

St. Petersburg State University
Graduate School of Management
Master in Corporate Finance Program

MODELLING OF SEQUEL PRODUCTION IN THE AMERICAN MOVIE INDUSTRY

Master's Thesis by the 2nd year student
Concentration – Master in Corporate Finance
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St. Petersburg

2017

ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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Описание цели, задач и основных результатов	<p>Цель данной работы состоит в построении и тестировании алгоритма для принятия решений кинопрокатчиками в отношении выпуска продолжений к уже выпущенному фильму. Для достижения поставленной цели мы подробно изучили теоретические и практические работы, которые посвящены поиску факторов, влияющих на выручку фильма. Мы также провели исследование изменений ключевых показателей у сиквелов по сравнению с первым фильмом.</p> <p>Предложенная модель состоит из элементов прогнозирования выручки и расходов. Модель генерирует прогнозы, которые впоследствии будут использованы при оценке инвестиций в покупку прав на экранизацию книги или сценария и принятия решения о съемке сиквела.</p>
Ключевые слова	Прогнозные сборы в кинотеатрах, кинопрокатная индустрия, метод Монте-Карло

ABSTRACT

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Master Thesis Title	“Modelling of sequel production in the American movie industry”
Faculty	Graduate school of management
Main field of study	080200 “Management” (specialization: Master of Corporate Finance)
Year	2017
Academic Advisor’s Name	Alexander V. Bukhvalov
Description of the goal, task and main results	<p>The goal of this research is to create and test a decision making algorithm that would allow the distributors to decide upon whether to shoot sequels for the already released movie or not. In order to achieve the defined research goal, we have thoroughly investigated the theoretical and practical works dedicated to identifying factors that affect box office revenue of movie releases. We have also conducted statistical analysis of changes in key determinants attributable to sequels and compared them with the parent movies.</p> <p>The suggested model consists of two elements: simulation of revenue and costs. Model generates forecasts that will then be used for decision whether to purchase script or book rights for sequel production or not.</p>
Keywords	Box office revenue prediction, motion pictures distribution, Monte Carlo method

CONTENTS

CONTENTS	6
INTRODUCTION	8
CHAPTER 1. LITERATURE REVIEW	10
1.1. Industry background	10
1.2. Factors affecting box-office success	12
1.3. Motivation for sequel production	18
1.4. Summary of Chapter 1	21
CHAPTER 2. MODEL DESIGN	22
2.1. General description of the model	22
2.2. Identifying the box office success factors	23
2.2.1. Sample description	23
2.2.2. Methodology and variables	27
2.3. Statistical analysis of sequel determinants	32
2.3.1. User rating and user reviews distribution	32
2.3.2. Modelling of user rating and user reviews	34
2.4. Simulating net profit for sequel releases	35
2.4.1. Cost calculation	35
2.4.2. NPV calculation	36
2.5. Summary of the Chapter 2	38
CHAPTER 3. MODEL FINDINGS	39
3.1. Sample description	39
3.2. Model findings	40
3.3. Discussion	43
3.4. Summary of Chapter 3	46
CONCLUSION	48
REFERENCES	49
APPENDICES	55
Appendix 1. Distribution of sample movies by director	55
Appendix 2. Distribution of sample movies by the main actor	55
Appendix 3. Descriptive statistics of variables for the regression	56
Appendix 4. Correlation matrix between variables	56
Appendix 5. Final regression statistics	57
Appendix 6. Time distribution of parent movies with only one sequel	57
Appendix 7. Time distribution of sequel releases in a sample ‘parent movie + 1 sequel’	57

Appendix 8. Time distribution of second sequel releases	58
Appendix 9. Test of distribution of user rating and user reviews.....	58
Appendix 10. Movie simulation results	59
Appendix 11. VBA simulation code	63

INTRODUCTION

The global movies and entertainment market has seen fluctuating growth rates over the period of 2011-2015 growing with a compound growth rate of 2.5%. Within the industry box office segment accounted for half of the market in 2015 with a total value of 39 bln USD. Geographically the United States keeps the leadership position in the market contributing with 33% of overall spending. However, developing markets see staggering growth in total spending on movies and entertainment as the general income level increases. Specifically China's movie market grew by 34% annually over the observed period with box office segment to be the most lucrative of all.

As the competition within the movie industry tends to strengthen, creating a successful and profitable film is a very challenging task. Firstly, films' production is expensive and their success is highly unpredictable. The median movie made in United States loses money. As average movie budget and marketing costs continue to escalate beyond 200 mln USD with intensifying competition on the entertainment market, studios are actively seeking for success formulas of revenue generating films. However, since every movie is unique in its contents, identifying success features for a movie is complicated. The industry itself becomes difficult to analyze with the films' qualities being not easily described or measured as in cases of other consumption goods.

Beginning from the moment of initiating a movie, studios make financial decisions which story to choose among many other competing proposals, how much money to invest in production and then decide when exactly to sell rights. In the given context sequels should be viewed as an increasingly important strategy for new product introduction by film-making studios as they are based on movies that are already familiar to the public and can guarantee to film-makers some level of public interest without new investments. When the successful formula of plot, actors and timing is found in the first movie, studios are willing to try it again in a sequel film (Ravid, 1994).

In general, studies of the movie market have been concentrating on the factors that drive box office sales as well as understanding the performance difference between sequels and non-sequels, while very few studies to be focused on integrating the observed interrelations between factors and provide film studios with a workable tool of decision making about whether to continue with shooting sequels or not.

The research goal of this paper is to create and test a model that would be able to forecast the financial performance of shooting sequels and then test it on real life cases.

In order to achieve the outlined goal, we define the following objectives:

- To identify the theoretical background on movie industry and sequel production;

- To study existing literature on the factors that drive box office revenues and differences in performance between sequels and non-sequels;
- To propose an empirical methodology behind the simulation model;
- To build and describe a sample for the analysis;
- To run the model on a sample of movies;
- To interpret results and compare the model findings with the real life cases.

The research approach is practical and uses such methods as quantitative analysis using econometric tools built in the Stata software and simulation modelling in Excel.

The main sources of information that were used for the purposes of research were academic articles devoted to: theoretical studies of the movie industry, motivation to shot sequels, determinants of box office success of both sequels and non-sequels, on marketing strategies for sequels and their specificities. To gather data for modelling the film performance, we use special databases about the movie industry as IMDB.com, Metacritic.com and the AMPAS database for the data about Academy Awards.

In order to achieve the defined goal of the research, we structure the thesis as follows: introduction, three chapters that cover all the goals of the study and conclusion. The introduction constitutes goals and objectives of the research as well as the motivation and background of the study. The first chapter covers first two research objectives and is mainly focused on analyzing the findings of other scholars in the chosen problem field.

The second chapter covers mainly the third and the fourth research objectives since it is devoted to description the suggested architecture of the simulation model as well as the steps that were taken to build it and the sample of movies used for this purpose. In the third chapter we analyze the practical results of running the model on a sample of new movies, analyze the performance of the model and interpret the results.

Finally, the conclusion summarizes the research in relation to the goals set. The research paper was also complemented with summaries at the end of each chapter to ease the process of reading. The appendices include sample descriptions as well as the VBA code used in the simulation model.

CHAPTER 1. LITERATURE REVIEW

In this section we will provide with an overview of a movie industry, its main actors and the stages of development of a film as well as the main factors that were documented to be determinants of the box office success of a movie. We then proceed with analysis of sequel production strategies and the application of real option in the decision making process of movie studios.

1.1. Industry background

The overall movie market is subject to a whole range of social cultural and political trends that are affecting both the contents and the distribution of films. The analysis of the external environment reveals that the main risks are political and technological. While the movie industry can adapt to social and cultural context by modifying the plot, actors and contents of movies, political and technological risks are becoming true impediments for distribution of movies in countries where censorship, quote imposing and pirating are widely spread.

Table 1. PEST analysis of film production industry.

Force	Positive influence	Negative influence
Political	Government support: experts, grants, locations' Intellectual patents	Censorship Rating requirements Impacts of lobbying groups on film and entertainment industry
Economic	Increase in GDP per capita Rise of average wages (especially in developing countries, China and India) Open financial markets	High competition for investments Shift of profit center to Asia-Pacific region Increasing cost of capital
Social	Diverse audience Increasing value of leisure time Growing population International cooperation and intercultural working teams	Rapidly changing trends in cinematography Tension in social rights movements (gender equality, sexual orientation equality, race equality etc.) Increasing working hours High value of word of mouth marketing
Technological	Development of different formats of cinemas	Internet pirating

	Development of technology (visual effects, 3D etc.)	Rapid changes in technological advancement and entertainment alternatives
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The value chain of producing a movie incorporates six stages lasting 4 years overall (Young et al. 2009):

1. Script development. The process takes approximately 2 years with only 10% of the scripts to be converted into actual films (Amram, 2003). This stage is finished when the script is accepted, the actors are attached and the financing secured, i.e. the studio greenlights the movie production.
2. Film production. The production part usually commences with the acquisition of rights to a story idea or script, which is developed to present the final draft to financiers and investors. The project producer accomplishes the tasks of finding the desirable personnel, scouting locations and forecasting costs. Numerous strategic decisions are made at this stage. The budget, as a significant determinant of revenues, is defined at this stage. Production stage defines the majority characteristics of a movie that have a later effect on film's revenues. Usually production stage 1.5 years and also includes post-production action such as final editing process, during which sounds and music are added to the movie.
3. The third stage is accompanied with making a decision whether to show the movie in theatres (95% chance) or to send it directly to a home video. The studio makes its investment into marketing and promotion activities.
4. Distribution phase. It starts after the first copy of the movie is produced. Multiple copies of the movie are then distributed to the theatres. Many marketing and distribution decisions are crucial at this stage for the box-office success of a movie. Strategic decisions about advertising strategies, release dates, international distribution as well as negotiations with partners about the number of screens are all made at this juncture. Close ties between production and distribution are worth mentioning. The research demonstrates that biggest films in terms of investment and performance tend to have both production and distribution stages managed by one firm. Control and coherence in the whole range of production-distribution decisions is viewed as a risk-decreasing factor (Vogel, 2011).

The distribution stage in cases of independent film producers also involves the step when the distributor pays to a film producer a prespecified amount of money, better known in industry terms as the Minimum Guarantee (MG). In exchange, they get the distribution rights for the movie. The exact amount of the MG is a result of the bidding process

between parties and is based on production and market knowledge of its participants (Walls, 2003). The study of 87 cases of sharing movie rights for MG conducted by Gemser et al. (2012) reveals that MG is a stronger predictor of movie rights revenues than any early-stage movie metrics like the production budget and the cast. This can be explained by decreased uncertainty about the new product success as the development process progresses as well as profound industry knowledge of the bidding parties.

5. During the first weekend after the movie is released to show in theatres, the fifth stage of decision making takes place. Here the strategic decisions are limited to scheduling the film's showings and pricing choices that the management of the movie theatres are making themselves (Eliashberg et al, 2008). This results in a fewer number of variables affecting the revenue success of the movie in contrast to the production and distribution phases.

However, the studio executives compare opening box office results and tracking information with forecasts. This allows decision makers to make adjustments about how more marketing costs to incur and how long to keep movies in the theatrical exhibition. The exact amount of the first weekend results is then frequently used for further financial decisions and present the most closely watched number in the industry. All future downstream financial deals are contingent on it (such as home video, international sales, television rights, etc.) (Amram, 2003; Epstein, 2005).

6. International distribution phase starts when movie is released in foreign countries. While assessing the international distribution part it is necessary to take into consideration the geographical positioning of movie theatres as well as the structure of national markets of movie production/distribution. For the research purposes it is worth observing that North American market shows oligopolistic structure in both production and exhibition. Six major studios occupy on average 85% of screens all theater screens available in a given week. The distribution market keeps its structure due to significant entry barriers that are associated with fixed costs of maintaining a sales network with offices across North America to negotiate and arrange contracts with theater operators for each film (Caves, 2000).

In this research paper the focus will be on the three key phases of the movie creation process: production, distribution and exhibition and what are the key variables there that affect the overall movie's revenue and cost structure.

1.2. Factors affecting box-office success

The movie industry has over one hundred years of history. However, during its most rapid expansion phase it operated with little or no research (Jowett, 1985). The amount of academic

literature has considerably multiplied beginning from 1977. Between 1996 and 2006 the number of yearly papers published never dropped below five (Hadida, 2009).

Two approaches to research into a movie industry can be distinguished among all the research papers on this subject (Elisashberg et al, 2006), (Chang & Ki, 2005). The first one tends to look into the psychological part of the movie success factors. It tries to understand the motivation of a consumer choice and often uses surveys for this goal.

