A study on box-office revenue

How user and expert ratings determine movie success

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Abstract

This paper investigates the difference in signaling power for box-office revenue between user ratings and expert ratings. We split these ratings up in to the quality and quantity of user and expert ratings. Using a multiple regression analyses we find there is a significant positive effect of the amount of ratings from users as well as experts on box-office revenue. Furthermore we find that, within the multiple regression model there is a negative effect between user and expert ratings on box-office revenue. This negative effect is caused by a mediation effect from the quantity of rating. To control for this effect, we performed simple regression on each of the independent variables. Within the simple regressions we found that user rating and expert rating had a significant positive effect on box-office revenue. The simple regressions also show that, the influence on box-office revenue from the quality and quantity of user rating is larger than that of expert rating.

Preface

This thesis was written to complete my Master Marketing, at the Erasmus University in Rotterdam. After months of hard work my master thesis has finally been completed. This would not have been possible without the help of many people. To begin, I would like to thank my thesis supervisor, Dimitris Tsekouras. Thanks to his guidance over the past months I was able to write this thesis. I would also like to thank my good friend, Bram van de Pasch. He was willing to read my thesis and share his thoughts about my research. Furthermore I would like to thank my parents, who always believed in me and supported me throughout my years in college and at the Erasmus University.

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1. Introduction

If we consider experience goods like movies, IMDB.com links expert reviews and ratings about their movies and gives consumers the possibility to rate movies or write a review. IMDB.com is one of the largest online databases of information related to movies, television programs and video games. It receives over 100 million[1] unique visitors every month. In 2009 the movie Transformers: Revenge of the Fallen[2] was released, which was the sequel of the 2007 movie the Transformers. This sequel received a 5.9 in user rating, with a total of around 161.000 votes. The critics' average rating (Metascore) was 35/100 with a total of 337 critics. Looking at the quality of rating, we could say that this movie was not considered very good. The quantity of user raters was quite high. The amount of user ratings this movie received made it number 70 out of 100.737 in the top most voted action titles on IMDB.com[3]. When we look at the box-office revenue of this movie[4], we see it earned a total of over $836 million with a production budget of $200 million.

In today's digital age we cannot avoid online reviews and ratings, whether about it concerns search goods like a new pair of shoes, or about experience goods like movies or hotels. These reviews could be written by professionals, the so called experts, or by consumers themselves. These days more and more sites offer the possibility for consumers to write reviews about products on their sites. Amazon offers users the possibility to write reviews about products and give a star rating from 1 to 5. Amazon currently has over 10 million reviews on their site covering all of its product categories. These reviews could be considered the online version of Word of Mouth. According to Chevalier and Mayzlin (2006), favorable reviews on a book on amazon.com resulted in an increase in sales of that book. They also concluded that an increase in average star rating over time also resulted in higher relative sales of that book over time. Liu (2006) researched the impact of word of mouth in the form of reviews on the box-office revenue of movies. He found that the volume and not the valence of reviews had significant explanatory power for aggregate box-office revenue. When it comes to user ratings, research done with data from Yahoo! Movies shows that the rating itself did not have explanatory power for box-office results, but the volume did (Duan et al. 2008).

Expert reviews are very common in the movie industry. These experts or critics are allowed to see a pre-release screening of a movie whereas a consumer might not have that privilege. After the critic has seen the movie they will write their professional opinion in the form of a review for whatever site

[1] http://en.wikipedia.org/wiki/Internet_Movie_Database
[2] http://www.imdb.com/title/tt1055369/
[3] http://www.imdb.com/search/title?genres=action&sort=num_votes,desc&start=51
[4] http://boxofficemojo.com/movies/?id=transformers2.htm

or magazine they work for. Consumer will then be able to read this review about upcoming movies and decide if the movie will be worth seeing in the cinema. According to research by Eliashberg and Shugan (1997), critics are considered predictors and not influencers of total box-office success.

When looking back at the example of Transformers 2 in the beginning of the introduction, we could hardly call this an unsuccessful movie. If we consider some of the research mentioned before, only the research from Duan et al. (2008) would explain this situation, where the rating itself was low, but the volume was high. When we consider Eliashberg And Shugan (1997), they were not correct. Critics in this case did not give a positive review and rating. According to their study the box-office revenue should have been less successful. On IMDB.com we see many of these differences in the metrics. This was just one example where a certain metric stood out. In this case it was the amount of users who gave their rating score. The research mentioned above done on amazon.com showed star rating did have an effect on sales (Chevalier and Mayzlin 2006), while the study from Yahoo! Movies showed no effect on box-office revenue from the star rating (Duan et al. 2008). We wonder if the same goes for IMDB.com or that this might not be the case.

Problem statement

In this paper, we will investigate the different metrics from IMDB.com and their signaling power for box-office revenue. We wonder if the quality and/or quantity of movie ratings from users as well as critics could be a signal for box-office revenue, and which best shows this. We are particularly interested in comparing the user generated metrics with experts generated metrics on IMDB.com. We divide these metrics into quality and quantity. When we refer to the metrics on IMDB.com we consider the following:

IMDB.com metrics:	Quality	Quantity
User generated	User rating	Amount of users who rated
Expert Generated	Metascore	Amount of critics who rated

By using a multiple regression analysis, we will examine the relationship between box-office revenues and the quality and quantity of movie ratings given by experts and users. With this result we will try to find out which metric will best indicate a movie’s box-office revenues, and if there is a significant difference in results between user generated content and expert generated content.

Academic and Managerial relevance

This study will add to the academic literature on several aspects. Current studies have shown some conflicting results when it comes to predicting box-office success of a movie. There are also no studies which examined the metrics of IMDB.com and their signaling power for box-office revenue. It also remains unclear what the trade off is between user generated content and that of professionals when it comes to movie ratings and the volume of ratings. Previous studies have mostly used reviews written either by critics or by consumers. Studies that have used user rating to predict box-office revenue of movies, used this on a smaller scale. Duan et al. (2008) used star rating from Yahoo! Movies. Star rating on Yahoo! Movies is of a much smaller scale then the user rating we can find on IMDB.com. We will give an example to indicate how large this difference is. The action movie on IMDB.com which has received the highest volume of user ratings is The Dark knight[5]. It has received over 702.000 votes. On Yahoo! Movies this movie was rated by 72.000 users. As you can see, there is a very large volume difference between the two sites. Because we will examine movies from IMDB.com, which have a much higher volume of user ratings, we will be able to give a more precise result. With this we hope to provide a more clear explanations for some conflicting results from previous research about movie ratings and their signaling power for box-office revenue.

This study could have several managerial implications depending on its outcome. If the result is able to show which metric(s) significantly signals box-office success for movies, this outcome could be transferred to other types of experience goods like music or videogames. It could also have some implications for other experience goods like hotels or restaurants. If this research is able to show a certain metric standing out, then managers of these types of experience goods know to put more emphasis on it. They could offer rating possibilities on their website, or always make sure you have some form of critics rating of your hotel or restaurant on your website. This off course all depends on which metric shows a significant result.

Research questions

In order to be able to find an answer to the problem statement, we have summarized it into one main question we will answer in this research:

- ***Is there a significant difference in the signaling power for box office revenue between user generated content and expert generated content?***

[5]http://www.imdb.com/search/title?genres=action&sort=num_votes,desc&start=1

2. Literature review and Hypotheses development

In this section of the paper we will show an overview of the literature on user generated content and expert reviews and ratings. More specifically, we will review the results of previous studies on reviews and ratings and its influential and predictive power on movie box-office revenue. These reviews or ratings are either written or given by professionals or by consumers themselves. When we talk about reviews which are written by consumers, we talk about User Generated Content. In section 2.1 of the paper we will talk about research done in the field of user generated content. We will discuss the effect of positive or negative reviews on consumers in general and its effect on movie box-office revenue. In section 2.2 of the paper we will discuss expert reviews and their influence on consumers. Mainly whether or not experts or movie critics could be considered influencers or predictors of movie box-office success. In section 2.3 of the paper we will discuss the literature results which show the difference between user generated content and expert generated content and their influence on consumer behavior. In section 2.4 we will give an overview of previous literature which has tried to predict movie box-office revenue with a various set of variables and their results. With these results, we will decide which factors we need to control in our regression model.

2.1 User generated content

User generated content (UGC) is content made by the general public rather than paid professionals. It is often referred to as "peer production". User generated content is mostly available on the internet in the form of blogs, wikis or reviews written about search goods or experience goods. We could call UGC a modern version of Word of Mouth. In this paragraph we will focus on UGC in the form of reviews and ratings and its predictive power and influence on consumer behavior.

