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Risk Sensitive Scheduling Strategies of Production Studios on the US Movie Market: an Agent-based Simulation

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Abstract. The movie industry is a highly differentiated context where production studios compete in non-price product attributes, which influences the box office results of a motion picture. Because of the short life cycle and the constant entrance of new competitive products, temporal decisions play a crucial role. Time series of the number of movies on release and the sum of the box office results of the ten top motion pictures (ranked by box office result for that week) present a counterphased seasonality in the US movie market. We suggest that a possible reason is a risk sensitivity adaptation in the behaviour of the movie's distributors. This paper provides a model supporting this hypothesis. We developed an agent-based model of a movie market, and we simulated it for 15 years. A comparable global behaviour exists when producers schedule the movies according to given risk-sensitive strategies. This research improves the knowledge of the US motion picture market, analyzing a real-world scenario and providing insight into the behaviour of existing firms in a complex environment.

Keywords: Movie market, Agent-based-modelling, Box office, Risk sensitivity, Risk preferences

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 [8,38] as a way to address the high risk related to the movie industry. Overall, the combination of these factors makes the competition landscape extremely uncertain [14]. The movie box office industry is a $ 11.4B a year business just in the North American market [1]. This economic importance has a dark side: the budget necessary to produce a successful motion picture. This is why dealing with risk on the film market is so important. Like other economic agents [23,37,49], production studies deal with uncertainty by 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 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.

We can see that the two time series are in counterphase and repeatedly intersect with a seasonal trend. We suggest that this pattern could derive from the risk-sensible behaviour developed by the producer studios to address uncertainty. This paper aims to support this hypothesis proposing a model in which the way production companies in the US movie market adapt their risk preferences fully accounts for the ob-

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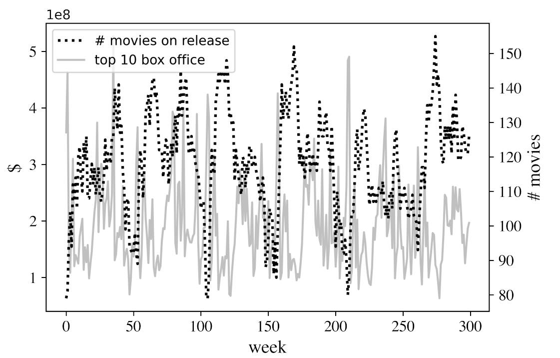

Fig. 1. Time series of the number of movies on release each week and of the box office results of the top 10 ranking movies for box office on the US movie market

servation. More precisely, we show how the observed macro-behaviour of the system could be generated by the low level interaction of producers that have certain attitudes toward risk. To reach this goal, we do not consider other factors, such as marketing or the influence of social media on the box-office result of a motion picture. Instead, the 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) decide regarding the production and scheduling of movies. The model simulates the competition dynamics and the effect of different scheduling strategies to manage risk. The calibration consists of two phases. The initialization of producers draws features from real-world data collected from a novel database, except for 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 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 is 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

Movie market research is a field with more than fifty years of history [41]. Hence, it is not in the scope of this paper to review the wide-ranging literature on the topic. We only provide an overview of the specific issues and sub-areas relevant to our study.

One of the more popular themes is the understanding of which factors influence the box office results [30]. The literature addressed this issue in various ways. There is a consistent interest in the influence of sociality on the box-office results. This can include the power of critics on the box office results [3] as well as the effects of social interactions, both physical [34] and virtual [33]. Similarly, word of mouth and internet reviews seems to influence the potential attendance success of a motion picture [24,32]. 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 (i.e., the influence of the cast composition on the box office result), and genre [8,38]. Recently, neural networks and other artificial intelligence techniques proved to be particularly effective in predicting box office success [19,40,53,54], popularity [31] and awards [28]. 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 [36].

Nonetheless, this research 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 [14]. 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, [44] and [50] focused on the different managerial strategies that production studies should follow to address the uncertainty [44] [50], while [4] concentrated on the development of a measure to define risk and expected shortfall on a movie market.