Table 2. Academic literature about the movie industry

Topics covered	Researchers
Movie enjoyment	(Möller & Karppinen, 1983; D'Astous & Touil, 1999)
Effect of prior information	(Burzynski & Bayer, 1977)
Segmentation of audiences	(Cuadrado & Frasquet 1999)
Consumer's evaluation and choice of films	(Austin 1986; Gazley et al. 2011)

The second approach concentrated on the economic approach to assessing the movies' success. This type of research literature addresses such aggregate movie-level variables such as budgets, release dates, ratings etc. While many researchers focused on examining relationships between variables and box office results of a movie, some of them suggested an alternative modelling strategy. Given the unbounded variance of movie revenues De Vany and Walls (1999) found that no robust OLS models can be established. Instead they turned to the probit and/or logit models to indicate film success and estimating whether movie's revenues are going to reach a particular threshold becoming a blockbuster. Collins et al. (2002) used the same approach applying it to the UK movie market and also got robust results while addressing the non-normality of the data via transforming continuous variables into discrete ones and incorporating it into probit/logit model.

Sharda and Delen (2006) applied neural networks to predict the financial success of a film and then compared the results with some other model examples (i.e. logistic regression, discriminant analysis and regression and classification trees). They found that neural networks predict the success category of a motion picture significantly better than peer models (with 75.2% accuracy within one category).

Movies can be characterized as experience goods since their characteristics, e.g. quality, cannot be observed in advance that makes it difficult for the customer make its consumption choices. In such a context, the role of information and recommendations of other people who already tested the good tends to amplify.

Moretti (2011) looks into the role that information plays onto the consumption patterns of experience goods. Social learning that he observes in the movie industry signifies that attracting a new customer has a multiplier effect on revenue making successful films more successful and deteriorating the revenue position of the more unsuccessful movies. When a film is observed to have a stronger than expected first-week demand, then the decline in viewership is half of those with weaker than expected first week demand, that provides evidence of social learning effect. Hereafter, we plan to describe other factors that were found to have an effect on the revenue performance of a movie.

1.1.1. Production budget

Among film-related variables, budget has been found to significantly and positively affect revenues (Litman & Kohl, 1989; Prag & Casavant 1994; Ravid 1999; Elberse & Eliashberg 2003; Chang & Ki 2005; Liu 2006). The cost of the productions may be also viewed as a signal of quality, as studios will only be willing to spend large sums of money on the films and concepts that have a high probability to be a box-office success.

1.1.2. Advertising and marketing spending

Zufryden (2000) researched the role of promotions on the box-office performance of new movies and found that marketing activity is a significant predictor of box-office success of a movie. Furthermore, spending on prints and advertising was observed to deflate the impact of budget but again being positively related with the final box-office success of a movie (Prag & Casavant, 1994; Basuroy et al. 2006; Hennig-Thurau et al. 2006).

1.1.3. Critic reviews

With these types of products, consumers often rely on expert opinions to help guide them in their purchase decisions. It is important that 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, consumer will then be able to read this review about upcoming movies and decide if the movie will be worth seeing in the cinema.

The opinions of critics are frequently used as explanatory variables in the context of financial performance (Simonton,2009;Hadida,2009). Eliashberg and Shugan (1997) have conducted one of the most extensive works on the influence of critical evaluations on the box-office success of movies. On the one hand, they were regarded as predictors indicating the films' quality and predicting its financial performance. On the other hand, critics reviews were attributed the role of influencers affecting the customers' choice of a movie. The study revealed a strong correlation of critics evaluations with later weeks' box office, but not the early weeks. The conclusion was that critics perform more as predictors rather than influencers. Another variable affecting the financial performance was found to be the genre familiar to the audience.

Study by Eliashberg and Shugan (1997) became the basis for an extensive analysis of critical reviews conducted by Basuroy et al. (2003). They compared the impact of negative and positive reviews on the box office results of movies and how the effects can be moderated by stars and budget. Negative reviews were found to be stronger in how they can hurt the film revenues than how positive reviews can help movie performance. They also examined two moderators of critical reviews, stars and budget. The result was that inviting well-known stars and investing more money can help films to sustain a certain level of revenues for movies with negative reviews, but do little for those with good reviews. The managerial application of this work includes recommendation for movie producers to work intensively with critic reviews especially in the first week of a movie release and channel resources on avoiding negative reviews rather than inflating number of positive ones.

These findings are consistent with research of Thorsten et al. (2006) who examine the impact of studio efforts on the opening weekend and long-term box office on a sample of 331 films. They find that quality (in the form of ratings and indices) is the primary long-run success driver, while studio actions can generate short-term success after the release.

Desai & Basuroy (2005) found that the influence of star power and critic reviews is diminished when the variable representing genre is introduced. Positive reviews are also found to be particularly impactful on the demand of certain genres (Reinstein & Snyder 2005). Overall, research demonstrates that evaluations and the quality of a film seem to have a strong positive relation with the revenue (Litman & Kohl 1989; Ravid 1999; Collins et al. 2002; Zuckerman & Kim 2003).

1.1.4. User generated content

User generated content is content made by the general public rather than paid professionals. In recent years there has been a big increase in the amount of content generated by users. 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). Chevalier and Mayzlin (2006) have found a significant explanatory power for box office and rating. More importantly, this explanatory power comes from the volume of reviews and not its valence (Liu 2006). According to Duan et al. (2008) this is due to the awareness effect that will increase product awareness among consumers through dispersion even if the review is bad (Dellarocas et al. 2007, Godes and Mayzlin 2004).

1.1.5. Rating provided by the Movie Rating System

The Motion Picture Association of America (MPAA) – a group made up of large studios – assign each of the movie to be released with one of the five ratings that help to classify films with regard to suitability for different audiences in terms of the contents.

Some of the researchers concentrated on the revenue maximizing potential of R-, G- and PG-rated movies. While G-rated films are intended for general audiences with all ages being admitted, R and PG ratings put some restrictions. PG is a weak for od restriction suggesting that a movie is suitable with parental guidance since some material may not be suitable for children. R-rating, in turn, indicate that movie involves strong and frequent language, violence, drug abuse and nudity for sexual purposes. No one under 17 years old is admitted to a movie theater without accompanying parent or guide to see an R-rated movie.

Evidence provided by Ravid (1999) and De Vany and Walls (2002) showed that the R rating does not significantly influence the movie-related revenues as well as R-rated films are less often “revenue hits” than any other category. Ravid and Basuroy (2004) advanced the research analyzing a sample of 175 movies and came up to a conclusion that though violent films and those featuring both sex and violence do not provide excess returns in contrast to other films but they increase revenues particularly in the international market. They were also found to contribute to the hedging strategies of studio executives since the revenue variances are lower, i.e. R-rated films lose money less often.

1.1.6. Cast and director

Another well studied subject in this field is the impact of cast on the financial success of a film. A variety of methods was used to investigate the relationship. While Litman (1983) utilized high-profile film participation rate of the actors, Basuroy & Chatterjee (2008) looked at awards while Prag & Casavant (1994) used personal industry knowledge to decide on superstardom status. Wallace et al. (1993) also tried to measure the impact of stars on the box office revenues of the

film. Among the control variables he used were the year of release, quality rating, parental guidance rating as well as country of origin, costs, length in minutes and genre.

However, Ravid (1999) documented the opposite. On a sample of 200 films that stars play no role in the financial success of a movie, when the budget seemed to take all the significance disregarding the source of spending.

The director rating was also included in some of the studies as one boosting movie's revenues. Litman & Kohl (1989) found the use of stars and top directors is positively correlated with box-office revenues.

1.1.7. Time of release and distribution

The time of release was also included in the list of potential factors to affect the box-office success. Sochay (1994) made a contribution in this field by introducing measures of competition between films in their opening weekend in the revenue function model of analyzed movies.

This study was further developed by Corts (2001). He makes a research into the release-date choices of distributors and finds that the release date depends on how the production is organized. When two films share a production company and a distributor, the movies are released further apart. This allows to soften the direct competition between the films. Fee (2002) examines the investment decisions of distributors to finance films. Among his findings is that the distributors are less willing to finance films with high "artistic stakes", meaning that the producer of the film also serves as its director and writer. Sorenson and Waguespack (2006) investigate the ties between the distributor and the principal participants of a movie project (such as director, producer, cast and writer). They find that such ties enhance the film's budget and marketing expenses affecting the overall revenues in a negative way.

The moment a movie is released was also documented to have an effect on the box-office performance of a movie. Some researchers also add year controlling for the peak years in movie viewership. Radas & Shugan (1998) found support for the effect seasonality has on movie performance. Movies released during peak seasons or peak years show better performance at the box-office than those released outside of that.

1.1.8. Genre

The relationship between the box-office revenue and genre still remains unclear. Researchers receive different results. Collins et al. (2002) concluded genre should be regarded as a control factor. The question is also aggravated by the fact that attributing a movie to a specific genre presents a difficult problem in research. The characterization of movies tend to be subjective since

quite a few films can be related to one particular category (Ravid, 1999). Taking the example of Titanic, one can agree that this is a love story as well as action adventure and historical film.

Among the findings about the impact of genres, we can highlight the observations of Prag and Casavant (1994) stating that the only significant genre dummy in their extensive study of 652 films was a drama variable negatively affecting the revenues. In Sochay (1994) study all of the genre variables were found to be insignificant.

1.3. Motivation for sequel production

With the expansion of the practice of sequels production, the literature has focused on the economic rationale of this activity of studios as well as analyzing the financial results of it.

The primary reason for shooting sequels is to leverage the success of the initial movie into corresponding brand extensions, when, for example titles such as The Pirates of The Caribbean, combine actors, plots and directors into a successful formula (e.g., Keller, 1998). Attaching an existing brand name to a new movie is particularly helpful to raise consumers' interest in the new product at the time of a launch (Keller, 2003). In the market of products whose diffusion function shows an exponential-decay pattern (e.g. books, movies, video games), using a brand recognizable to customers allows to generate higher revenues immediately after the new product has been made available to the public.

Research by Claycamp and Liddy (2009) and Milewicz and Herbig (2014) demonstrates that brand name is an important risk reducer for consumers. At the same time the producer can expect cost saving on using the same technologies, decorations, costumes and concept while expecting a certain customer base to be in place for the sequel.

However, defining whether a film can be considered a sequel or not can be a question in itself. Here, the similarity between the original movie and cast should be analyzed. The difference in time must be also seen as a defining factor for attributing a movie to the segment of sequels. Sometimes, the difference between the first and the second movie can be several decades, so that the latter one possesses more attributes of an original movie rather than continues the story of the preceding film.

The literature review reveals two approaches to analyzing the sequel performance. The first one includes comparing the performance of the sequel with the parent movie, and the second one is assessing sequels in contrast to other non-sequel films.

Following the first approach, the scholars tried to answer the question of how to predict the financial performance of sequels taking into consideration the results of the parent movie. Economic theory argues that sequels are destined to fall short of the performance of their parents. Basuroj and Chatterjee (2008) addressed different sequel characteristics in their study and found that sequels produce lower revenues than the parent movie offering smaller rate of return, while shorter time lags were found to positively affect the revenue generating potential of a sequel.

Some studies included a sequel dummy variable in their equations (e.g., Hennig-Thurau, Houston, and Walsh 2006). Their results showed that sequels generate higher revenues in contrast to comparable films. This, however, can be undermined by the fact that sequels are systematically provided with higher budgets and larger screens number (Basuroj and Chatterjee, 2008). Addressing the limitations of the studies above, it should be mentioned that they do not estimate the extension value of individual movies and the degree of fit between the parent and a sequel. These limitations were addressed in the study of a brand extension success factors conducted by Thorsten et al (2009). They found distribution intensity and brand awareness of a parent film to be of critical importance to a sequel's success. They further developed an approach for monetizing the brand extension value of products.

One of the evidences of cost efficiency of producing sequels was presented by Basuroj et al. (2006). Using the signaling theory they analyzed how customers perceive different information about the quality of the movie and how it affects their go/non-go decision to the movie theatre. Among their findings is the positive interactions between sequels and ad expenditures. This relationship implies that the same level of advertising spending will generate more box office revenues for sequels than for non-sequels. Consequently, studios can potentially spend less money on advertising sequels than on other films to generate certain revenue.

While the first critical decision for movie makers is whether to proceed with shooting a sequel, the second question is the actual time of a release of a new movie, e.g. how quickly the sequel should follow the parent. The current practice is mixed. There are some franchises that keep the constant time intervals between release of movies (e.g. X-men), while some accelerate the release of sequels (e.g. The Matrix). Of course, studios may not have the full control and sometimes need to postpone shooting of a sequel due to the acting schedule of the cast involved. For example, the release date of The Mission Impossible 3 needed to be postponed due to the agreement of Tom Cruise to star in Collateral film. Anyway, the studios are aimed at maximizing revenues and keeping strong the positive associations between the parent movie and a new release. The research shows that the accessibility of these associations depend upon their strength in memory (Wyer and Srull, 1986) as well as retrieval cues provided by the studios in marketing of the sequel (Lynch and Srull, 1982).

