Risk sensitivity of production studios on the US movie market: an agent-based simulation

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Abstract

The movie industry is a highly product differentiated industry where firms mainly compete in non-price product attributes. The success of a movie on the film distribution market depends on a variety of factors. Because of the short life cycle, the rapid decay in revenues, and the constant entrance of new competitive products, temporal decisions play a crucial role. The time series of the number of movies on release and the sum of the box office results of the ten top movies (ranked by box office result for that week) show that a seasonality emerges in the US movie market. Moreover, the two time series are on counterphase. We suggest the reason is a risk sensitivity adaptation in the behaviour of the movie's distributors. This paper tests this hypothesis. We develop an agent-based model of a movie market, and we simulated it for 20 years. We show that a comparable global behaviour exists when producers schedule the movies according to given risk-sensitive strategies. Our analysis improves the knowledge of the US motion picture market and may support film producers on how to change their scheduling decisions.

Keywords

movie market, agent-based-modelling, box office, releases, risk sensitivity, risk preference

1. Introduction

The movie industry is a peculiar industry in which a small number of companies compete with each other to get the attention of a fixed number of customers. Moreover, the motion picture is a unique product that can not be differentiated by price. The research on the area for a long time has concentrated on understanding the factors that influence the box office success of a film [1, 2] as a way to address the high risk related to the movie industry. Besides, the combination of these factors makes the competition landscape extremely uncertain [3]. The movie box office industry is an 11.4$ billion a year business only in the North American market [4]. This economic importance has a dark side: the entity of the budget necessary to produce a successful motion picture. That is why dealing with the risk on the film market is so important. Such as other entities [5, 6], production studies deal with uncertainty developing and adapting their risk preferences. Consequently, the risk-sensible actions of individuals could affect the global behaviour of the system. Figure 1 shows the time series of the normalized number of movies on release each week and the box office results of the top 10 ranking movies (ranked for box office) on the US movie market.

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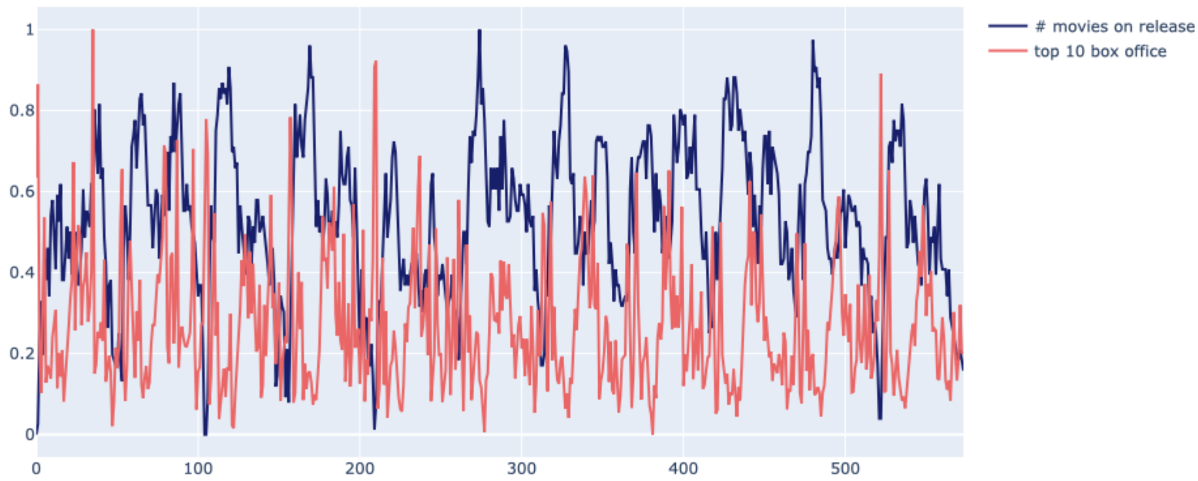

Figure 1: Time series of the number of movies on release each week and of the box office results of the top 10 ranking movies for box office on the US movie market (both values are normalized)