In recent years there has been a big increase in the amount of content generated by users. This is due to the increased use of social platforms and the increased interaction possibilities with internet sites. Thanks to the internet, the scale and scope of word of mouth has dramatically increased. Online reviews have become a major source of information for consumers. Word of mouth in the form of reviews can be seen as a motivating factor in consumer purchasing decisions (Park et al. 2007, Bansal and Voyer 2000, Wangenheim and Bayón 2003). Chevalier and Mayzlin (2006), found that an increase in average star rating over time, also resulted in higher relative sales of that book over time. They concluded that the valance of word of mouth had a significant positive effect on sales (Forman et al. 2008). When it comes to comparing user generated reviews with expert reviews, Creamer (2007)[6] says that peer reviews are preferred over expert reviews by a margin of 6 to 1. This shows the high influence reviews written by consumers have on other consumers. When we consider the quality and quantity of reviews, we should consider several things. Consumers will focus more on the quality aspect for negative reviews, and will focus more on the quantity aspect when it comes to positive reviews (Park and Lee 2007). According to previous studies (Chevalier and Mayzlin 2006, Park and Lee 2007, Phelps et al. 2005) the larger amount of positive reviews a product receives, the bigger the positive effect will be on consumers.

When we consider Word of Mouth in the form of reviews and ratings on movies and its effect on box-office results, studies have found several things. Word of mouth in the form of reviews has found to have significant explanatory power for box office results for movies. More importantly, this explanatory power comes from the volume of reviews and not its valence (Liu 2006). When we consider the user rating given to a certain movie, research shows a similar result. The numerical value of the rating does not yield explanatory power, however the quantity of it does (Dellarocas et al. 2007, Duan et al. 2008). It feels somewhat contradictory, that even though a movie could receive a low user rating or a negative review, the amount of users who gave their rating or wrote a review still has a positive effect on box-office results. Simply put, a bad movie in the eyes of consumers could still get a high box-office result. According to Duan et al. (2008) this is due to the awareness effect that will increase product awareness among consumers through dispersion (Dellarocas et al. 2007, Godes and Mayzlin 2004). Berger et al. (2010) argue that even bad publicity can increase the purchase likelihood, because of increasing product awareness. When we consider a situation, where a person is browsing a certain movie website and is confronted with a bad review. It could be the first time this person actually hears about this movie, thus the negative publicity could still have a positive effect.

We split up the user generated content on IMDB.com into quality and quantity. When we consider the quality, we consider the rating given. The literature reviews provide us several results. Positive star rating on amazon.com on books, showed to have a significant positive effect on sales. So the valence of word of mouth positively influences sales (Chevalier and Mayzlin 2006, Forman et al 2008). When we focus on results of research done on UGC and its effect on box-office revenue, we can draw a different conclusion. When looking at the quality of user rating, research found there was no significant effect on box-office revenue. The numerical value of rating did not yield explanatory power (Dellarocas et al. 2007, Duan et al. 2008). However the research done by Dellacoras et al. (2007), attempted to predict box-office revenues. In our study we are examining the ratings, after

[6] http://adage.com/article/news/reviews-wal-mart-wakes-power-people/119456/

the movie is no longer in the cinema. When looking at the results on rating found by Mayzlin (2006), on star rating on amazon.com, we find that Amazon and imdb.com have a few crucial things in common. One thing, which should not be of great importance to the hypotheses forming, is the fact that imdb.com was taken over by Amazon in 1998. However, what is important in helping to formulate our hypotheses is that both sites prominently show a star rating. Amazon.com offers the options to rate their products on scale of 1 to 5 stars, as you can see in figure 2.1. which shows a picture of what a user sees when perhaps wanting to buy the DVD “The Dark Knight”.

Figure 2.1

Imdb.com applies the same rules on their site. They offer users the options to rate movies on a scale of 1 to 10 stars. The site then calculates an average rating given to this movie. When looking up the movie “The Dark Knight” you will see the following:

Figure 2.2

It should be clear, that the main thing that “pops out” is the user rating. Based on research results from Chevalier and Mayzlin (2006) and Forman et al. (2008), we expect to see a positive, but small effect on box-office revenue. This provides us the following hypothesis:

H1: The quality of user rating has a significant positive effect on box-office revenue.

When we consider the quantity of user rating, we look at the amount of users who gave their rating to a certain movie. When looking at the quantity of user ratings, research found there was a significant effect on box-office revenue (Liu 2006). The volume of user rating yields significant explanatory power for box-office revenue (Dellarocas et al. 2007, Duan et al. 2008). So even though a movie could have received a low user rating, as long as there was a large amount of users who rated, it could positively influence box-office revenue. Certain research claimed this to be due to the awareness effect (Duan et al. 2008, Berger et al. 2010). With these results we formulate the following hypothesis:

H2: The quantity of user rating has a significant positive effect on box-office revenue.

2.2 Expert generated content

In today's digital age we cannot avoid online reviews, whether it's about purchasing search goods like a new pair of shoes, or experience goods, like booking a hotel room. When we consider an experience good[7], we think about a product or service where it is hard to observe its characteristics, such as quality or price. Examples of these types of products are: wine, hotel rooms, restaurants, books and movies. With these types of products, consumers often rely on expert opinions to help guide them in their purchase decisions. It is arguably hard to measure the effect experts opinions have on market outcome, because one can understand there to be a high correlation between expert reviews and "true quality" of a product or service. We are wondering how much consumers are actually influenced by these expert opinions in the form of ratings or reviews written in magazines, newspapers or certain web pages. In this paragraph we will look at expert reviews and ratings on several types of experience goods. We will end by focusing on research done on expert reviews on movies, and their effect on box-office revenue. Are these experts or so called critics influencing the consumer in their movie going experience and thus indirectly predicting the box office revenue of the movie or are they actually influencing the box-office revenue?

Vermeulen and Seegers (2009) studied the impact of reviews (expert and non-expert) on consumers and the making of their travel arrangements. They found that expert reviews did not have a greater impact than non-expert reviews on the attitude of consumers towards hotels. We can also consider experts in the form of endorsers. Research has showed that expert's sources of information are particularly effective in new markets (Chandy et al. 2001). This result can be attributed to the fact that in young markets, consumers' knowledge of this product may be limited, and therefore motivates them to carefully find and process information. Sorensen and Rasmussen (2004) researched the impact of the New York Times' book reviews on sales. They found a significant impact of reviews on sales. Negative as well as positive reviews increases book sales. However, positive reviews had a greater impact than negative reviews on sales. According to Sorensen and Rasmussen this suggested reviews also have a persuasive effect. The impact of expert reviews on relatively

[7] http://en.wikipedia.org/wiki/Experience_good

unknown authors is also greater then on more known authors, showing that the results are consistent with research done by Chandy et al (2001). Gergaud et al. (2012) researched whether or not consumers quality perceptions of restaurants was influenced by expert opinions in the Michelin restaurant guide. They found a strong and significant effect on consumers' décor quality perception of restaurants. However consumers did not adjust their food quality perceptions. Wine is also an experience good where expert rating can be influential. Robert M. Parker Jr.[8] is one of the leading U.S. wine critics. He rates wines on a 100 point scale in his newspaper "The wine advocate[9]". Research done on the effect of the critic rating awarded by Robert Parker on the "en primeur[10]" price of Bordeaux wine found that the rating given by Parker had a significant effect on wine prizes (Ali et al. 2008, Dubois and Nauges 2010).

Let us consider expert reviews and ratings in the movie industry and their effect on consumers, and thus on box-office revenue. Eliashberg and Shugan (1997) examined whether film critics could be seen as influencers of movie success or if they were predictors of movie success. They performed a study on weekly rather than cumulative revenue to determine the impact of film reviews on movie success. They found that film reviews are positively related to late and cumulative box office receipts, but do not correlate significantly with early box office revenue. This means that critics according to Eliashberg and Shugan are considered predictors of box office success rather than influencers. A positive critic review could be seen as a signal for success of a movie. Litman and Kohn (1989) also suggested that critic ratings are key predictors for box-office success. In their research they found that critical reviews and ratings had significant effect on box-office revenue. Ravid (1999) found significant support for the correlation between the amount of reviews (whether it was positive or negative) and received revenues. The more reviews a movie received, the higher the revenues. Wyatt and Badger (1984) researched the influence a positive or a negative review had on an individual to go and see a movie. They found there was only little effect on the interest of an individual to go and see a movie. Research by Reinstein and Snyder (2005) showed that early positive reviews increases the number of consumers attending a movie in total over its entire run. That increase of attendance would come at the expense of competing movies. Consumers would use the quality of a certain review as a signal to help decide what movie to go and see at the cinema. Boatwright et al. (2007) researched the impact of individual film critics on box office performance. They found an opposite conclusion to the one found by Eliashberg et al & Reinstein et al. In their research they found critics in their role as opinion leaders are correlated with the coefficient of innovation in the Bass model framework. This can be seen as being an influencer of movie success.