Regarding competition, some papers focused on the positioning to perform a good box office result, such as debut at number 1 [47] or avoiding to fail early by surviving enough weeks on the market [29]. Gutierrez-Navratil et al., in two consecutive papers, address the indirect interaction of different producers strategies [20], arguing that, if not colluding, major distribution

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 mouth on the box office revenues
Delre et al. 2007	Explore the social influences on movie market inequalities
Bothos et al. 2010	Predict Oscar award winners
Broekhuizen et al. 2011	Explore the social influences on movie market inequalities in different cultures
Delre et al. 2017	Analyze the dynamics of competition between two production studios
Iasello 2017	Explain the racial minority under-representation in Hollywood movies
Satoh and Matsubara 2021	Predict the box office result

studios achieved a significant rate of coordination on the release scheduling [21].

From a methodological perspective, we identified seven studies [7,9,13,15,16,25,47] 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 summarises the main findings. A significant number of studies focus on how social influences relate to and impact movie production and success [9,13,15,25], while some try and predict awards [7] and the box office [47]. [16] models the competitive dynamics of two production studios with a focus on advertisement, investments in quality and market positioning. In contrast to previous studies, the present work focuses on temporal decision making, specifically on adaptive, risk-sensitive strategies for the scheduling of movie releases.

The Covid pandemic has had an enormous impact on the entertainment industry [39] and the movie industry in particular [27,51], with box office suffering its worst revenue loss in more than 25 years. The film industry has had to adapt to the changes [26], with streaming services as one strategy [35,43]. Nevertheless, the traditional revenue streams for movies remains important even as digital technology adapts and consumer habits change [48].

We have outlined the main strands of the literature in this short overview of the topic. More comprehensive reviews of the literature were recently published [10, 11].

3. Agent-based model

The simulation model employed in this paper aims to imitate the competition dynamics between production studios in the US motion picture market. The purpose of the model is to explain how the market's global behaviour derives from decision makers' risk preferences. Hence, the model focuses on the movie production studios (from now on "producers", for simplicity). We have decided to employ an agent-based modelling technique because it suits the representation of individual behaviours and appraises their effect on the overall system [6]. Moreover, this methodology is already employed to study different markets behaviour, such as financial markets [42] or innovation dynamics [18]. Each simulation runs for 780 time-steps. Since every step stands for a single week, every simulation covers a period of 15 years. This agent-based model contains two kinds of entities: movies and producers.

3.1. Movies

Movies are passive objects, which means that they can not perform any actions. Hence, they can be created, scheduled, released and retired by the producers, which are the only active objects of the simulation model (the agents). Each movie has the following five main features:

1. owner: the producer agent that creates the movie for the first time, decides the release date and when to withdraw it from theatres.
2. quality: a feature that embodies the goodness of the movie. It represents the share of the success not addressed to its production budget.

3. budget: the number of dollars that a producer invested in the creation of the movies. Intuitively, it connects to the relevance of a movie for the production studio.
4. weeks needed to completion: the number of time steps a producer necessitates to develop a movie. It depends linearly on the budget, representing the relationship between the size of a motion picture in terms of cast, special effects and the number of weeks needed to shoot and mount it.
5. potential market: the number of potential spectators, which is the number of people that would want to see the movie in a theatre. For simplicity, we assume that each release could be viewed only a single time by each person. Accordingly, when a given number of spectators attend the theatres to see the movie, its potential market diminishes by the same number for the following time step, because some of the people that would go to watch the film have already seen it.

3.2. Producers

The "producers" agents stand for the production and distribution companies that compete in the US movie market. In this model, we are not interested in representing the overall behaviour of a production studio but only its production and release strategy in terms of budget allocation and scheduling decisions. Consequently, the modelling of producer agents follows some simplifying assumptions.

Producers aim at maximizing profit, and they do not cooperate with other agents. It means that, for example, two producers can not talk to each other and find a deal regarding the scheduling of two concurring films. Moreover, each producer knows the other producers and their scheduling activities. This 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). More precisely, each producers know only the budget and the release week of the movies scheduled by other producers. These information become available when the movie is scheduled. Furthermore, the information related to the competitive landscape is computed in the same way by each agent. Producers are heterogeneous for how this knowledge is employed to make scheduling decisions (e.g., their risk preferences). Hence, the model accounts for competition by indirectly connecting heterogeneous agents of the same kind.

