Simulating the Motion Picture Market: why do the hits take it all?

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Abstract

Why are shares of the motion picture market so unequally distributed? Do the different qualities of the movies account for such an enormous difference in the market shares? Are mass media campaigns so effective to convince almost all movie visitors to see the same movies? Or are there social processes that affect the movie visitors' decision making and direct them to visit the same movies? In this paper we propose an agent based model based on micro movie goers decision-making that generates the observed macro characteristics of the market. The model is calibrated using a survey conducted on movie goers and it explains the stylized characteristics of the market in terms of social influence and coordinated consumption. Simulation results indicate that (1) the chances for successful movies to become a hit are higher in entertainment consumption markets than in art consumption markets and (2) if the marketing efforts of movie labels increase, then market shares become more unequally distributed and the differences between the two markets tend to disappear.

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Simulating the Motion Picture Market: Why do the Hits take it all?

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Introduction

Movies revenues are distributed very unequally. In 2001, 20% of the movies collected 75% of the revenues and in 2002, 20% of the movies collected the 73% of the revenues. Figure 1 shows the distribution of movies' revenues in the US market averaged for the last 6 years (2000-2005). They are ranked from the highest revenue to the lowest revenue, from the first position until the 250th position[1]. It is evident that big successful movies take it all and all the rest have to put up with very low shares of the market. For example, in 2001, when the mean of the 250 richest movies was $32,000,000, *Harry Potter Sorcerer's Stone* (1st in rank) earned almost $300,000,000 and *The Caveman's Valentine* (250th in rank) earned only $687,000. In 2002, when the mean was $37,000,000, *Spider Man* (1st in rank) earned more than $400,000,000 and *The Piano Teacher* (250th in rank) earned $1,012,000.

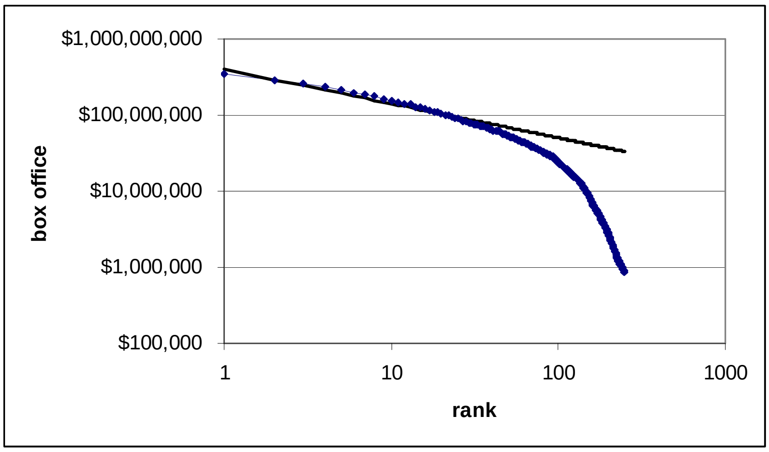

Figure 1. Rankings of movies' box office revenues in the USA market (average from 2000 until 2005)

The distribution of the revenues depicted in figure 1 follows a power low for the first 50 movies of the rank: $revenue_i = c * (rank_i)^{-\gamma}$ where i indicates the movie, $c \approx 400{,}000{,}000$ is the intercept and $\gamma \approx 0.45$ is the slope of the line. After the 50th position the distribution follows a sharp cutoff due to an exponential decay indicating an even more inequality of the market. The variance of the distribution is very high and the mean is almost meaningless because it heavily depends on the upper tail (those movies that hits the market and take big part of it). Moreover, this ranking pictures only a limited part of the market, the more successful 250 movies of the year. The inequality of the market is even more evident when we consider the complete market. In fact it is well known that the motion picture market is one of the riskiest for producers, especially for less known and independent labels (De Vany, 2004). These companies often manage low budgets, they are unable to compete against the big labels (especially in the pre-launch mass media advertisement) and they often encounter a loss.