[8] http://en.wikipedia.org/wiki/Robert_M._Parker,_Jr.
[9] http://en.wikipedia.org/wiki/The_Wine_Advocate
[10] http://en.wikipedia.org/wiki/En_primeur

They also found critics to be more influential in platform-release movies rather than wide-release[11] movies. When thinking about this, its sounds very logical. Hollywood marketers spare no expense to getting their core audiences to see their upcoming big movies. They have huge marketing budgets to spend on advertising and trailers to inform you on their upcoming blockbusters.

The research results we managed to find, mostly show that expert rating had a significant effect either on sales or on consumer perceptions. We found that the wine critic Robert Parker significantly influences the prices of “en primeur” wines with his critic rating. In the research about critic ratings and its effect on box-office revenue we find some conflicting results. Some research find only little effect on box-office results (Wyatt and Badger 1984), where others find a more significant effects . (Litman and Kohn 1989, Reinstein and Snyder 2005). There also seems to be no agreement on the matter, if critics are influencers or predictors of box-office revenue. For our thesis however, it is irrelevant whether critics can be seen as predictors or influencers. The studies agree that critic ratings have a significant effect on box-office revenue. Therefore:

H3: The quality of expert rating has a significant positive effect on box-office revenue.

We found only limited research, which addressed the influence of the quantity of expert reviews on box-office revenue. Research showed there was significant support for the correlation between the amount of reviews and received revenues (Ravid 1999). We can conclude that, the quantity of reviews has a significant effect on box-office revenue. We base this assumption on the fact that, positive as well as negative reviews seem to influence revenues (Sorensen and Rasmussen 2004). This would be in line with the awareness effect we discussed in paragraph 2.2. Based on these results we hypothesize the following:

H4: The quantity of expert rating has a significant positive effect on box-office revenue.

2.3 User rating vs Expert rating

As stated in the problem statement of the thesis, we are particularly interested in comparing the user generated content with expert generated content. We want to know which has a higher signaling power for box-office revenue of movies. So we need to ask ourselves, what influences the movie going consumer more, is it the critic review or the review written by a user? In this paragraph we will look at some comparing research that has been done between the difference of influence of expert reviews and user reviews.

[11] http://en.wikipedia.org/wiki/Wide_release

As stated earlier, according to Creamer (2007), peer reviews are preferred over expert reviews by a margin of 6 to 1. According to Archark et al. (2011), consumer reviews are viewed as more trustworthy and credible as opposed to expert reviews. In a survey among 5.500 web consumers conducted by Bizrate[12], published in the Los Angeles times[13], it showed that 59% of all respondents considered consumer generated reviews more valuable then expert reviews. Huang and Chen (2006) examined the herding in product choices on the Internet. They found that the recommendations of other consumers have a higher influence than recommendations from an expert. This result is also confirmed in research done by Dellarocas (2006). When we look at expert reviews and user generated reviews in the movie industry, we have found the following results. Levene (1992) did a study among students from the University of Pennsylvania and collected 208 usable surveys. She concluded that a positive critic review was ranked tenth as a decisive factor to go and watch a movie. Word of mouth from a friend, was considered one of the most deciding factors to go and see a movie. The same sort of conclusion was drawn by Faber & O'Guinn (1984), who found that critic reviews on movies were rated less credible then friends' comments.

These results help us draw the following conclusions. There is a clear consensus among researchers, that users prefer the reviews of other users over those of experts to (Archark et al. 2011, Creamer 2007). They believe them to be more credible and trustworthy. When looking at the movie industry, we also found users to be of higher influence then experts in persuading someone to go see a certain movie (Levene 1992, Faber and O'Guinn (1984). In accordance with trying to answer the problem statement, we are interested in finding out the difference in signaling power on box-office revenue between user generated content and expert generated. We stated earlier in the thesis that we divide this content into quality and quantity. The results we found help us formulate the following hypotheses:

H5: The quality of user generated content has greater signaling power for box-office revenues then the quality of expert generated content.

H6: The quantity of user generated content has greater signaling power for box-office revenues then the quantity of expert generated content.

[12] http://www.bizrate.com/
[13] http://articles.latimes.com/1999/dec/03/news/mn-40120

2.4 Predicting box-office success

In the multibillion dollar industry that is movies, one can understand the need for predictive power of success. Movies are considered experiential products, thus it can be difficult for consumers to evaluate the quality of a movie until they have seen it. For movies, unlike physical products, it is easier to adapt to a certain demand. They can either stop showing movies at certain cinemas or increase the amount of cinemas showing the movie. However to be able to decide how many cinemas will show the movie that is being released is obviously important. Thus you can understand the need for early forecasts of box-office success of an upcoming movie. In order to predict success, you can use several variables. In previous paragraphs we discussed the effect of critic and user reviews on box-office revenue. In this paragraph we will show which other variables have a significant effect on box-office revenue. With these results we can create the correct regression model and find an answer to the problem statement. Important variables that will be discussed in this paragraph are: website promotions, the use of stars, production budget, seasonality, MPAA rating, movie genre, award nominations.

Lots of studies have been done research to predict the box-office performance of a movie. Each study does it from a different point of view with a different set of variables. Zufryden (2000) researched the role of website promotions on the box-office performance of new movies. He hypothesized that the amount of activity on a films website would be an indication of success. Greater activity over time, increases the awareness of the movie and consequently the visitors' intention to see the film. Zufryden (2000) found that website activity is a significant predictor of box-office success of a movie.

Litman & Kohl (1989) found the use of stars and top directors is positively correlated with box-office revenues. A study done by Ravid (1999) also researched the effect stars and budgets had on box-office success. He hypothesized that stars (and perhaps big budgets) would signal high returns and/or high revenues. He found no significant support for the role of stars on the box-office success of a movie. However he did find significant support for the effect of big-budgets on high box-office revenues.

The moment a movie is released also has an effect on the box-office performance of a movie. Radas & Shugan (1998) found support for the effect seasonality has on movie performance. Movies released during peak seasons show better performance at the box-office then those released outside of the peak seasons. However researchers give different answers to which season would be the best. According to Litman (1983) the best moment for release would be Christmas. Sochay (1994) on the other hand found evidence that the summer months are the best time to release a movie. Sochay explains the difference in results between his research and that of Litman (1983) is due to the amount of competition at that moment. The successful season can shift from summer to Christmas when distributors try to avoid strong competition.

Besides seasonality as an influence on box-office success, we also have the MPAA[14] rating as a possible influencer. The MPAA rating territories a film's thematic and content suitability for certain audiences. Sawhney & Eliashberg (1996) created a two-step model to predict box-office success. They took the decision making process of a possible customer and divided it in the time to decide and time to act as steps. Their result showed that movies with a restricted rating (R) performed worse at the box-office, than those without a restriction rating. Medved (1992) confirms this and shows G-rated movies have the highest median box-office result, followed in order by PG, PG-13 and R-rated movies. Sochay (1994) also found that R-rated movies perform significantly worse than other MPAA rated movies. Ravid (1999) provided evidence from his model that G and PG rated movies have a positive effect on box-office success.

When it comes to genre and its effect on box-office success, several earlier named researchers have results on these matters. Sawhey and Eliashberg (1996) find that drama genre has a slower time to act parameter then other genres, whereas action has a faster time to decide then other movie genres. Neelamegham & Chintagunta (1999) found that the thriller genre is the most popular genre across countries, while romance genre is the least popular. This result feels counter intuitive with the result from Ravid (1999). He found that thrillers are the most popular genre, but they are usually rated R, yet R-rated movies perform worse than other MPAA rated movies. Even though some researchers find some significant results when it comes to genre, nothing very conclusive can really be drawn from this research. Other research from Collins et al. (2002) found that genre and its effect on box-office success remains less certain. They concluded genre should be regarded as a control factor and not as a predictive variable. Walls (2005) found similar results. None of the genre classifications individually were significant, however he did find them to be significant as a group.