It is observable that the two time series are in counterphase and repetitively intersect with a seasonal trend. We suggest that it derives from the risk-sensible behaviour developed by the producer studios to address uncertainty. This paper aims at confirming this hypothesis, showing how production companies in the US movie market adapt their risk attitudes. To reach this goal, we follow a three-step process. First, we develop an agent-based model (ABM) of the US movie market. In the model, agents (the production studios) decides regarding the production and scheduling of movies. The model simulates the competition dynamics and the effect of different scheduling risk strategies. The calibration consists of two phases. The initialization of producers draws from real-world data collected from a novel database, except risk sensitivity. Later, we simulate the model and calibrate the global behaviour on the time series shown in Figure 1, adjusting the risk preferences of agents. Finally, the resulting risk sensitivities of the producers' agent are compared with the other producers' features. The analysis highlights a direct relationship between the producers' investments and their risk aversion and an inverse relationship between the amount of budget invested by a company and the variability of the risk aversion.

The rest of the paper proceeds as follows. In Section 2, an overview of the research about the movie market is provided. Section 3 shows the model employed for this research, while Section 4 describes the calibration methodology. The main results of this research are deployed in Section 5. Finally, Section 6 presents the conclusions.

2. Background

Research around the movie market is a field that has more than fifty years of history [7]. Hence, it is not in the scope of this paper to review the literature on the topic. We only provide an

Table 1
Main research on the movie market that employs agent-based modelling

Source	Brief description
De Vany and Lee 2001	Observe effect of word of mounth on the box office revenues
Delre et al. 2007	Explore the social influences on movie market inequalities
Broekhuizen et al. 2011	Explore the social influences on movie market inequalities in different
Delre et al. 2017	Analyze the dynamics of competition between two production studios
Iasello 2017	Explain the racial minority underrepresentation in Hollywood movies
Satoh and Matsubara 2021	Predict the box office result

overview of the specific issues and sub-areas affected by our study.

One of the more popular themes is the understanding of which factors influence the box office results. Literature addressed this issue in various ways. The is a consistent interest in the influence of sociality on the box-office results. It can affect the power of critics on the box office results [8] as well as the effects of social interactions, both physical [9] and virtual [10]. Similarly, the sentiment of word of mouth and internet reviews seems to influence the potential attendance success of a motion picture [11, 12]. In these papers, usually, a large set of independent pre-release variables are employed to investigate how they affect the future success of a movie, such as production budget, critic rating, MPAA rating, star power, and genre [1, 2]. Recently, the box office success of a motion picture is forecast employing new predictive technologies. Neural networks and other artificial intelligence techniques proved to be particularly effective on this task [13, 14, 15]. Also, big data analysis on specific kinds of interactions has the potential to improve the forecasting power on the box office result of a movie [16].

Nonetheless, these researches tend to under-evaluate the presence of a complex and uncertain environment and the importance of competition. De Vany and Walls first investigated these subjects, focusing on a possible strategy (the inclusion of more stars in the cast of the movie) to reduce the risk of the box office [3]. They concluded that there did not exist any viable strategy to eliminate the uncertainty because it is not possible to appraise the causal effect of each factor on the success of a movie. Analogously, Ribera and Sieber 2009 and Von Rimscha 2009 focused on the different managerial strategies that production studies should follow to address the uncertainty [17] [18], while Bi and Giles concentrated on the development of a measure to define risk and expected shortfall on a movie market [19].

Regarding competition, papers focused on the positioning of the positioning to perform a good box office result, such as debut at number 1 [20] or avoiding to fail early surviving enough weeks on the market [21]. Gutierrez-Navratil et al., in two consecutive papers, address the undirect interaction of different producers strategies [22], arguing that, if not colluding, major distribution studios achieved a significant rate of coordination on the release scheduling [23].

From a methodological perspective, we identified six studies [24, 25, 26, 27, 20, 28] which employed agent-based modelling to study the movie market, especially to take into account the role of low-level interaction on the global output (which in general is the box office result of movies). Table 1 resumes the main findings.

Nevertheless, as stated at the beginning of the section, this is just an overview of the topic. More comprehensive reviews of the literature were recently published [**?** 29].