Though being a more psychologically oriented study, the research of Sood and Drèze (2016) is quite remarkable in explaining the difference why some sequels fail in keeping the revenue level with the parent. They examined movie sequels on the perceived similarity with the parent movie and the subsequent likelihood of satiation of the viewers. They analyzed how adding new genres and actors in the sequel affect the satisfaction of people with the film, as well as the effect of different naming strategies. Surprisingly, dissimilar sequels were rated higher by survey participants than similar sequels, while named titles (e.g. Daredevil: Taking It to the Streets) were rated higher in the IMDB.com database than numbered titles (e.g. Cars 2). They come up to a conclusion that a naming strategy can be especially useful for boosting the opening-weekend reception.

While all the previous research was aimed at assessing the one-time effect of shooting a sequel and comparing it with ordinary movies, Dhar et al.(2011) set a goal to examine how the effectiveness of a sequel strategy changes over time. Though the sample is limited only to 26 nationally distributed films, they got the results congruent with studies Hennig-Thurau et al. (2009) who concentrated on shorter time periods.

The remarkable thing Dhar et al.(2011) observe is that parent movies have higher total week attendance, while sequel movies have higher ratio of first-week to second-week attendance. They also continue the questioning line started by Eliashberg et al. (2006) about the reasons why there is no a rising trend in the number of sequels produced. One of the cases, is that sequels are more costly to make in contrast to parent movies. This is explained by a fee increase of the main cast for a movie. Their participation is usually crucial for the success of a sequel but due to the success of the first movie, they are willing to set higher fee level for new films. Furthermore, it is a complicated task to bring the same production and artistic team together due to the scheduling issues.

This research primarily deals with the question whether to proceed with the decision of shooting a sequel and when exactly plan a release in case of a positive answer. Studies in this field provide limited practical tools providing film producers with a practical tool of decision making and forecasting of potential results. Model that is going to be a final outcome of this study will incorporate elements of Monte-Carlo simulation in order to suggest movie producers a workable strategy.

Based on the theoretical review conducted in this chapter we are going to create a model of forecasting sequel revenue streams while employing such variables as production budget and user generated content.

1.4. Summary of Chapter 1

In this chapter, we delve into the industry specifics of movie production as well as review the theoretical background on factors of box office success. We then delve deeper into the sequel production strategy assessing the results of sequel production with non-sequels as well as the parent movie.

The research findings are mostly consistent between each other and find production budget, advertising, critic reviews and the distribution intensity to be positively correlated with the revenue generating power of movies. However, the research demonstrates that the period when the effect takes place is different in time. Advertising, high production spending and renowned cast can produce strong opening weekend results, but the effect weakens overtime whereas critic reviews gain more influence.

Sequels, in turn, are seen as more cost effective in contrast to non-sequels and a certain level of success can be guaranteed since this new movie is based on a proven success concept and loyal viewers of a parent movie. Sequels were found generate less revenue than the parent movie, though better than other non-sequel films especially in the first weekend. At the same time, production of a sequel is congruent with potential problems of scheduling the same cast and increased fees of the actors involved.

Based on the theoretical review presented in this chapter we outline 2 hypotheses that need to be checked in the empirical part of the study, summary of the hypotheses is presented in Table 3.

Table 3. Summary of hypotheses to be tested

H	Description
H1	<i>The determinants of box office performance of a sequel release can be modelled</i>
H2	<i>The constructed model of box office performance has sufficient predictive accuracy to serve as a basis for managerial decisions</i>

CHAPTER 2. MODEL DESIGN

2.1. General description of the model

The problem set by this research paper is to make a strategic decision whether to shoot continuations of the initial movie or not. The criteria upon which the decision is based is net present value of revenues from a movie. In a model we plan to predict the costs and revenue of a sequel. For these reasons we are going to use two methods for our research: statistical and regression analyses.

Regression analysis

One main regression is built in the study and is aimed at finding the intercorrelation between the box office of the opening weekend and various characteristics of the movie production, distribution and exhibition process.

In order to predict the first weekend box office results, a linear multivariate regression “determinants of box office” has been built. The basic model is the following:

First Weekend box office = $\alpha + \beta_1 * X + \beta_2 * Y + \beta_3 * Z + \varepsilon$, where

- X – vector of variables, which reflect the production and distribution process;
- Y – vector of variables, which reflect the contents of the movie;
- Z – vector of variables, which reflect the popularity of cast and director;
- $\beta_1, \beta_2, \beta_3$ – vectors of unknown coefficients;
- ε – random variable.

The dependent variable – size of the premium paid is calculated using the methodology of Moeller et al.: the deal value divided by the market value of equity of the target 1 month prior to the deal announcement (Moeller et al., 2004).

We group all the independent variables into three categories: variables, which characterize the production and distribution process; variables, which characterize the contents of the movie; and variables, which characterize the popularity of cast and director.

Statistical analysis

The obtained determinants of box office success will then be tested upon the degree of uncertainty associated with them on a sample of sequels. This would help to identify the variables which then be simulated via Monte-Carlo simulation and inserted into the model.

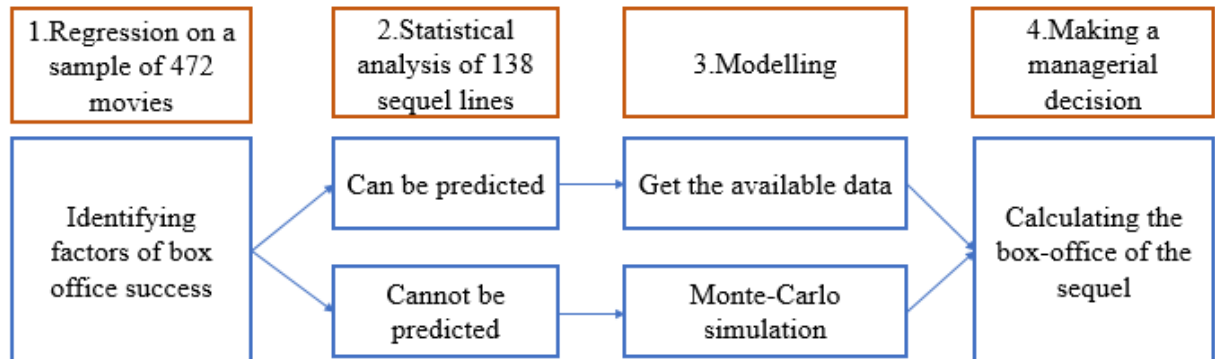


Figure 1. The process of creation a model for sequel strategies

The cost side of movie preparation will be derived from the existing literature that covers the practical aspects about the cost side of shooting sequels.

2.2. Identifying the box office success factors

2.2.1. Sample description

For sample selection, the database of 5044 films was chosen. It was collected by the community known as Kaggle that hosts the competitions for specialists in machine learning. In order to collect a final sample out of this dataset a certain criteria for selection were established. The goal of using these criteria was to pick up comparable movies in terms of size, contents and audience.

Criterion 1: Movies are produced in the United States of America and were released in the English language.

Criterion 2: All movies in the sample have to be released in the US theatres within the period starting from 1 January 2000 till December 31, 2016.

Criterion 3: Films have gathered more than \$10 mln. in its opening weekend that demonstrates a certain scale of marketing and distribution efforts as well as the comparable size of target audience.

Criterion 4: Films' production budget exceeds \$1 mln. dollars. This help to exclude low-budget movies made by independent studios that unexpectedly become a success such as *Paranormal Activity*.

Criterion 5: all movies included in the sample got at least 300 user reviews on the IMDB.com web-site. User reviews are not only indicators of the public interest in a certain film, but serves as a proxy of the number of people who watched the movie.

Criterion 6: information about the production budget and opening weekend results should be available.

These selection criteria left us with a sample of 472 movies with more than 20 movie releases in each year (except for the year 2016). The peak year is 2004 when 39 sample movies were shown in theatres (see Table 4).

Table 4. Sample size

Year	Sample movies	Percentage
2000	26	6%
2001	30	6%
2002	30	6%
2003	33	7%
2004	39	8%
2005	28	6%
2006	28	6%
2007	26	6%
2008	29	6%
2009	23	5%
2010	26	6%
2011	28	6%
2012	28	6%
2013	35	7%
2014	33	7%
2015	21	4%
2016	9	2%
Total	472	

Total revenue generated by the sample movies is 67.2 bln USD with *A Million Ways to Die in the West* to be the most successful movie in the box office with gross ticket sales of 750 mln USD. The average total revenue of the sample movies is 142 mln USD with the first week box office contributing 43 mln USD to it. 45 per cent of all the movies in a sample fall within the range of generating from 15 to 29 mln USD, with 6 per cent of films getting more than 100 mln USD in the first week end (see Figure 2).

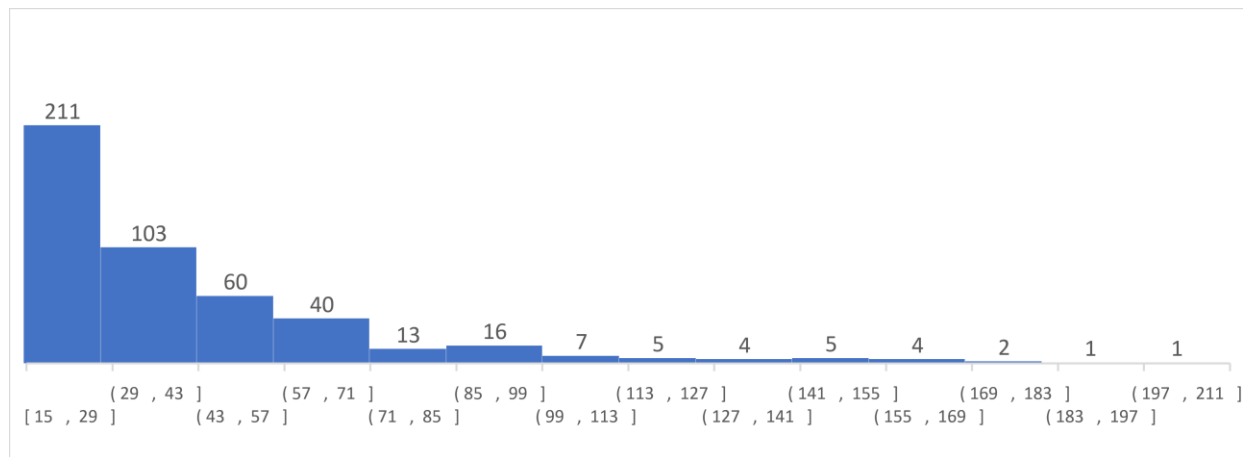


Figure 2. Distribution of sample movies by first week box office, mln USD

The movies in the sample were shot by 262 directors in general. The biggest number of films was produced by M. Night Shyamalan and Steven Spielberg with 8 movies produced by each of them. 163 directors are presented in the sample only with one movie (see Appendix 3). The most popular actors are the following: Johnny Depp is the main actor in 14 sample films, Tom Cruise with 11 movies and Tom Hanks, Denzel Washington, Will Smith and Matt Damon with 9 movies for each of them (see Appendix 4).

The average IMDB user score for the sample movies is 6.7 out of 10 possible. The highest in the sample was generated by The Dark Knight (2008) that received 9.0 and the lowest one was obtained by Epic Movie (2007) with the score of 2.3. The user reviews number has been volatile for the sample and varied between 300 and 4660.

As for the MPAA rating, the vast majority of them was given PG13 rating by the American movie association. It means that these movies have restrictions for children under 13. They can watch PG13 movies in the theatres only if being accompanied by parents. The second biggest part of sample movies was given an R-rating, i.e. people under 17 years old can watch these movies only being accompanied by parents. The smallest share of movies are G-rated, meaning that they can be watched without any restrictions by the general public. It is worth mentioning that there are no NC-17 (No One 17 & Under Admitted) rated movies in the sample, that is the strictest rating in the system.

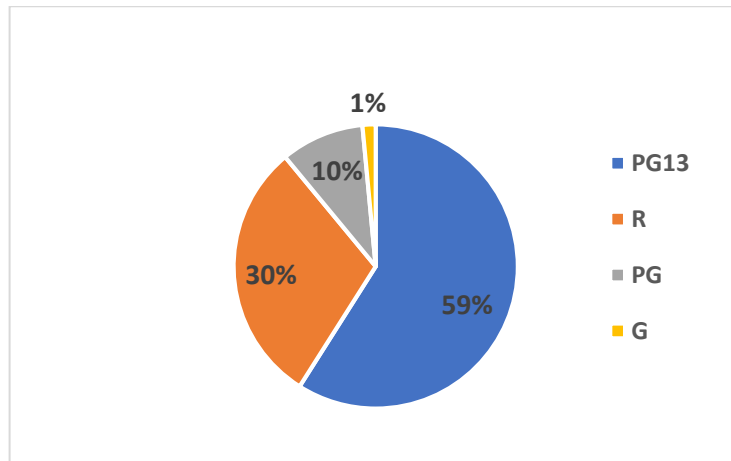


Figure 3. Distribution of sample movies by MPA rating

As for the genres, movies are usually attributed to several genres. For the research purposes we have used the first genre value in a dataset implying that it best characterizes the movie contents. Almost half of the movies were attributed to the action genre with comedy and adventure to be the next most popular genres (see Table 5).