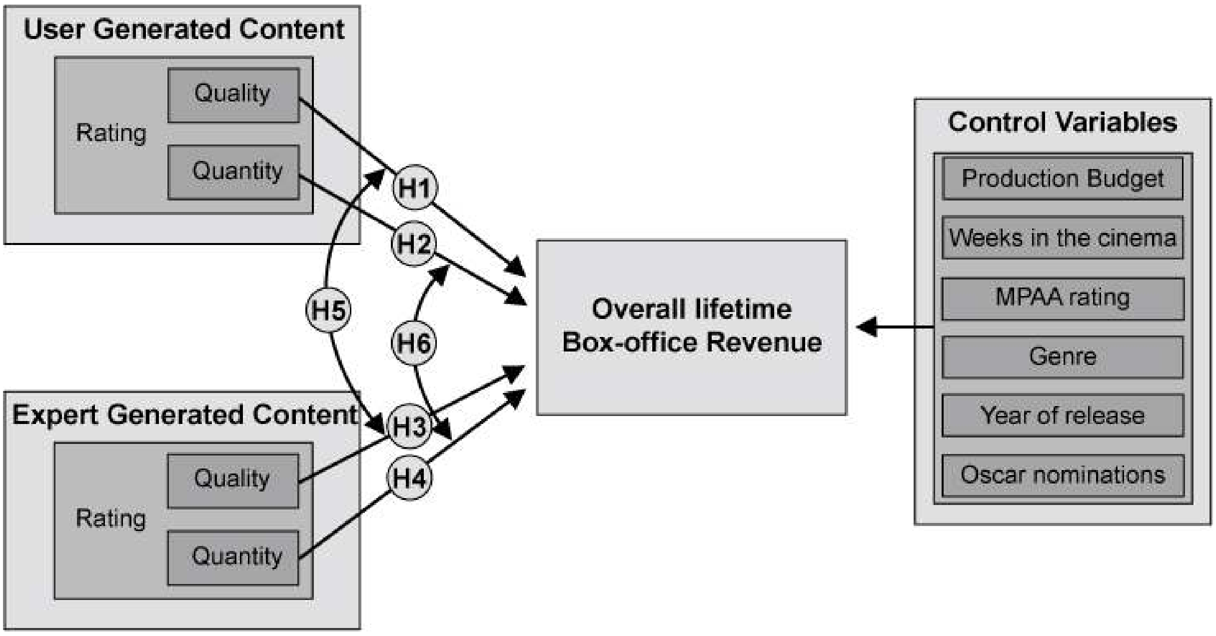
The last variable to consider when trying to predict financial success is Academy Award nominations and wins. Litman (1983) found that Academy award nominations or winnings are significantly related to box-office success. Litman & Kohl (1989) found that being nominated for an award is only significant for the best film category. Eventually winning the award did not have any significant effect on the box-office success of a movie. Nelson et al. (2001) in their study about the value of an Oscar nomination and award. They found that a nomination or award for the top prizes like best actor/actress and best picture had a significant positive effect on box-office success.

[14] http://en.wikipedia.org/wiki/Motion_Picture_Association_of_America_film_rating_system

These literature reviews showed which variables, besides user rating and expert ratings were also important in influencing box-office revenue. We will explain how we will implement certain results into the regression model in the Methodology part of the thesis.

2.5 Conceptual framework

To provide a visualization of the hypotheses for the key dependent variable and independent variables and their relationships, we created a theoretical framework. The arrows indicate expected relationships between the variables.



3. Methodology, dataset and variables

In order to test the effect of user and expert rating on box-office revenue, we needed to collect data for these variables. The data we collected comes from two important sites. The first site is imdb.com. This is one of the largest movie database sites on the web. From this site we extract data about user rating and expert rating. We supplement this data with box-office revenues from boxofficemojo.com. In paragraph 3.1 we will describe our sample selection. In paragraph 3.2 we will discuss the different variables that we used in our research. In paragraph 3.3 we will describe how we collected the data. In paragraph 3.4 we will show the regression model equation we have created to answer our hypotheses.

3.1 Sample selection

In order to test the hypotheses, we need to collect data on ratings and box-office revenue. We start by making a selection of movies. We want to examine the box-office revenues of movies which are as recent as possible. We also preferred movies that were released worldwide, to avoid issues of having movies, which did not have a critic rating on imdb, or a very low amount of user ratings, which could give a distorted view. Thus we have decided to research the top 100 grossing movies from 2008, 2009 and 2010. To make sure we did not have movies in our selection that were still running in the cinemas, we have excluded the years 2011 and 2012. To see which movies were the top grossing movies of the years 2008-2010 we go to boxofficemojo.com. This site had some limitations. It was not able to sort by worldwide all time gross. We were only able to sort by domestic gross[15]. This did not prove to be a great issue. The top grossing movies are all Hollywood made. Movies either have a world wide release, or are first released in the American market, and still represented the top movies of each year we wanted to research.

3.2 Variables

We need information on several variables to create the correct model in order to answer our hypotheses.

3.2.1 Dependent variable

We want to know the effect of ratings on total life time box-office revenue. There for, box-office revenue would be our dependent variable.

[15] http://boxofficemojo.com/yearly/chart/?yr=2008&p=.htm

We used boxofficemojo.com to see the total lifetime box-office revenue of each movie we selected.

Figure 3.21 shows a screenshot of how this is presented on boxofficemojo.com.

The area that is marked in red shows the amount of box-office revenue this movie has earned worldwide. The areas marked in blue and yellow show control factors which will be discussed in paragraph 3.2.3.

Figure 3.21: Screenshot movie information boxofficemojo.com

3.2.2 Independent variables.

The independent variables for our model will be the ratings given by users and experts. These ratings as well as several control variables we can find on imdb.com. Figure 3.22 shows a screenshot of what users will see on imdb.com when they look up a movie.

Figure 3.2.2: Screenshot movie information imdb.com

The areas that are circled and numbered 1 to 6 show important independent variables and control variables.

We will describe the independent variables below:

1) Average rating given by users

This represents the quality of user rating. Based on research results from Chevalier and Mayzlin (2006) and Forman et al. (2008), we expect to see a positive, but small effect on box-office revenue.

2) Amount of users who gave their rating

This will represent the quantity of user rating. The literature research showed that the quantity of user rating had a significant effect on movies box-office revenues (Liu 2006, Dellarocas et al. 2007, Duan et al. 2008)

3) Amount of experts who wrote a review and rated the movie.

This will represent the quantity of expert rating. The literature research showed significant support for the correlation between the amount of reviews and received revenues (Ravid 1999).

4) Average rating given by experts

This will represent the quality of expert rating. The literature research showed that the quality of expert rating is a key predictor for box-office revenue (Eliashberg and Shugan 1997, Litman and Kohn 1989, Reinstein and Snyder 2005)

3.2.3 Control variables

According to the literature research, there are several important variables, which act as control variables. We will first discuss the control variables which are shown in figure 3.21.

Production budget:

The area marked in blue in figure 3.21 shows the production budged of the movie. Our literature research found significant support for the effect of big-budgets on high box-office revenues (Ravid 1999).

Weeks of release:

The area marked in yellow in figure 3.21 shows the amount of weeks a movie ran in the cinema. The longer a movie is in the cinemas, the longer it can receive box-office revenue, and thusly an obvious factor we need to control for.

Year of release:

We will research the top 100 grossing movies from 2008-2010. User will have had a longer time to rate movies from 2008 on imdb.com, than those which were released in 2010. Thus we need to control for this. We created the dummy variables: DUM_2008, DUM_2009, DUM_2010.

This is the MPAA rating given to the movie:

The MPAA rating territories a film's thematic and content suitability for certain audiences. Research showed this had a significant effect on box-office revenues (Sawhney, Eliashberg 1996; Medved 1992; Sochay 1994; Ravid 1999). To control for this we created the following dummy variables: DUM_G, DUM_PG, DUM_PG13, DUM_R.

Types of genres the movie belongs to:

Research about the effect of genre on box-office revenue remains unclear. They found mixed results on the effect of it had on box-office revenue. Collins et al. (2002) concluded genre should be regarded as a control factor. To control for this, we created a dummy variable for every movie genre[16] we found on imdb.com.

Award Nominations:

The last factor we need to control for is Award nominations. The research showed that there was a significant effect on box-office revenue when a movie was nominated for the top awards. These are best film and best actor/actress. Eventually winning the award had no significant effect on box-office revenue (Nelson et al. 2001, Litman and Kohl 1989, Litman 1983).

3.3 Procedure of collecting data

Like we described in paragraph 3.1, we selected the top 100 movies from the years 2008, 2009 and 2010. We manually looked for information on each single movie and registered all the necessary information in an excel file. We used boxofficemojo.com for the data on the dependent variable, life time box-office revenue. We also used this site for information on two important control variables, production budget and weeks in the cinema. We then looked up the movie on imdb.com and put the information on ratings, genre and MPAA rating in excel.

3.3.1 Data limitations

Out of the 300 movies we selected, 50 movies lacked one or more independent variables. For research purposes we deleted these movies from our sample. This left us with a sample size of 250 movies.

[16] The genres we created dummies for are: Action, Adventure, Animation, Fantasy, Romance, Drama, Comedy, Thriller, Musical, Horror, Scifi, Family, Crime, Mystery, History, Sport, War, Biography

3.4 Multiple regression

In order to test the effect of ratings on box-office revenue, we will construct a multiple regression model. We described all our variables in the previous paragraphs. This gives us the following multiple regression equation:

$$Box-office\ revenue = \beta_0 + \beta_1 . Quality\ of\ user\ rating + \beta_2 . Quantity\ user\ rating +$$
$$\beta_3 . Quality\ of\ expert\ rating + \beta_4 . Quantity\ of\ expert\ rating +$$
$$\sum \beta_{5-32} . All\ control\ variables + \varepsilon$$

4. Results and Analysis

To answer our hypotheses, several statistical tests were done. These statistical test and there results will be discussed in this chapter. In paragraph 4.1 we will show the descriptive statistics of our sample. In paragraph 4.2 we did a multiple regression analyses. In paragraph 4.3 we check for multicollinearity with a correlation matrix and a collinearity diagnostic. In paragraph 4.4 we ran several simple regressions of our main independent variables. In paragraph 4.5 we will test for a mediation effect within independent variables. In paragraph 4.6 we will summarize our hypotheses testing results.