Like the movies, also the producer agents are characterized by some features:

1. mean budget: the average production cost of motion pictures developed by a specific producer, in dollars.
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 distributions for the budget decision of each producer (power law, gamma, uniform), which parameters are calibrated before the simulation to provide a realistic behaviour.
3. frequency of release: the mean number of new releases which start to be in production each week. The number of new movies which starts to be under production affects the number of the ones released later. The time lag relates to the sum of making time and the release delay due to scheduling strategy.
4. risk sensitivity: preferences in the scheduling decision-making. It affects the behaviour of the producers in addressing competition with other movies when taking a scheduling decision. Agents with high-risk sensitivity try to avoid competition (e.g., risk-averse), while agents with low-risk sensitivity schedule their motion pictures with other movies and seek competition (e.g., risk-seeking).

3.3. Actions of producers

Producers can take 4 actions about a movie: the generation, the making, the scheduling date and the retiring from the theatres.

Producers decide whether to create a new movie by computing a Poisson random variable, which λ is the frequency of release of the producers, one of its features. The output of the generation activity is a movie object with a budget and quality. The budgets are 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. It is a simplification, which derives from the unclear relationship between the goodness of a movie and its box office results.

Producers work on a movie as long as 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 in a movie, the longer a producer takes to complete it. This making phase concludes when the completion rate of the motion picture is equal to 100%.

Movies scheduling is the principal activity of producers and the focus of the model. At each time step, producers compute a competition index 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 their 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). Finally, a producer should pick the most favourable week to release the film. This week should be in the following 2 years. It implies another simplification embodied in the model: no movies can be scheduled more than 2 years after the conclusion of the production. There is no scientific evidence for the maximum time span release, but practitioners suggest it is variable and in average it lies between 3 and 6 months. Hence, the maximum 2 years span is a reasonable assumption. Within the suitable weeks, the producer selects the one with the minimum absolute difference between the desired competition index and the expected competition index. Accordingly, it schedules the motion picture for that date.

The last available action for a producer is to retire a film. It can happen only when a combination of factors are present:

1. the audience that attended the movie in the theatres during a week is less than the week before.
2. the motion picture is on release for at least three weeks, so that a movie can not be retired in the first or second week of screening.
3. the potential market is below a given share of the initial potential market.
4. the box office result of the movie is below the average, weighted for the budget (so that a low budget movie is not supposed to achieve the same box office results of a blockbuster).

3.4. Environment

The actions of agents are activities that cause modifications in the environment or other agents. In this

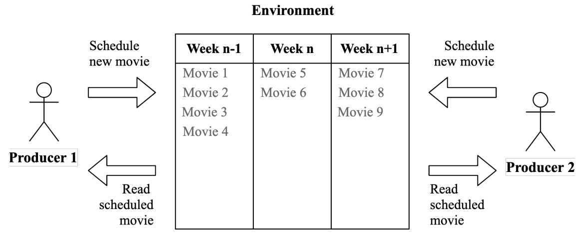

Fig. 2. Relationship between the environment and the producer agents)

model, agents do not directly interact, but they affect each other behaviours only by means of modifying the scheduling landscape [2]. Figure 2 clarify the actions taken by the agents and their relationship with the environment, by making explicit the way the environment mediate the way agents access to the resources (which, in this case, are the audience attendance) [52].

The environment of the model includes also the audience. The modelling of the public ignores the heterogeneity in individuals' preferences. It implies that each person belonging to the potential audience is not interested in attending movies of a specific gender but only "famous movies" (with high budget) and "good movies" (with high quality). So, each film has a potential initial market, which is affected by its quality and budget. Specifically, the value is a share 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 of potential spectators is constant. It means there is no seasonality in movie attendance, that the size of the potential market does not change, and that the interest in attending cinema remains constant during the years. The precise relation between budget, quality and box office results is extended in the calibration section. The audience of a movie also depends on the competition that it is suffering. The presence of other movies affects the weekly box office results of a film only if the sum of the potential markets of the motion pictures on release that week is above the total number of potential viewers. 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 t, and $\sum pa$ sum