Table 5. Distribution of sample movies by genre

Genre	Movies	Share
Action	224	47,5%
Comedy	64	13,6%
Adventure	57	12,1%
Drama	44	9,3%
Horror	25	5,3%
Crime	21	4,4%
Biography	21	4,4%
Mystery	7	1,5%
Sci-Fi	2	0,4%
Animation	2	0,4%
Fantasy	2	0,4%
Romance	1	0,2%
Animation	1	0,2%
Documentary	1	0,2%
Total	472	

2.2.2. Methodology and variables

In order to identify the determinants of box-office revenue of a movie, a set of 30 variables was collected and grouped in three clusters. To explain the behavior of the first week box office revenue, a regression model is built. In this particular section we investigated the different movie metrics and their signaling power for first-week box-office revenue. The proper variables were chosen based on the research results described in the previous chapter. The variables included in the initial regression model are presented below with a brief explanation.

Table 6. Description of variables

Variable	Empirical definition	Measurement approach
Dependent variable		
FW	US box office earnings of a movie in millions of dollars in the first week	The amount of ticket sales in dollars in the first weekend after release (Deniz and Hasbrouck, 2012).
Independent variables		
Production and distribution		
Year	Year	The year of release (Basuroy and Chatterjee, 2008)
Scr	Number of theatres where movie is shown	Represents distribution intensity (Basuroy and Chatterjee, 2008; Basuroy, Desai and Talukdar, 2006)
Bud	Production budget of a movie	Normalized production costs (Basuroy and Chatterjee, 2008)
Dur	Duration of the movie in minutes	Allows to distinguish between short and long movies

		(Kappuswamy and Baldwin, 2012)
Contents		
Anim, rom, bio, doc, hor, adv, crim, myst, dram, com, fant, sci, act	Genre	Categorical variable for movies that divides them into one of 13 genres by IMDB.com (Deniz and Hasbrouck, 2012)
Pg13, g, r, pg	MPAA rating	4 mutually exclusive variables; 0-1 meaning for each movie (Deniz and Hasbrouck, 2012; Ravid, 1999)
Critrev	Critic reviews	Number of critic reviews on IMDB.com that presents the expert generated content (Pangarker and Smit, 2013)
Rat	Average user rating	Average grade given to a film by the general public on the IMDB web-site (Ravid and Basuroy, 2004)
Usrev	Number of user reviews	Number of user reviews on IMDB.com that presents the user generated content and the hype around a movie (Pangarker and Smit, 2013)
Votus	Number of votes	Number of votes for a particular movie on IMDB.com web-site. Allows to control for the rating variable and eliminate those

		with low number of votes and thus big rating
Cast and director		
Dirfac	Director's FaceBook likes	Number of likes indicates the popularity of directors among public and can be viewed as alternative to counting Oscars and
Act1fac	The main actor's FaceBook likes	Stands for popularity of particular actors
Castoffac	The number of likes on FaceBook given to the whole cast	Stands for popularity of the whole cast

The sources used for data collection were IMBD and boxofficemojo.com. IMDB.com is one of the largest online databases of information related to movies, television programs and video games. It receives over 100 million unique visitors every month. From this website we extract data about user rating and expert rating. We supplement this data with box-office revenues and other specific movie information from boxofficemojo.com, which is also considered to be one of the biggest databases of movie industry information.

To obtain better understanding of interrelations between these variables, a simple correlation test between variables and dependent variable was conducted (see Table 7). As in the articles of other researchers, box office performance positively correlates with the number of theatres where the movie is demonstrated, the production budget as well as reviews about the movie and rating. MPAA ratings turned out to have no clear connection with the box office performance. Among the genres tested, only documentary, crime and biography happened to have statistically significant correlation with the weekend revenue. Among the variables that describe the popularity of actors and directors, only FaceBook likes of the cast turned out to be statistically correlated, though the measure of correlation is relatively small.

Table 7. Correlation test results

Variable	Corr. Coefficient. With US Box Office in the first weekend	p-value	Significant ($\alpha=.05$)
Theatres	0,670	0,000	YES
Budget	0,600	0,000	YES
User reviews	0,450	0,000	YES
Critic reviews	0,450	0,000	YES
Votes of users	0,450	0,000	YES
Duration	0,270	0,000	YES
Year	0,260	0,000	YES
Rating	0,190	0,000	YES
Documentary	0,170	0,000	YES
Cast FB likes	0,170	0,000	YES
Crime	0,100	0,030	YES
Biography	0,090	0,050	YES
Main actor FB likes	0,050	0,240	NO
Drama	0,040	0,380	NO
Director's FB likes	0,040	0,300	NO
R	0,040	0,390	NO
Fantasy	0,008	0,850	NO
Horror	-0,001	0,970	NO
Comedy	-0,006	0,890	NO
Animation	-0,010	0,760	NO
Thriller	-0,010	0,380	NO
G	-0,013	0,782	NO
PG	-0,014	0,760	NO
PG13	-0,025	0,580	NO
Mystery	-0,030	0,460	NO
Sci-Fi	-0,030	0,410	NO
Romance	-0,030	0,420	NO
Adventure	-0,050	0,270	NO
Action	-0,060	0,160	NO

We then examined the model by employing ordinary least squares approach using the stepwise procedure. The final model is listed in Table 8 and 9. It explains approximately 57 per cent of the variation in the first week box office revenue variable. The significant predictors are Theatres, Production Budget, User Reviews, Rating and Crime with each of them having a positive effect on box office performance.

Table 8. Model coefficients

	Coefficients	t-value	Coefficients	t-value	vif	R ²
Theatres	0.00068***	11.35				0.4898
Budget	0.19620***	5.85				
User reviews			0.0004***	8.05	1.13	0.5558
Critic reviews			0.0005**	2.57	1.43	0.4960
Votes of users			9.4200***	1.27	1.57	0.5442
Duration			0.0015	1.34	1.68	0.4906
Year			-0.0118**	-2.15	1.59	0.4938
Rating			0.1144***	4.55	1.53	0.5111
Cast FB likes			0.4300	0.43	1.51	0.4888
Crime			0.2380 **	2.03	1.51	0.4966
Biography			0.1050	0.88	1.50	0.4895

Table 9. Model Summary

	Coefficients	Std. Err.	p-value
Theatres	22 491***	1 760	0.000
Budget	.0617784 ***	.016835	0.000
User reviews	10 314***	1 420	0.000
Rating	2 325 241***	771 110	0.003
Crime	8 059 189 **	3 435 136	0.019
Cons.	-6 312 807***	7 299 090	0.000
R ²	0.5697		
Adjusted R ²	0.5649		
Significance	0.0000		
Notes: *** Denotes significance at 1% level ** Denotes significance at 5% level *Denotes significance at 10% level			

The formula for the final regression is the following:

$$\text{First weekend box office} = -6\,312\,807 + 22\,491 * \text{theatres} + .0617784 * \text{budget} + 10\,314 * \text{user reviews} + 8\,059\,189 * \text{crime} + 2\,325\,241 * \text{rat},$$

Since we used normalization for running the regression, we divided both first weekend box office (fw) and production budget (bud) by the maximum amount given in the sample. If we want to quantify the effect of change in each variable, we need to decode this by multiplying back the number we used to normalize both Fw-variable and Bud-variable.

Spending one additional 1 mln USD on production is forecasted to increase opening results by 61 778 USD. By exhibiting a new in one more theater, movie studios can generate 22 491 USD of

revenue. Shooting films of the crime genre is forecasted to bring 8 mln USD in ticket sales. The most powerful variable affecting the ticket sales is the IMDB score. Increase by one score point can bring 3.6 mln USD.

A number of users who reviewed the movie has a positive coefficient. When we consider this result in a practical example, it would mean that the explanatory power of first-week revenue comes from the volume of reviews and not only from its valence, which is due to the awareness effect that increases the movie awareness among consumers through dispersion even if the review is bad. One additional user review can add 10 314 USD to first weekend sales.

In order to check the validity of the results, we need to check this regression model for the heteroscedasticity, normality of error distribution and multicollinearity. All of the tests showed the results in favor of the model that made it possible to include the regression in the final model.

2.3. Statistical analysis of sequel determinants

Out of five determinants of box office performance we have identified in the previous chapter, three of them can be controlled by movie studios while preparing movie for a release. These factors are the number of theatres for exhibition, genre and the production costs. The other two, i.e. user rating and user reviews, do not appear to be apt to be affected by movie producers and present a source of uncertainty for managers. On a sample of 138 lines of sequels we plan to investigate how these two variables used to change comparing sequels' ratings and reviews with the parent movies and preceding sequel.

2.3.1. User rating and user reviews distribution

For the analysis of user rating distribution, two samples of sequels were collected from IMDB.com website and boxofficemojo.com. We started with a dataset of 1024 sequels from the year 1973. For the purpose of consistency of the results we have limited our sample with sequel lines that satisfy the following criteria.

Criterion 1. The parent movie was released after 2000.

Criterion 2. The box office performance of the first week is more than 10 mln USD.

Criterion 3. There is a clear sequel link between movies that is expressed in the similar name of movies and/or cast.

Manually we have identified 138 lines of movies 'parent movie + sequel' and among them there were also 38 movie lines 'parent movie+2 sequels'. Totally, we obtained 314 observations.

Analyzing the dynamics of shooting sequels in time with the first sample, we can observe that each year there was a changing dynamics for prolongation of movies as sequels. In the years 2000-2004 more movies were prolonged in the form of sequels with a relative decrease in the following four years. The wave of new original movies to be prolonged as sequels came again in 2010-2012 with overall 33 movies to be released and then continued as sequels. For the subsequent sequels, 2003rd and 2004th years were the highest in the number of releases with 13 and 15 sequels to be demonstrated in movie theatres. The highest number of second sequel releases can be observed in the years 2014 and 2015 with total number of 10 second sequels in movie theatres (see Appendix 1).

As for the user rating dynamics (see Table 8), we can see that the original movies had an average rating of 6.6 with the highest rating to be received by The Dark Knight (2008) with the score 9.0 and the lowest rating of 3.6 to be received by Dungeons & Dragons (2000). The first sequel was on average rated lower. First sequels gained 6.0 that represents an 8% decrease in contrast to parent movies. Out of 138 movie lines only 18 sequels gained a user score higher than the original movie. While analyzing the user reviews dynamics of the first sample, we can observe that the volatility of user reviews is much higher. As this variable represents hype around a movie, we can conclude that sequels gain less viewers' attention than the original movies that can be clearly seen in sequels getting on average half the number of the critic reviews (-54%) the first movie received. Only 2 sequel movies managed to receive more user reviews than the first one.

Table 8. 'Parent + sequel' movie lines

	Parent movie		Sequel movie		Difference		
	Rating	Reviews	Rating	Reviews	Years	Rating	Reviews
Minimum	3,60	4	3,10	2	0	-43%	-96%
Average	6,57	677	6,01	332	3,18	-8%	-54%
Maximum	9,00	5084	8,70	2729	15	36%	38%

As for the sample with 38 movie lines 'parent + 2 sequels' (see Table 9), one can observe that the first movie is rated even higher than the original movie in the first sample. However, for the first sequels the same decrease in user rating is documented (-8%). The second sequels, in turn, are rated by viewers even more positively. These films gain 2 per cent higher rating on average than their preceding story lines. The user reviews demonstrate much more volatile dynamics. Though, the difference between the first sequel and the parent movie is almost the same in the second sample as in the first sample (-47%), the hype around the second sequel is close to the level of the first movie (-18% to the results of the preceding movie) that goes in line with the average rating dynamics for the same sample.