4.1 Descriptive statistics

Table 4.1 will show the variation in the quality and quantity of user and expert rating in the dataset we formed. This way you can get an overview of the sample of movies we selected. It shows the mean, median and the minimum and maximum of each variable in the sample we selected.

Descriptive Statistics

	N					
	Valid	Missing	Mean	Median	Minimum	Maximum
User rating given	**250**	**0**	**6,4**	**6,5**	**3,3**	**8,9**
Amount of users who rated the movie	**250**	**0**	**82.607**	**60.335**	**3.537**	**704.961**
Expert rating given	**250**	**0**	**5,3**	**5,3**	**1,7**	**9,5**
Amount of experts who rated the movie	**250**	**0**	**235**	**221**	**39**	**576**
Total life time revenue	**250**	**0**	**$217.942.005**	**$153.145.008**	**$31.198.531**	**$1.063.171.911**

Table 4.1

According to the descriptive statistics we can conclude several things. On average in our sample we see that user rating is slightly higher than expert rating, 6.4 > 5.3. It is interesting to see that the range of rating is larger with experts then with users when looking at the minimum and maximum of rating given. The amount of “paid professionals” who review and rate movies is limited, thus it is obvious that the amount of expert ratings is lower than the amount of user ratings. All users who register themselves on imdb.com are allowed to rate any movie on the site. Registering on imdb.com is free of charge and possible for everyone.

4.2 *Multiple regression*

In order to test the effect of user and expert ratings on lifetime box-office revenue we have constructed a multiple regression model. In this regression we use all independent variables and control variables mentioned in paragraph 3.2.

The histogram of the dependent variable, total life time revenue is shown below:

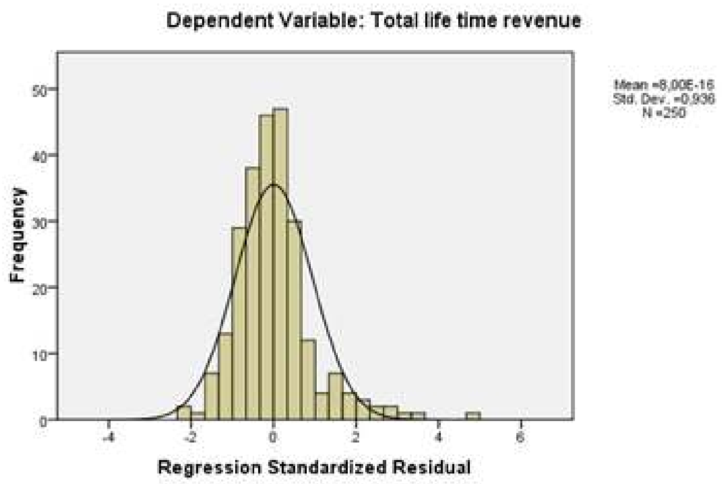


Figure 4.1

In the histogram we can see that the result shows a skewed distribution. This is due to a number of outliers within the sample. To correct for this, the total life time revenue was logged. The histogram of the logged revenue (lnRevenue) can be seen below:

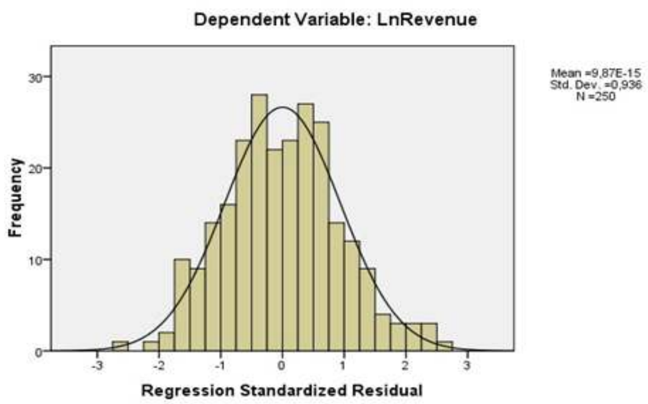


Figure 4.2

The histogram now shows a more normal distribution, then when the revenues were not logged. With the logarithm of total lifetime box-office revenue as dependent variable (LnRevenue), and independent variables and control variables described in paragraph 3.2 we constructed the following model:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,847**[a]	**,717**	**,677**	**,47873**

Table 4.2.1

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
(Constant)	**18,055**	**,319**		**56,565**	**,000****
User rating given	**-,112**	**,054**	**-,144**	**-2,062**	**,040***
Amount of users who rated the movie	**1,882E-6**	**,000**	**,181**	**2,293**	**,023***
Expert rating given	**-,071**	**,035**	**-,140**	**-2,050**	**,042***
Amount of experts who rated the movie	**,002**	**,001**	**,282**	**3,084**	**,002****
CONTROL VARIBALES[B]					

a. Dependent Variable: LnRevenue

b. To save room, the control variables were not shown. You can see the full model in the appendix

* Significant at .05 level
**Significant at .01 level

Table 4.2.2

The model we created has an R^2 of 0,717, which means that 71,7% of the variation in the dependent variable (LnRevenue) can be explained by our model.

The independent variables in our multiple regression are all significant. If we look at the quantity of rating, we see that both the amount of users who rated the movie, as well as the amount of critics who rated the movie have a positive coefficient. This indicates we support the hypotheses 2 and 4. The quality of rating however, shows some very counter intuitive results. Even though both user rating and expert rating are significant, they have a negative coefficient. When we consider this result in a practical example, it would mean that if the box-office revenue increases, the rating from users as well as experts decreases. To try and find a reason why the rating coefficients are negative we run a new multiple regression with only the independent variables. This way we can see if the effect is somehow due to the control variables.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,567[a]	,322	,311	,69940

Table 4.2.3

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1 (Constant)	18,856	,319		59,020	,000**
User rating given	-,139	,072	-,179	-1,934	,054
Amount of users who rated the movie	4,577E-6	,000	,440	4,916	,000**
Expert rating given	-,015	,044	-,029	-,337	,736
Amount of experts who rated the movie	,002	,001	,280	2,978	,003**

a. Dependent Variable: LnRevenue

* Significant at .05 level

**Significant at .01 level

Table 4.2.4

The model without the control variables explains 32,2% of the variance in LnRevenue. The user rating and expert rating still show a negative coefficient, but this isn't relevant since the two variables are now no longer significant. The reason why the independent variables of user rating and expert rating are no longer significant could be due to multicollinearity.

4.3 Multicollinearity

In order to explain why we have negative coefficients for user and expert rating and why they are not significant in table 4.2.4, we will run some more analyses. One of the reasons could be, that we have multicollineary within our multiple regression. Multicollinearity means, that there is a strong correlations between two or more predictor variables within the multiple regression model. This could form a substantial problem in our research. We are trying to find out the difference in signaling power for box-office revenue, between users and experts. If predictors are highly correlated and account for similar variance within the dependent variable, we cannot know which of the variables is most important.

According to Field (2009), one way to identify multicollinearity is to scan a correlation matrix. Field (2009) says there is an indication of multicollinearity if the correlation between two variables is above 0.8 or 0.9. He considers this a good "ball park".

Correlations

	User rating given	Amount of users who rated the movie	Expert rating given	Amount of experts who rated the movie
User rating given	1			
Amount of users who rated the movie	,626**	1		
Expert rating given	,774**	,506**	1	
Amount of experts who rated the movie	,651**	,793**	,603**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.3.1

The correlation matrix shows that there are a few predictor variables which have a very high correlation between each other. The correlations between the ratings from users and experts is 0.774, and the correlation between amount of experts and users is 0.793. According to Field (2009) our results are not passed the critical area of 0.8, but it is obviously very close to it. The risk of multicollinearity is there.

Another way to check for multicollinearity is with various collinearity diagnostics which SPSS is able to produce. One of them is the variance inflation factor (VIF). If the VIF is greater than 5, then it could be a good indication for a multicollinearity problem. Related to the VIF is the tolerance statistic (1/VIF). When the tolerance level is below 0.2, then there should be some concern for a multicollinearity problem.

Coefficients[a]

		Collinearity Statistics	
Model	Sig.	Tolerance	VIF
1 (Constant)	,000		
User rating given	,054	,324	3,086
Amount of users who rated the movie	,000	,345	2,896
Expert rating given	,736	,378	2,645
Amount of experts who rated the movie	,003	,313	3,191

a. Dependent Variable: LnRevenue

Tabel 4.3.2

Our collinearity statistics show no immediate issue of multicollinearity. The lowest tolerance value is from “Amount of experts who rated the movie”. This is 0.313, which is larger than the critical level of 0.2. Although it is not at the critical level, it still gives us some form of concern. We are unsure about the reason for the changes in significance between table 4.2.2 and 4.2.4.

