Advertising and Word-of-Mouth in Motion Picture Industry

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Abstract

Motion picture industry is characterized by extensive advertising and word-of-mouth among (potential) consumers. We develop a simple computational model of consumer behavior to study the interaction between these two forces. WOM is affected by the mismatch between consumer’s expectations and realized quality of the film. As a result, intensive advertising is running a risk of generating overly negative WOM, while moderate levels of advertising generate positive WOM that is complementary to advertising efforts. The most striking finding is that not only marginal returns to advertising are decreasing, but they also become negative. This effectively means that for intensive advertising campaigns an additional commercial might result in the reduction of the audience.

1 Introduction

The motion picture industry has always advertised heavily (Caves, 2001). But in recent years movie advertising budgets have been increasing fast. They have grown 50% between years 1999 and 2005 and hit 60% of the total production costs.

At the same time the industry is characterized by intensive word-of-mouth communication among (potential) consumers. This makes sharing of experience and influencing late-comers’ decisions an easy task. Word-of-mouth is a powerful force which, through multiple exchanges can reach and influence large portion of the society (Lau and Ng, 2001; Brown et. al. 2007). Word-of-mouth augments advertising in diffusion of information across the potential customers. However, unlike advertising, which has a clear aim of inducing people to buy a product, word-of-mouth does not have an ultimate target as it is not coordinated. The important implication of this difference is that it is possible, and

*Part of this work has been done when I was at MERIT, Maastricht University and at the Center for Complexity in Business, University of Maryland. I thank both institutions for their hospitality and support.
in fact pretty plausible, that negative sentiment about the product diffuses through peer-to-peer interaction. Due to the fact that consumer interaction plays somewhat similar but at the same time very different role from advertising, makes studying the interaction between these two forces interesting.

It is believed that negative word-of-mouth has effects of substantially larger size than its positive counterpart (Mahajan et al. 1984; Park and Lee 2009). This belief has been recently verified in a range of industries like airlines (Lou, 2007), online bookstores (Chevalier and Mayzlin, 2006) and computer games (Yang and Mai, 2010). Detrimental effects of negative word-of-mouth have been reported by early investigators like Singh (1990) and Smith and Vogt (1995), who find that negative word-of-mouth significantly reduces perceived credibility of advertising as well as brand attitudes and purchase intentions. Dissatisfied consumer outrage has taken a central stage in deeper investigations (e.g. Bechwati and Morrin, 2003). Consumer efforts in response to dissatisfaction have been found to be even higher in case of business-to-business customers where each buyer is considerably larger in size (Ferguson and Johnston, 2010).

Intuitively, this asymmetry across the sentiment directions can be understood by acknowledging the important role of time in purchase dynamics. Not all the people (willing to buy a product) buy a product immediately. Purchases are postponed and sales are stretched in time. Positive word-of-mouth can accelerate this process but only to a limit. However, due to the disappointment aversion (Gul, 1991), negative word of mouth has a power of permanently halting product sales at any point in time.

One more characteristics of the motion picture industry is that it supplies an experience product. Therefore, a judgement about the quality of your purchase can be not precise. As potential consumers are aware of this fact, their perceptions are susceptible to word-of-mouth coming from consumers that have already seen a movie.

In this paper we present an agent based model in order to analyze the interaction between advertising and information diffusion through social networks. We combine above-listed features of the movie industry with the well-known psychological finding about the effects of disappointment and propose the following model.

2 The model

The economy consists of constant number $I$ of consumers that are indexed by $i$. A new film appears on the market. It has an objective quality that is distributed across the population as $x_i \sim \mathcal{N}(\mu_x; \sigma_x^2)$ (or in general with an arbitrary distribution $x_i \sim PDF_x$). However, this quality is not known to consumers prior to seeing the movie. As we measure the quality from the standpoint of general public, rather than from the standpoint of a film critic, spurious relation between the quality and movie returns are removed in our framework (Holbrook, 1999).

Each consumer has an internal quality requirement $y_i$ for going to the movies. She only goes to see the movie if her expectation for its quality is no less then $y_i$. This simple
mechanism ensures that consumer behavior is consistent with a disappointment aversion as formulated by Gul (1991). This variable is distributed across population as $y_i \sim N(\mu_y; \sigma_y^2)$ (or in general case as $y_i \sim PDF_y$). This implies that consumers are heterogenous with respect to the disappointment aversion rate.

