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Quality, advertisement and social influences in cultural market: The case of motion picture.

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***Abstract*—In the motion picture industry the winner takes it all. Every year a few blockbuster movies such as Avatar, Pirates of the Caribbean, and Toy Story gather most of the Box Office sales while many other movies obtain very low sales. Why do movie goers cluster so much on the same movies? In this paper we propose an agent-based model in which the movie goer's decision-making depends on external influence such as advertisement, internal influence such as imitation, shared consumption influence such as the desire of visiting a movie with someone else and movies' quality. We study how the movie goer's decision-making determines Box Office sales. We find that the average importance consumers attach to movies' quality is low, much lower than the importance consumers attach to external, internal and shared consumption influences. Moreover, we find that the dispersion of Box Office sales is mainly determined by the internal and external forces of the market. Finally we find that additional investments in ad expenditure budgets are particularly beneficial for high budget movies of high quality whereas low budget movies and movies of poor quality do not substantially benefit from additional advertising.**

1. INTRODUCTION

The winner takes it all is a principle which applies to many economies. According to this basic and general principle, a few successful hits get the largest part of the market shares whereas the rest obtain very low shares (Frank and Cook, 1995). The winner takes it all principle applies to entertainment industries as well (Vogel, 1998). For example, in the motion picture industry, a few blockbuster movies like *Avatar*, *Pirates of the Caribbean*, *Toy Story*, *The Avengers* are the real leaders of the market. They gather most of the revenues of the cinema market and the many other movies obtain very low shares (Elberse and Oberholzer-Gee, 2006). For example, in 2003, when the mean of the revenues 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, or in 2009, when Avatar obtains the highest box office of all times, about $750 million, the 250th in the rank, *The Merry Gentleman* obtains only $348,000. Figure 1 shows the distribution of movies' revenues in the USA market averaged from 1981 until 2011. They are ranked according to their revenue, from the first position until the 250th position. The variance of the distribution is very high and the mean is not very informative as it heavily depends on the upper tail[1].

The Gini index is a measure of statistical dispersion representing how much a given distribution deviates from a perfectly equal distribution. It is usually used to measure the dispersion of the income distribution of a nation's residents and also to indicate dispersions of income (http://en.wikipedia.org/wiki/Gini_coefficient) or market shares (Salganik, Dodds and Watts, 2006). We use the Gini index to measure the dispersion of movies' Box Office sales at the cinema theaters. A Gini index of zero indicates perfect equality of revenues, that is a hypothetical market where all movies gain the same, and a Gini index of one indicates a hypothetical maximal inequality with a single movie getting the revenue of the entire cinema theatrical market. From 1999 until 2011 Box Office revenues have always shown very high dispersion, with a Gini index of about 0.5. Questions arise on whether and how social influences could be responsible for the success of certain movies. Could it be that other people visiting a movie trigger a person's interest to visit that movie too? And does the fact that most people consider visiting a movie as a social event, and hence go with companions, has an impact on the sales of a movie? How strong these effects are compared to other effects such as quality and advertising?

FIGURE 1 ABOUT HERE

In our ABM of the movie market we formalize artificial consumers that decide on visiting a particular movie according to external influence such as advertisement, internal influence such as imitation, shared consumption influence such as the desire of visiting a movie with someone else and movies' quality. In this way it is possible to disentangle the different drivers of agent's decision making to visit a movie, and hence get a clear picture of how these factors determine the success or the failure of the movies released in the market.

Understanding the drivers of movies' success is crucial for studio producers' managers, and within this context it is very relevant to understand how social processes may ignite a social avalanche that creates a success (e.g., Elberse, 2013). Experiments with our ABM show that the dispersion of Box Office sales is mainly determined by the internal and external forces of the market and not by the real qualities of the movies. In addition we find that additional investments in ad expenditure budgets are particularly beneficial for movies with high advertising budgets whereas movies with low ad budgets do not substantially benefit from additional advertising.

2. THE AGENT BASED MODEL

2.1. The demand

We simulate the motion picture market for one year with *N* consumers and *M* movies. Each simulation time step represents a week and at each step a fraction $NEW\_ENTRIES_t$ of movies enter the market. Each movie *j* enters the market at time T_j and remain in the market for *MOVIE_LENGTH* time steps. Thus, at each time step *t* agents choose among a given number of available movies, which we indicate with $AVAILABLES_t$.