Why are shares of the motion picture market so unequally distributed? Do the different qualities of the movies account for such an enormous difference in the market shares? Are mass media campaigns so effective to convince almost all movie visitors to see the same movies? Or are there social processes that affect the movie visitors' decision making and direct them to visit the same movies? In this paper we propose a simulation model based on micro movie goers decision-making that generates the observed characteristics of the market. The model explains these stylized facts in terms of social influence and coordinated consumption.

Market shares characteristics as described above are typical for markets with very strong social influence among firms and/or consumers (Ijiri and Simon, 1974; Kohly and Sah, 2003). For example, Salganik et al. (2006) have showed how the high level of social influence in cultural markets causes inequality and

[1] Movie data have been collected from www.variety.com

unpredictability of the market shares. In these kinds of market the individual consumer decision making is highly driven from what other consumers do and it is very likely that herd behaviors are initiated by minor events and that they involve a high percentage of the consumers (Banerjee, 1992; Bikhchandany et al. 1992; De Sornette et al. 2004). These social processes generate herd behaviour and consequently they create a high level of inequality in market shares (Kohly and Sah, 2003; De Groot, 2005). At the same time these markets become very fashionable and uncertain because it is extremely difficult to forecast and to direct how consumers will collectively respond to the introduction of a new product (De Vany and Walls, 1996). In this sense, the motion picture market is a clear example of this kind of market. From the side of the demand, movie visitors talk a lot about movies and they often decide together which movie to visit. From the side of the supply, movie producers have to face a high level of uncertainty. Before any movie is released, it is very difficult to forecast social processes like word-of-mouth (WOM), social influence and coordinated consumption. Producers hope that their movies are able to build "legs" that allow them to remain in the top classifications for more than 10 weeks (De Vany and Lee, 2001). But only a few of them will make it and will become hits. All the rest is either pushed out of the top classifications very fast or it does not enter it at all[2,3].

Because of these market characteristics, many models have been proposed to formalize different aspects of the motion picture market and especially to forecast the box-office sales. De Vany and Walls (1996) propose a sequential Bayesian model with a Bose-Einstein process in order to explain this distribution. In this realization of the Bose-Einstein process persons sequentially decide whether to go to see the movie (accept) or not to go (reject). The probability of going to the movie depends on how many others have already accepted and on the satisfaction of others that have already accepted. Consequently, the model is able to generate path dependence and very auto correlated time series: the decision of a person depends on what the previous have done. This is a common feature of those models that generate herd behaviors (Banerjee, 1992; Bikhchandany et al., 1992). Moreover the model is able to formalize both positive and negative WOM because the quality of the movie unfolds while persons decide whether to go or not. This analysis brings evidence of increasing returns caused by information feedback. However, the sequential decision making of the agents is not realistic. Usually people decide together about the movie they want to see. And, remarkably, mass media effects are not included.

Sawhney and Eliashberg (1996) introduce a simple parsimonious model that is able to explain movie box-office returns during time by formalizing only two factors of the movie visitor decision making: time to decide λ and individual time to visit γ. The model is attractive because of its simplicity and, most of all, it contributes to the field because it introduces a distinction between two classes of box office returns that has been adopted later by many other models (for example Hidalgo et al, 2006 and Ainslie et al. 2005): "blockbuster" vs "sleeper". The former is the classical mainstream Hollywood movie whose returns, driven by a high mass media campaigns before the launch of the movie, are very high at the first weekend when the movie is released, and then they decrease exponentially in the following weeks; the latter is the typical art-house movie whose returns are relatively low when the movie is released, then they increase in the first 3-5 weeks thanks to a positive WOM and finally they decrease in the following weeks. This model is theoretically relevant because of its parsimony but it is of little use for marketers and managers because it does not forecast movie returns before they are released. In order to fill this gap Eliashberg et al. (2000) propose MOVIMOD: a much more detailed model of how a new movie penetrates in the market. The model includes several parameters (both individually oriented such as WOM, individual interests, memory decay, etc. and movie oriented such as theme, informative advertising, convincing advertisement, etc.) and these parameters are calibrated by direct elicitation from respondents who are exposed to the advertisings and to the whole movie before the movie is released. MOVIMOOD shows a high forecasting power in different cultural contests like the Netherlands and USA.