$v_t^i$ is the belief that consumer $i$ holds about the quality of a movie at time $t$. Initial beliefs about the quality of a movie are distributed in population as $v_0^i \sim N(\mu_v; \sigma_v^2)$ (or in general case as $v_0^i \sim PDF_v^0$). Changes in beliefs as time progresses are incorporated into $v_t^i \sim PDF_v^t$.

If there is no social interaction or advertising, we can calculate how widely the given movie will be watched by the society. We can compute this value using a random matching mechanism

$$\bar{z} = \int PPDF_v^0(z) \times CDF_y(z)dz$$

$$= \frac{1}{4} \int \frac{1}{\pi \sigma_v^2} \exp \left( -\frac{(z - \mu_v)^2}{2\sigma_v^2} \right) \left( 1 + \text{erf} \left( \frac{z - \mu_y}{\sqrt{2\sigma_y^2}} \right) \right) dz$$

Equation (1) and its special case (for $v_0^i$ and $y_i$ being normally distributed) (2) give the share of consumer base that will watch a movie given the average initial belief that consumers hold about the quality of the movie. Equation (2) is plotted on figure 1 for the case when $\sigma_v = \sigma_y$.

Notice that due to the fact that consumers do not interact and exchange their impressions about the movie, the actual quality of the movie does not affect the number of people that will see it. On figure 1 we also identify the average accepted

$^1$Throughout the whole paper we consider the arrangement when $\sigma_v = \sigma_y = \sigma_x$. 

Figure 1: Benchmark diffusion quantities. The plot is calibrated by the relationships $\sigma_x = \sigma_y = \sigma_v$ and $\mu_x^l - \mu_x^b = \mu_x^h - \mu_x^m = 1.25\sigma_x$.
quality of the society – $\mu_y$, which is measured on abscissa together with the initial average expected quality, $\mu_v$.

For the analysis in section 3 we use these three types of movies. We define an average quality movie, a movie for which $\mu_x = \mu_y$. Which intuitively means that in absence of interaction the movie will be watched by half of the population. We denote the quality of an average (medium quality) movie by $\mu^m_x$. Corresponding values of low and high quality movies are denoted by $\mu^l_x$ and $\mu^h_x$, respectively. We define these products such that $\mu_y - \mu^l_x = 1.25\sigma_y$ and $\mu_y - \mu^h_x = -1.25\sigma_y$. In our setup this means that a low quality movie in the absence of consumer interaction will be watched by around 21% of the population, while a high quality movie will be seen by 79% of the potential customers. We also identify these three types of movies on figure 1.

Now we introduce two central forces in our model that can affect consumer decisions – interaction and advertising. Let’s take them one by one in a reverse order. Producers of the movie can advertise a product. Advertising is costly. Producers can advertise only before the movie hits the theaters. This is in line with the common practice of the industry – Elberse and Anand (2007) find that 90% of advertising in motion picture industry is done before the release. They also find that pre-release advertising has a significant positive effect on expectations potential consumers hold about the movie. We assume that advertising is effective and it can increase $\mu_v$. However, we assume that advertising cannot make tastes more homogenous, thus it cannot affect $\sigma_v$. Of course, driving $\mu_v$ to a higher level requires more spending. From the figure 1 one can clearly see that higher advertising expenditures would result into higher sales. However, this is only true when there is no communication among consumers.

To model the word-of-mouth interaction, we assume that there is a static, given social network that specifies the interaction structure among consumers. Information about the movie streams through this social network and affects the nodes (consumers). However, not all the nodes are functional at any time period. We assume that only the people who have not seen the movie update their beliefs. Once the person has seen the movie she has no reason to act on the information communicated to her by the social network. Therefore, the node corresponding to this consumer becomes dysfunctional – no new information passes through it.

Consider people going to the movie theatre one by one (i.e. each time period only one person can go to see the movie). Who goes at time $t$ is randomly selected from the people whose $v^i_t \geq y_i$. Once a person goes to a movie, she realizes $x_i$, and deduces the final impression about the movie $v^{T}_i = x_i + a(x_i - v^i_t)$, where parameter $a \geq 0$ controls the strength of the effect of the mismatch between the expectations and objective quality on the final impression of a person.