We use a logit formulation to define the probability that agent *i* visits movie *j* at time step *t* (1) and model agent *i*'s attraction to movie *j* at time step *t* as in (2). For agent *i*, the attraction A_{ijt} of movie *j* at time step *t*, depends on four components: *internal influence*, *external influence*, *shared consumption influence* and *quality*, respectively weighted by β_1, β_2, β_3, and β_4. Internal influence determines how much agent *i* copies other agents' choices, external influence identifies how much agent *i* is affected by the pre-release marketing campaign, shared consumption influence indicates how much agents' choices depend on the availability of companions to visit the movie with, and the quality component indicates how much agent *i* choice depends on movie *j*'s quality.

$$P\left(agent\ i\ visits\ movie\ j\ at\ time\ step\ t \mid i\ has\ not\ visited\ \ j\ yet\right) = \frac{\exp\left(A_{ijt}\right)}{\sum_{m=1}^{AVAILABLES_t} \exp\left(A_{imt}\right)} \tag{1}$$

$$A_{ijt} = \underbrace{\beta_1 \cdot x_{jt}}_{\substack{\text{external}\\ \text{influence}}} + \underbrace{\beta_2 \cdot y_{jt}}_{\substack{\text{internal}\\ \text{influence}}} + \underbrace{\beta_3 \cdot z_{ijt}}_{\substack{\text{shared}\\ \text{consumption}}} + \underbrace{\beta_4 \cdot q_{jt}}_{\substack{\text{quality}\\ \text{level}}} \tag{2}$$

[1] Source: www.boxofficemojo.com

The weights β_{1}, β_{2}, β_{3}, and β_{4} indicate how much importance agent *i* attaches to each component and β_{1}, β_{2}, β_{3}, and β_{4} set the average weights of the consumers. In our ABM, movies are like new innovations that launch, diffuse and exit the market. Our model borrows from other simulation models of diffusions and formalizes internal and external influences in a very similar fashion. However, respect with these models, our formalization allows us to simulate several competing diffusions and analyze the distribution of Box Office sales. In order to simulate a market with a realistic competition, we empirically validate our ABM using vast information from the real cinema market. In section 3, following the rigorous guidelines by Rand and Rust (2011), we set the number of movies released per year, how many movies enter the market at each time step ($NEW\_ENTRIES_t$), how many weeks they remain available in the theaters (*MOVIE_LENGTH*) and how many agents attend at each week ($ATTENDANCE_t$) based on the US theatrical market.

Finally, as our main goal is to study the macro outcomes of the market at the aggregate level, we opt for an ABM with a very simple formalization of the individual interactions among agents. For example, we did not explicitly formalize agents' connections and adopt a fully connected network in which each agent is connected to any other agent.

2.2. The supply

The attraction associated to internal influence x_{jt} is based on a herding effect with agents imitating other agents that have visited the movie at the previous time step. We assume that such a herding phenomenon increases when more agents have visited movie *j* at the previous time step:

$$x_{jt} = \frac{VISITS_{jt-1}}{N} \tag{7}$$

As for the external influence force y_{jt}, we derive it from movie *j*'s advertising budget. As in the real cinema market where studios spend almost the entire advertising budget before the movie release, in our ABM we model movies' launch with a pre-release advertising campaigns. When movie *j* launches at T_j it is characterized by an external influence $y_{jT_j} = \exp\left(-\omega \frac{\overline{AD\_BUDGET}}{AD\_BUDGET_j}\right)$. This formalization assumes that, everything else being equal, the advertising effect depends on the ad expenditures that movie *j* invests in the pre-release marketing campaign (AD_BUDGET_j) and on the average ad expenditures that movies invest in the market ($\overline{AD\_BUDGET}$). We opt for an S-shaped functional form that reflects the empirical relation between the advertising budget and the external influence (Lilien and Rangaswamy 2003). Here ω=[0, Inf] determines the overall effectiveness of the pre-release advertising campaigns in the motion picture market. We adopt a S shaped functional form for the advertising effect, which is in line with findings that show diminishing returns between advertisement investments and their effects on consumer's awareness and behavior and with inconclusive marketing campaigns that may result from insufficient amount of money spent in advertising (Lilien and Rangaswamy, 2003; Tellis, 2006). After launching, in the following weeks, y_{jt} evolves as specified in (8). Here, the external influence component decays depending on δ=[0, 1] which formalizes the retention rate of advertising messages over time. At higher levels of δ, consumers retain the advertising messages for a longer period (Lilien and Rangaswamy 2003; Hanssens et al 2001).