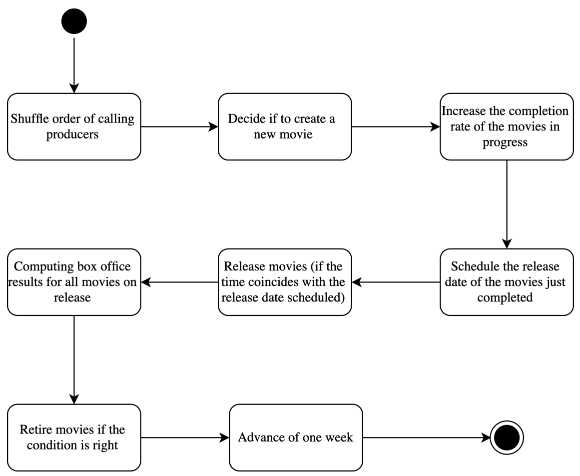

Fig. 3. Scheduling process of the model for each time step

of the potential audience of all the movies on release at the time t.

3.5. *Technical features*

This agent-based model has two outputs. One is the normalized expected number of movies on release, while the other is the normalized box office results of the top ten movies on release (ranked by box office). We design the model to have these outputs so that its global behaviour can be compared with data from the US movie market. This feature makes the calibration possible process. The scheduling of the model is sequential: each agent is called just after the other. To guarantee realism and not advantage any specific producers in the scheduling decisions, the order of the agents changes for each time step. The shuffling was implemented to avoid a single producer to take advantage for being always the first one to schedule movies. Without the shuffling mechanism, the first producers and the last producers would (in average) see a different number of movies already scheduled when they take a scheduling decision. This would make the model not neutral, and could potentially affect the goodness of the calibration.

Figure 3 depicts the scheduling process, and Algorithm 1 the main loop of the model.

The simulation model was implemented using Python 3.8 and written in pure Python, without using any specific framework for agent-based simulation model[1].

[1]The model and the dataset use for calibration are available at the following Zenodo repository: https://doi.org/10.5281/zenodo.6027233.

Algorithm 1 Main Loop of the Simulation

for t in $[1...t_{max}]$ **do**
  shuffle AGENTSLIST
  for i in AGENTSLIST **do**
    sample number new movies
    if number of new movies > 0 **then**
      agent i create new movies
      new movies added to MOVIELIST_i
    for each m in MOVIELIST_i not completed **do**
      agent i increases completion of m
    for each m in MOVIELIST_i completed AND not scheduled **do**
      agent i computes competition index for following weeks
      agent i schedules m the best week
    for each m in MOVIELIST_i scheduled for t **do**
      agent i releases m
  compute box office of movies on release
  for i in AGENTSLIST **do**
    for each m in MOVIELIST_i with retire conditions **do**
      agent i retires m

4. Calibration

The previous section describes a model which represents a real-world system. Therefore, it was necessary to initialize it with actual data to achieve valid results. It means, for example, that certain features should be taken from the real world (such as the budget distribution for new movies or the frequency of release). In addition, it was also necessary to calibrate its global behaviour to obtain a trend comparable to the one observed in the US movie market. Specifically, calibrating means to test different sets of risk preferences of producers. The purpose of this activity is to discover a set of producers' risk preferences that generates a macro behaviour comparable to the real one. 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 stage consisted in reproducing generating producers in the model which embodies features extracted from real data. It drew on a novel database of 4012 movies released between 2000 and 2019, collected from IMDb and specifically developed from this research. The database included release year, box office results, budgets, and production houses. Later, we estimated the attendance for each movie from the box office results and the attendance data extracted from the MPA THEME 2019 report [1]. From this database, we could select some features that contribute to making the behaviour of producers studios adhere to reality:

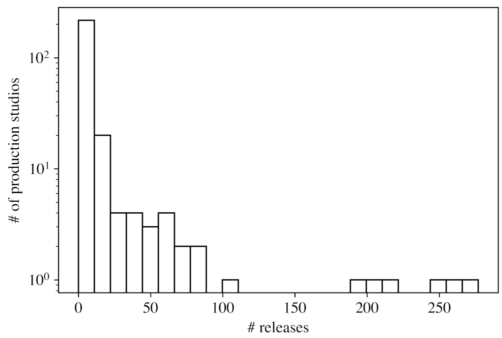

Fig. 4. Distribution of production studios on the US movie market per number of releases.

