting (and variations on those) 1 = won an award based on technical aspects; 0 = no award won based on technical aspects	IMDb
Amount of technical awards	Amount of awards won for the technical aspects of the movie	These include the following categories: editing, cinematography, best sound, visual effect, production design, sound mixing and best lighting (and variations on those)	IMDb
Instagram followers	Amount of followers on Instagram	Amount of Instagram followers for the official movie account or a large fan account	Instagram
Twitter followers	Amount of followers on Twitter	Amount of Twitter followers for the official movie account or a large fan account	Twitter
Facebook likes	Amount of likes on Facebook	Amount of likes for the official Facebook page	Facebook
Genre: Drama	Drama (genre)	1 = Drama; 0 = other	IMDb/Box Office Mojo
Genre: Children	Children (genre)	1 = Children; 0 = other	IMDb/Box Office Mojo
Genre: Action	Action (genre)	1 = Action; 0 = other	IMDb/Box Office Mojo
Genre: Horror	Horror (genre)	1 = Horror; 0 = other	IMDb/Box Office Mojo
Genre: Comedy	Comedy (genre)	1 = Comedy; 0 = other	IMDb/Box Office Mojo
Genre: Other	Other (genre)	1 = Other genre; 0 = any of genre above	IMDb/Box Office Mojo
Sequel	Movie that is part of a sequel.	The first film in the series is also counted as a sequel 1 = sequel; 0 = no sequel	IMDb/Wikipedia
Remake	Movie remake from earlier produced movies	1 = remake; 0 = no remake	IMDb/Wikipedia
Story adaptation	Movie as a story adaptation from a book/theatre play/comic	1 = story adaptation; 0 = no story adaptation	IMDb/Wikipedia
Current star power actor	Star actors based on current *IMDb* “STARmeter”	0 = no star power 1 = actor is in top 5000 2 = actor is in top 500 3 = actor is in top 100	IMDb
All time star power actor	Star actor measured by lists based on best actors in the 2000s	1 = star power; 0 = no star power	IMDb/The Numbers
Star power directors	Star directors based on current *IMDb* “STARmeter”	1 = star power; 0 = no star power	IMDb
Competition	Competition for the attention of the audience	Amount of movies released in the same season per year, calculated by the amount of movies released in the same season – 1	-

Level of competition	Competition for the attention of the audience, categorized	1 = low competition (between 1 and 3 movies released at the same time) 2 = medium competition (between 4 and 6 movies released at the same time) 3 = high competition (7 or more movies released at the same time)	-
Season	Season the movie was brought out	1 = winter 2 = spring 3 = summer 4 = autumn	IMDb
Box office revenue	Box office revenue of the movie	Total box office revenue worldwide in US $	Box Office Mojo
Budget	Production budget of the movie	Production budget in US $	IMDb/Wikipedia
Profit	Profit made by the movie. Box office revenue subtracted by the budget	Total profit worldwide in US $ (box office revenue – budget)	-
Rating MPAA	MPAA rating	1 = G 2 = PG 3 = PG-13 4 = R	IMDb
Distributor	Distributor of the movie	1 = major distributor (Universal Pictures, Sony Pictures, Disney, Warner Bros, Paramount Pictures, Lionsgate, Focus Features, Touchstone, 20th Century Fox, Columbia Pictures, New Line Cinema); 0 = other	IMDb/Box Office Mojo/Wikipedia
Land of production	Land of production	1 = USA based 2 = USA in cooperation with other country 3 = other countries	IMDb
Duration	Duration of the movie in minutes	-	IMDb