4.4 Simple regressions

A simple regression cannot have a multicollinearity problem, because it only contains one predictor variable. Because of this we will run four simple regression analyses to test each of our independent variables separately. We will give a summery in one table. The full simple regressions can be found in the appendix of the thesis.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,257[a]**	**0,066**	**0,062**	**0,81591**
2	**,536[b]**	**0,287**	**0,284**	**0,7129**
3	**,224[c]**	**0,05**	**0,046**	**0,82269**
4	**,495[d]**	**0,245**	**0,242**	**0,73351**

a. Predictors: (Constant), User rating given

b. Predictors: (Constant), Amount of users who rated the movie

c. Predictors: (Constant), Expert rating given

d. Predictors: (Constant), Amount of experts who rated the movie

Table 4.4.1

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	Sig.
1	User rating given	**0,200**	**0,048**	**0,257**	**0,000****
2	Amount of users who rated the movie	**5,57E-06**	**0,000**	**0,536**	**0,000****
3	Expert rating given	**0,115**	**0,032**	**0,224**	**0,000****
4	Amount of experts who rated the movie	**0,004**	**0,000**	**0,495**	**0,000****

1. Dependent Variable: LnRevenue

**Significant at .01 level

Table 4.4.2

The first thing we notice is that all our independent variables in the simple regressions are very significant at a 0.01 level. Combined with the fact that all the important independent variables were also significant in the main multiple regression, we can confirm the hypotheses 1,2,3 and 4. We also see that the betas from user rating and expert rating are no longer negative, but show a positive effect in the simple regressions. This could indicate that there is a mediation effect, which causes the quality of rating to show a negative coefficient in the multiple regression.

4.5 *Mediation effect*

There is a possible mediation effect when you get the following situation. If a mediator is included in a regression analyses, the effect of the independent variable on the dependent variable is reduced and the effect of the mediator remains significant. Below we will show you this situation in our research for user generated content and expert generated content:

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	**18,949**	**,308**		**61,447**	**,000****
	User rating given	**-,100**	**,053**	**-,129**	**-1,887**	**,060**
	Amount of users who rated the movie	**6,410E-6**	**,000**	**,616**	**9,011**	**,000****

a. Dependent Variable: LnRevenue

**Significant at .01 level

Table 4.5.1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	**18,006**	**,157**		**114,349**	**,000****
	Expert rating given	**-,060**	**,035**	**-,117**	**-1,696**	**,091**
	Amount of experts who rated the movie	**,005**	**,001**	**,565**	**8,206**	**,000****

a. Dependent Variable: LnRevenue

**Significant at .01 level

Table 4.5.2

In the simple regression in table 4.4.2 we have shown that user rating has a significant positive effect on box-office revenue. However when we include the mediator of “amount of users who rated the movie”, the independent variable “user rating given” is no longer significant and has a negative coefficient. The exact same thing happens to expert rating in table 4.5.2.

A method for testing the significance of a mediation effect is the Sobel test[17]. In our situation the mediator is the quantity of user and expert rating. In order to do the Sobel test, we first need the unstandardized coefficient results from separate regressions from users and experts. First we regressed the mediator on to the independent variable. In our situation, we will test quality on to the quantity of user rating and expert rating.

[17] http://en.wikipedia.org/wiki/Sobel_test

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	**-215059,034**	**23904,638**		**-8,997**	**,000****
	User rating given	**46799,833**	**3705,243**	**,626**	**12,631**	**,000****

a. Dependent Variable: Amount of users who rated the movie

**Significant at .01 level

Table 4.5.3

We see there is a significant positive relation between user rating and the amount of users who rated the movie.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	**47,185**	**16,481**		**2,863**	**,005****
	Expert rating given	**35,595**	**2,989**	**,603**	**11,909**	**,000****

a. Dependent Variable: Amount of experts who rated the movie

**Significant at .01 level

Table 4.5.4

This table shows there is also a significant positive relation between expert rating and the amount of experts who cared the movie.

The second step is that we need to regress the independent variable on to the dependent variable. We already did this in table 4.4.2. It shows that there is a significant positive relationship between users and LnRevenue as well as experts and LnRevenue.

By using an interactive calculation tool[18], we will test whether a mediator carries the influence of our independent variable to the dependent variable. We first test the mediation effect for users:

[18] http://quantpsy.org/sobel/sobel.htm

1. Run a regression analysis with the IV predicting the mediator. This will give a and s_a.
2. Run a regression analysis with the IV and mediator predicting the DV. This will give b and s_b. Note that s_a and s_b should never be negative.

To conduct the Sobel test

Details can be found in Baron and Kenny (1986), Sobel (1982), Goodman (1960), and MacKinnon, Warsi, and Dwyer (1995). Insert the a, b, s_a, and s_b into the cells below and this program will calculate the critical ratio as a test of whether the indirect effect of the IV on the DV via the mediator is significantly different from zero.

Input:			Test statistic:	Std. Error:	*p*-value:
a	46799.83305684	Sobel test:	7.83408354	0.03327532	0
b	0.000005570141	Aroian test:	7.81901967	0.03333943	0
s_a	3705.243	Goodman test:	7.8492348	0.03321109	0
s_b	0.000000557727	Reset all	Calculate		

Figure 4.3

With the results from the Sobel test, we find there is a significant mediation effect (p-value <0).

When checking the mediation effect for experts with the Sobel test, we get the following result:

Input:			Test statistic:	Std. Error:	*p*-value:
a	35.595	Sobel test:	4.61013707	0.03860514	0.00000402
b	0.005	Aroian test:	4.59638088	0.03872068	0.0000043
s_a	2.989	Goodman test:	4.62401752	0.03848926	0.00000376
s_b	0.001	Reset all	Calculate		

Figure 4.4

The results show there is a significant mediation effect (p-value <0).

Because of this mediation effect, which has a negative effect on the coefficients and the significance of our user and expert rating within the multiple regression model, we will use the results from the simple regression to answer H5 and H6. When we want to know, which independent variable has a larger effect on our dependent variable (LnRevenue), we simply compare the standardized coefficients with each other. In table 4.4.2 we see that the standardized coefficient from user rating (0,257) is larger than that of expert rating (0,224).Thus the quality of user generated content has a larger effect on box-office revenue, than expert generated content. This confirms H5.

If we look at the multiple regression analysis from table 4.2.2, we see that the standardized coefficient from the quantity of expert generated content (0,282) is larger than the quantity of user generated content (0,181). This would make us reject H6. However, we concluded with further analyses that our multiple regression model had several problems. First we have some slight form of multicollinearity. The correlation matrix as well as the collinearity diagnostics show we are very close to the critical areas. Besides the multicollinearity issue we also showed we had a significant mediation effect in our model. Because of these reasons we will use the result from the simple regression to answer H6. In the simple regression from the quantity of users and experts, we see that the standardized coefficient is larger for users, than for experts (0.536 > 0,495). This confirms H6 for our research.

4.5 Hypotheses testing

In this paragraph we will summarize the results of our hypotheses:

Hypotheses	Accepted/Rejected
H1: The quality of user rating has a significant positive effect on box-office revenue	**Accepted**
H2: The quantity of user rating has a significant positive effect on box-office revenue	**Accepted**
H3: The quality of expert rating has a significant positive effect on box-office revenue	**Accepted**
H4: The quantity of expert rating has a significant positive effect on box-office revenue.	**Accepted**
H5: The quality of user generated content has greater signaling power for box-office revenues then the quality of expert generated content	**Accepted**
H6: The quantity of user generated content has greater signaling power for box-office revenues then the quantity of expert generated content.	**Accepted**

5. Discussion

In this chapter we will discuss our research, implications and limitations. In paragraph 5.1 we will discuss the results from our research and give some practical explanations. In paragraph 5.2 we will give some academic and managerial implications of our results. In paragraph 5.3 we will discuss the limitations of our research and make some suggestions for future research to be done.

5.1 Results discussion

Our research helps show the difference in signaling power between user rating and expert rating on box-office revenue. We split this up into the quality and quantity of rating. In the multiple regression all the independent variables showed to have a significant effect on box-office revenue. However, there was one surprising result. In the main multiple regression model the coefficients from user and expert rating were negative. Meaning that if box-office revenue increases by one unit, keeping all the rest constant, according to the model, the user and expert rating decreased.