These models formalize movies' box office one by one. It is beyond their scope to explain why just a few movies gain a lot and so many movies gain only a few. Only a few works have attempted to introduce models that focus on the competition among movies (Krider and Weinberg, 1998) and that try to explain the complete distribution of movie revenues (Ainslie, et al. 2005). Using a logit model for the market shares of each movie of the market, Ainslie et al. (2005) are able to estimate parameters such as attractiveness of the movie in the opening week, peak of attractiveness and speed of attractiveness in increasing and decaying during time. In this way they depict an overview of the motion picture industry studying the relationship between advertisement and sales and finding that production labels effectively use different strategies in releasing their movies understanding both when to compete against other labels and when to avoid competition.

However, the main query remains unsolved: why are movies' box offices so unequally distributed? Our model proposes a social explanation for this research question. We present it in there step: first we make two

[2] Moreover the movie market is very suitable for this kind of studies because of at least 4 more reasons: (1) macro data of market dynamics are easily available, (2) the movie life cycle is very short and easy to follow, (3) price is almost everywhere given and fixed, (4) usually movie visitors visit the movie at the cinema theatre only once.

[3] The motion picture market is not the only one to show these characteristics. Also books and CDs show similar characteristics (Sornette et al. 2004; Sorensen, 2004; Kohli and Sah, 2003).

assumptions based on theory and we collect empirical evidence to support them through a survey. This survey represents a micro calibration of our model. Second, we present our agent-based model describing how it formalizes the process of WOM, social influence and coordinated consumption. Third and finally we present preliminary results showing how the inequality of the market depends on these social aspects of the model.

Micro-Calibration of the model: evidence from a survey on movie visitors

We collected data in Groningen (the Netherlands) about movie visitors that visited two movies in two different cinemas. The movies were *Brothers* and *The Interpreter*. We obtained a dataset of 774 observations (454 for Brothers and 320 for The Interpreter). These movies were selected because considered two typical examples of two different types of movies: *art-house* movie, Brothers, and *mainstream* movie, The Interpreter (Sawhney and Eliashberg, 1996). We hypothesized that movie goers' attitudes and behaviors substantially differ for the two kinds of movies. While art-house movies are visited by movie goers that consider cinema as art consumption, mainstream movies are visited by those that believe that visiting a movie is entertainment consumption. Moreover, while visitors of art-house movies choose which movie to see according to their personal preferences and they collect carefully information about it through selected mass media sources, visitors of mainstream movies are more socially affected and they do not select carefully information coming form mass media.

The distinction between these two classes of movies has been recently studied especially on the side of the production and on the side of their returns (Sawhney and Eliashberg, 1996; Hidalgo et al. 2006). Art-house movies are usually independently made with low budgets and they are produced and distributed from small labels. On the contrary, mainstream movies are those like Hollywood movies with usually high budgets and big labels that study, prepare and realize the movie, its promotion, the launch and also the distribution. Finally these two different kinds of movie use also different strategies in order to enter the market: art-house movies are usually sleepers and they often use the *platform release strategy*, the mainstream movies are usually blockbusters and they often use the *wide release strategy* (Sawhney and Eliashberg, 1996). The former strategy opens with relatively low advertisement and low exhibition intensity (low number of screens). After a few weeks it increases the exhibition and it rides the positive word-of-mouth. Finally, it drops down following the demand. The latter strategy consists of distributors that heavily promote the movie before its release and they offer a high level of exhibition intensity (high number of screens) during the opening week. During the following weeks the promotion decreases drastically and the exhibition intensity usually drops following the demand. Consequently moviegoers usually visit the movie right when it is released and decrease drastically during the following weeks. Figure 3 shows returns of the two movies in the USA and it confirms that the selection of the movies was theoretically grounded. The two graphs reflect the typical behaviors described above: increasing attendance until a maximum and then a fast decay for the art-house movie, and monotonic exponential decay for the mainstream movie[4].