7.2 Descriptive statistics

Key descriptive statistics

Variable	N	Mean/%***	Median	SD	Minimum	Maximum
Ratings of consumers	320	6.92	7	0.86	2.4	8.7
Amount of ratings consumers	320	202,146	172,334	151,335	2806	1,064,768
Amount of followers on Instagram*	68*	124,100	11,750	308,076	83	1,600,000
Amount of followers on Twitter	84*	181,716.714	15,000.0	411,255.0477	290.0	1,990,000.0
Amount of likes on Facebook	319*	1,848,703	404,801.0	4,427,686.825	22	32,345,280.0
Ratings of critics’	318*	5.967	6.100	1.6657	1.8	9.5
Amount of ratings critics	318*	34.55	36.00	7.326	8	51
Awards	320	82%				
Amount of awards	320	14.43	5.000	25.979	0	192
Peer awards	320	16 %				
Amount of peer awards	320	0.51	0.00	1.586	0	12
Nomination awards	320	97 %				
Amount of award nominations	320	30.26	14.00	38.341	0	209
Nomination peer awards	320	32%				
Amount of peer award nominations	320	1.72	0.00	3.660	0	17
Awards based on content	320	81%				
Amount of awards based on content	319*	12.65	4.00	22.486	0	155

Awards based on technical aspects	320	28%				
Amount of awards based on technical aspects	318	1.59	0.00	5.721	0	72
Movie featured in 3D or IMAX	160**	21 %				
Drama	320	32%				
Children	320	7%				
Action	320	29%				
Horror	320	7%				
Comedy	320	26%				
Other	320	3%				
Sequels	320	25%				
Remake	320	8%				
Story adaptation	320	34%				
Current star power actors						
No star power	320	3%				
Low star power	320	22%				
Medium star power	320	48%				
High star power	320	27%				
All-time star power actors	320	52%				
Star power directors						
No star power	320	54%				
Low star power	320	40%				
Medium star power	320	4%				
High star power	320	2%				
Amount of movies released in the same period	320	4.86	5.00	1.975	0	9
Level of competition	320					
Low competition	320	27%				

Medium competition	320	54%				
Low competition	320	19%				
Season						
Winter	320	18%				
Spring	320	31%				
Summer	320	24%				
Autumn	320	28%				
Box office revenue (in US $)	318*	218,893,874	129,779,887	252,762,727	22,836	1,516,045,911
Budget (in US $)	312*	63,442,668	40,000,000	57,612,744	7,000	260,000,000
Profit (in US $)	310*	159,561,527	82,356,454.50	215,913,756.40	-202,523,164	1,326,045,911
Rating of MPAA						
G	315*	3%				
PG	315*	9%				
PG-13	315*	45%				
R	315*	41%				
Major distribution company	320	71%				
Land of production						
USA	320	55%				
USA in cooperation with other countries	320	36%				
Other countries	320	9%				
Duration of the movie	320	115.063	112.0	19.0219	77.0	191.0

*Missing variables. Zero values excluded from the analysis.
**Variable analyzed from 2008
***Percentage of units of analysis with the value ‘yes’