Once a person exits the theatre, she communicates $v^{T}_i$ to her friends, who update their beliefs according to $v^j_f = v^{j-1}_f + b(v^{T}_i - v^{j-1}_f)$, where $b \in [0;1]$ is a measure of how much people trust the judgement of their social contacts. These friends communicate $v^f_j$’s further to their contacts. Further down the line people update their beliefs with
\[ v_m^t = v_m^{t-1} + b^k(v_n^t - v_m^{t-1}), \]

where \( m \) receives the information from \( n \), and \( k \) is the shortest (currently functional) path length from the person that went to the movies (\( i \)) to \( m \). Modeling consumer interaction this way implies that social distance affects negatively the weight that consumers put on each other’s judgements. After the information diffusion the node corresponding to the consumer \( i \) becomes dysfunctional. As a consequence functional social network gets modified.

### 3 Results

In order to discuss the implications of the model we run the economy until \( v_i^t < y_i \) for all the people who have not seen the movie and measure the success of the setup by the share of consumer population that has seen the movie.

We employ the Monte-Carlo methodology. We run each setup 200 times for different random initial values and average them. Therefore, any point on the figures presented below comprises the average of 200 runs. Standard deviations in all the cases are extremely small, therefore we do not present them in plots.

In sections below we discuss effects of movie quality, trust, network architecture and the mismatch between expected and actual quality of the movie. Although these variables, except the network architecture, are continuous, for the purpose of the presentation of results we discuss only three values for each parameter - low, medium and high. Therefore we define three levels of trust – \( b_l, b_m \) and \( b_h \); three values of mismatch effect – \( a_l, a_m \) and \( a_h \); and three values of network density – \( d_l, d_m \) and \( d_h \). We will explore three types of social network architectures: lattice (that we denote by \( L \)), preferential attachment (denoted by \( P \)) and random network (denoted by \( R \)).

Every run has five parameters that specifies the characteristics of the economy. These are the quality of the movie, the trust in the society (strength of WOM), the strength of the mismatch between expected and realized quality of the movie, social network architecture and its density. Therefore each setup can be characterized by a set of five values \((\mu_x; b; a; A; d)\), where \( A \in \{L, P, R\} \) denotes the topology of the social network. For instance, \((\mu^l_x; b^h; a^m; P; d^l)\) would tell us that we are analyzing the case of the low quality movie in a society with high level of trust, medium level of the mismatch effect and sparse preferential attachment social network. These notations will be used in the process of reporting results.

We perform numerical simulations in the same setup as we have plotted the figure 1. Which are \( \sigma_x = \sigma_y = \sigma_v \) and \( \mu_x^m - \mu_x^l = \mu_x^h - \mu_x^m = 1.25\sigma_x \). Exact numerical values for the parameters do not affect the results. But we anyway report them in table 1 in the appendix.

### 3.1 The effect of quality

The effect of the movie quality is pretty straightforward. Even though quality did not matter in case when consumers did not communicate (the benchmark case that we have
Figure 2: The effect of trust on total sales.

presented in figure 1), it becomes very important once consumers start to interact and exchange their opinion about the movie. As it can be anticipated without detailed investigation, movies with higher quality would sell at larger quantities for any given level of an average expected quality. No additional effect of trust, network structure or density can ever reverse this trend.

3.2 The effect of trust

The situation is much more complicated in case of trust. Comparing the numerical simulation outcomes to the benchmark diffusion quantities given in figure 1 gives us the effect of trust. This is due to the fact that no communication can be viewed as communication with zero trust.

Figure 2 presents the total sales of an average quality movie in case of communication taking place on lattice architecture. The left panel presents the situation when social network is sparse, while the right panel presents the situation in a denser network. The sales in the benchmark situation are given on both of the panels. Recall that for this movie \( \mu_x = \mu_y \).

As one can clearly see from figure 2 the communication moderates the effects of advertising. For low levels of advertising advertising, when \( \mu_0 \) is low (compared to the actual quality of the movie) communication complements the advertising and helps increase the sales. However, if advertising is too fierce, communication decreases the sales. This is very intuitive as fierce advertising drives consumer expectations up and a typical viewer gets disappointed with the movie. As a consequence negative word-of-mouth spreads and decreases the likelihood of other people seeing a movie. The higher the level of trust between members of the society (\( b \)) the more pronounced is the communication effect.