3. Agent-based model

This model simulates the competition dynamics between production studios in the US movie market. The purpose is to understand how its global behaviour derives from decision makers' risk preferences. Hence, the model focuses on the movie production studios (from now on "producers", for simplicity). We employ agent-based modelling because it is well-suited to simulate individual behaviours and appraise their effect on the overall system [30]. This model contains two kinds of entities: movies and producers. Each simulation runs for 780 time-steps, which stands for 15 years divided into time steps of one week.

Movies are passive objects and can be created, scheduled, released and retired by the producers. Each movie owns five main features:

1. owner: the producer agent that creates the movie for the first time.
2. quality: the goodness, that is the share of the success of a movie not addressed to its production budget.
3. budget: the number of dollars that a producer invested in the creation of the movies.
4. weeks needed to completion: the number of time steps a producer necessitates to develop a movie. It depends linearly on the budget.
5. potential market: the number of spectators that want to see the movie in a theatre. For simplicity, we suppose that each movie could be seen only one time by each spectator. So, when a given number of spectators attend the movie, the potential market of the movie diminishes the same number for the following week.

The "producers" agents stand for the production and distribution companies that compete in the US movie market. The modelling of producer agents follows some assumptions. They tend to maximize the profit and not to cooperate with other agents. Besides, each producer knows the other producers (as well as their scheduling activities). The last point implies that whenever a producer schedules the release of a movie, the other producers know its scheduled release date and the budget (but not its quality). This information process acknowledges both the business intelligence activities of movies firms and the presence of non-perfect information (e.g., the producers do not know in advance the quality of movies scheduled by other producers). Besides, the information related to the competitive landscape is computed in the same way by each agent. Heterogeneity relates to how this knowledge is employed to make scheduling decisions. Hence, the model accounts for competition by indirectly connecting heterogeneous agents of the same kind.

Four features characterize producers:

1. mean budget: the mean budget of the movies develops by a specific producer.
2. budget distribution: the distribution of the budgets of the movies developed by a specific producer. The analysis of real data permits the identification of three kinds of feasible distributions for the budget decision of each producer: power law, gamma, uniform.
3. frequency of release: the mean number of new releases scheduled for each new week.
4. risk sensitivity: preferences related to the competition during the scheduling decision-making. Agents with high-risk sensitivity try to avoid competition (e.g., risk-averse), while agents with low-risk sensitivity schedule their movies with other movies and seek competition (e.g., risk-seeking).

Producers decide about the creation, the completion, the scheduling and the retiring of a movie.

The decisions related to creating new movies are taken by computing a Poisson random variable, which lambda is the frequency of release of the producers. The creation activity generates the budget and the quality. The budget is sampled from the distribution of the budgets of the producer. The quality of a new movie is independent of the producers and sampled from a continuous uniform distribution between 0 and 1.

Producers work on a movie when its rate of completion is below 100%. The speed of completion is constant from all the producers. So, the time of completion depends solely on the budget: the higher is the investment on a movie, the longer a producer takes to complete it.

The scheduling of movies is the main activity of producers and the focus of the model. At each time step, producers compute an index of competition for the following weeks. This index is the difference between the normalized expected number of movies on release and the normalized budget of the top ten films on release (ranked by budget). Then, producers decide which kind of competition index fit the movie. This choice involves risk sensitivity of the producers and features of the movie (in terms of quality and budget). Thirdly, producers pick the moment in the following two years with the minimum absolute difference between the desired competition index and the expected competition index and schedule the movie for that date.

The last feasible action for a producer is the retiring of a movie. It happens only when a combination of factors are present:

1. the audience in a week is less than the audience in the week before.
2. the movie is on release for at least three weeks
3. the potential market is below a certain share of the initial potential market.
4. the box office result of the movie is below the average, fixed for the budget (so that a small movie is not supposed to obtain the same result of a blockbuster).