7.3. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Year	-												
2. Ratings consumers	.122*	-											
3. Amount of ratings consumers	.073	.521**	-										
4. Instagram followers	-.335**	.085	.217	-									
5. Twitter followers	-.177	-.083	.336**	.743**	-								
6. Facebook likes	.096	.015	.243**	-.036	.140	-							
7. Ratings critics’	.092	.691**	.356**	.122	.000	-.056	-						
8. Amount of ratings critics’	.239**	.297**	.454**	.030	.063	.058	.455**	-					
9. Awards	-.022	.295**	.272**	-.020	.015	.121*	.390*	.342**	-				
10. Amount of awards	.097	.438**	.466**	-.057	-.062	.020	.582**	.358**	.246**	-			
11. Peer awards	-.013	.367**	.351**	-.139	-.137	-.024	.436**	.331**	.200**	.615**			
12. Amount of peer awards	-.019	.302**	.329**	-.095	-.106	-.004	.427**	.260**	.149**	.837**	.651**	-	
13. Nominations	-.031	.140*	.139*	.101	.108	.044	.237**	.302**	.198**	.097	.077	.057	-
14. Amount of nominations	.172**	.487**	.485**	-.037	-.058	-.024	.646**	.519**	.304**	.814**	.650**	.666*	.142*
15. Peer nominations	.040	.430**	.392**	.111	.303**	.087	.494**	.389**	.286**	.486**	.569**	.375**	.124*
16. Amount of peer nominations	-.038	.383**	.334**	-.060	-.046	-.055	.471**	.344**	.212**	.617**	.658**	.644**	.084
17. Content awards	.000	.412**	.306**	.178	.167	.132*	.460**	.329**	.908**	.261**	.189**	.152**	.230**
18. Amount of content awards	.091	.464**	.442**	-.052	-.065	.016	.603**	.356**	.254**	.982**	.604**	.787**	.093
19. Technical awards	.055	.331**	.335**	.049	-.025	.049	.440**	.210**	.287**	.517**	.448**	.431**	.070
20. Amount of technical awards	.067	.279**	.381**	-.054	-.066	.011	.317**	.222*	.130*	.695**	.433**	.725**	.044
21. 3D or IMAX	.382**	.122*	.189*	-.068	.078	.222**	.056	.205**	.024	.083	.052	.067	.061
22. Genre: Drama	-.017	.369**	-.002	-.127	-.025	-.110*	.328**	.079	.093	.292**	.275**	.240**	.047
23. Genre: Action	.068	.148**	.240**	-.105	.015	.092	-.213**	.150**	.013	-.114*	-.089	-.085	-.002
24. Genre: Comedy	-.036	-.176**	-.191**	-.036	-.152	.074	-.081	-.133*	-.097	-.116*	-.098	-.081	-.058
25. Genre: Horror	.011	-.128*	-.105	-.057	-.106	-.030	-.086	-.170**	-.003	-.067	-.083	-.079	-.022
26. Genre: Children	.110*	.026	-.019	-.135	-.140	.242**	.052	.025	.062	.021	.053	.007	.049
27. Genre: Other	-.106	.009	.047	.840**	.691**	-.055	.005	-.010	-.091	-.056	-.081	-.060	.034
28. Sequel	-.050	-.048	.206**	.293**	.524**	.242**	-.063	.069	.077	-.076	-.107	-.082	.020
29. Remake	.062	-.279**	-.142**	-.097	-.073	.091	-.236**	-.169**	-.169**	-.107	-.093	-.049	.052
30. Story adaptation	.077	.192**	.171**	.190	.247*	.040	.168**	.215**	.024	.166**	.108	.108	.053
31. Current star power actors	.268**	.027	.135*	.131	.200	-.022	.031	.301**	.044	.058	.159**	.075	-.003

32. All-time star power actors	-.151**	-.011	.152*	.223	.219*	-.110*	.001	.200**	.075	-.007	.122*	.051	.079
33. Star power directors	.039	.204**	.306**	.222	.224*	.037	.233**	.245**	.167**	.150**	.076	.115*	.091
34. Movies released in the same period	.082	.054	.134*	.037	.056	-.024	.033	.112*	.013	.110*	-.040	.053	.024
35. Level of competition	.089	.055	.109	-.038	.034	-.039	.038	.114*	.009	.119*	.010	.062	.033
36. Season	.095	-.012	.079	.152	.108	.070	.044	.088	-.031	.010	-.062	-.067	-.065
37. Box office revenue	.229**	.099	.498**	.200	.439**	.378**	.048	.352**	.185**	.162**	.177**	.129**	.136*
38. Budget	.205**	-.093	.320**	.232	.364**	.247**	-.114**	.330**	.099	-.004	.043	.034	.088
39. Profit	.248**	.131*	.480**	.173	.417**	.373**	.062	.293**	.171**	.181**	.177**	.135*	.086
40. Rating MPAA	.009	.031	.013	-.110	-.162	-.112*	-.020	.035	-.001	.053	.025	.035	-.103
41. Distribution company	-.008	-.079	.171**	.216	.163	.132*	-.045	.285**	.062	.016	-.047	.031	.162*
42. Land of production	-.051	.153**	-.074	.227	.027	-.165**	.086	-.149**	-.025	.082	.141*	.078	-.015
43. Duration	-.009	.224**	.288**	.193	.324*	-.023	.165**	.342**	.195**	.209**	.279**	.248**	.084