Table 9. 'Parent + 2 sequels' movie lines

	Parent movie		1st sequel		Difference		
	Rating	Reviews	Rating	Reviews	Years	Rating	Reviews
Minimum	3,8	59	3,1	11	1,0	-43%	-92%
Average	6,8	985	6,3	549	2,3	-8%	-47%
Maximum	8,8	5084	8,7	2426	6,0	14%	9%

Table 9. 'Parent + 2 sequels' movie lines (continued)

	2nd sequel		Difference		
	Rating	Reviews	Years	Rating	Reviews
Minimum	3,2	2	1,0	-31%	-100%
Average	6,2	538	2,5	-2%	-18%
Maximum	8,9	3230	12,0	27%	80%

There is also a clear difference between releases of the movies in the first and the second sample. While it took 3.14 years on average to produce and set in theatres the first sequel in the first sample, the same results for the second sample is 2.3 years. The production of the second sequel took movie studios more time, i.e. 2.5 years on average. The time difference between the first and the second sample can be explained by the fact, that trequel movie lines were initially intended to be with a third movie, that made them shoot some scenes of all three movies simultaneously that facilitated the production process at later stages. For both samples both change in rating as well as change in user reviews were tested in Stata and were documented to be randomly distributed (Appendix 2).

2.3.2. Modelling of user rating and user reviews

We use the obtained data for simulating the user rating for new sequel production and the number of user reviews. In order to simulate user rating, we need to get the interval for random distribution. After we have eliminated three movies with extreme rating change (+27% for Boogiman 2, +36% for Gragon podzemelie and -43% for The Butterfly Effect 2), we can observe that the rating for sequels varies within the range of -33 per cent and +10 per cent compared to the rating of the previous movie. For the trequel the interval of variation is smaller and depends on the value obtained while simulating the user rating for the sequel. For the simulation purposes we use the interval after eliminating two extreme rating changes (The Butterfly effect 3 got 27 per cent higher rating due to low base and V/H/S Viral with its rating decrease of 31 per cent). In our model we plan to use rating distribution between -17 per cent and +13 per cent of the rating of the previous movie (see Table 10).

Table 10. User rating interval for sequel movies used in simulation

	For sequels	For trequels
Maximum change in rating with the preceding movie	+10%	+13%
Minimum change in rating with the preceding movie	-33%	-17%

The variation analysis of user reviews demonstrate that sequel performance can vary greatly from the previous movie. For the movie lines that got more than 400 reviews for the parent movie, sequel used to get from 10 per cent of its quantity to 110 per cent. For the purposes of valuation we plan to use the following formula in our simulation implying that it captures the randomness of the distribution.

Number of reviews, $X = \frac{1}{3}X_0 + Rnd \frac{2}{3}X_0$, where X_0 is a number of reviews for the very first movie.

After analysis of the distribution for all the movie lines in the sample, we can conclude that the variation of user rating and user reviews can hardly be predicted. While rating can serve as a proxy to the quality part of the movie, a high score cannot still be guaranteed by a good script and visual effects. 87 per cent of sequels in our sample received lower user rating than the parent movie and only one sequel managed to get more user reviews than the previous film. These results can be partially explained by the expectations that the viewers already have before coming to the movie theatre in contrast to the situation when they watch a brand new film. Such findings prove the fact that even though sequels can be viewed as brand extensions of original movies, the financial performance of them is still highly unpredictable and thus needs simulation.

2.4. Simulating net profit for sequel releases

2.4.1. Cost calculation

On the cost side, there are three main groups of spending that need to be incorporated into the model. The first one is the production budget. It includes fees to the cast, technical effects, salaries to crew and decorations, etc. As for the forecast of production costs, movie studios can budget it in advance and this value can be approximated to the spending on the parent movie.

The second group of costs is marketing and advertising. It includes spending on promotion activities. Since academic literature states sequels to be more effective in terms of attracting audience and thus the marketing spending can be increased modestly for promotion of sequels.

The third group of costs is distribution and it is largely dependent on the negotiation power of the movie studio. We analyzed these costs based on the revenue received by studios in the USA and worldwide. As for the global distribution costs, they are an uncertainty because the movie producers do not know in advance what exact sum of money they will give to distributors – it depends on the revenue they will receive in domestic market and abroad. As we analyzed on our sample, the average share of USA revenue in total revenue is 38% and for non-USA revenue it is 62%. Distribution costs account for 33% of revenue in USA and 50% of international revenue (Kuppuswamy and Baldwin, 2012). Thus, we calculated that the final average revenue percentage which goes to US distributors is 12%, while for international distributors it is 31% of total revenue. As for standard deviation, it is 3% for USA and 5% for all other countries. Consequently, we have 43% as an average amount of revenue which goes to the distributors and 5% standard deviation.

Since our model analyzes the financial performance of a movie totally in the USA, we can take one third of all ticket sales as a share that will go directly to distributors and representing the costs of movie studios.

2.4.2. NPV calculation

After obtaining revenue and costs for all the movies we subtracted taxes that were calculated by multiplying the difference between all the revenues and costs by the average effective tax rate that is 31,17% (see Table 11). This number is the average of effective tax rates of 6 biggest movie studios.

Table 11. Effective tax rate for the major movie studios

Studio	Effective tax Rate	Source
DreamWorks Animation	30,0%	http://ir.dreamworksanimation.com/phoenix.zhtml?c=185803&p=irol-newsArticle&id=1666899
Twenty-First Century Fox Inc.	24,0%	http://csimarket.com/stocks/singleProfitabilityRatiosy.php?code=FOXA&itx
Walt Disney Co	33,8%	http://www.forbes.com/pictures/mef45fkfh/22-walt-disney/
Time Warner	34,0%	https://www.nerdwallet.com/blog/investing/tax-rate-paid/

Liberty Media Corp	28,1%	http://csimarket.com/stocks/singleProfitabilityRatiosstm.php?code=LMCA&itx
Comcast Corp	37,1%	http://csimarket.com/stocks/singleProfitabilityRatiosstm.php?code=CMCSA&itx
Average	31,2%	

The next step for NPV calculation is discounting profits to the current moment of time, e.g. the point of making decision. The assumption of the model is that we shoot every film in 2 years, so, for example, if we want to get the NPV for shooting the third film we will need to discount profits of this film and all the previous ones for the period 2, 4 and 6 years.

Model was intended to be a universal one despite what studio exactly has the rights to shoot the movie. This made it necessary to take an average WACC measure to discount profits. Thus, for this objective the average WACC for 8 major movie-production companies was calculated. As a result, WACC equal to 9% was obtained and then implemented into the discounting formula (see Table 12).

Table 12. Weighted-average cost of capital for major film-production companies

№	Name on the company	WACC
1	DreamWorks Animation	8,68%
2	Twenty-First Century Fox Inc.	10,01%
3	Walt Disney Co	12,34%
4	Lions Gate Entertainment Corp	8,28%
5	Time Warner Inc.	8,55%
6	Liberty Media Corp	8,07%
7	Comcast Corp	7,98%
8	Sony Corp	8,73%
	Average WACC	9,08%

For the purposes of decision making 3 NPVs are calculated: NPV of shooting 3 consecutive films, NPV of shooting just 2 films, and NPV of shooting just 1 additional film. These numbers were the criteria for making investment decisions.

2.5. Summary of the Chapter 2

In this chapter, we establish the methodology for the component parts of the model, explaining what success factors of movie release can be forecasted and what need to be simulated. We run a regression on a sample of 472 movies identifying the relation between the first week's revenue and a list of potential revenue determinants identified in the previous chapter. Among the tested variables, the user rating and number of user reviews were found to be significant and be subject to random distribution. At the same time, on a sample of 138 sequel lines we found certain patterns in the rating and reviews distribution of sequels that would allow us to run simulation building its distribution on the rating of the parent movie. The distribution costs are largely dependent on the structure of revenue between domestic and international markets. Via running 100 iterations attributing values to variables that follow random distribution and interrelating it with the performance results of the original movie that might be extended in the form of sequel, we finally get the potential financial performance of sequels.

For the purposes of this study we test 29 variables in total to identify determinants of box office success: 4 variables connected with distribution intensity and production costs, 4 variables associated with hype around a movie and quality of its contents, 4 categorical variables to describe the MPAA rating, 3 variables are associated with the popularity of cast and screen director, 12 variables are genre related and 1 variable presenting the year of release.

Via the empirical study, we have proven the hypotheses 1 and 2. The box office success of a movie was found to be significantly dependent on five factors. Furthermore, we analyzed the distribution of factors on both the revenue and cost side and concluded that they cannot be simulated via Monte-Carlo in a given interval that we obtained via analysis. All these findings served as building blocks for the model.

In the next chapter the model is going to be tested on a sample of 12 movies and results will be compared with the actual managerial decisions made by the movie rights owners.

CHAPTER 3. MODEL FINDINGS

The model is based on processing the input information about the potential sequel (e.g. production costs, genre, etc.) as well as the performance results of the parent movie (e.g. user rating, user reviews, etc.). The process of forecasting revenue from the sequels is described in Figure 3.

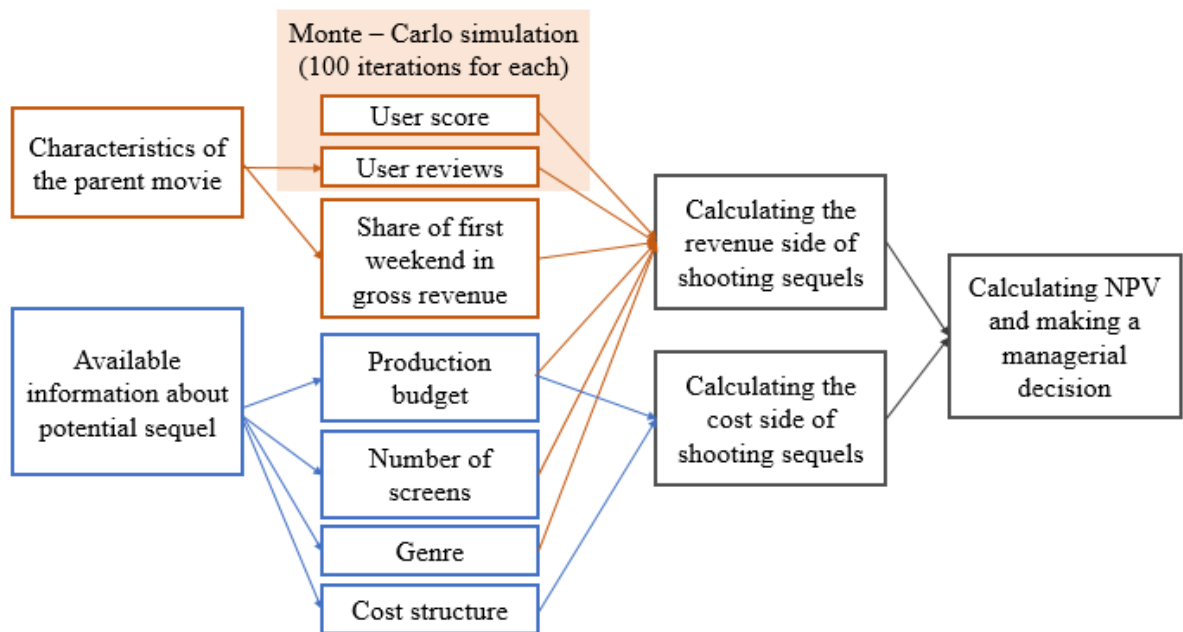


Figure 3. The process of running simulation for predicting sequels' performance

In a model we forecast financial results for shooting 3 sequel movies with a time lag of 2 years. For each movie user score and user rating are simulated via 100 iterations in an interval described in previous chapter. The next step is to check the accuracy of the model via out-of-the-sample test.

3.1. Sample description

For the purposes of model testing we have chosen movies that satisfy the following criteria:

- 1) Their production budget is within the comparable with those films used for the running the regression, e.g. are within the range of 150 mln USD and 370 mln USD as well as were shot after 2000.
- 2) They were not included in the first sample that was used to generate a regression model.
- 3) All the information about the marketing costs, critics reviews, revenues and distribution should be available.
- 4) Movie production studios have already decided upon the future development of the plot and whether to shoot a sequel or not. Overall, movies in a sample can be divided into three

groups: films that were successful in box office and had sequels already, films that were successful and have sequels planned and films that were unsuccessful in the release and for which sequels were banned.

These criteria were satisfied by the following list of movies:

Table 13. Movie sample for model testing

Movie	Year	User rating	Production budget, mln USD	Opening weekend, mln USD	Gross Box Office, mln USD	Genre
Cars	2006	7,2	120	60	240	Animation
Golden Compass	2007	6,1	180	14	70	Adventure
Ratatouille	2007	8,0	150	47	206	Animation
Pirates of the Caribbean	2003	8,1	140	46	305	Action
Alice in Wonderland	2010	6,4	200	116	334	Adventure
Lone Ranger	2013	6,5	215	29	89	Western
Pacific Rim	2013	7,0	190	37	101	Action
Avatar	2009	7,9	120	77	760	Action
Fantastic Four	2015	4,3	120	25	56	Adventure
Madagascar	2005	6,9	75	61	193	Animation
U.N.C.L.E.	2015	7,3	75	13	45	Action
Green Lantern	2011	7,0	200	53	116	Adventure
The Departed	2006	8,5	90	27	132	Crime

The movies were specially selected to present different genres, including crime as it is a part of our final regression and have various movie ratings. So, the lowest rating has been received by Fantastic Four, while the highest one (8.5) was obtained by The Departed.