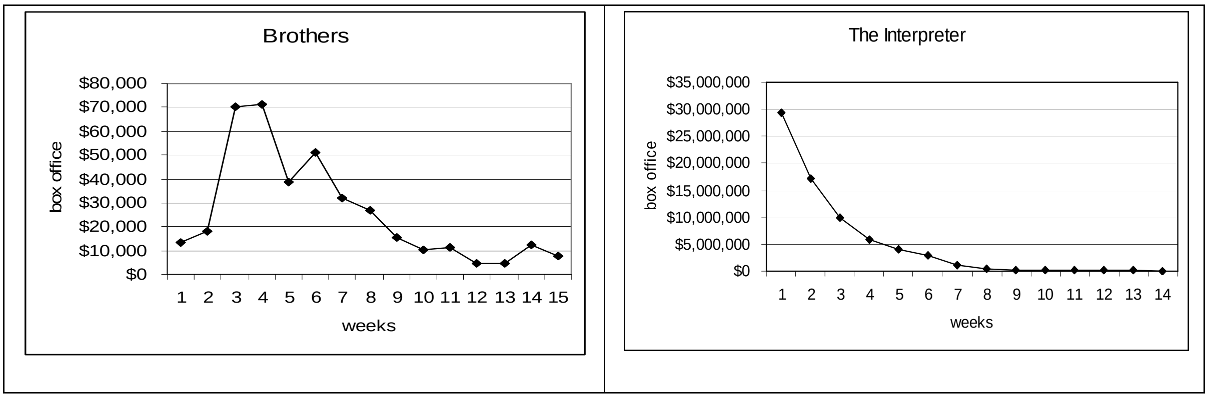

Figure 3. Returns in USA for the movies Brothers and The Interpreter

[4] Notice that the two movies are also very different in revenues. The distributor of Brothers is Independent Film Channel (IFC) FILMS. The final total box office of this movie in the USA theatres has been less than $400000. The Interpreter is distributed by UNIVERSAL. After a massive promotion before the launch, the movie enters the USA classification at the first place obtaining a final total box office of more than 70 millions of dollars, almost 20 times the total revenue of Brothers.

These two movies were selected as representative of two different venues of the same market (art-house movies vs blockbusters). In particular we hypotheses that (1) visitors of blockbuster movies are more socially affected than visitors of art-house movies and that (2) visitors of blockbuster movies visit movies less often than visitors of art-house movies. These differences in attitudes and behaviors are a result of this different kind of consumption[5]. We performed the Mann-Whitney test and the two independent samples t-tests in order to find significant differences in the median and the mean of the obtained variables for the two movies. Table 1 and table 2 show the results for the behaviours and the attitudes of the movie goers. Movie visitors significantly differ both in their attitudes and in their behaviors in the directions specified by our hypotheses[6].

Table 1. Mann Whitney test. Ranks on movie goers' behaviors for the 2 movies Brothers and The interpreter

		N	Mean Rank	Sum of Ranks
How many times per year do you go to the cinema?	The interpreter	312	319.3413462	99634.5
	Brothers	442	418.5531674	185000.5
	Total	754		

Test statistics

How many times per year do you go to the cinema?	
Mann-Whitney U	50806.5
Wilcoxon W	99634.5
Z	-6.18384
Asymp. Sig. (2-tailed)	.000

Table 2. Group Statistics on movie goers' attitudes for the 2 movies Brothers and The Interpreter

	Brothers vs The Interpreter	N	Mean	Std. Deviation	Std. Error Mean
I go to see a movie at the cinema in order to spend nice time with friends/partner/family	The Interpreter	311	1.97	.926	.053
	Brothers	447	2.26	1.047	.050

Independent samples t test

	Levene's Test for Equality of Variances		t-test for Equality of Means				
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
I go to see a movie at the cinema in order to spend nice time with friends/partner/family	14.455	.000	-3.927	756	.000	-.290	.074
			-4.014	714.054	.000	-.290	.072

The agent based model

In this section we present our agent based model that simulates the competition of the motion picture market and which is based explicitly on the moviegoer's decision-making. Moviegoers are agents situated in a regular torus (a regular lattice with wrapped edges), they are informed about movies both by mass media campaigns and via friends that have already seen the movie (WOM). They can decide to pick up a movie at each time step of the simulation. The macro dynamics are generated by a micro decision-making rule that is based on 6 factors:

- Quality of the movie;
- Relation between preferences of the moviegoers and movie's theme;
- Social influence (movies with high attendance attract more);

[5] The questionnaire movie visitors answered included questions like: "how often do you go to cinema in a year" and "how much do you agree with the following sentences: -I go to see a movie at the cinema in order to see a high quality movie-; or -I go to see a movie at the cinema in order to spend nice time with friends/partner/family- and movie visitors answered using a 5 point scale (from "totally agree" until "totally disagree").