	14	15	16	17	18	19	20	21	22	23	24	25	27
14. Amount of nominations	-												
15. Peer nominations	.626**	-											
16. Amount of peer nominations	.786**	.603**	-										
17. Content awards	.318**	.304**	.221**	-									
18. Amount of content awards	.813**	.482**	.605**	.274**	-								
19. Technical awards	.548**	.460**	.454**	.231**	.484**	-							
20. Amount of technical awards	.510**	.315**	.437**	.122*	.552*	.451**	-						
21. 3D or IMAX	.091	.162**	-.021	.010	.057	.136*	.154*	-					
22. Genre: Drama	.319**	.313**	.370**	.135*	.317**	.160*	.095	-.234**	-				
23. Genre: Action	-.099	-.107	-.136*	-.031	-.152**	-.028	.044	.255**	-.444**	-			
24. Genre: Comedy	-.148**	-.148**	-.151**	-.125**	-.102	-.173**	.109	.010	-.408**	-.382**	-		
25. Genre: Horror	-.094	-.134*	-.111*	.008	-.065	-.001	-.054	-.052	-.187**	-.175**	.161**	-	
26. Genre: Children	.018	.077	-.060	.008	.019	.137*	.021	.436**	-.161**	-.067	.234**	-.074	-
27. Genre: Other	-.041	.054	-.042	-.038	-.061	-.001	-.014	-.008	-.130*	-.122*	-.112*	-.051	-.051
28. Sequel	-.070	-.053	-.096	.116*	-.095	-.077	.009	.211**	-.317**	.395**	-.074	-.070	.102
29. Remake	-.148**	-.101	-.118*	-.152**	-.110*	-.127*	.077	.093	-.076	-.119*	-.146**	.151**	-.079
30. Story adaptation	-.218**	.253**	.242**	.052	.172**	.119*	.068	.060	.239**	-.015	-.185**	-.117*	-.039
31. Current star power actors	.210**	.112*	.158**	.052	.065	.019	.010	.031	.121*	.028	-.081	-.136*	-.168**
32. All-time star power actors	.126*	.155**	.206**	.082	.013	-.037	-.057	-.085	.048	-.079	.056	-.134*	-.035
33. Star power directors	.208**	.192**	.083	.194**	.144*	.077	.109	-.059	.043	.073	-.147**	-.016	-.181**
34. Movies released in the same period	.067	-.013	.032	.058	.109	.025	.088	.060	-.023	.059	.030	-.062	.000
35. Level of competition	.096	.007	.094	.039	.123*	.038	.080	.068	.007	.062	.013	-.062	-.006
36. Season	.051	.025	-.041	-.037	.009	.106	.004	.094	.025	-.055	.028	-.006	.122*
37. Box office revenue	.184**	.283**	.117*	.172*	.127*	.224**	.199**	.577**	-.262**	.349**	-.040	-.131*	.300**
38. Budget	.032	.139*	-.008	.030	-.054	.185**	.159**	.491	-.327**	.495**	-.109	-.162**	.299**
39. Profit	.190**	.275**	.127*	.176**	.151**	.208**	.193**	.547**	-.211**	.269**	-.009	-.135*	.271**
40. Rating MPAA	.066	-.012	.057	-.009	.063	.013	.008	-.227**	.074	-.013	-.120*	.179**	-.427**
41. Distribution company	.034	.087	.054	.035	.001	.024	.050	.194**	-.222**	.201**	.096	-.152**	.147**
42. Land of production	.070	.101	.156**	-.015	.081	.118*	.060	-.093	.223**	-.074	-.174**	.001	-.149**
43. Duration	.278**	.300**	.327**	.152**	.191**	.221**	.194**	.003	.231**	.155**	-.346**	-.105	-.253**

	28	29	30	31	32	33	34	35	36	37	38	39	40
28. Sequel	-												
29. Remake	-.032	-											
30. Story adaptation	-.121*	-.062	-										
31. Current star power actors	-.009	.019	.203**	-									
32. All-time star power actors	-.043	-.069	.072	.301**	-								
33. Star power directors	.089	-.043	-.019	.153**	.058	-							
34. Movies released in the same period	-.015	.020	.087	.101	.079	-.024	-						
35. Level of competition	-.044	.033	.120*	.104	.097	-.055	.922**	-					
36. Season	.038	-.036	.014	-.032	-.027	.035	.094	.034	-				
37. Box office revenue	.409**	-.042	.071	.104	.100	.023	.079	.060	.085	-			
38. Budget	.275**	.019	.062	.152**	.091	.044	.084	.050	.074	.725**	-		
39. Profit	.400**	-.051	.064	.081	.077	-.003	.075	.060	.082	.971**	.595**	-	
40. Rating MPAA	-.191**	.051	-.022	.115*	-.006	.166**	-.013	.011	-.062	-.275**	-.245**	-.239**	-
41. Distribution company	.159**	.058	.053	.112*	.155**	.095	.071	.011	.032	.322**	.367**	.256**	-.101
42. Land of production	-.065	.042	.117*	-.041	.007	.043	-.084	-.070	-.091	-.149**	-.152**	-.122*	.130*
43. Duration	.008	-.054	.131*	.242**	.158**	.278**	.038	.074	-.033	.251**	.324**	.193**	.176**