3.2. Model findings

For movie the input data about the parent movie was inserted as well as costs for sequels were forecasted and used to plan profits. The detailed results are provided in the Appendix 10.

The movies, that had already sequels released, our model showed positive NPV for all installments of the franchise. Moreover, the prediction about the number of the movies to produce was also correct, the best example in the franchises *Pirates of the Caribbean* and *Madagascar*. For the movies that already have their sequels released first weekend results were compared with those predicted by the model (see Table 14). The model was effective in predicting the revenue streams for franchise movies showing variance of around 10-29%. At the same time some movies demonstrated big variance from the model's estimations. *Fantastic Four 2* movie was more successful in raising first week box office partially due to the introduction of a new story line. *Alice in Wonderland 2* turned out to be a failure since a renowned screen director for the first movie Tim Burton was replaced by James Bobin who had little experience in creating Hollywood-scale movies.

Table 14. Comparison of model financial forecast with real life performance

Movie title	First weekend revenue planned	First weekend revenue obtained	Variance	Remarks
Cars 2	73,3	66,0	-10%	
Alice in Wonderland 2	56,0	26,0	-54%	Was shot by a different director
Pirates of the Caribbean 2	111,2	135,0	21%	
Pirates of the Caribbean 3	126,5	114,0	-10%	
Pirates of the Caribbean 4	116,5	90,0	-23%	
Fantastic Four 2	32,1	58,0	81%	A new story line was introduced
Madagascar 2	62,6	63,0	1%	
Madagascar 3	66,0	60,0	-9%	

Movies that have sequels planned also showed the same results as our model, for instance the franchise of *Cars* according to our model should include 3-4 sequels, and the subsequent are planned by the studio and they are stated in the release schedule of the studio, here the great example is *Avatar* with 4 sequels planned (See Table 15).

Finally, the movie flops that were originally developed as a franchise showed the negative NPV for sequel production. Since the production of the sequel was shut down for all of the analyzed movies, it can be considered that the movie studios made similar conclusions. Here the good example is *Green Lantern*, where even the leading actor expressed his support for the decision of shutting down the franchise despite the signed contract for possible extension of the movie universe with sequels. Also, *Golden Compass* with seemingly OK results from the perspective of critics and user reviews will probably not spawn the sequel due to the pressure from religious groups and not huge success in box office.

Table 15. Comparison of model decision results with reality

	NPV, \$ mln	Decision	Reality
Alice in Wonderland	52	Shoot	Sequel in 2016
Avatar	1065	Shoot	4 movies planned
Cars	43	Shoot	Cars 3 in 2017
Fantastic Four	-60	To sell rights	Fantastic Four 2 was cancelled and crossed out from release schedule
Golden Compass	25	Shoot	Closed due to religious pressure
Green Lantern	-89	To sell rights	Ryan Reynolds said “No” to Green Lantern 2
Lone Ranger	-8	To sell rights	Planned sequel was cancelled
Madagascar	11	Shoot	Madagascar 2 & 3 were filmed
Pacific Rim	77	Shoot	In 2015 the sequel has been delayed indefinitely
Pirates of the Caribbean	332	Shoot	Released in 2011
Ratatouille	177	Shoot	Ratatouille 2 is planned in 2016/2017

The man of U.N.C.L.E.	-27	To sell rights	The movie will not spawn the sequel
The Departed	40	Shoot	Sequel and prequel were announced to be produced

All in all, the model shows the results that correspond with the reality which shows the quality of the predictions. In conclusion, the model can be used to predict the success of future installments of the franchises based on the first movie being hit or a flop in order to increase the possible revenue of the movie producers and decrease of probability of production of unsuccessful installment.

3.3. Discussion

3.3.1. Discussion and findings

In this section, we discuss and explain the received results from the modelling process, and also provide managerial implications on the findings.

As it can be viewed from the previous sections, the regression analysis run on the sample of 472 movies confirm the existence of significant relationship between such factors as user generated content, production budget, genre and the box office results of a movie. The observed relationships then allowed to build a model for projecting revenue generating potential of sequels. We will look at each of the stages of conducted research and then compare them with other academic findings.

Starting from the discussion of determinants of the box office success of a movie, the production cost variable was positive and highly significant. This is consistent with the results of Litman (1983), Ravid (1999), Pangarker and Smit (2013) and Terry et al. (2005). This can be explained by the fact that big budget films usually have well-known cast, special effects and large advertising budgets, that are aimed at attracting big viewership. As a factor describing distribution power of a movie, number of screens has been tested and found to play a strong positive role on the weekly box office revenue.

Out of genre variables only Crime has been observed to positively influence box office results. The analyzed academic literature has not provided similar results upon the role of the criminal genre. Nevertheless, Deniz and Hasbrouck (2012) identified positive relationship between Animation, Sport and Adventure genres on the movies' box office revenue.

The social media data have been found to be insignificant. Facebook likes for the cast and director as well as for the movie have been observed to have little power in predicting box office revenues. However, some papers found that the popularity of a leading actress is crucial to the success of a movie (Apala et al., 2013).

As for the user generated content, user rating and user reviews have been observed to influence the revenue and raise interest towards movie among audience. This goes in line with other works, where researchers test the influence of both negative and positive reviews while seeing bigger impact of negative reviews rather than positive ones (Basuroy et al, 2003).

Overall, the regression results go in line with the observations of other researchers that also used regression analysis and neural networks to identify the success formula of a movie.

The second stage of the research has been aimed at identifying patterns between the performance of movies within one sequel line. This type of research was not conducted by the academics outlined in the literature review, so the results cannot be directly compared. The main conclusions of the second stage of the research were that on average sequels perform worse than the parent movie in terms of the obtained user rating and user reviews. Furthermore, the variance in these factors is larger when comparing parent movie and the first sequel rather than between first and second sequels. These findings are in accordance with the observations of Basuroy and Chatterjee (2007) who also found that sequels do not match the box office revenue of the parent movie.

Further analysis of the sequel and parent movie characteristics allowed us to understand that user reviews and user ratings are a source of uncertainty for sequels since in a chosen sample they had a random distribution. This then allowed us to organize a model that would take the random nature of these parameters into account.

In order to check the accuracy and managerial applicability of the model, it was tested on a sample of 13 movies with different box office results of the parent movie in order to check the prediction power of the revenue generating potential of sequel movies. The modeling results coincide with the real-life decisions of movie makers as well as the actual revenue generated by sequels. The predicted box office performance was comparable with that of the released sequels. With two movies being eliminated for the reason of their considerable qualitative difference with parent movie, the average difference between planned and actual performance for the first week revenue equals to 11 per cent.

The constructed model has moderate predicting power since the regression model in the basis of it was explaining only 56% of movies' revenue performance. The neural networks, in turn have

higher functionality and can predict the revenue performance with up to 93% accuracy (Kaur and Nidhi, 2003; Ghiassi, Lio and Moon, 2015). On the other hand, utilization of Excel for the purpose of model construction and the relative simplicity of the model architecture can be viewed as its strong side. The model can be tailored by industry users if some important factors as changes in cast or distribution patterns take place.

3.3.2. Managerial implications

Our findings indicate a number of managerial implications for both movie makers and investors that operate in the motion industry.

First and foremost, the regression analysis suggest that managers should be aware of the fact that user reviews and ratings are an important indicator for the audience whether to view a particular movie or not. Although in our research we analyzed the total number of reviews, it is therefore important to make sure that not only quantity of reviews is a trigger for people to watch a movie, but also their quality. Movie studios should invest in marketing activities not only during the pre-release phase of a movie, but also promote the movie via paid user ratings and user reviews.

From the investor point of view, the data analysis suggests that big budget movies attract more money in the box office and their revenue streams are largely dependent on the distribution power of the film studio. The more screens will be allocated for a movie release, the more revenue this movie is going to generate. According to the research results, movies with criminal elements in its plot are expected to be more financially attractive when compared with other movie genres.

As can be inferred from our research, shooting a sequel is not necessarily a safe strategy for movie studios. Brand extensions on average attract less viewers' interest and get smaller rating score. However, their box office performance can be approximated with the suggested algorithm based on the movie metrics of the parent movie. Consecutively, sequels can be viewed as a hedging element in the portfolio of movie studios as sequel's revenue streams can be projected with a certain level of accuracy. In the business landscape of unpredictable entertainment industry sequels play a valuable role of saving time and money on search of potential blockbusters.

As our research demonstrates, in order to get the estimated revenue streams from a sequel, certain criteria towards the quality and production should be fulfilled. A new screen director can change considerably the revenue projections of a movie, while addition of a new story line can boost the box office performance.

This research has important implications for the Russian motion industry as well. Our findings imply that there are certain factors that determine the movie ticket sales. In the Russian motion industry movie producers and investors use the method of “analogues” to predict the movie performance. They compare the ticket sales of a previous film with a similar storyline and genre. While this method can be called intuitive, our model suggests more objective approach to estimating the revenue potential of a film.

3.3.3. Limitations and directions for further research

A number of limitations are associated with this study. The first one is the limited functionality of regression analysis for the purposes of identifying determinants of box office success and predicting future revenue. Neural networks can provide with accuracy two times higher than regression and can increase its predictive power with every new item analyzed.

The second limitation, is the limited number of variables to be tested. Future research should also include such parameters as marketing budget, awards and nominations by screen director and cast, as well as the time aspect of a movie release. Some periods like Christmas and other holidays were estimated to have a positive influence of a movie box office performance.

Another limitation of the research lies in the approach how the model was tested. Only 13 out-of-sample movies were chosen to generate forecasts. Increase of test sample would allow to better estimate the predicting accuracy of the model.

As for the sequel performance analysis, one of the limitation lied in the lack of qualitative analysis between movies in sequel lines. For the future research adding new variables such as screen director, plot similarity and presence of main cast could potentially give new insights on factors affecting sequel performance.

3.4. Summary of Chapter 3

In this chapter we outline how we do the model testing, provide results and then discuss the findings.

The described stage allowed us to accept the second hypothesis of our study that was stated as follows: The constructed model of box office performance has sufficient predictive accuracy to serve as a basis for managerial decisions.

The control sample was divided into two groups: parent movies with sequel extensions already released and movies without sequels but with particular plans about sequel extensions to be

announced. For the first group, model demonstrated 20% variance from the actual performance, thus showing less accuracy than neural networks already in use for these purposes. For the second subsample, the constructed model demonstrated results comparable with the real decisions made by movie producers. Only one movie was not prolonged though it was expected to generate positive NPV.

Finally, in the discussion part the analysis of the results was conducted, limitations of the research were specified and some suggestions for further research were provided.

CONCLUSION

The main goal of this research was to create and test a decision making algorithm for movie studios to allow them make a financial forecast whether it will be profitable to shoot sequels or not. Using a multiple regression, we have identified a number of variables affecting box office success of a movie. Explaining 56% of box office results in the first weekend it provided us with 5 significant determinants of first week revenue that were used in a model.

The developed model, in turn, incorporates two techniques to supplement each other, i.e. statistical and regression analyses, and finally produces an algorithm for practitioners (distributors of motion pictures). The algorithm is intended to enable movie studios to make managerial decisions about whether to purchase rights and shoot the sequel if the parent movie was already released.

Big sample size employed in this study allowed to identify key determinants of box office performance and then use it as a basis for predicting future ticket sales in the first week after the movie release. Since two variables, i.e. user rating and user reviews, were found to be randomly distributed, we used the Monte Carlo simulation for forecasting revenues. We analyzed 138 sequel lines to obtain the interval of variations of these factors between the sequels and the preceding movies.

The model allowed to predict the minimum first weekend box office needed to make profitable sequels and trequels as well as the probability of a positive net present value of a sequel project. The variance between the revenue forecast and the revenue obtained turned out to vary within 20 per cent with two movies having considerable difference in performance. It could be explained with the fact of new director shooting the sequel in contrast to the parent movie (*Alice in Wonderland* case) and new plot line introduced in the sequel movies (*The Fantastic Four* case).

In order to conduct a thorough analysis, we used 73 references; and the contribution of this study is creation and testing of a decision making algorithm for the movie studios. However, there is clearly a scope for future research. The work can be expanded via suggesting strategies to enhance box office performance of sequels after release, further investigation of the relatedness of sequels in one movie line, an analysis of marketing tools to increase hype around a movie and thus bringing more user reviews.