Besides, the difference between two panels demonstrates the influence of the network density on effects of trust. Recall that after every act of consumption one node in the social network becomes dysfunctional. This means that at some point in time parts of

\footnote{In this an every subsequent figure the industry characteristics presented in blue is the one that is different in setups on left and right panels. For example in this case (the case of figure 2) density of the network is presented in blue. Which means that left and right panels of the figure are produced in the same setup except the density of the social network.}
a social network might get disconnected. In this environment higher density means that for any given number of viewers larger part of the network stays connected. If network is disconnected in two subnetworks the information coming from any given viewer cannot reach viewers in a subnetwork disjoint to the one this consumer belongs to. Then, as sparse networks get easily fragmented, they localize the information at later stages of industry development. This is the reason why sales stay at a low level for any level of advertising in setups with denser networks and high level of trust - WOM from dissatisfied customers can reach large parts of the network.

Figure 2 depicts the scenarios when the mismatch between anticipated and actual quality does not affect the final impression of the viewer \((a = 0\) and therefore \(v_i^T = x_i\)). When the mismatch between the anticipated and actual quality of the movie affects the sentiment that viewer is diffusing through social network, variance in word-of-mouth increases. This means that negative word-of-mouth becomes even more negative, while positive word of mouth becomes even more positive. Figure 7 presents the changes that higher values of \(a\) introduce in the results. As it can be anticipated, due to the polarization of the sentiments helping hand of WOM towards the advertising at low levels increases (because most of the word-of-mouth is positive for advertising at low intensities). But for higher quantities of advertising WOM becomes more effective deterrent of the sales. This is especially pronounced for higher levels of trust, and is present in networks of all densities.

Figure 8 shows the similar scenarios with the movie of higher quality \((\mu_x = \mu_x^h)\). In accordance to the intuition higher quality movies can capitalize on overly positive WOM at low levels of advertising. This effect is amplified by the sparse social networks, that localize few disappointed viewers.

Figure 9 presents the similar scenarios with different network topologies. In upper panels of the figure we replace the lattice topology with preferential attachment, while in lower panels we examine a random social network. Both of these networks are less structured compared to the lattice topology that we have used in the baseline scenario in figure 2. Both of them have lower average shortest path length. Therefore, sentiments get propagated in these networks faster. The result is that we achieve higher returns for lower levels of advertising and lower returns for higher levels of advertising.

### 3.3 The effect of mismatch between expected and actual quality

In order to study the effect of the level of mismatch between the expected and actual quality of the movie, we present the figure 3, where we plot sales for a low quality movie \((\mu_x = \mu_x^l)\) with a moderate trust level. Here, again, interaction is taking place on a lattice. The left panel reports the results for the social network with a low density, the right panel reports on a denser network.

Due to the reason that we have mentioned in section 3.2, we can clearly see that the more mismatch affects consumer impressions the stronger moderator it becomes for the advertising. In other words, stronger mismatch effect increases the advertising returns.
for low levels of advertising and decreases returns for higher levels of advertising. This is claim does not depend on the density of the social network.

In appendix we give few more tables that demonstrate how the effect of the mismatch changes when we vary the quality of the movie and the structure of the social network. Figure 10 presents the results for the higher quality movie ($\mu_x = \mu^m_x$), while figure 11 presents the results for the preferential attachment and random social network structures. The main intuition carries over to other values of parameters.

### 3.4 The effect of network architecture

In this section we study the effect of the social network topology. We have used three topologies: lattice, preferential attachment and random. Figure 4 presents the results for the constant values of $a$ and $b$. For generating the left panel we have used a space network, for generating the right panel dense network has been used.

Figure 4 demonstrates the main implication of the model. For any low levels of advertising preferential attachment network has highest returns out of all three topologies. This is due to the fact that the preferential attachment has shortest average shortest path length out of all three architectures. As WOM for low levels of advertising is positive - lower average shortest path length guarantees faster diffusion of positive sentiment through
social network. However, for the high intensity of advertising the ranking of structures depends on the density of the network. For sparse networks lattice is the most beneficial structure, while for dense networks random network results in highest returns.

To understand why this is the case we have to notice the difference between high and low levels of advertising. Besides the fact that at low levels WOM is positive and in high levels it is negative there is another crucial difference. It is that high levels of advertising results in higher sales. Every time a sale takes place the node in the social network becomes disfunct - it does not pass any further WOM. Therefore, higher sales result higher number of disfunctional nodes. As sales are random in our model, each visit to the movie theatre can be viewed as a random error in the social network (a la Albert et al. 2000). At low advertising intensity these errors do not change the functional social network architecture much. However, at high sales functional network changes significantly in the process.

