2012-24 / October 2012

Document de travail

IF YOU LOVE IT – I'LL PROBABLY HATE IT : LOCAL INTERACTION AMONG CONSUMERS OF INFORMATION GOODS

Zakaria Babutsidze
OFCE-Sciences Po and SKEMA Business School

If you love it - I'll probably hate it: Local interaction among consumers of information goods*

Zakaria Babutsidze

OFCE and SKEMA Business School

zakaria.babutsidze@sciences-po.fr

October 23, 2012

Abstract

We present a computational model of consumer behavior. Consumers possess expectation-based reference-dependent preferences and are disappointment averse. They interact with each other on static social network. They exchange and update their beliefs about the quality of the product. Individual beliefs are updated only until the individual consumes the product. We discuss non-repetitive, sequential consumer choices. The model generates the oversized effect of negative consumer sentiment compared to the positive sentiment from the symmetric individual behavior. We demonstrate that word-of-mouth generated through face-to-face communication can interact with advertising in complex ways. In particular we show that both consumers' trust in word-of-mouth and density of the social network are negatively effecting the returns to product promotion. Finally, the model conforms to the well-known advise for producers to "underpromise and overdeliver".

1 Introduction

Interaction among individuals is a pervasive phenomenon. Consumers are not an exception. They routinely exchange their views with each other in private and on public forums. Private interaction occurs among social contacts and is referred to as local interaction, while activities on public forums go under the heading of global interaction. Economic implications of two types of interaction can be very different (Brock and Durlauf, 2000). However, they both contribute toward generating an important source of information – word-of-mouth (WOM). Word-of-mouth is a powerful force which can reach large portion of the society (Lau and Ng, 2001; Brown et al., 2007). It can strongly influence consumer decisions and shape the demand faced by producers.

Word-of-mouth is particularly important in industries where consumers are not certain about the quality of the product they are purchasing. This collects service industries,

*Part of this work was done when I was at MERIT, Maastricht University and visiting Center for Complexity in Business, University of Maryland. I wish to thank both institutions for their hospitality and support. Comments from Alessio Delre, David Gill, Marco Janssen, Yogesh Joshi, PJ Lamberson, Bill Rand and Bulat Sanditov and other participants of various meetings in Maastricht, New York, Santa Fe and Washington DC are also acknowledged.

where quality of the service is largely affected by personal factors and has, therefore, large variance, and information goods industries, which sell goods whose nature cannot be exhaustively verified. Examples of the industries in the first group are haircuts, taxi or other services. Examples of those in the second group are motion pictures, books, software etc. In the case of the first group we deal with the repetitive purchases but information about the quality is not easily elicited from previous experience due to the large variance in quality of delivery. In the second case we deal with non-repetitive purchases, therefore, eliciting the quality from the previous purchase is impossible. In all of these industries consumers rely heavily on word-of-mouth (Anderson, 1998; Godes and Mayzlin, 2004; Joshi and Musalem, 2012). They aggregate the information communicated to them through different sources in order to make a decision.

Besides giving a fair chance to consumers to collect information about the product, consumer interaction plays another important role on the market. In fact, information about other people's past purchases affects the satisfaction the consumer derives from the act of consumption. This idea is referred to as the reference-dependent preferences and was comprehensively modeled by Koszegi and Rabin (2006). Empirical support to expectations-based reference-dependent preferences is pervasive (Loomes and Sugden, 1987; Johansson-Stenman and Martinsson, 2006; Choi et al., 2007; Knetsch and Wong, 2009; Card and Dahl, 2011; Crawford and Meng, 2011). A related stream of literature suggests that reference-dependence leads to disappointment aversion (Bell, 1985; Gul, 1991; Koszegi and Rabin, 2007). There is a sizable empirical support for disappointment-aversion too (Pope and Schweitzer, 2011; Gill and Prowse, 2012).