	41	42	43
41. Distribution company	-		
42. Land of production	-.213**	-	
43. Duration	.092	.086	-

Note: N = 320 for all but four variables, namely Amount of followers Instagram (N = 68), Amount of followers Twitter (N = 84), Amount of content awards (N = 319) and Amount of technical awards (N = 318).
*$p < .05$. ** $p < .01$ (two-tailed significance).

7.4 Dates of data collection

Year	Date of retrieval
2000	5-4-2016
2001	5-4-2016
2002	5-4-2016
2003	6-4-2016
2004	6-4-2016
2005	7-4-2016
2006	7-4-2016
2007	8-4-2016
2008	8-4-2016
2009	10-4-2016
2010	14-4-2016
2011	18-4-2016
2012	19-4-2016
2013	19-4-2016
2014	20-4-2016
2015	20-4-2016

7.5 List of films in the final sample

(500) Days of Summer
1408
2 Fast 2 Furious
25th Hour
50 First Dates
8 Mile
A History of Violence
About Time
Alexander
Ali
American Gangster
American Hustle
American Psycho
Angels and Demons
Ant-Man
Are You Here
Argo
Atonement
Australia
Babel
Bad Boys II
Bandits
Battleship
Beerfest
Before Sunset
Beowulf
Best in Show
Big Hero 6
Billy Elliot
Black Hawk Down
Blended
Blow
Blue Crush
Blue Valentine
Body of Lies
Brick
Bridget Jones: The Edge of Reason
Bridget Jones's Diary
Brokeback Mountain
Brooklyn
Bruce Almighty
Cabin Fever
Captain America: The 1 Soldier
Captain Philips
Casino Royale
Catch me if you can
Catwoman
Changeling
Charlie Wilson's War
Chef
Chicago
Chicken Little
Chocolat
City of God
Clash of the Titans
Click
Closer
Cold Mountain
Colonia
Confession of a dangerous mind
Creed
Dark Shadows
Date Night
Death Proof
Demolition
Despicable Me
Despicable Me 2
Die Another Day
Dogtooth
Dreamcatcher
Drive
Dude, where is my car?
Eastern Promises
Edge of Tomorrow
Ella Enchanted
Enemy
Enemy at the Gates
Eternal Sunshine of the Spotless Mind
Evan Almighty
Evolution
Ex Machina

Fantastic Four
Fast and Furious 6
Final Destination
Flight
Footloose
Fracture
From Hell
Frozen
Furious 7
Gigli
Gone Girl
Grindhouse
Hairspray
Halloween
Hard Candy
Harry Potter and the Deathly Hallows: Part 1
Harry Potter and the Half-Blood Prince
Hitman
Hollywoodland
Hot Fuzz
House of 1000 Corpses
House of Wax
How to Train Your Dragon 2
I am Legend
I am Number Four
I Love You, Man
Ice Age: Continental Drift
Ice Age: Dawn of the Dinosaurs
Identity
Idiocracy
In Bruges
In Time
Inside Out
Insidious
Iron Man 3
It Follows
Jarhead
Journey to the Center of the Earth
Jumper
Just Go With It
Keeping the Faith
Kick Ass
Kill Bill: Vol. 1
Kill Bill: Vol. 2
Kingdom of Heaven
Kiss Kiss Bang Bang
Lara Croft Tomb Raider: The Cradle of Life
Law Abiding Citizen
Legally Blond
Les Intouchables
Life as we know it
Life of Pi
Lilo & Stitch
Little Nicky
Lone Survivor
Love & Basketball
Love is All You Need
Love, Rosie
Lucy
Machete
Mad Max: Fury Road
Madagascar
Mamma Mia!
Man on Fire
Memories of a Murder
Midnight in Paris
Minority Report
Miss Congeniality
Mission: Impossible II
Moneyball
Monster
Moonrise Kingdom
Moulin Rouge
Mr. Nobody
Nacho Libre
Nanny McPhee
Napoleon Dynamite
Never Back Down
Night at the Museum
No Country for Old Men
No Strings Attached
Not Another Teen Movie
Now You See Me
O Brother, Where Art Thou?
Oblivion
Ocean's Eleven