The modelling of the audience does not consider heterogeneity in the preferences. It means that each individual of the audience is not interested in attending movies of a specific gender but only ”famous movies” (with high budget) and ”good movies” (with high quality). For this reason, it is possible to define the potential initial market for each movie, starting from quality and budget. This value is a fraction of a total potential market, which stands for the overall number of spectators that would go to the cinema to see a movie. In this model, the total number

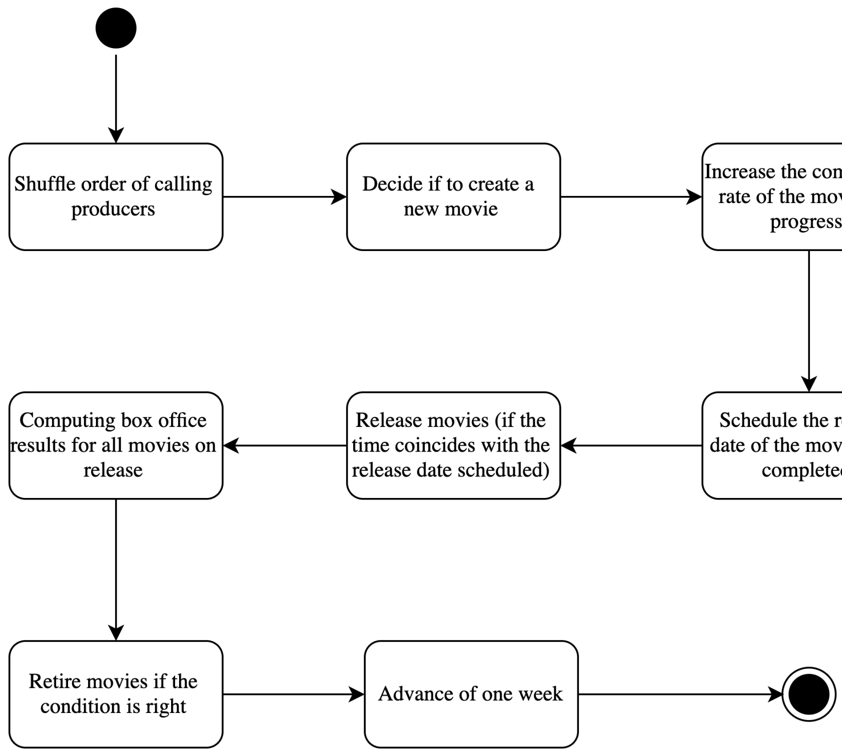

Figure 2: Scheduling process of the model for each time step

of potential spectators is constant. The specific relationship between budget, quality and box office results is deepened in the calibration section. The audience of a movie also depends on the competition that it is facing. The competition affects the weekly box office of a film only if the sum of the potential markets of the movies on release that week is above the total number of potential spectators. In this case, the audience is distributed between all the possible movies using their residual potential spectators. Mathematically, it is

$$d_i = \frac{pa_i}{\sum pa}$$

with d_i attendance of a movie i at time t, pa_i potential audience of movie i at the time i, and $\sum pa$ sum of the potential audience of all the movies on release at the time t.

The model has two outputs: the normalized expected number of movies on release and the normalized box office results of the top ten movies on release (ranked by box office). The scheduling of the model is sequential. The order of the producers changes for each time step to guarantee realism and not advantage any specific producers in the scheduling decisions. Figure 2 depicts the scheduling process.

The simulation model was implemented using Python 3.8, and every simulation run on a Windows machine equipped with a 3.30GHz Intel(R) Core(TM) i5-4590 CPU and 4.0 GB RAM.

4. Calibration

This model represents a real-world system. Hence, to achieve valid results, it was necessary to initialize it with actual data. Besides, it was possible to calibrate its global behaviour to obtain a trend comparable to the one observed in the US movie market. These two phases differed in relevance, methodology and were sequential. For these reasons, each subsection of this paragraph outlines a specific calibration step.

4.1. Initial Calibration

This phase consisted of reproducing authentic producers in the model and adjusting their behaviour according to real-world data. It drew on a database of 4011 movies collected from IMDb. The database included titles, box office results, budgets, and production houses. Lately, we estimated the attendance for each movie from the box office results and the MPA THEME 2019 report [4]. Using this database, we were able to perform the following activities:

1. identification and selection of the real producers working on the US movie market in the time range between 2000 and 2019.
2. identification of the budget invested by each producer for every movie;
3. identification of the distribution of budgets for each selected producer;
4. identification of the box office result for every movie released by selected producers;
5. identification of a relationship between the budget of a movie and the box office result;
6. identification of a relationship between budget and time of production.