If consumers are disappointment averse and producers are operating on a market where word-of-mouth is important, practice of advertising becomes risky. Advertising is seen by consumers as the promise of certain quality (Nelson, 1970, 1974; Milgrom and Roberts, 1986). This drives up consumers reference points and effectively reduces their satisfaction from the actual consumption. This might generate negative word-of-mouth that might hurt sales. However, when we are dealing with the non-repetitive sales advertising seems more attractive, especially when firms can choose the timing. If a firm advertises the product before its release there is no other information in the system (e.g. WOM) to counteract its effect. In fact the experience in many information goods industries has indeed been that of intense advertising (Caves, 2001). This trend has been accelerating. For example, in the motion picture industry advertising budgets have jumped by 50% between years 1999 and 2005 and hit 60% of the total production costs (Elberse and Anand, 2007).

The contribution of advertising toward generating of negative word-of-mouth can be substantial. It is believed that negative word-of-mouth has effects of significantly 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

(Singh, 1990; Smith and Vogt, 1995) These studies find that negative word-of-mouth significantly reduces perceived credibility of advertising as well as brand attitudes and purchase intensions. Dissatisfied consumer outrage has taken a central stage in deeper investigations (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 of considerably larger size and business link retention decisions are thought through thoroughly (Ferguson and Johnston, 2011). Furthermore, negative experience with the product is believed to lead to higher likelihood that the consumer will engage in word-of-mouth communication (Richins, 1983; Anderson, 1998).

The real danger of deceiving customers has generated a strand of business literature advising firms to "underpromise and overdeliver" (Parasuraman et al., 1991; Dixon et al., 2010). Large majority of papers in this tradition discuss strategies of retention of customers. Consequently, they concentrate on repeated purchases, and thus, discuss mostly service sectors (Ho and Zheng, 2004; Bolton et al., 2006). A notable exception is a recent paper by Joshi and Musalem (2012) that analyzes monopolistic setup with non-repetitive purchases. The authors split the consumer population in two segments: influentials and followers and analyze the effects of influential-follower communication on producer's choice of quality signal. In their paper communication is of a global type, there is no structure to it.

In this paper we propose a simple computational model that departs from the usual "underpromise and overdeliver" literature in the spirit of Joshi and Musalem (2012) in modeling non-repetitive purchases. Thus applications that we have in mind are those with information goods. However, in contrast with Joshi and Musalem (2012), we discuss a setup with local interactions. We assume that there is a static underlying social network that governs the process of consumer interaction. In particular, consumers interact only with their friends exchanging information about the product. Thus, in our case the interaction carries face-to-face character, rather than impersonal activity on public forums. Furthermore, we introduce the new idea that consumers do not change beliefs about the product quality once they have consumed it. This effectively introduces the dynamics in the functional social network as after each consumption act one node in the network does not pass WOM any further. In this respect our work relates to the work on network error tolerance in physics (Albert et al., 2000). This setup allows a researcher to study certain aspects of consumer behavior in greater detail. In this particular paper we take on the challenge of analyzing the effect of trust and social network architecture.

We model sequential purchasing decisions that are stretched over time. This allows us to demonstrate the asymmetry of positive and negative word-of-mouth in our setup where behavioral response to the sentiment communicated to the consumer is independent of its nature (i.e. positive or negative WOM). Besides, we find somewhat counter-intuitive effects of consumers' trust in communicated information and that of social network density. In particular we find that both, high trust and high density of the social network, are reducing sales. The interpretation of the results lies in the sequentiality of the consumption process, which is a feature manifested in real life. On the other hand, the topology of the social network matters only in certain cases. In addition to this our model conforms to the advise of "underpromise and overdeliver". In particular, we find that intense advertising campaigns that are interpreted as signals of high quality can actually decrease the number of consumers.

The remainder of the papers organized as follows. Section 2 introduces the model, section 3 discusses the results of the paper, section 4 discusses the implications of the model with respect to the optimal level of advertising and section 5 concludes.

2 The model

The economy consists of constant number (I) of consumers (indexed by i). A new product is placed on the market by the monopolistic producer. We assume that the price of the product is relatively small with respect to the consumer budgets and we can abstract from it. Prices in information goods industries are highly standardized and producers have little discretion in this respect. For example, consider the motion pictures industry where movie tickets have uniform prices in the same theatre.