When networks are sparse there is not much clustering, which means there is not much redundancy in the network. Therefore, lattice networks easily get fragmented into disconnected sub-networks that localize the negative WOM and result in higher sales for higher levels of advertising. However, if the network density is high lattices are more resistant to the random attacks (due to high redundancy) and it is random networks that have higher likelihood of being fractured into disconnected sub-networks. Then, returns to advertising are the highest in case of dense random social networks at higher levels of advertising. In any case, networks generated by preferential attachment are more resistant to random errors than Erdos-Reny random graphs in line with the findings by Albert et al. (2000).

As we can see from the figures 12 and 13 these results carry over for different values of other parameters. The figure 14 demonstrates that the difference becomes dramatic for high values of trust in the society. The reason for this is that trust amplifies the role of the shortest path length in the dynamics. If paths are long, low trust makes WOM decay quickly. However, if trust is high information sent by a node will reach (and influence) other nodes even if the path is long (except if it is infinite, which is the case if sender and receiver are in different disconnected components of the network).

### 3.5 The effect of network density

Figure 5 presents the contrast between the outcomes of scenarios with different densities. The left panel presents the sales for the low quality movie, while the right one for a movie with the moderate quality. These are runs using lattice topology, but the results do not change with the change of the network architecture (figure 17). As we can see returns to advertising are higher for denser networks when advertising is not intense, and for sparser networks when advertising is intense. This result carries over for the other levels of mismatch between expected and actual quality (figure 15) and becomes dramatic for high values of trust in the society (figure 16).
4 Returns to advertising

Heavy advertising practices in the movie industry raise the question of the optimality of these expenditures. As we can see from many figures in this paper (e.g. the left panel of figure 2) movie sales level off after some point. Which means that additional advertising efforts do not increase sales. Therefore, marginal returns to advertising fall to zero. As marginal cost of advertising will never go to zero, we can claim that advertising with the intensity where marginal returns to product promotion are zero will be not optimal. It will be waste of resources. Although we cannot pinpoint the optimal advertising level (as we do not have advertising costs in our model), we can be sure that the optimal rate of advertising in any arrangement has to be in the area where sales are still increasing.

However, our model has another interesting implication. Even if we would have assumed that marginal cost of advertising could fall to zero, the model implies that advertising efforts will still be bounded from above. Figure 6 demonstrates the finding that after certain level marginal returns to advertising become negative (i.e. more advertising results into less sales). This is due to the fact that too aggressive of an advertising campaign is bound to leave behind large numbers of disappointed people. And the negative word-of-mouth will discourage late-comers from going to the cinema.

The point after which the advertising becomes consumption-deterrent is reached at lower advertising levels for poor quality movies, but even hits can suffer from it. The turning point lies at lower advertising levels for the denser networks (this can be clearly seen by comparing figures 6 and 18) and for the societies with high levels of trust.

Finding is robust in changes of network topologies. However, one peculiarity emerges. Random social network in presence of low levels of $a$ seems to maintain positive returns for much higher levels of advertising compared to the other two architectures (lattice and preferential attachment), which behave similar to each other and to random network with high values of $a$. This effect is reported on lower panels of figure 19. The reason for this is that low expectation mismatch effect ($a$) WOM is not that negative therefore consumption continues at up to a certain level. However, because networks are dense, out of all the architectures random network will suffer the most. Which means that average
shortest path length will increase in random networks. And negative WOM once again will get localized that would allow certain parts of the network to continue consuming even further. However, when \( a \) is high, WOM is overly negative and consumption stops at lower level, earlier than random network gets fractured into pieces that can localize WOM. Similar behavior does not emerge in other two topologies. This is due to the fact that scale free networks (that are generated by the preferential attachment algorithm) are known to be good resistants to random errors (Albert et al. 2000). In our model consumption can be viewed as the error in network. Lattices are also good resistants because they possess a structure that allows them to avoid fracturing into pieces.