1. the identification and the selection of production studios operating on the US movie market in the time range between 2000 and 2019;
2. the estimation of the budget invested by each producer for every movie;
3. the classification of the probability distribution of budgets for each selected producer;
4. the collection of the box office result for every movie released by selected producers;
5. the examination of the relationship between the budget of a movie and the box office result;
6. the examination of the relationship between the budget of a movie and the duration of its production phase.

Activities 2 and 4 were trivial and did not require any specific investigations. Similarly, activity 6 followed a pre-existent studio [2], and so we will not discuss it in this paragraph. The rest of this section deepens the process underlying the other activities.

4.1.1. Producers identification and selection

The database we employed for this preliminary initialization analysis contained 263 unique producers. We were able to characterize each of them for the number of movies released in the time range between 2000 and 2019. Consequently, we selected only the 27 producers with at least 20 releases (e.g., with a mean of movies released per year equal to or greater than 1). Figure 4 shows the original distribution of producers, categorized per number of movies released.

4.1.2. Budget distribution for producers

The database analysis showed that probability distributions of the movie's budget vary from production studio to production studio. What is more, none of the distributions appeared to be normal. Consequently, it was required to recognise a set of feasible probability distributions and test how good they would fit for the movies released by each producer. More specifically, we followed a two-step process. First, we observed the distributions of each producers, and we found a set of probability distributions that could fit all of them. The candidate probability distributions were gamma, power-law and uniform distribution. Afterwards, we fit all the candidate distributions to the real data and computed the Kullback–Leibler divergence between the different fitted distributions and the real data. For every producers, we assigned the distribution with the lowest divergence. Table 2 shows the results of the process.

4.1.3. Relationship between budget and box office results

Previous researches proposed the existence of a correlation between the movies budgets and box office results [8,38]. Using our dataset, we tested this relationship during the specific time range we examined. The purpose of this investigation is to identify the specific connection for the set of movies we planned to use to calibrate the model. Also, we intended to address the share of the box office 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 film). To collect this information, we developed a linear regression between the box office and the attendance of each movie in the database. The results pointed that a linear relationship explains the 54.1% of the variability of the result. We considered the rest of the variability affected by other factors. In the model, we generically modelled them as "movie quality".

4.2. Behaviour Calibration

In the introduction of this paper, we affirmed that this research aimed at reproducing the 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. We observe the top 10 movies because that is the data we had available from BoxOfficeMojo. Nonetheless, the pattern we observe is likely a representative trend because of the underlying Pareto distribution of box office results. The initial calibration had the goal of generating a system of producers which represent accurately the production

[2] https://archive.is/gOzVf

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

Distribution	Occurrences
Gamma	19
Power law	6
Uniform	2

studios operating on the US movie market. In this situation, it was already possible to simulate the model imposing to producers random risk preferences. Some preliminary attempts showed that only in some simulations the global behaviour of the agent-based model was comparable with the observed in the real world. This phenomenon suggested the existence of a set of risk preferences parameters that make the whole simulated system behave analogously to the system under investigation. Therefore, we chose to calibrate the individual risk preferences of the producers to minimize the difference between the real-time series and the ones resulting from the simulation, using as the target the time series shown in Figure 1. We called r the normalized number of movies on release in a week (dotted dark line) and as b the normalized values of the sum of the box office results for the top 10 films in a week, ordered per box office result (dotted lighter 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 250 generations with a population of 500 individuals. The algorithm simulated each member of the population 20 times. The algorithm implemented an elitism strategy, and it maintained the third percentile of the best solutions at each generation. The crossover strategy adopted is uniform. It consisted in shifting the genes (in this case, the risk preferences) at 20% of the positions, which were randomly chosen. Finally, we used a mutation rate of 10% to address the low size of the population.

5. Limitations

This section shows some limitations of the work that we highlight before presenting the model results.

Firstly, the goal of the simulated market was to propose a possible reason for the counter-phased seasonality of the number of films on release in a given week and the income of the top 10 movies (ranked for box office success) in the same range of time. We did not address the adaptation of the preferences, so producers do not change their attitudes toward uncertainty in time.

Secondly, the behaviour of producers was modelled under the assumption that they tend to maximize their profit. Nevertheless, their economic performances are not studied.