These negative coefficients for ratings feel very counterintuitive. To try and find a statistical cause for this result, we performed several other statistical tests. One of the reasons for the negative coefficient could be some form of multicollinearity. To check for this, we tested the correlation between the predictor variables. We found several high correlations. This was not a surprising result. We expected a high amount of correlation, between ratings from users and experts and between the amount of ratings from users and experts. Users as well as experts rate the same movie. It would be illogical that these ratings would be far apart. We also did a collinearity test, but this also showed no immediate multicollinearity problem. When we checked for a mediation effect, we found that the quantity of ratings had a significant indirect effect on our independent variables of quality.

When thinking about a practical explanation, what comes to mind is that our sample had the top 100 grossing movies of 2008,2009 and 2010. This means that it always contained the “blockbusters” of each year. The blockbuster movies have high marketing budgets to promote their movies. The actual quality of the movie is not always relevant. Think back about what we wrote in the introduction of the thesis, where we gave the example of the movie Transformers 2. It had a very high amount of user and expert ratings, but a very low quality of rating from users as well as experts. With certain movies, the cinema experience can add a lot more enjoyment then other movies. So in the example of Transformers 2, the high amount of special effects can be more pleasurable in the cinema with a big screen and surround sound, compared to watching it at home on your couch. Thus still attracting a large audience to go and see the movie, while the quality is not very high. When we think about low quality, we should think about a weak story line, or bad acting.

In our regression model we also have some limitations. We control for production budget, but this is not the same as a marketing budget. Some movies just get promoted more than others, but we do not control for this difference. With these promotions, they create a much higher form of awareness. When thinking about awareness, we should think about trailers that are shown on television. Some trailers hardly get shown on television, while others are frequently shown. This created a higher form of awareness which positively influences box-office revenue (Duan et al. 2008). We only measure the quantity of ratings, but do not measure the true level of awareness of a certain movie among the public.

For now we looked at this result, from the point of view, that we have an increase in revenue, and a decrease in rating. We can also approach this result from an opposite point of view to try and explain the negative coefficient from user rating. In our literature research we found that, when a consumer reads a review to help them in their purchasing decisions, they will focus more on the quality aspect for negative reviews, and more on the quantity aspect for positive reviews (Park and Lee 2007). So if a movie in general would receive positive reviews, but it had only a small amount of reviews, this could lead to lower revenues.

If we try to explain the negative coefficient from experts, we could argue that in general a movie critic prefers art house movies over the usual action packed blockbusters. They would rate these types of movies higher than the non-art house movies. In general, art house movies do not earn the high amount of box-office revenues that the blockbusters would earn. This is due to a difference in marketing budgets, production budgets and general awareness. In our research we controlled for "award nominations", however not all the nominated movies were in our sample. The reason is, because some of the movies which were nominated by critics for a possible "best picture" award, did not always manage to reach the list of the top 100 grossing movies of that year. A good example is the movie Winter's Bone[19]. It was nominated for "best picture" of 2010. The leading actor and actress were also nominated for an award for "Best actor/actress". The experts rating on imdb.com was 90/100, which could be considered a very high rating. We know that the average expert rating in our sample is 5.2. The revenues of this movie however were not very high. They earned a worldwide gross of "only" 18.8 million[20], while the lowest earning movie in our sample still earned 31 million. This is an example of a possible explanation, where we have a high expert rating, but a low box-office revenue.

[19] http://www.imdb.com/title/tt1399683/
[20] http://boxofficemojo.com/movies/?id=wintersbone.htm

Because of the significant mediation effect in our multiple regression, we created a simple regression in order to test the effect of the independent variables on the dependent variable without the presence of a mediator. These results showed that the quality and quantity of user and expert rating have a positive effect on box-office revenue without the presence of a mediator. In order to compare the users with the experts, we looked at the standardized coefficients. According to the simple regression results, the standardized coefficients for quality as well as quantity from users are higher than those of experts. This confirms our hypotheses, that the quality and quantity of user ratings have a greater signaling power for box-office revenue than those of experts.

5.2 Academic and Managerial implications

Our study tried to shed light on the difference of signaling power between the quality and quantity of expert and user rating. Our research results adds to the academic literature, because previous research did not compare users and experts, like we have in our study. Previous academic studies involving data from imdb.com only focused on written reviews from users. Our study focuses on the ratings that are given by users and experts, which are visible on imdb.com. The main contributions of our study consist of:

- Showing the effect of imdb.com ratings from users and experts on box-office revenue.
- Showing that the quality of user rating displayed on imdb.com has greater signaling power for box-office revenue then the quality expert rating on imdb.com.
- Showing that the quantity of user ratings on imdb.com has a greater signaling power for box-office revenue, than the quantity of expert ratings.

Managerial implications for our research could be that, results from our research could be transferred to similar types of experience goods like video games or music. We show the importance of user generated content on revenues. Our results show the significant influence that quality as well as the quantity of ratings has on revenues. If this theory would be applied by producers of video games, it could be possible for them to create a model to predict video game sales by measuring the quality and quantity of ratings. So for them, it is important to offer users the ability to rate their video games. Right now, when you want to read a review about a video game, chance has it you will end up at gamespot.com. However this site can hardly be compared with the amount of people who rate movies on imdb.com. In order to be able to create some sort of predictive model, they need a significant amount of users to actually rate their video games. Producers of these games should somehow promote the “trend” of rating their video games. These results could then have very interesting management implications.

5.3 Limitations and future research

One of the main issues in our results was the presence of a mediation effect. Although we showed, there was a significant indirect effect from a mediating factor on the independent variables of quality; we could not statistically show why this effect occurred.

In our research we only used data from imdb.com. With our research we are able say something about the effect the quantity of ratings have on box-office revenue. However, we still only researched a select group of the population. One could argue that, even though imdb.com has over 100 million unique visitors each month, not everyone who goes to the cinema to watch a certain movie, has looked up the rating this movie received on imdb.com. They base their decision to go see a movie on other variables we did not control for within our study, yet the money they spend on their cinema ticket, is part of our dependent variable, the total life time box-office revenue.

Another limitation could be that, when someone rates a movie, he will already see the current rating the movie has received. We do not measure whether or not this person is perhaps influenced by the rating he sees from experts as well as other users who rated before him.

We were able to see that quantity positively influences box-office revenue, however we do not know what influences this quantity. What future research could do, is perhaps analyze blogs or forums on word hits or other factors of possible upcoming movies. Other things to perhaps control for, could be to see how many times certain trailers were viewed, or the amount of TV airtime trailers received.

6. Conclusion

Our research started by examining the difference in signaling power for box-office revenue between users and experts. We split the rating up in to quality and quantity. Quality refers to the rating given by a user or expert, and quantity refers to the amount of users and experts that gave their rating. We used the ratings from imdb.com and checked the top 100 grossing movies from 2008,2009 and 2010. Our results show that ratings from experts and users both have a significant effect on box-office revenues. Our multiple regression analysis with all the dependent variables and control variables, showed some interesting results. It showed that the quality of ratings had a negative effect on box-office revenue. This proved to be a very counterintuitive result, and further analysis showed this negative effect was due to two important things:

- Our model had a possible multicollinearity problem.
- The negative coefficient of the quality of ratings was due to a mediation effect.

By doing the Sobel z-test to test the significance of a mediation effect, we found that the negative coefficient of the quality of rating was caused by a mediation effect from the quantity of ratings. Because of these two main reasons we consider our multiple regression model untrustworthy, and thus used the results from simple regression analyses to answer our hypotheses. The result from the simple regression showed that the quality and quantity of user ratings have a significant positive effect on box-office revenue. They also showed that users are of higher influence then experts on box-office revenue.

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Appendix 1

Full multiple regression model:

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	18,055	,319		56,565	,000
	User rating given	-,112	,054	-,144	-2,062	,040
	Amount of users who rated the movie	1,882E-6	,000	,181	2,293	,023
	Expert rating given	-,071	,035	-,140	-2,050	,042
	Amount of experts who rated the movie	,002	,001	,282	3,084	,002
	Movie production budget	6,804E-9	,000	,444	8,016	,000
	Amount of weeks a movie was in the cinema	,049	,009	,303	5,543	,000
	Dummy for G rating	-,159	,270	-,031	-,588	,557
	Dummy for PG rating	-,023	,168	-,011	-,139	,890
	Dummy for PG-13 rating	,000	,082	,000	,006	,995
	Action	-,020	,088	-,011	-,227	,820
	Adventure	,078	,108	,042	,722	,471
	Animation	,303	,158	,112	1,924	,056
	Fantasy	,024	,114	,009	,210	,834
	Romance	,023	,102	,011	,225	,822
	Drama	-,081	,088	-,047	-,921	,358
	Comedy	-,105	,100	-,061	-1,044	,298
	Thriller	-,127	,101	-,061	-1,257	,210
	Musical	,695	,350	,074	1,987	,048
	Horror	,138	,153	,045	,904	,367
	Sci-Fi	-,203	,133	-,068	-1,520	,130
	Family	,064	,156	,022	,408	,684
	Crime	,064	,110	,026	,585	,559