Activities 2 and 4 were automatic, while activity 6 followed a pre-existent studio [31]. The rest of the paragraph deepens the other activities.

4.1.1. Producers identification and selection

The database contained 263 producers. We were able to characterize each of them for the number of movies released in the time range between 2000 and 2019. Then, we selected only the 27 producers with at least 20 releases (so, with an average of movies per year equal to or greater than 1).

4.1.2. Budget distribution for producers

A preliminary analysis of the probability distribution of the movies suggests that budgets are statistically distributed in several ways, and none of them was normal. Therefore, it was necessary to identify a set of possible probability distributions and test how good they would fit for the movies released by each producer. We tested gamma, power-law and uniform distribution. Table 2 shows the results of the analysis.

For each producer, we selected the probability distribution that fitted the best the data from the database.

Table 2
Distribution of probability distribution of budgets for producers, calibrated on real data

Distribution	Occurrences
Gamma	19
Power law	6
Uniform	2

4.1.3. Relationship between budget and box office results

Previous studies suggested that there was at least a correlation between the movies budgets and box office results [1, 2]. Using our dataset, we aimed to explain this relationship during the specific time range we examined. Moreover, we intended to address which share of the success derived from the budget. We estimated the other part was descending from other factors (such as genre, the RPAA code, the cast, the director and the overall quality of the product). To obtain this information, we developed a linear regression between the box office and the attendance of each movie in the database. We found out a linear relationship that explains the 54.1% of the variability of the result. We considered the rest of the variability to be a consequence of other factors, generically modelled as "movie quality" in this work.

4.2. Behaviour Calibration

In the introduction, we stated that this work aimed at reproducing a counterphased global behaviour observable on the aggregate time-series of the US movie market between the total number of movies on release and the box office results of the top 10 ranking movies. After the initial calibration, it was already possible to simulate the model imposing to producers random risk preferences. We noticed that only in some simulations the global behaviour of the agent-based model was comparable with the observed in the real world. Consequently, we decided to calibrate the individual behaviour of the producers to minimize the difference between the real-time series and the ones resulting from the simulation. Especially, we picked the time series shown in Figure 1. We called r the normalized number of movies on release in a given week (blue line) and as b the normalized values of the sum of the box office results for the top 10 movies in a certain week, ordered per box office result (red line). The calibration aims at replicating the following features:

1. the number of periods in which $r > b$.
2. the mean difference between b and r when $b > r$.
3. the number of intersections between b and r.
4. the mean value of r
5. the mean value of b

We employed a genetic algorithm to complete this activity. The utility function minimized was the distance between the five features shown above between the simulated data and the US movie market data. The algorithm ran for 200 generations with a population of 500 individuals. The algorithm simulated each member of the population 20 times.