[6] In this extended abstract we present only a part of the complete calibration of the model; in a final complete version of the paper we will include further analysis on mass media and WOM effects. Then we will simulate markets with the exact distributions of values obtained by this survey.

- Coordinated consumption (moviegoers prefer to see a movie with some friends);
- WOM (information about the quality of movies is passed by those that have seen the movie to those that have not seen them yet);
- Mass media effect

Among those movies agent *i* is informed about, it selects the best movie *j* according to (1) and it decides to see it if and only if $U_{ij} >= U_{iMIN}$, where U_{iMIN} is the minimum satisfaction agent *i* wants from any movie.

$$U_{ij} = \beta_j \cdot f(a_j, w_j, \gamma) + (1-\beta_j) \cdot f(q_j, m_j, p_i, \delta) \quad (1)$$

$$f(q_j, m_j, p_i, \delta) = q_j \cdot \left[1-(m_j - p_i)^{\delta}\right] \text{ (individual component)} \quad (2)$$

$$f(a_j, w_j, \gamma) = a_j \cdot w_j / \left(a_j^{\gamma} + w_j^{\gamma}\right) \text{ (social component)} \quad (3)$$

The agent's utility consists of two components: a function describing the individual utility and a function describing the social utility. Concerning the individual utility, q_j is the quality of the movie *j*, $\left[1-(m_j - p_i)^{\delta}\right]$ is the distance between preferences of agent *i* p_i, and the theme of movie *j* m_j. Concerning the social utility, agents evaluate what their neighbors do[7]. Two important concepts are formalized in the utility function: the coordination in consumption w_j (the proportion of friends that are informed about the movie and that have not seen it yet) and the social influence a_j (the proportion of friends that have already seen the movie). It is easy to observe how the function of the individual component behaves. It is proportional to the quality of the movie and it increases at an increasing rate when the movie meets the preference of the agents. It is less straightforward to understand how the function of the social component behaves. It increases at an increasing rate when both w_j and a_j are increasing. However, w_j and a_j are related to each other: because they are proportions of same personal networks, they cannot sum up to more than 1. Then, an increase in a_j can correspond to a decrease in w_j and vice versa. Figure 2 displays the shape of the social component function for $\gamma = 1$.

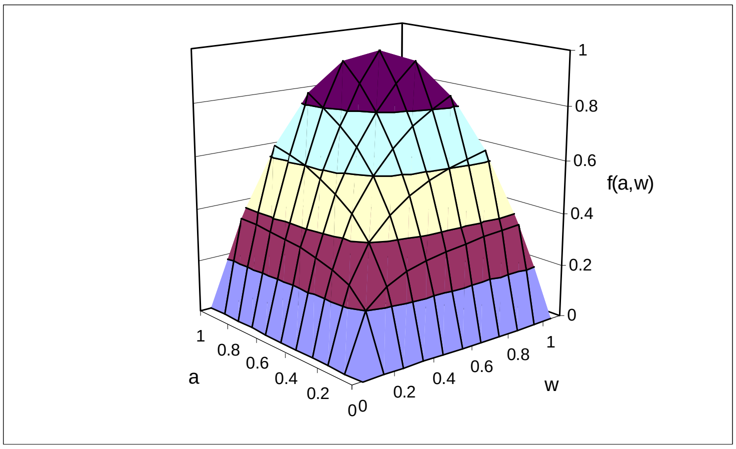

Figure 2. The shape of the social component function in the utility function of the moviegoer

The social component and the individual component are weighted by the parameter β_i. This is a key parameter of the model because it indicates the attitudes of the agents towards the consumption. We use our empirical dataset in order to calibrate this parameter: simulation settings with high β_i formalize markets where movie goers tend to see mainstream movies and simulation settings with low β_i formalize markets where movie goers tend to see art-house movies.