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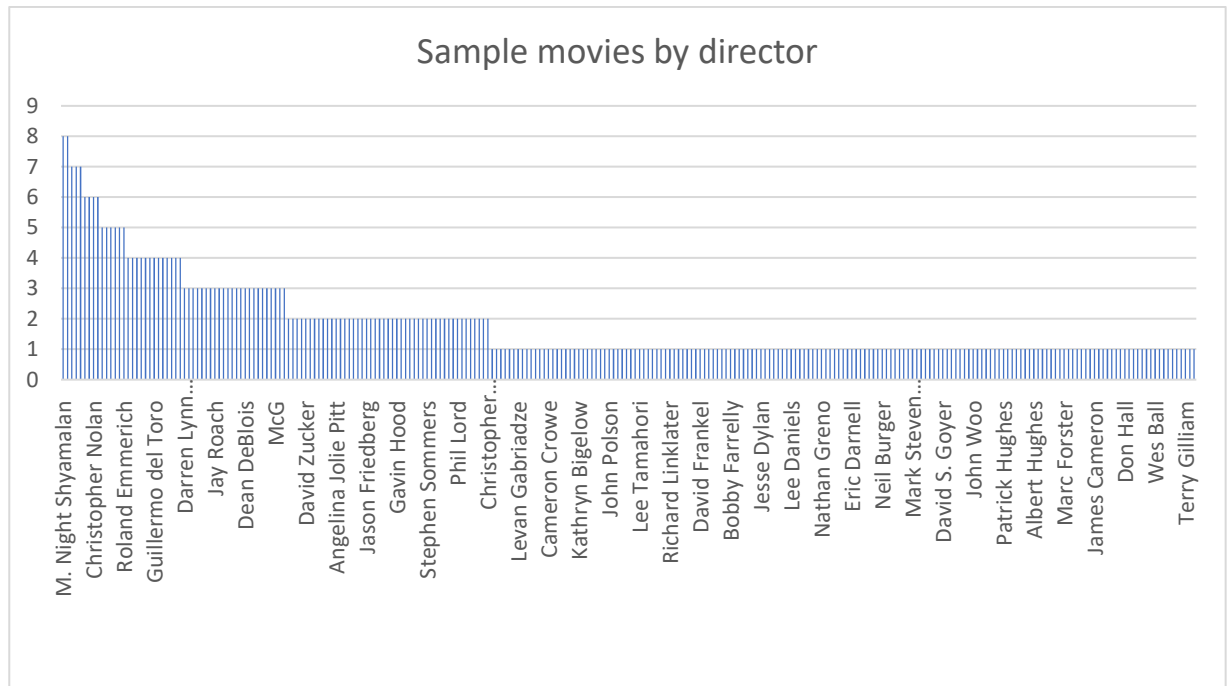
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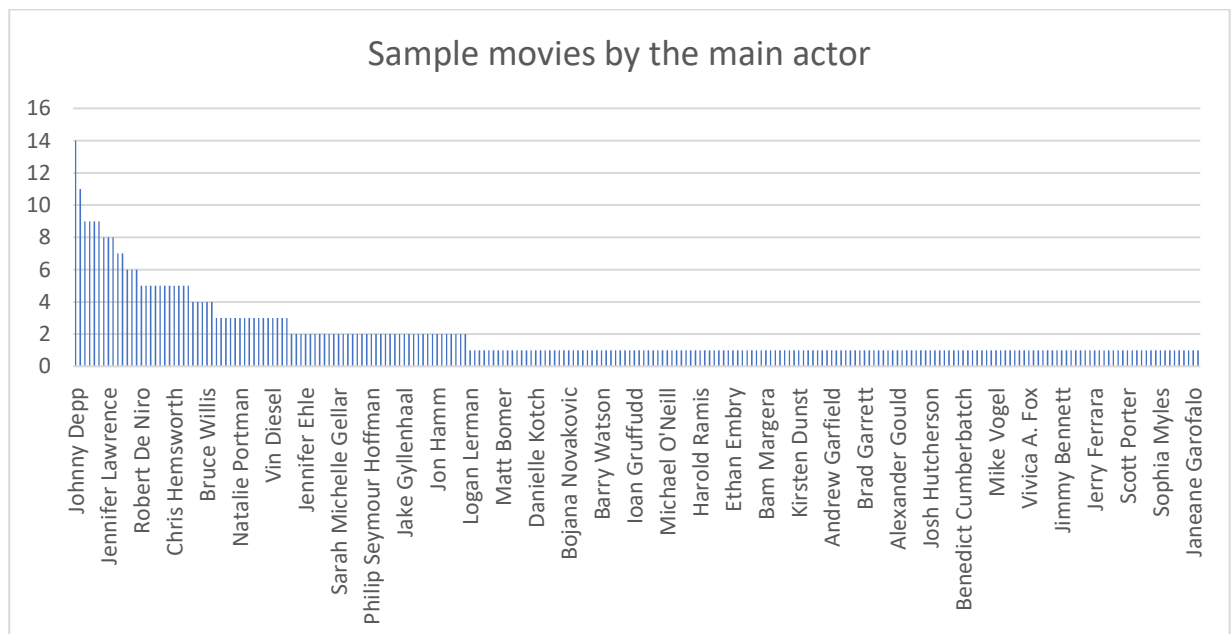
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APPENDICES

Appendix 1. Distribution of sample movies by director



Appendix 2. Distribution of sample movies by the main actor



Appendix 3. Descriptive statistics of variables for the regression

Variable	Obs	Mean	Std. Dev.	Min	Max
fw	472	4.26e+07	3.16e+07	1.50e+07	2.09e+08
bud	472	9.04e+07	6.04e+07	1000000	3.00e+08
tot	472	1.42e+08	9.88e+07	3.25e+07	7.50e+08

Variable	Obs	Mean	Std. Dev.	Min	Max
scr	472	3256.059	550.1741	837	4468
imdb_score	472	6.736864	.948525	2.3	9
usrev	472	777.0869	577.0967	301	4667
critrev	472	307.0148	142.1127	70	813
dur	472	120.464	23.3796	74	240

dirfac	472	1545.614	4481.29	0	22000
act1fac	472	13163.91	31001.58	93	640000
votus	472	262852.6	203797.1	25960	1676169
casttotfac	472	20503.88	34993.62	146	656730
movfaclik	472	26070.9	39841.2	0	349000

Appendix 4. Correlation matrix between variables

	fw	bud	tot	scr	imdb_s~e	usrev	critrev
fw	1.0000						
bud	0.6047	1.0000					
tot	0.8665	0.5615	1.0000				
scr	0.6781	0.6816	0.5765	1.0000			
imdb_score	0.1924	0.1377	0.3645	0.0290	1.0000		
usrev	0.4537	0.3424	0.5047	0.2393	0.2777	1.0000	
critrev	0.4584	0.4519	0.4371	0.4051	0.4174	0.3973	1.0000
dur	0.2726	0.3936	0.2973	0.1541	0.4019	0.4151	0.4027
dirfac	0.0471	0.0674	0.1017	0.0193	0.2903	0.3049	0.2958
act1fac	0.0537	0.0532	0.0386	0.0597	0.0808	0.0193	0.0499
casttotfac	0.1706	0.1320	0.1311	0.1397	0.1104	0.0850	0.1511
movfaclik	-0.0109	0.0125	0.0154	0.0447	0.0088	-0.0344	0.0407

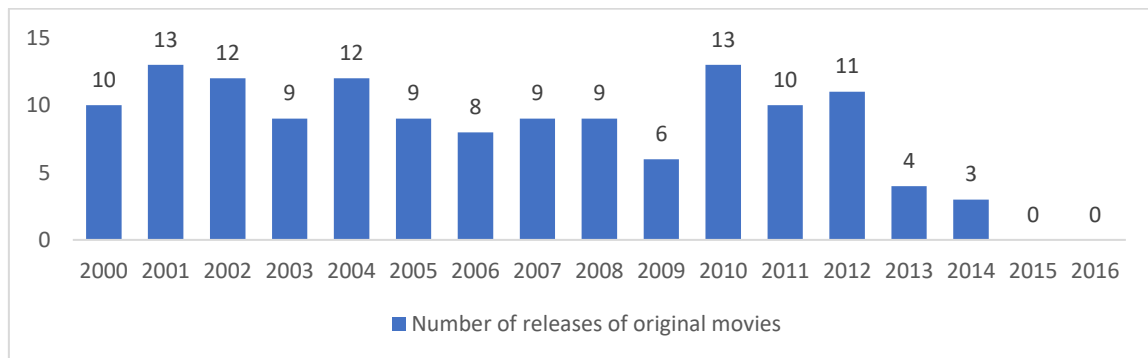
	dur	dirfac	act1fac	castto~c	movfac~k
dur	1.0000				
dirfac	0.2530	1.0000			
act1fac	0.0382	0.0574	1.0000		
casttotfac	0.0952	0.1080	0.9561	1.0000	
movfaclik	-0.0022	-0.0262	0.1011	0.0897	1.0000

Appendix 5. Final regression statistics

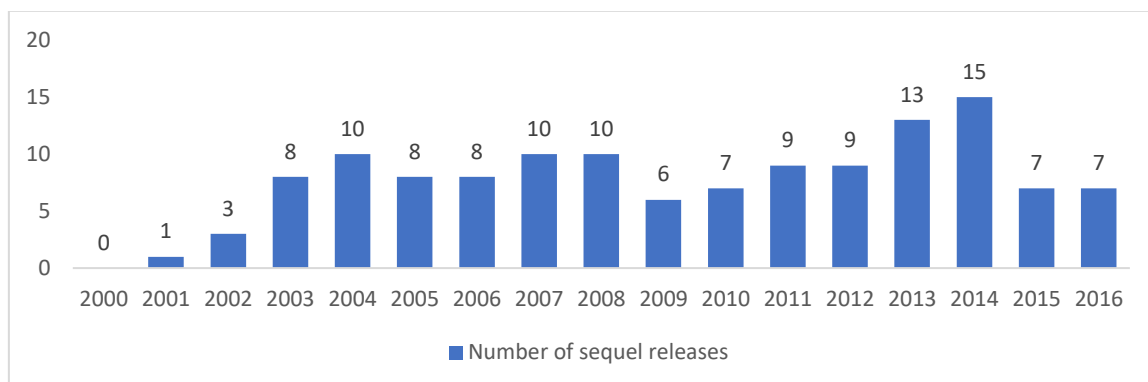
Source	SS	df	MS	Number of obs = 455		
Model	1.3186e+17	5	2.6372e+16	F(5, 449) =	118.88	
Residual	9.9604e+16	449	2.2183e+14	Prob > F =	0.0000	
Total	2.3146e+17	454	5.0983e+14	R-squared =	0.5697	
				Adj R-squared =	0.5649	
				Root MSE =	1.5e+0	

fw	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pc	.0617784	.016835	3.67	0.000	.0286933	.0948636
rat	2325241	771110.4	3.02	0.003	809807.8	3840675
scr	22491.39	1760.63	12.77	0.000	19031.29	25951.49
crim	8059189	3435136	2.35	0.019	1308249	1.48e+07
usrev	10314.07	1419.74	7.26	0.000	7523.909	13104.23
_cons	-6.31e+07	7299090	-8.65	0.000	-7.75e+07	-4.88e+07

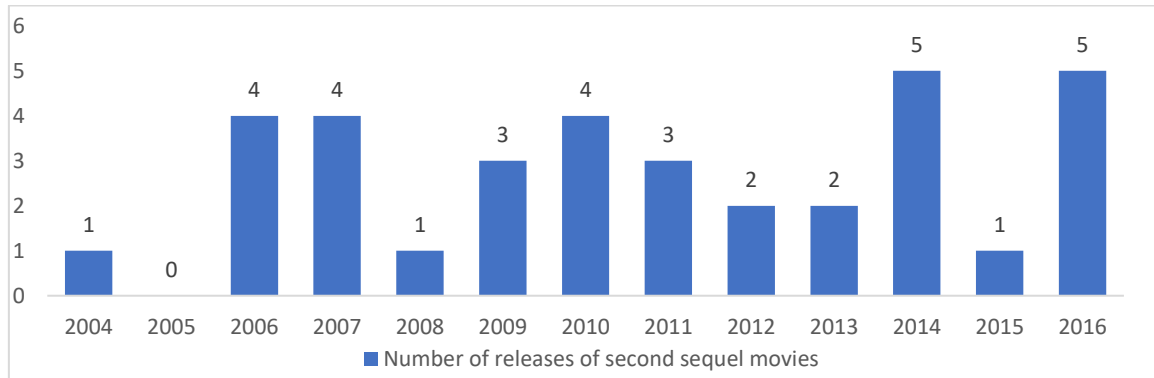
Appendix 6. Time distribution of parent movies with only one sequel



Appendix 7. Time distribution of sequel releases in a sample 'parent movie + 1 sequel'



Appendix 8. Time distribution of second sequel releases



Appendix 9. Test of distribution of user rating and user reviews

Sample 'parent + sequel movie lines'