Mystery	-,059	,132	-,019	-,449	,654
History	-,206	,213	-,040	-,969	,334
Sport	-,619	,279	-,092	-2,216	,028
War	-,031	,233	-,005	-,133	,894
Biography	,336	,225	,074	1,491	,137
Dummy for 2008 release	,045	,082	,025	,556	,579
Dummy for 2009 release	-,009	,080	-,005	-,108	,914
Oscar nomination best Movie	,172	,181	,049	,951	,343
Oscar nomination best actor/actress	-,171	,190	-,048	-,898	,370

a. Dependent Variable: LnRevenue

Correlation matrix

Correlations

		User rating given	Amount of users who rated the movie	Expert rating given	Amount of experts who rated the movie
User rating given	Pearson Correlation	1	,626**	,774**	,651**
	Sig. (2-tailed)		,000	,000	,000
	N	250	250	250	250
Amount of users who rated the movie	Pearson Correlation	,626**	1	,506**	,793**
	Sig. (2-tailed)	,000		,000	,000
	N	250	250	250	250
Expert rating given	Pearson Correlation	,774**	,506**	1	,603**
	Sig. (2-tailed)	,000	,000		,000
	N	250	250	250	250
Amount of experts who rated the movie	Pearson Correlation	,651**	,793**	,603**	1
	Sig. (2-tailed)	,000	,000	,000	
	N	250	250	250	250

**. Correlation is significant at the 0.01 level (2-tailed).

Collinearity diagnostic:

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	18,856	,319		59,020	,000		
	User rating given	-,139	,072	-,179	-1,934	,054	,324	3,086
	Amount of users who rated the movie	4,577E-6	,000	,440	4,916	,000	,345	2,896
	Expert rating given	-,015	,044	-,029	-,337	,736	,378	2,645
	Amount of experts who rated the movie	,002	,001	,280	2,978	,003	,313	3,191

a. Dependent Variable: LnRevenue

Simple Regressions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,257[a]	,066	,062	,81591

a. Predictors: (Constant), User rating given

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	17,571	,308		57,041	,000
	User rating given	,200	,048	,257	4,180	,000

a. Dependent Variable: LnRevenue

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,536**[a]	**,287**	**,284**	**,71290**

a. Predictors: (Constant), Amount of users who rated the movie

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	**18,380**	**,064**		**285,125**	**,000**
	Amount of users who rated the movie	**5,570E-6**	**,000**	**,536**	**9,987**	**,000**

a. Dependent Variable: LnRevenue

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,224**[a]	**,050**	**,046**	**,82269**

a. Predictors: (Constant), Expert rating given

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	**18,237**	**,174**		**104,560**	**,000**
	Expert rating given	**,115**	**,032**	**,224**	**3,622**	**,000**

a. Dependent Variable: LnRevenue

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,495**[a]	**,245**	**,242**	**,73351**

a. Predictors: (Constant), Amount of experts who rated the movie

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	**17,835**	**,121**		**147,030**	**,000**
	Amount of experts who rated the movie	**,004**	**,000**	**,495**	**8,971**	**,000**

a. Dependent Variable: LnRevenue

Checking for a mediation effect:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,626[a]**	**,391**	**,389**	**63317,173**

a. Predictors: (Constant), User rating given

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	**-215059,034**	**23904,638**		**-8,997**	**,000**
	User rating given	**46799,833**	**3705,243**	**,626**	**12,631**	**,000**

a. Dependent Variable: Amount of users who rated the movie

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,603[a]**	**,364**	**,361**	**77,73530**

a. Predictors: (Constant), Expert rating given

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	**47,185**	**16,481**		**2,863**	**,005**
	Expert rating given	**35,595**	**2,989**	**,603**	**11,909**	**,000**

a. Dependent Variable: Amount of experts who rated the movie

Appendix 2

The movie selection used for our sample:

Released 2008:	
The Dark Knight	The spiderwick chronicles
Iron Man	Fool's Gold
Indiana Jones and the Kingdom of the Crystal Skull	Seven Pounds
Hancock	Role models
Wall-E	The Happening
Kung fu panda	Forgetting Sarah Marshall
Twilight	Baby Mama
Madagascar 2	Burn After reading
Quantum of Solace	Saw 5
Dr. Seuss' Horton hears a who!	The Strangers
Sex and the city	The tale of Despereuaux
Gran Torino	Australia
Mamma Mia!	The house bunny
The chronicles of Narnia: Prince caspian	Nim's Island
Slumdog Millionaire	Made of honor
The Incredible Hulk	The sister hood of the traveling pants 2
Wanted	Speed racer
Get Smart	Prom Night
The curious case of Benjamin Button	Rambo
Four Christmases	Welcome Home Roscoe Jenkins
Bolt	Max Payne
Tropic Thunder	Righteous Kill
Bedtime stories	Body of Lies
The Mummy: Tomb of the dragon emperor	Lakeview Terrace
Journey to the center of the earth	Harold and Kumar escape from Guantanamo Bay
Eagle Eye	The secret life of Bees
Step Brothers	Death Race
You don't mess with the zohan	Changeling
Yes Man	The reader
10.000 BC	Fireproof
High school Musical 3: Senior Year	Doubt
Pineapple express	The Love Guru
Valkyrie	Milk
21	Quarantine
What happens in Vegas	Nick and Norah's Infinite playlist
jumper	Zack and Miri Make a Porno
Cloverfield	Leatherheads
The day the earth stood still	Space Chimps
27 dresses	Untraceable
Hellboy 2: The golden army	Defiance
Vantage point	

Released 2009:	
Transformers: revenge of the fallen	Funny people
Harry Potter and the Half-Blood Prince	My bloody valentine
The Twilight Saga: New Moon	Old dogs
Up	Land of the lost
The Hangover	My Sister's Keeper
Star Trek	Precious
The blind side	Underworld: Rise of the lycans
Alvin and the chipmunks: The Squeakqual	The Lovely bones
Sherlock Holmes	Year One
Monsters vs Aliens	The Unborn
Ice Age: Dawn of the Dinosaurs	Planet 51
Night of the museum: Battle of the smithsonian	Drag me to hell
2012	Duplicity
The proposal	Crazy Heart
Fast and Furious	Surrogates
G.I. Joe: The Rise of Cobra	Ninja assassin
Paul Blart: Mall Cop	Invictus
Taken	State of play
A christmas Carol	Notorious
Angels and Demons	The Informant!
Terminator Salvation	The men who stare at goats
Cloudy with a chance of meatballs	500 day's of summer
Inglourious Basterds	Push
G-Force	9
District 9	Did you hear about the morgans
It's complicated	The Stepfather
Couples Retreat	Brothers
Paranormal activity	Dance Flick
Watchmen	
The Princess and the Frog	
Public enemies	
Julie and Julia	
The Ugly Truth	
Up in the air	
Knowing	
Where the wild things are	
Zombieland	
Coraline	
Law abiding citizen	
Obsessed	
The Final Destination	
The taking of pelham 1 2 3	
Friday the 13th	
The time traveler's wife	
Bride Wars	

Released 2010	
Toy Story 3	The sorcerer's Apprentice
Alice in wonderland	A Nightmare on Elm street
Iron Man 2	The last song
The Twilight saga: eclipse	The wolfman
Inception	Get him to the greek
Despicable Me	Resident evil: Afterlife
Shrek forever after	Why did i get married to
How to train your dragon	Tooth fairy
Tangled	Secretariat
The Karate Kid	Easy A
Tron Legacy	Takers
True Grit	Legend of the Guardians: The owls of Ga'Hoole
Clash of the Titans	Life as we know it
Grown ups	Letters to Juliet
Little Fockers	Wall street: Money never sleeps
Megamind	Predators
The King's Speech	Hot tub time machine
The Last airbender	Kick-ass
Shutter Island	Killers
The other guy's	Saw 3D
Salt	Cop out
Jackass 3-D	Cats and dogs: the revenge of kitty galore
Valentine's Day	Edge of Darkness
Black swan	Gulliver's Travels
Robin Hood	Death at a funeral
The chronicles of Narnia: The voyage of the dawn leader	Step up 3D
The expendables	The last Exorcism
Due Date	Legion
Yogi Bear	Burlesque
Date Night	The crazies
The social network	For colored girls
Sex and the city 2	The Back-up Plan
The book of eli	Vampires suck
The Fighter	The american
The Town	Green zone
Prince of Persia: The sands of time	Marmaduke
Red	Hereafter
Percy Jackson and the Olympians	Love and other drugs
Paranormal activity 2	She's out of my League
Unstoppable	Scott Pilgrim vs. The world
Eat pray Love	Charlie st. Cloud
Dear John	Morning Glory
The A-Team	How do you know
Knight and Day	Daybreakers
Dinner for schmucks	Nanny McPhee Returns
The Tourist	The Switch
The Bounty Hunter	Brooklyn´s Finest
Diary of a wimpy kid	Machete