Agent *i* evaluates the utility of each movie it is informed about and it decides to visit the movie with the highest utility. But how are the agents informed about the movies? They receive information about movies both via WOM and via mass media. WOM and mass media campaigns are introduced into the simulation as simple information flows: concerning WOM, if an agent has seen a movie, it informs its neighbors about that movie;

[7] Each agent has eight friends (Moore Neighborhood).

concerning mass media campaigns, for each movie *j* it is associated a marketing effort r_j that is the probability of informing each agent about movie *j* at any time step of the simulation. The higher the value of r_j, the higher the mass media effort and the more agents are informed about movie *j*.

In order to study how movie revenues are distributed into the market, we collect market shares s_k for all the *M* movies of the market:

$$s_k = \frac{v_k}{\sum_{j=1}^{M} v_j} \tag{4}$$

Then we study market dynamics and success inequality of movies computing the Gini coefficient *g* which varies from 0 (completely equal market shares for all movies) to 1 (a single movie takes it all):

$$g = \frac{\sum_{i=1}^{M} \sum_{j=1}^{M} |s_i - s_j|}{2 \cdot M \cdot \sum_{k=1}^{M} s_k} \tag{5}$$

Preliminary results

We simulate a market where movies differ in quality (i.e. q_j is uniformly distributed between 0 and 1) but they are oriented towards the same segment (i.e. m_j =0.5 for all movies and δ=2) and they have equal resources for advertising (r_j is equal for all movies). In this way we can vary β_i simulating different markets: a high $\overline{\beta}$ ($\overline{\beta}$ =[0.5, 1.0]) represents a market oriented towards an entertainment consumption and a low $\overline{\beta}$ ($\overline{\beta}$ =[0.0, 0.5]) represents a market oriented towards an art consumption. Moreover we vary r_j simulating different levels of advertising (the higher r_j, the higher the competition among movies based on the advertisement). Finally we set γ=1 implying that social influence and coordinated consumption have equal and symmetrical effects. For each condition, 20 simulation runs are conducted (these runs were enough for the results to converge). Results are collected after 100 time steps and averages are reported.

Preliminary simulation results are presented in Table 3[8].

Table 3. Gini coefficient values for different markets (entertainment consumption vs art consumption) and for different levels of marketing effort

	High $\overline{\beta}$ (entertainment consumption)	Low $\overline{\beta}$ (art consumption)
$r = 0.001$	0.6320	0.4911
$r = 0.005$	0.5474	0.4122
$r = 0.01$	0.5943	0.4123
$r = 0.05$	0.7299	0.6790
$r = 0.1$	0.7436	0.7137

The first result is that the Gini coefficient, *g*, is higher for the market oriented towards the entertainment consumption than for the market oriented towards the art consumption. When movie goers perceive cinema as entertainment, their decisions depend more on what other movie goers decide to do, then those few movies that are well received by the movie goers have an additional advantage given by coordinated consumption and social influence and tend to become hits more easily. They have even more chances to either conquer higher market shares or to lose respect to the competitors. Consequently, at the aggregate level, the box office distribution becomes more unequal. The analysis of movie histories and the observation of the Gini coefficient, *g*, during the time of the simulation runs show also that market share differences increase during time. This means that at the beginning of the competition, successful movies build their success just on their quality but, later on, movies that obtain slightly higher market shares become real hits thank to social processes like social influence and coordinated consumption. This result indicates that the entertainment segment of the motion picture market,

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[8] Further analysis including different mechanism of competition (Ainslie et al. 2005; Adner and Levinthal, 2001) and more detailed results including the movie histories will be included in the final complete version of the article.

which is the biggest part of it, is very risky for the producers and that movies become successful only when they are able to hit the market driven by social processes like WOM, social influence and coordinated consumption.