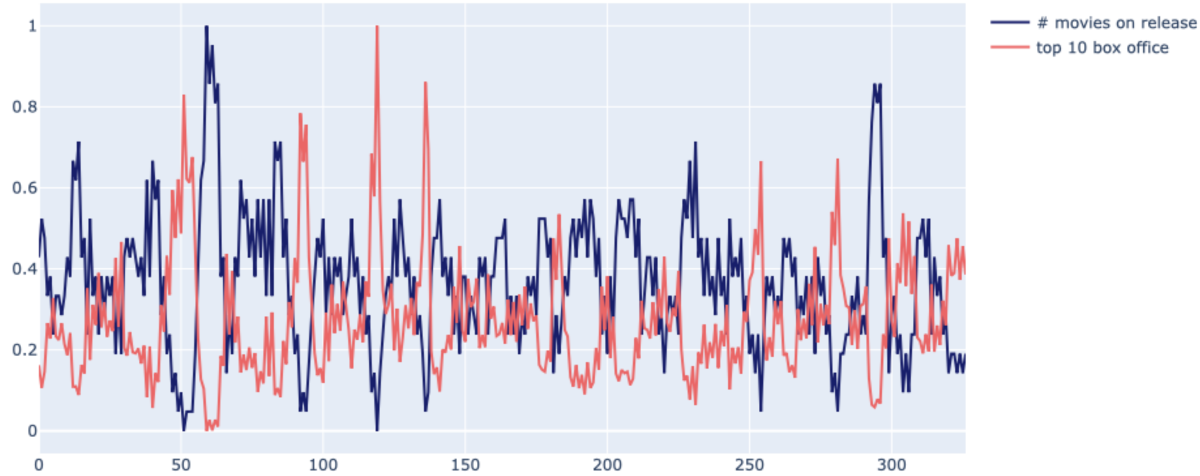

Figure 3: Simulated data time series of the number of movies on release each week and of the box office results of the top 10 ranking movies for box office (both values are normalized)

5. Results

The simulation and the calibration of the model allowed us to achieve two main results:

1. the replication of the macro behaviour
2. specific risk sensitivity assigned to each producer, and the relationship between that and its features

5.1. Behaviour Replication

The macro behaviour replicated can be observed in Figure 3.

Figure 3 presents the same feature as Figure 1 in terms of counterphased behaviour and phase alternation. Therefore, we found that the macro behaviour present in the US movie market could be (at least partially) replicated by simply imposing basic rules regarding the presence of risk-sensible scheduling. This result highlighted the importance of risk preferences in the decision process of entities, especially when dealing with complex environments and trade-offs. While this result is domain-specific, it is comparable to pre-existent results in the literature related to different application domains [32, 6, 5]. Nevertheless, there were some differences between the two curves. It is observable that the periodicity of the seasonality and the amplitude of some sections varied. We proposed that the origin of these differences could be the cognitive simplicity of the producers, which, between the other limitations, do not have memory. For example, producer agents did not remember which moment of the year was best suited for releasing high budget movies. Therefore, the seasonality could not precisely fit real data. The difference in magnitude also descended from cognition simplicity. Producers did not know the plans of the other producers before a competitor movie became scheduled. It affected the regularity of the height of the spikes for both r and s.