$$y_{jT_j} = \delta^{t-T_j} \cdot \exp\left(-\omega \frac{\overline{AD\_BUDGET}}{AD\_BUDGET_j} \right) \tag{8}$$

The consumption of experience goods such as movies strongly depends on whether they are consumed together with other consumers. Many studies have shown how the decision making of the movie goers is strongly driven by the desire to have a joint experience with someone else. To formalize shared consumption influence we adopt a simple formalization based on the social influence of potential joint consumers who have not yet purchased. Assuming that agent *i* wants to go to the cinema at time step *t* with g_i companions, we model shared consumption influence z_{ijt} as the probability that none of her or his g_i companions have seen movie *j* already (9). Here $\sum_{k=T_j}^{t-1} VISITS_{jk}$ indicates how many agents have already visited movie *j* at time *t* and thus the overall effect refer on the fraction of agents that have not seen the movie yet and can potentially still go. The utility derived from shared consumption decreases when there are fewer other agents available, because it is more difficult to find companions with whom to visit the movie (Weinberg, 2003). Moreover, the probability that all companions have not seen yet the movie decreases also with g_i because the more companions agent *i* wants to include in the shared consumption, the more likely it is that some companion has already seen movie *j* and will steer the group's visit toward other movies. This simple formalization of shared consumption influence strongly depends on an important assumption: consumers do not visit a movie at the cinema more than once. If they have visited a movie at the theaters they are not interested to see the same movie with other companions.

$$z_{ijt} = \prod_{k=1}^{g_i} \left(1 - \frac{\sum_{l=T_j}^{t-1} VISITS_{jl}}{N\_AGENTS} \right) \tag{9}$$

Finally in our ABM when movie *j* launches and spreads into the market it is also characterized by a quality level q_{jT_j} that corresponds with the overall judgment of the movie among consumers, Q_j (10).

$$q_{jt} = Q_j \tag{10}$$

3. EMPIRICAL VALIDATION OF THE ABM

Rand and Rust (2011) propose rigorous guidelines to validate ABMs. They particularly stress the importance of empirical validation, which is the process of determining how well the implemented model corresponds to reality using real data. They define empirical input and empirical output validations as two forms of validation that confirm that the real data being added to the model are accurate and that the output of the ABM corresponds with real data. These two forms of validations differ from micro-face and macro-face validation that instead ensure that the micro-mechanisms of the agents and the macro-patterns of the model correspond "on face" to the real world and do not need empirical confirmation. In this section, we empirically validate our ABM with data of the real US market, including ad expenditures, production budgets, peer review scores, etc. In Table 1 we list the parameters of our ABM, including their description, their values, and how we validate them.

TABLE 1 ABOUT HERE

In order to validate our ABM, we use overall statistics on the US cinema market. In addition, we build up a rich dataset on movies released in the US market from 1999 until 2011, including the 150 movies with the highest Box Office sales year by year, which corresponds to more than 95% of the total yearly revenues of the industry. Besides Box Office sales, our database includes the weekly ad expenditures and the peer reviews scores of each movie. In the next subsections we illustrate how we use this information on the real US cinema market to empirically validate our ABM.

3.1. Empirical validation of the number of movies per year, new releases per week, movies' life cycle length and weekly attendance

We begin setting M = 521 and *MAX_LENGTH* = 15 as in the US cinema market, from 2000 until 2010, an average of 521 movies were released each year and obtain 98% of their Box Office sales within the first 15 weeks of their life cycles. Then, investigating the releasing date of these movies and the total Box Office sales of the market, we could also empirically validate $NEW\_ENTRIES_t$, and A_t that are the number of newly released movies per week and the fraction of N that visit the cinema at each time step t.