The quality of the product is judged subjectively by each consumer. Thus, the quality is consumer specific. We denote the quality of the product as judged by consumer i with x_i. We also denote the distribution of x_i across population with Ξ. Due to specificity of information goods we assume that quality of the product is not known to a consumer prior to consuming the product. Realistically, Ξ is also unknown to the public. As we measure the quality from the standpoint of general public, rather than from the standpoint of a critic, the spurious relation between the quality and returns that is present in many information goods industries (Holbrook, 1999) is absent from our framework.

Each consumer has an internal quality requirement y_i for considering buying the product. She purchases the product only if her expectation for product's quality no less then y_i. This simple mechanism ensures that consumer behavior is consistent with a disappointment aversion (Bell, 1985; Gul, 1991). The distribution of y_i across population is denoted by Ψ. This implies that consumers are (potentially) heterogenous with respect to the disappointment aversion rate. The quality requirement is a private piece of information and also Ψ is not known to the public.

At any point in time each consumer holds a belief about the quality of the product. We denote this belief by v_i^t. The initial distribution of beliefs across the population is denoted by Ω^0. Changes in quality beliefs of each consumer as time progresses are incorporated into $v_i^t \sim \Omega^t$.

If there is no social interaction or advertising, we can calculate the expected sales of a given product. We can compute this value using a random matching mechanism. This will be the expected share of the people for whom initial belief about the quality of the movie exceeds her quality requirement. It is given by

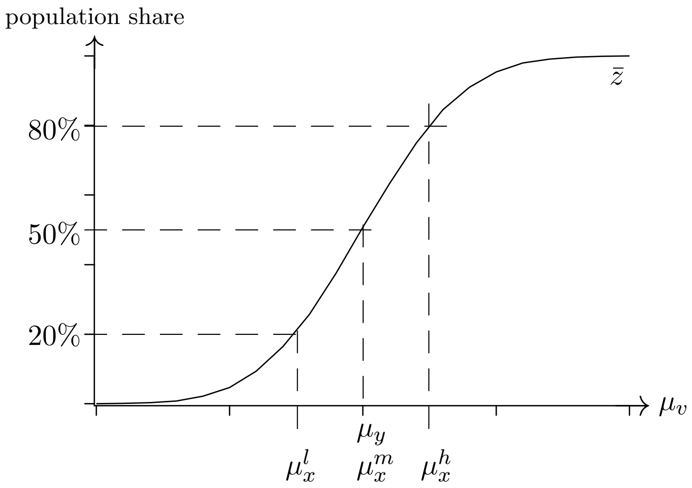

Figure 1: Benchmark diffusion quantities.

Note: The plot is calibrated by the relationship $\sigma_y = \sigma_v$.

$$\bar{z} = \Omega^0(z) \times \psi(z)\mathrm{d}z, \tag{1}$$

where $\psi = \Psi'$.

To make the demonstration of the major findings feasible, in the reminder of the paper we assume that our variables have more specific distributions. In particular we assume that all three of our key variables are normally distributed: $\Xi = \mathcal{N}(\mu_x; \sigma_x^2)$, $\Psi = \mathcal{N}(\mu_y; \sigma_y^2)$ and $\Omega^0 = \mathcal{N}(\mu_v; \sigma_v^2)$. In this case the expected share of the consumers that will buy the product is given by

$$\bar{z} = \frac{1}{4} \int \frac{1}{\pi\sigma_v^2} \exp\left(-\frac{(z-\mu_v)^2}{2\sigma_v^2}\right) \left(1 + \mathrm{erf}\left(\frac{z-\mu_y}{\sqrt{2\sigma_y^2}}\right)\right) \mathrm{d}z. \tag{2}$$

Equation (2) is plotted on Figure 1 for the case when $\sigma_v = \sigma_y$.[1] On the ordinate we measure the share of the population that is expected to buy the product, while on abscissa we measure the average expected quality (belief) of the product. As it can be seen, higher (average) belief about the quality of the product results in higher sales. Notice that due to the fact that consumers do not interact and exchange their thoughts about the product, the actual quality of the product does not affect sales. On Figure 1 we also identify the average accepted quality in the population – μ_y. Quite intuitively, when average expectation is equal to average quality requirement we can expect half of the society to buy the product.