Oldboy
Olympus has Fallen
Once upon a time in Mexico
One Day
Orphan
Pandorum
Passion
Pearl Harbor
Pineapple Express
Pirates of the Caribbean: Dead Man's Chest
Pirates of the Caribbean: The curse of the Black Pearl
Pitch Perfect 2
Predestination
Pride & Prejudice
Primer
Prince of Persia: The Sands of Time
Project T/Tomorrowland
Public Enemies
Punisher: War Zone
Rambo
Rent
Resident Evil
Rise of the Guardians
Robin Hood
Room
Running Scared
S.W.A.T.
Safe Haven
Salt
School of Rock
Secret in their Eyes
Sex and Lucia
She's out of my League
Skyfall
Snow White and the Huntsman
Snowpiercer
Splice
Spy Kids
Spy Kids
Star Trek into Darkness
State of Play
Step Brothers
Stuck in Love
Super 8
Super Troopers
Sweeney Todd: The Demon Barber of Fleet Street
Take Shelter
Talladega Nights: The Ballad of Ricky Bobby
Tangled
Ted
Teenage Mutant Ninja Turtles
Terminator Genisys
The Amazing Spider-Man 2
The A-Team
The Aviator
The Babadook
The Beach
The Best of me
The Bourne Supremacy
The Butterfly Effect
The Cabin in the Woods
The Captive
The Cat in the Hat
The Cell
The Day after Tomorrow
The Descendants
The Exorcism of Emily Rose
The Expendables
The Fall
The Fast and the Furious: Tokyo Drift
The Fault in our Stars
The First Time
The Forbidden Kingdom
The Fountain
The Good Dinosaur
The greatest game ever played
The Green Inferno
The Hangover Part II
The Hateful Eight
The Hitchhiker's Guide to the Galaxy
The Holiday
The Hours
The Hurt Locker
The Illusionist

The Incredible Hulk
The Last House on the Left
The League of Extraordinary Gentlemen
The Lord of the Rings: The Two Towers
The Lovely Bones
The Machinist
The Man from Earth
The Man from U.N.C.L.E.
The Nanny Diaries
The New World
The Night Before
The Notebook
The Other Guys
The Perfect Storm
The Perks of Being a Wallflower
The Pianist
The Place Beyond the Pines
The Prestige
The Princess Diaries 2: The Royal Engagement
The Proposal
The Pursuit of Happyness
The Raid: Redemption
The Reader
The Rookie
The Sisterhood of the Travelling Pants
The Sisterhood of the Travelling Pants II
The Social Network
The Spectacular Now
The Strangers
The Three Musketeers
The Time Machine
The Town
The Transporter
The Twilight Saga: Breaking Dawn - Part 2
The Wicker Man
Thor
Tinker Tailor Soldier Spy
Traffic
Trainwreck
Transformers: Age of Extinction
Transformers: Dark of the Moon
Transformers: Revenge of the Fallen
Twilight
The Imitation Game
Unbreakable
Underworld
Unfaithful
Up
Van Helsing
Van Wilder
Vanilla Sky
Vertical Limit
Vicky Cristina Barcelona
Waitress
War of the Worlds
We're the Millers
Wet Hot American 3
What Women Want
When in Rome
White House Down
Wild
Wreck-it Ralph
X-Men
X-Men Origins: Wolverine
X-Men: First Class
X-Men: The Last Stand
Y Tu Mama Tambien
Year One
Zoolander