The second result of the simulation experiments indicates that the higher the level of marketing effort r_j, the higher the Gini coefficient g and the lower the differences in market shares distribution between the entertainment consumption market and the art consumption market. In these simulation runs we assume that movies enter the market at the same time, they compete for the same potential market with equal marketing resources. In this simple and artificial setting we can directly observe the effects of social influence and coordinated consumption. When marketing efforts are high, movie goers are informed about more movies, social processes are ignited soon and easily leading to an unequal distribution of the market shares. Moreover, under these conditions, the entertainment segment and the art segment become more similar to each other. Because movie goers know about more movies, differences in quality decreases in absolute terms and then, respect to quality, the weight of social effects increases. Thus also movie goers that are more oriented towards an art consumption become more sensitive to social processes and once again the market dynamics are driven towards more extreme distributions of market shares.

References

Adner, R. and Levinthal, D. (2001) Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation, *Management Science*, 47(5), 611-628.

Ainslie, A. Dréze, X. and Zufryden, F. (2005) Modeling Movie Life Cycles and Market Share, *Marketing Science*, 24 (3), 508-517.

Banerjee, A. V. (1992) A Simple Model of Herd Behavior, *Quarterly Journal of Economics*, 107, 797-817.

Bikhchandany, S. and Hirshleifer, D. and Welch, I. (1992) A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades, *Journal of Political Economy*, 100, 992-1026.

Cuadrado, M. and Frasquet, M. (1999) Segmentation of Cinema Audience: an Exploratory study Applied to Young Consumers, *Journal of Cultural Economics*, 23, 257-267.

De Vany, A. S. and Walls, W. D. (1996) Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry, *The Economic Journal*, 439, 1493-1514.

De Vany, A. S. and Lee, C. (2001) Quality Signals in Information Cascades and the Dynamics of the Distribution of Motion Picture Box Office Revenues, *Journal of Economic Dynamics and Control*, 25, 593-614.

De Vany A. (2004) *Hollywood Economics: How Extreme Uncertainty Shapes the Film Industry*, Routledge, London.

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

Eliashberg, J. Jonker, J. J. Sawhney, M. S. and Wierenga B, (2000) MOVIEMOD: An Implementable Decision Support System for Prelaunch Evaluation of Motion Pictures, *Marketing Science*, 19, 226-243.

Groot, R. D. (2005) Levy Distribution and Long Correlation Times in Supermarket Sales, *Physica A*, 353, 501-514.

Hidalgo, C. A. R. Castro, A. and Rodriguez-Sickert, C. (2006) The Effect of Social Interactions in the Primary Consumption Life Cycle of Motion Pictures, *New Journal of Physics*, 8, 52.

Ijiri, Y. and Simon, H. A. (1974) Interpretation of Departures from the Pareto Curve Firm-Size Distributions, *Journal of Political Economy*, 82, 315-332.

Kohli, R. and Sah, R. (2003) Market Shares: Some Power Law Results and Observations, Harris School Working Paper, series 04.1, http://www1.gsb.columbia.edu/mygsb/faculty/research/pubfiles/rk35/Kohli%5Fmarket%5Fshares%2Epdf

Krider, R. Charles, E. and Weinberg, B. (1998) Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game, *Journal of Marketing Research*, 35(1), 1-15.

Janssen, M. A. and Jager W. (2003) Self-Organisation of Market Dynamics: Consumer Psychology and Social Networks, *Artificial Life*, 9 (4).

Moss S. (2002) Policy Analysis from First Principles, *Proceedings of National Academy of Science*, 99, 7267-72.

Salganik, M. J. Dodds, P. S. Watts, D. J. (2006) Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market, *Science*, 10, 854-856.

Sawhney, M. S. and Eliashberg, J. (1996) A Parsimonious Model for Forecasting Box-Office Revenues of Motion Pictures, *Marketing Science*, 15, 113-131.

Sorensen, A. T. (2004) Bestseller Lists and Product Variety: The Case of Book Sales, working paper, http://www.stanford.edu/~asorense/papers/bestsellers.pdf

Sornette, D. Gilbert, T. Helmstetter, A. and Ageon, Y. (2004) Endogenous versus Exogenous Shocks in Complex Networks: an Empirical Test Using Book Sales Rankings, *Physical Review Letters*, 93, 228701-4.