3.2. Empirical validation for external influence

Regarding the external influence component, we could empirically set AD_BUDGET_j and estimate ω and δ values. Using real weekly advertising expenditures of movies launched in the US market from 2000 to 2010, we randomly extract AD_BUDGET_j from a Normal distribution, with the mean and variance of the real advertising expenditures of the week movie j is released and estimate. Then, using the total advertising budgets of the movies of our database and their Box Office sales we estimate ω and δ values for each movie. Our estimation procedure converged for 1857 out of 1950 movies, providing the following results: average(ω)=2.56; std(ω)=1.11; max(ω)=8.2; min(ω)=0.04; average(δ)=0.62; std(δ)=0.16; max(δ)=0.99; min(δ)=0.24. Thus, in our ABM we set ω=2.5 and δ=0.6. In the technical appendix we provide further details about ad expenditures data, Box Office sales data and the results of our estimations.

3.3. Empirical validation for shared consumption

Using statistics on group sizes for visiting movies (FFA 2013) we can validate g_i, that is the number of companions with whom agent i visits a movie. On average, from 2007 until 2012, 9.3% of the tickets sold were single visits, 43.7% involved couples, 20.2% included groups of three, 13.3% were groups of four, and 13.5% involved groups with five or more consumers. The distribution of group visits remained stable, with no significant changes across the five-year span. In our simulation, at each time step we re-assign g_i values to each agent. In the Technical Appendix we provide information year by year on groups' attendance.

3.4. Empirical validation for quality

We could empirically validate Q_j values using three movies' variables: production budget, peer and expert judgments. We created a quality measures according to the following formula:

$$Q_j = \frac{Ln(P\_BUDGET_j) + PEER\_JUDGMENT_j + EXPERT\_JUDGMENT_j}{3} \tag{11}$$

Our database of movies launched in the US market from 2000 to 2010 also contains production budgets, peer and expert judgments. In our simulation, for each AD_BUDGET_j randomly drown we select the corresponding values for P_BUDGET_j, $PEER\_JUDGEMENT_j$ and $EXPERT\_JUDGEMENT_j$ and determine Q_j.

4. RESULTS

4.1. Simulation experiment 1. The effects of quality, external and internal influences on the dispersion of movies' Box Office sales

In this simulation experiment we simulate different scenarios to analyze how the importance consumers attach to internal, external, shared consumption influences and quality impacts the motion picture market. In particular, we focus on three main aspects of the motion picture market:

- *Distribution of Box Office sales.* In each scenario we compute the GINI coefficient which indicates whether Box Office sales differ across movies.

$$GINI = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{\left|VISITS_i - VISITS_j\right|}{2N^2 \cdot \overline{VISITS}} \tag{12}$$

  This index varies between 0 and 1.

- *The difference between the rankings of quality and Box Office sales.* In each scenario we compute an overall index which indicates whether the good movies are also and the most visited movies. For each movie j, Q_RANK_j and BO_RANK_j indicate its positions in the quality and Box Office rankings, respectively. Then we can compute an overall index of the market based on the sum of the absolute differences of the rankings:

$$RANK\_DIFF = \sum_{j=1}^{N}\frac{\left|Q\_RANK_j - BO\_RANK_j\right|}{N^2/2} \tag{13}$$

  This index varies between 0 and 1.

- *Movie life cycles.* In each simulation scenario, we also compute an index representing the life cycle of the movies. For each movie j, it is possible to keep track of the Box Office sales along the life cycle of the movie. Thus, we calculate the percentage of the Box Office sales in opening week respect to the cumulative Box Office sales and the average percentage over the movies in the market.

We design an experimental design with 625 simulation scenarios using a wide range of values: β_1 = [0.1, 0.3, 0.5, 0.7, 0.9], β_2 = [0.1, 0.3, 0.5, 0.7, 0.9], β_3 = [0.1, 0.3, 0.5, 0.7, 0.9] and β_4 = [0.1, 0.3, 0.5, 0.7, 0.9]. Table 2 presents the results of the experiment. It reports the coefficients of three regression models, estimating the effects of internal, external, shared consumption influences and quality (independent variables) on the three market indicators described above.

TABLE 2 ABOUT HERE

The most important driver of Box Office sales' dispersion is internal influence. If consumers attach more importance to internal influence, the GINI index increases, indicating a larger gap between successful and unsuccessful movies. This effect is trivial because when consumers attach more importance to internal influence they copy each other more and their visits tend to converge more to the same movies. The effects of external influence, shared consumption influence and quality display more interesting results. While their directions are straightforward; it is interesting to compare their magnitude. The impact of external influence is surprisingly bigger than the effects of shared consumption and quality. Moreover, the effect of quality is really low, indicating that the big gap between successful and unsuccessful movies does not crucially depend from the fact that consumers visit good movies and avoid bad movies.