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rat	138	0.94929	5.494	3.845	0.00006

. swilk rev

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rev	138	0.97492	2.718	2.257	0.01201

Sample 'parent + 2 sequels'

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rat2	38	0.93667	2.406	1.842	0.03271
rev2	38	0.35911	24.355	6.698	0.00000

Appendix 10. Movie simulation results

1. Movie Cars

1. Cars

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,252	6,210	6,040
	Reviews		327,8	303,7	503,5
	1st weekend revenue		73,3	74,7	74,6
	Profit		54,9	50,9	48,9
	NPV		24,0	44,0	60,0
Reality	Rating	7,2	6,2	The release is planned in 2017	
	Reviews	581,0	289,0		
	First weekend revenue obtained	60,0	66,0		

2. Golden compass

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		5,392	5,406	5,340
	Reviews		480,1	626,4	516,1
	First weekend revenue		32,8	30,5	23,8
	Profit		27,6	21,6	14,2
	NPV		14,0	25,0	32,0
Reality	Rating	6,1	Closed due to the religious pressure		
	Reviews	665,0			
	First weekend revenue obtained	26,0			

3. Alice in Wonderland

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		5,687	5,739	5,768
	Reviews		419,3	505,9	718,4
	First weekend revenue		56,0	65,1	69,3
	Profit		62,2	67,1	69,6
	NPV		26,0	51,0	71,0
Reality	Rating	6,4	6,2	Sequel was released in 2016, no yet more info	
	Reviews	726,0	184,0		
	First weekend revenue obtained	116,0	28,0		

4.
Avatar

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,963	6,977	6,982
	Reviews		1 938,5	2 193,8	1 506,2
	First weekend revenue		111,2	126,5	116,5
	Profit		1 362,1	1 361,7	1 396,6
	NPV		585,0	1 078,0	1 501,0
Reality	Rating	7,9	4 more movies are in the process of shooting		
	Reviews	3 046,0			
	First weekend revenue obtained	77,0			

5. Pirates of the Caribbean

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		7,3	7,4	7,3
	Reviews		792,0	2 059,7	1 051,6
	First weekend revenue		111,2	126,5	116,5
	Profit		423,4	445,8	346,9
	NPV		181,0	345,0	449,0
Reality	Rating	8,1	7,3	7,1	6,7
	Reviews	2 110	1 835,0	1 238,0	484,0
	First weekend revenue obtained	116,0	135,0	114,0	90,0

6. Ratatouille

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		7,190	7,208	7,247
	Reviews		501,4	440,0	456,9
	First weekend revenue		76,3	78,5	79,6
	Profit		233,6	229,8	243,6
	NPV		97,0	177,0	249,0
Reality	Rating	8,0	Ratatouille 2 is planned to be released in 2017		
	Reviews	617,0			
	First weekend revenue obtained	47,0			

7. The Lone Ranger

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		5,9	5,9	5,9
	Reviews		246,8	456,2	668,7

	First weekend revenue		76,5	81,0	85,7
	Profit		-2,5	-4,2	-13,7
	NPV		-1,4	-3,0	-8,1
Reality	Rating	6,5	Planned sequel was cancelled		
	Reviews	708,0			
	First weekend revenue obtained	29,0			

8. Pacific Rim

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,2	6,2	6,2
	Reviews		988,0	840,1	531,7
	First weekend revenue		80,9	85,2	90,1
	Profit		92,2	89,9	78,6
	NPV		37,0	68,0	91,0
Reality	Rating	7,0	In 2015 the sequel has been delayed		
	Reviews	1 104,0			
	First weekend revenue obtained	37,0			

9. Green Lantern

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,229	6,209	6,210
	Reviews		532,0	493,9	217,1
	First weekend revenue		74,6	78,8	82,7
	Profit		-107,4	-120,8	-135,6
	NPV		-90,0	-85,0	-80,0
Reality	Rating	7,0	Green Lantern 2 was abolished		
	Reviews	548,0			
	First weekend revenue obtained	53,0			

10. The Man from U.N.C.L.E.

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,524	6,438	6,516
	Reviews		175,5	234,3	275,3
	First weekend revenue		56,4	59,0	61,0
	Profit		-29,6	-41,7	-50,8
	NPV		-12,0	-27,0	-42,0
Reality	Rating	7,3			
	Reviews	349,0			

	First weekend revenue obtained	13,0	Directors announced that the movie will not spawn the sequel
--	--------------------------------	-------------	--

11. Fantastic Four

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		3,830	3,799	3,774
	Reviews		571,8	468,7	422,3
	First weekend revenue		32,1	36,3	39,7
	Profit		-70,9	-79,3	-92,0
	NPV		-29,0	-57,0	-85,0
Reality	Rating	4,3	5,6		
	Reviews	664,0	442,0		
	First weekend revenue obtained	26,0	58,0		

12. Madagascar

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		6,674	6,645	6,638
	Reviews		298,6	168,9	213,4
	First weekend revenue		62,6	66,0	70,5
	Profit		12,8	10,1	5,4
	NPV		5,0	9,0	11,0
Reality	Rating	6,9	6,7	6,9	Is at the stage of planning
	Reviews	349,0	125,0	158,0	
	First weekend revenue obtained	47,0	63,0	60,0	

13. The Departed

		Parent movie	1st Sequel	2nd Sequel	3rd Sequel
Forecast	Rating		7,519	7,581	7,501
	Reviews		1 509,7	819,0	1 488,7
	First weekend revenue		87,9	91,1	93,1
	Profit		54,2	50,4	48,8
	NPV		22,0	40,0	55,0
Reality	Rating	8,5	Both sequel and prequel are announced		
	Reviews	2 054,0			
	First weekend revenue obtained	47,0			

Appendix 11. VBA simulation code

```
Sub film7()
```

```
Dim vard(2) As Double, varu(2) As Double, sumrat(2) As Double  
Dim fw(2) As Double, pc(2) As Double, mb(2) As Double, sumfw(2) As Double  
Dim rev(2) As Double, dcosts(2) As Double, sumdcosts(2) As Double  
Dim prof(2) As Double, sumprof(2) As Double, npv(2) As Double  
Dim scr(2) As Double, scr0 As Double  
Dim ebt(2) As Double, sumebt(2) As Double, finebt(2) As Double
```

```
Dim minfw(2) As Double
```

```
Dim npvtot As Double
```

```
Dim rat As Double  
r0 = Cells(3, 3).Value  
k1 = Cells(2, 16).Value  
k2 = Cells(3, 16).Value  
k3 = Cells(4, 16).Value  
a1 = Cells(5, 16).Value  
trcoef = Cells(4, 3).Value  
dc = Cells(9, 3).Value  
sigma = Cells(10, 3).Value  
wacc = Cells(13, 3).Value  
scr0 = Cells(7, 3).Value  
t = Cells(6, 16).Value
```

```
For x = 0 To 2  
    varu(x) = Cells(11, 4 + x).Value  
    vard(x) = Cells(12, 4 + x).Value  
    pc(x) = Cells(5, 4 + x).Value  
    mb(x) = Cells(6, 4 + x).Value  
    minfw(x) = Cells(7 + x, 16).Value  
Next x
```

```
For y = 0 To 999
```

```
x = 0  
    rat = r0 * vard(x) + Rnd() * (r0 * varu(x) - r0 * vard(x))  
    sumrat(x) = sumrat(x) + rat  
    scr(x) = scr0 * 1 / 3 + scr0 * 2 / 3 * Rnd()  
    fw(x) = rat * k1 + pc(x) * k2 + scr(x) * k3 + a1  
  
    sumfw(x) = sumfw(x) + fw(x)  
    rev(x) = fw(x) * trcoef  
    dcosts(x) = _  
    Application.WorksheetFunction.Norm_Inv(Rnd(), rev(x) * dc, rev(x) * sigma)  
    sumdcosts(x) = sumdcosts(x) + dcosts(x)  
    ebt(x) = rev(x) - mb(x) - pc(x) - dcosts(x)
```

```

sumebt(x) = sumeibt(x) + ebt(x)
finebt(x) = sumeibt(x) * 1 / 100
prof(x) = finebt(x) * t
npv(x) = prof(x) / (1 + wacc) ^ (2 + 2 * x)
'''
Cells(35 + y, 2 + x).Value = npv(x)
    npv1 = npv1 + npv(x)
'''
If npv(x) > 0 And fw(x) < minfw(x) Then
    minfw(x) = fw(x)
End If
'èíáö ìðîííà

```

x = 1

```

rat = rat * vard(x) + Rnd() * (rat * varu(x) - rat * vard(x))
sumrat(x) = sumrat(x) + rat
scr(x) = scr0 * 1 / 3 + scr0 * 2 / 3 * Rnd()
fw(x) = rat * k1 + pc(x) * k2 + scr(x) * k3 + a1

```

```

sumfw(x) = sumfw(x) + fw(x)
rev(x) = fw(x) * trcoef
dcosts(x) = _
Application.WorksheetFunction.Norm_Inv(Rnd(), rev(x) * dc, rev(x) * sigma)
sumdcosts(x) = sumdcosts(x) + dcosts(x)
ebt(x) = rev(x) - mb(x) - pc(x) - dcosts(x)
sumeibt(x) = sumeibt(x) + ebt(x)
finebt(x) = sumeibt(x) * 1 / 100
prof(x) = finebt(x) * t
npv(x) = prof(x) / (1 + wacc) ^ (2 + 2 * x)
'''
Cells(35 + y, 2 + x).Value = npv(x)
    npv2 = npv2 + npv(x)
    If npv(2) > 0 And fw(0) < minfw(x) Then
        minfw(x) = fw(0)
    End If
'èíáö ìðîííà

```

x = 2

```

rat = rat * vard(x) + Rnd() * (rat * varu(x) - rat * vard(x))
sumrat(x) = sumrat(x) + rat
scr(x) = scr0 * 1 / 3 + scr0 * 2 / 3 * Rnd()
fw(x) = rat * k1 + pc(x) * k2 + scr(x) * k3 + a1

```

```

sumfw(x) = sumfw(x) + fw(x)
rev(x) = fw(x) * trcoef
dcosts(x) = _
Application.WorksheetFunction.Norm_Inv(Rnd(), rev(x) * dc, rev(x) * sigma)
sumdcosts(x) = sumdcosts(x) + dcosts(x)

```



```

ebt(x) = rev(x) - mb(x) - pc(x) - dcosts(x)
sumebt(x) = sumeibt(x) + ebt(x)
finebt(x) = sumeibt(x) * 1 / 100
prof(x) = finebt(x) * t
npv(x) = prof(x) / (1 + wacc) ^ (2 + 2 * x)
'ïðîâîï
Cells(35 + y, 2 + x).Value = npv(x)

```

```

npv3 = npv3 + npv(x)

```

```

If npv3 > 0 And fw(0) < minfw(x) Then
    minfw(x) = fw(0)
End If
'êïîâö ïðîâîïâ

```

```

Next y

```

```

For x = 0 To 2

```

```

    Cells(15, 4 + x).Value = sumrat(x) * 1 / 1000
    Cells(18, 4 + x).Value = fw(x)
    Cells(19, 4 + x).Value = sumfw(x) * 1 / 1000
    Cells(17, 4 + x).Value = rev(x)
    Cells(23, 4 + x).Value = sumdcosts(x) * 1 / 1000
    Cells(24, 4 + x).Value = finebt(x)
    Cells(25, 4 + x).Value = finebt(x) * (1 - t)
    Cells(26, 4 + x).Value = prof(x)
    Cells(27, 4 + x).Value = npv(x)
    Cells(7, 4 + x).Value = scr(x)
    Cells(34, 2 + x).Value = minfw(x)

```

```

Next x

```

```

Cells(29, 3).Value = (npv1 + npv2 + npv3) * 1 / 1000
Cells(30, 3).Value = npv1 * 1 / 1000
Cells(31, 3).Value = npv2 * 1 / 1000 + npv1 * 1 / 1000

```

```

Cells(29, 4) = WorksheetFunction.CountIf(Range("B35:B1034"), ">0")

```

```

End Sub

```

```

Private Sub CommandButton1_Click()

```

```

    pred = Cells(19, 4).Value

```

```

    predrat = Cells(15, 4).Value

```

```

    MsgBox ("The Lone Ranger 2 according to our model would raise " & Round(pred, 1) & " mln
dollars in its first week. Rating of the second film in the model will possibly be around " &
Round(predrat, 1) & ". In fact producers are not going to shoot a sequel")

```

```

End Sub

```

```

Private Sub CommandButton2_Click()

```

```

    npvfin = Cells(29, 3).Value

```

```

    MsgBox ("NPV of shooting three films alltogether is " & Round(npvfin, 1) & " mln dollars. We
suggest not to continue this film at all. Shooting even a second film is unprofitable")

```

```

End Sub

```