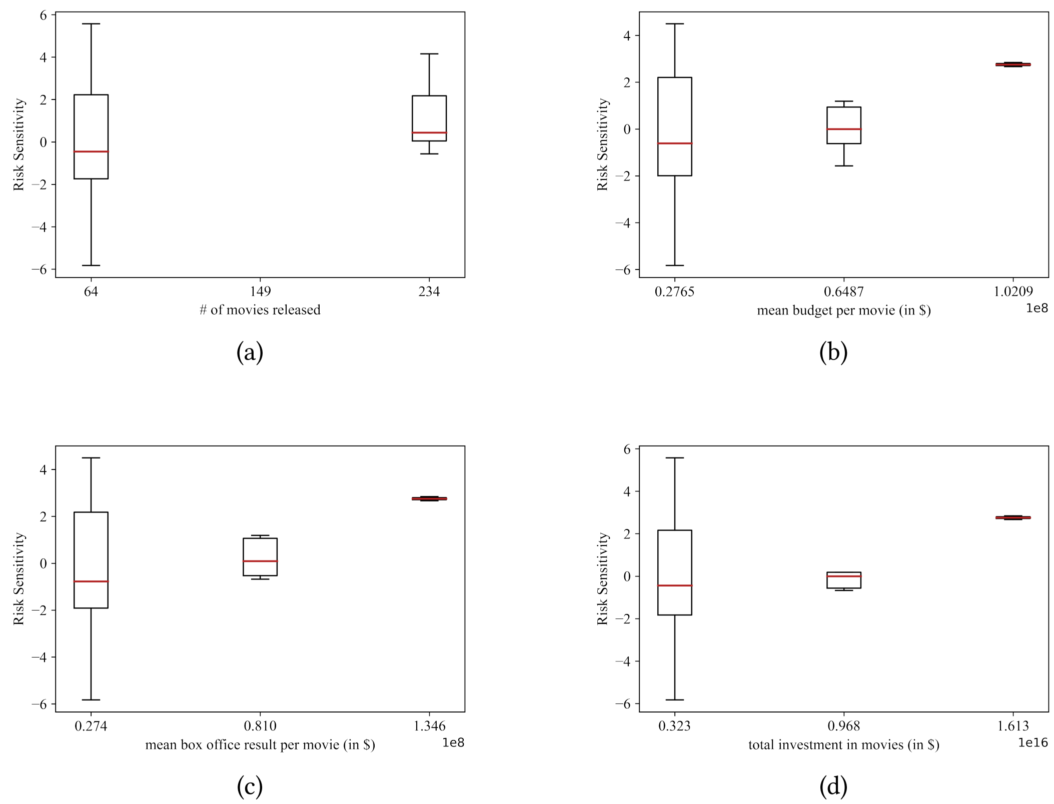

Figure 4: Distribution of risk sensitivity of producers per (a) total number of movies released, (b) mean budget of movies, (c) mean box office result of movies and (d) total investment in movies

5.2. Risk sensitivity of producers

This conclusive analysis compared the risk sensitivities of producers resulting from the behaviour calibration with the US movie market data about producers' behaviour gathered during the individual calibration. Figure 4 exhibits the outcomes of this study. In each subfigure, the 27 production studios are represented in one of the three boxplots. Each box included the point located in one-third of the total area.

Each subfigure deemed a different variable: the total number of movies released, the mean budget per movie, the mean box office result per movie, and the total amount of investment in dollars, which is the sum of the budgets of all the movies released. We computed every variable for each producer for the time range 2000-2019.

The figures owned two notable features. First, the mean risk sensitivity increased with the growth of each variable. It was interesting for a twofold reason. On the one side, it was coherent with previous findings in risk preferences literature, for which entities tend to be more cautious when the stack increases [33, 5]. On the other, it was consistent with empirical observations related to the kind of movies released. In the last ten years, a substantial number of released were remakes or sequels of previous works [34]. It was a behaviour adopted mainly by big production studios, which tries to minimize the risk of a flop. Hence, our analysis is coherent with these findings. The second remarkable characteristic regards the variability of the results. With higher stakes, the variability of the risk sensitivity decreased. We suggested that it could be a consequence of the market structure, for which the specific macro behaviour could arise when the small producers have high variability in risk preference while big producers are similarly risk-averse.

6. Conclusions

This paper provides a possible explanation to the seasonal and counterphased behaviour of the time series of the number of movies on release and the sum of the box office results for the top 10 movies released (ranked for box office result) in the US movie market data. In this work, we replicate it by developing and calibrating an agent-based model of the US cinema market. Moreover, we identify relationships between the calibrated risk sensitivity and the real features of the producers, for which we suggest that:

1. the higher is the amount of budget invested by a producer, the higher is its risk aversion.
2. the higher are the investments, the lower is the expected distance of its risk sensitivity from the mean risk sensitivity of other producers in the same investment range.

The work has some limitations and some related future developments:

- the purpose of the model was to understand the reason for the counterphased seasonality of the number of released and the box office results of the top 10 movies (ranked for box office success in a certain week). The model proposes a potential interpretation of this phenomenon, but it did not show the adaptation of the preferences. This specific issue could be addressed by the following work.
- The movie market is calibrated not with all the possible movies but only with the principal. While we consider it sufficient to study the dynamics of the most important producers, there is the possibility of an underestimation of the impact of smaller producers on the overall behaviour.
- we considered the US movie market between 2000 and 2019. So, the insurgence of the COVID-19 pandemic is not included. Future studies could analyze the effect of a disruptive event that lead to a 32 billion dollars loss globally [35].
- the behaviour of producers were modelled under the assumption that they maximize the profit. Nevertheless, we do not analyze the economic performance of producers. Possible future developments include the analysis of each risk strategy on the producers' performance. What is more, it could be investigated if and how the distribution of risk preferences in the producers on the competitive landscape affects the overall profitability of the whole market.

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