Our analysis also suggests that the gap between good movies and successful movies depend mainly on how much importance consumers give to internal influence and quality and that the percentage of the opening week strongly depends on the external influence.

Our experiment allows us to identify the most realistic simulation scenarios. In the real market *GINI*=0.504; *RANK_DIFF*=0.405 and *OPENING*=35%. The three simulation scenarios with the closest values to the real values are presented in Table 3. These results clearly indicate that in the real market consumers attach high importance to shared consumption and low importance to quality.

TABLE 3 ABOUT HERE

5.2. Simulation experiment 2. Increasing advertising budget

Our ABM allows us to investigate budget allocation strategies. In particular we can study whether an additional investment in advertising expenditures and a heavier marketing campaign is efficient. Such an instrument is one of the most efficient managerial tools that studio producers can use to positively affect the success of their movie. In this simulation experiment we study what happens when a studio increases the pre-release ad expenditures for the movie is about to launch.

We cluster the simulated movies based on four variables: expert review, peer review, advertising budget and production budget and clearly identified three clusters. In Figure 3 we plot the movies based on their advertising budgets and on the quality measure used in our ABM and we color them based on the cluster they belong to, so that we can sharply identify the three clusters. It is clear that the three selected clusters depend much more on the advertising budget than the quality measure. Red, blue and green dots indicate movies with high, medium and low ad budgets. Finally, we use the centroids of these five clusters to simulate what would have happen if studio producers had increased the advertising budgets of these five movies by 30%. We simulate this change in ad expenditures in five different simulation runs, all with the most realistic scenario' values, i.e. $\beta_1 = 0.5$, $\beta_2 = 0.5$, $\beta_3 = 0.7$ and $\beta_4 = 0.1$.

TABLE 4 ABOUT HERE

FIGURE 3 ABOUT HERE

Figure 4 shows the results of this simulation experiment. The benchmark indicates the movie's visits without any additional budget. Interestingly, we find that movies with low and medium ad budgets do not obtain significant improvement, whereas movies with high advertising budgets do much better and significantly improve their success with additional advertisement.

FIGURE 4 ABOUT HERE

5. CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

The motion picture industry is often considered a risky industry because studios have to invest high budgets to produce and market artworks whose quality is highly uncertain. Movies' quality depends very much on artistic talent, creativity and intangible assets so that it is very difficult to predict whether a script may result in a good or bad product and whether the public will eventually like and buy it.

Our results suggest that this is not true. The importance consumers attach to quality is not the main driver of Box Office dispersion. The importance people attach to quality determines whether good movies are successful and bad movies are unsuccessful and indeed we observe that good movies have much more chances to be successful than bad movies, but the gap between good and successful movies exists and it is mainly due to the fact that people are strongly affected by external influences such as advertisement and social influences such as imitation and shared consumption. We found that on average the importance consumers attach to advertisement is more important than the importance they attach to quality. This suggests that this industry is not a very risky industry because quality is unpredictable. This industry is very risky because people do not give importance to quality and only a few movies succeed to ignite imitation (Salganik, Dodds and Watts, 2006).

The results of our second experiment provide support for the so called "blockbuster strategy" (Elberse, 2013), which suggests to concentrate studio's investments towards a few big projects. Although theoretical and empirical works have shown that the marginal effects of advertising campaigns decrease when they become big (Tellis, 2006) and that high advertising investments in cultural markets such as the motion picture market, are inefficient (Elberse and Anand, 2007; Joshi and Hanssens, 2009) the blockbuster strategy suggests to insist with heavy investments for high-budget projects.

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TABLE 1. The parameters of the ABM

Parameter	Description	Values
N	Number of agents	5,000
M	Number of movies released per year	521
$\mathit{NEW\_ENTRIES}_t$	Number of new entries per week	Min = 3 (week 1); Max = 14 (week 38)
$\mathit{ATTENDANCE}_t$	Weekly attendance, or fraction of N that visit the cinema at time step t	Min = .3 (week 37) Max = 1 (week 52)
$\mathit{MOVIE\_LENGTH}$	Number of weeks of a movie life cycle	15
$\mathit{AD\_BUDGET}_t$	Advertising budget of movie j	Min = $0, Max = $60.8 million, <AD_BUDGET>= $11.7 million
Ω	Strength of advertising messages	2.56
δ	Retention rate of advertising messages	0.62
g_i	Number of movie visit companions of agent i	9.3% alone, 43.7% in couples, 20.2% in groups of three, 13.3% in groups of four, and 13.5% in groups of five or more
β_1	Overage importance people attach to internal influence	[0.1, 0.3, 0.5, 0.7, 0.9]
β_2	Overage importance people attach to external influence	[0.1, 0.3, 0.5, 0.7, 0.9]
β_3	Overage importance people attach to shared consumption influence	[0.1, 0.3, 0.5, 0.7, 0.9]
β_4	Overage importance people attach to quality	[0.1, 0.3, 0.5, 0.7, 0.9]