Thirdly, the behaviour of the organizations is stylized. In the real world, decision-makers take decisions according to different factors and sometimes non-rationally. Moreover, the success of a movie can be influenced by various details. We did not address this complexity. For example, the perceived goodness of a motion picture can be affected by the poster graphic and the cast composition. These are elements that in the real world can be relevant to understanding the success of a given motion picture and that our model ignores. On the contrary, we addressed all these things under the general term "quality". It is a substantial simplification of reality, and we adopted it with the purpose of studying the influence of a single component of the movie system.

Finally, we did not consider the seasonality of the audience in the model [17,56]. Instead, we model the audience to be constant during the year. This decision has the precise purpose of generating a seasonal behaviour that does not depend on the underlying attendance seasonality and explaining the role of risk preferences in this adaptation. Nevertheless, we consider it relevant to highlight it before presenting the results.

6. Results

The simulation and the calibration of the model allowed us to achieve two main results. The first was the replication of the macro behaviour of the US motion picture market, especially for what regards the presence of a counterphased and seasonal trend of the number of movies on release and the top 10 movies for box office results. The second finding involved the identification of a specific risk sensitivity for each production studio. From the analysis of this last outcome, it was possible to identify some relationship between production studios features and resulting risk sensitivity. We found that bigger studios tend to be more risk-averse, while smaller studios have a wider variety of strategies.

6.1. Behaviour Replication

Figure 5 presents the simulated macro behaviour of our in-silico movie market. The figure represent a single run, but this behaviour can be reproduced with the provided code, and it is consistent across executions. It retains the same main features as Figure 1 in terms of counterphased behaviour and phase alternation. Accordingly, we observed that the macro behaviour present in the US movie market could be (at least partially) replicated by imposing basic rules concerning the existence of a risk-sensible related to film scheduling. There were some differences between the two figures. It is observable that the periodicity of the seasonality and the amplitude of some sections varied. We suggested that the origin of these discrepancies could be the cognitive primitiveness of the producers, which, between the other limitations, do not own any 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-world 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. In addition, our simulated environment did not present any seasonality in theatres attendance. There were no incentives for producers in remembering the best moments of the year to release a movie with given characteristics. This finding showed how relevant were production studios' risk preferences in understanding the overall dynamics of a movie market. This result also underlined the pertinence of studying risk preferences of entities that decide in intertwined systems, especially when the environment is complex and the decision landscape presents trade-offs. Our findings are domain-specific, but they are comparable to pre-existent results in the literature related to different application domains [23,49,55].

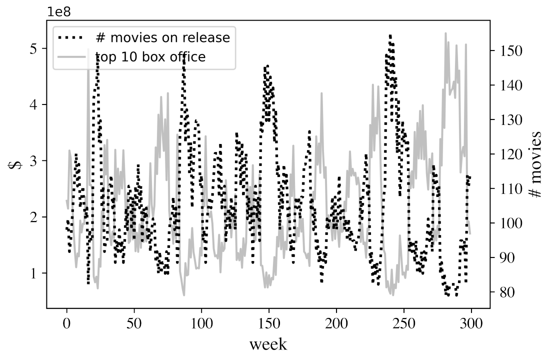

Fig. 5. Simulated data time series of the number of movies on release each week and of the box office results of the top 10 ranking movies for box office

6.2. 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 6, Figure 7, Figure 8 and Figure 9 exhibits the outcomes of this examination. In each figure, each of the 27 production studios is represented as a point of the scatter plot. In each figure, the producers divide into two clusters. Each cluster contains the points whose value of the independent variable is above or below a given threshold. This threshold is computed as it follows:

$$x_{threshold} = \frac{x_{max} - x_{min}}{2}$$

For each cluster, a box plot resumes the distribution of the risk sensitivity of the producers that belong to it.

Each figure considers a different independent variable: Figure 6 addresses the total number of movies released; Figure 7 the mean budget per movie; Figure 8 the mean box office result per movie; Figure 9 the total amount of investment in dollars, which is the sum of the budgets of all the movies released. For every production studio, the independent variable is calculated for the period between 2000 and 2019. In all four figures, the dependent variable is the risk sensitivity resulting from the calibration process. We developed the model such as a negative value of risk sensitivity im-