As we can see in our model aggressive advertising might become consumption-deterrent due to the exceedingly negative WOM that it generates. Anand and Shachar (forthcoming) provide a different reason for consumption-deterrent advertising. They study the information provision role of the advertising on proliferated markets. Unlike our setup, in their model advertising is not content free. If provides information about the characteristics of the product. Therefore, in the presence of multiple options advertising increases the probability that consumers will be matched with the products that they like the most. As a consequence, non-content-free advertising might reduce sales if consumers exposed to it understand that the product is not what they would like to buy. So, in the setup of Anand and Shachar (forthcoming) advertising can be consumption-deterrent due to the mismatch between the consumers preferences and (at least) “partially-observable” characteristics of the product, while in our setup advertising can be consumption-deterrent due to the mismatch between the information received through advertising and through word-of-mouth.

5 Conclusion

In this paper we have presented a simple computational model of motion picture viewer behavior in order to analyze the interaction between advertising and word-of-mouth that diffuses through social interactions. The most striking result is that if advertising is too intensive, marginal returns to advertising becomes negative. This effectively means that
advertising results in a smaller number of consumers going to see the movie. This is due to the fact that advertising drives viewer expectations high and as a consequence leaves large number of them disappointed due to the mismatch between their expectations and realized movie quality. This triggers negative WOM that affects consumption intentions of following (potential) customers.

Empirical research into the motion picture industry has found that marginal returns to advertising is indeed too low, however not negative. Elberse and Anand (2007) find that on average movie sales increase only by 0.65 dollars for an additional dollar spent on advertising. Looking at these results from the lancet of the model discussed in this paper, these findings point to the fact that advertising is at inefficiently high levels.

An important shortcoming to the present model is that although it tells us that firms over-advertise it offers no explanation of why this can be the case. The reason for this is that the model is stylized and discusses returns to advertising in absence of competitors. Advertising in our framework works only for creation of the market. However, in the real world advertising has is also used as a competition tool. Therefore decisions about the intensity of advertising become strategic. In these environments it is easy to imagine that advertising is growing at inefficiently high levels due to producers trying to keep up with the competition for market shares. However, our research warns that these kind of overly aggressive advertising campaigns can reduce not only the market share of a movie, but also the size of the whole movie market.

References


Appendix

In the appendices B through F in industry characteristics specification, characteristics in red is the characteristics that is different from the benchmark figures discussed in the body of the text.

A Parameter values for numerical analysis

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<tr>
<th>parameter</th>
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<tr>
<td>$\mu^l_x$</td>
<td>The average quality of a poor movie</td>
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<tr>
<td>$\mu^m_x$</td>
<td>The average quality of a moderate movie</td>
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<td>$\mu^h_x$</td>
<td>The average quality of a good movie</td>
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<tr>
<td>$\sigma^l_x = \sigma^m_x = \sigma^h_x$</td>
<td>The variance of the quality</td>
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<tr>
<td>$\sigma_v$</td>
<td>The variance of initial quality expectations</td>
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<td>Low effect of mismatch</td>
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<td>$d^h$</td>
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<tr>
<td>$I$</td>
<td>The number of consumers</td>
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Table 1: Parameter values for the numerical analysis.
### B Trust

![Graph](image1)

$(\mu^m_x; \bullet; a^m; L; d^l)$

Figure 7: Changes in trust effects due to mismatch.

![Graph](image2)

$(\mu^h_x; \bullet; a^h; L; d^l)$

Figure 8: Changes in trust effects due to movie quality.

![Graph](image3)

$(\mu^m_x; \bullet; a_m; L; d^m)$

$(\mu^m_x; \bullet; a^m; L; d^m)$

$(\mu^h_x; \bullet; a^h; L; d^m)$

$(\mu^h_x; \bullet; a^h; L; d^m)$

Figure 9: Changes in trust effects due to network topology.
C Mismatch

Figure 10: Changes in the effects of mismatch due to quality.

Figure 11: Changes in the effects of mismatch due to network topology.
D Topology

![Figure 12](image1)

Figure 12: Changes in effects of topology due to mismatch.

![Figure 13](image2)

Figure 13: Changes in effects of topology due to movie quality.

![Figure 14](image3)

Figure 14: Changes in effects of topology due to trust.

Note: Graphs in figure 14 have been plotted on a different scale from other comparable graphs and also from each other. The same applies to figure 16 in appendix D.
E Network density

Figure 15: Changes in effects of density due to mismatch.

Figure 16: Changes in effects of density due to trust.

Figure 17: Changes in effects of density due to network topology.
F Returns to advertising

Figure 18: The effect of changes in network density on returns to advertising.

Figure 19: The effect of changes in network topology on returns to advertising.