TABLE 2. Simulation experiment 1.

Parameter	Description	GINI	RANK DIFF	PERC_OPENING
β_1	Overall importance consumers attach to internal influence	.778**	.038**	-.445**
β_2	Overall importance consumers attach to external influence	.518**	.527**	.789**
β_3	Overall importance consumers attach to shared consumption influence	-.174**	.033*	.230**
β_4	Overall importance consumers attach to quality	.079**	-.775**	-.108**
R^2		.91	.88	.89

Notes: *p<0.05; **p<0.01.

TABLE 3. The most realistic simulation scenarios.

	β_1	β_2	β_3	β_4	GINI	RANK DIFF	PERC_OPENING
Real market values					.504	.405	35%
The best simulation scenario	0.5	0.5	0.7	0.1	.503	.463	31%
The second best simulation scenario	0.5	0.5	0.9	0.3	.487	.342	32%
The third best simulation scenario	0.5	0.5	0.9	0.1	.483	.473	32%

FIGURE 1. Revenues in the motion picture market in US from 1981 until 2011.

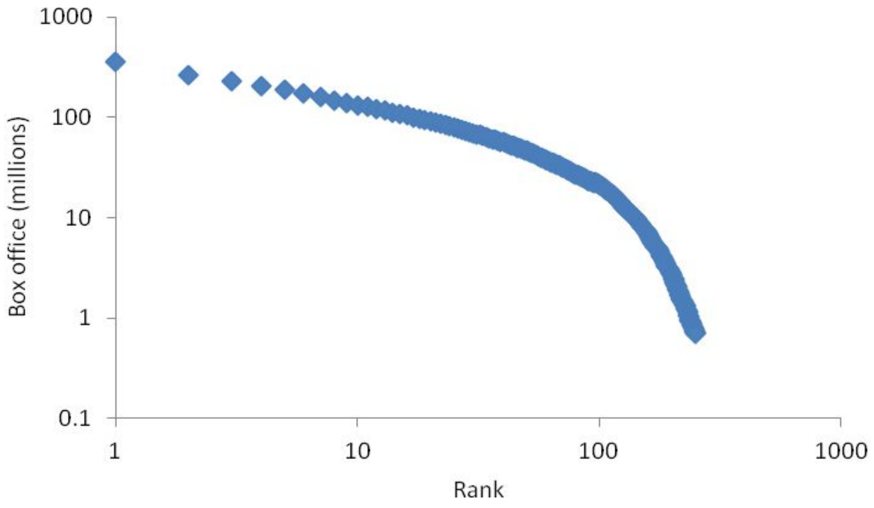

FIGURE 2. Movies' clusters.

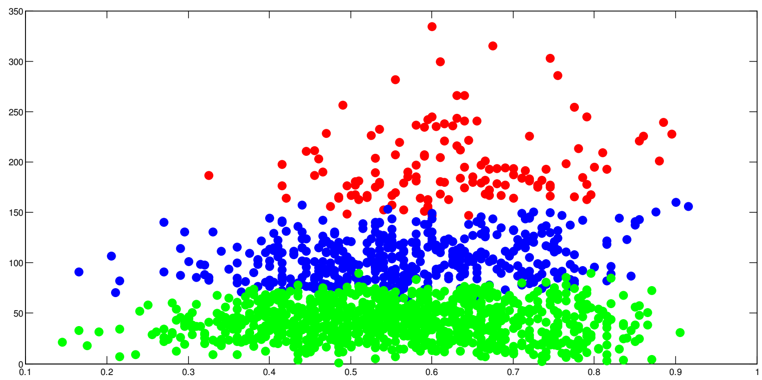

FIGURE 4. Investing in ad expenditures.