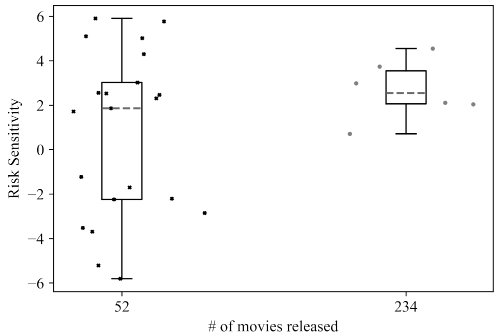

Fig. 6. Distribution of risk sensitivity of producers per total number of movies released

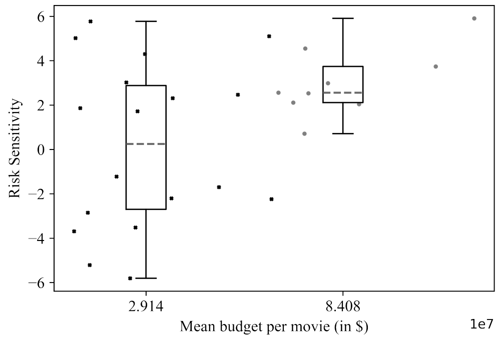

Fig. 7. Distribution of risk sensitivity of producers per mean budget of movies

plies a risk-averse behaviour, while a positive value of risk sensitivity indicates a risk-seeking behaviour.

Considering the four figures together, they owned two notable features. First, both the mean risk sensitivity or the minimum risk sensitivity of a cluster increased with the growth of each variable. It was remarkable 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 [23,37]. On the other, it was compatible with empirical observations related to the kind of movies released. In the last ten years, a substantial number of releases consisted of remakes or sequels of previous works [5]. It was a behaviour adopted mainly by big production studios, which attempts to reduce the risk of a flop and the consequently monetary loss. Hence, our findings are coherent with these findings. The second distinctive element concerns the variability of the results. With higher investments, the variability of the risk sensitivity decreased. It can be seen clearly in Figure 7 and Figure 9. 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. Additionally, larger producers have probably a stronger influence on the calibration process, since they affect more the overall trend of the simulated system. So, a part of the larger variability of the small producers could be addressed to the calibration technique employed.

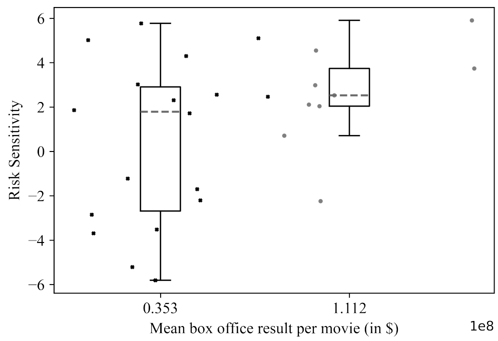

Fig. 8. Distribution of risk sensitivity of producers per mean box office result of movies

7. Conclusions

This paper provides a possible explanation to the seasonal and counter-phased 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 the data by developing and calibrating an agent-based model of the US cinema market. More generally, the model provides a way to generate and partially explain high-volatility time series via a novel mechanism, and can give insight into why such apparently erratic behaviour can emerge in socio-economic systems, which complements other work on stochastic modelling [12] or chaotic dynamics [45,46].

Moreover, we identify relationships between the calibrated risk sensitivity and the features of the producers, for which we suggest that:

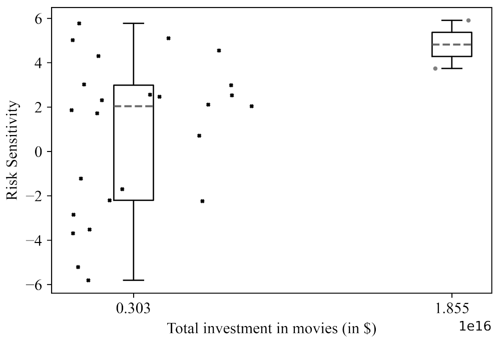

Fig. 9. Distribution of risk sensitivity of producers per total investment in movies

1. the higher are the resources invested by a producer, the higher is its risk aversion.
2. the higher are the resources invested by a producer, 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 future developments. Firstly, the purpose of the model was to understand the reason for the counter-phased 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 suggests a potential explanation of this phenomenon, but it did not explain the adaptation of the preferences. Future works could address this issue.

Secondly, 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 [22] on risk preferences of production studios. Thirdly, 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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