For the feasibility of the analysis in section 3 we use three types products. We define a medium quality product as a product for which $\mu_x = \mu_y$. Which means that in absence of interaction and advertising the product will be purchased by half of the population. We denote the quality level of a medium quality product by μ_x^m. Values of low and high quality movies are denoted by μ_x^l and μ_x^h, respectively. We define the low quality product as a product that will be purchased only by 1/5 of the population and the high quality product as a product that will be purchased by 4/5 of the population. Similar

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

to the definition of the medium quality product, both of these definitions subsume the absence of interaction and advertising in the economy. Combining these definitions with the normality of Ξ, Ψ and Ω^0 distributions, and further assuming $\sigma_x = \sigma_y = \sigma_v \equiv \sigma$, it follows that $\mu_y - \mu_x^l = \mu_x^h - \mu_y \approx 1.26\sigma$. We use this relation to calibrate the numerical analysis of the model. We identify these three types of products on Figure 1.

Now we introduce two central forces in our morel that can affect consumer decisions – interaction and advertising. Let's take them one by one in a reverse order. Producers can advertise the product. Advertising is costly. We assume that producers can advertise only before the product is placed on the market. This is in line with the common practice in wide range of information goods industries. These industries build "buzz" on anticipation of the product. The advertising sounds more credible when there are no critical reviews available to counteract it. For example, in motion picture industry the pre-release advertising amounts to 90% of total advertising expenditures (Elberse and Anand, 2007). Similar behavior can be observed in publishing and software industries. To model the effect of the advertising, we assume that it can increase μ_v - the average expected quality of the product. This is in line with findings by Elberse and Anand (2007), who report that that pre-release advertising has a significant positive effect on expectations potential consumers hold about the product. However, we assume that advertising cannot make tastes more (or less) homogenous, thus it cannot affect σ_v. Although we do not model the costs of averting explicitly, we assume that driving μ_v to a higher mark requires more spending, all else being equal. From the Figure 1 we can clearly see that in absence of consumer interaction higher advertising expenditures result into higher sales.

To model the face-to-face interaction, we assume that there is a static, given social network that specifies the interaction structure among consumers. Information about the product streams through this social network and affects the nodes (consumers). As we have mentioned in the introduction to the paper, purchases of information goods are usually non-repetitive. To use an example of the motion picture industry again, the percentage of the people who go to the movies multiple times to see the same film is negligible. At the point where one purchases the information good she also fully realizes its value, which was hidden from her prior to the experience. To take these features into account we model the dynamics of the effective social network. We assume that only the people who have not purchased the product yet, update their beliefs. Once the person has bought the product she has no reason to act on the information communicated to her by the social network. Therefore, the node corresponding to the consumer that purchased the good at time t becomes dysfunctional thereafter and no new information passes through it.

Consider people purchasing the product one by one (i.e. each time period only one person can purchase the good). Who makes the purchase at time t is randomly selected from the people that are eligible. Eligibility is based on two criteria. First, that this person has not already purchased the product. And second, that he is willing to buy it ($v_i^t \geq y_i$). Once a person makes a purchase, she realizes x_i, and deduces the final impression about the product in a following way:

$$v_i^T = x_i + a(x_i - v_i^t), \tag{3}$$

where parameter $a \geq 0$ controls the strength of the effect of the mismatch between the expectations she held prior to consuming the product and the subjective quality on the final impression of a person. We assume a is a characteristic of the society and do not model it on a personal level. This behavior subsumes the expectation-based reference-dependent preferences (Loomes and Sugden, 1987; Koszegi and Rabin, 2006; Crawford and Meng, 2011). As beliefs are updated dynamically the same individual might enter and exit the pool of eligible consumers several times until he consumes the product or until there set of eligible consumers is empty. Thus, the decision of purchase timing from individual prospective is not completely exogenous (Brocas, 2012).

To put it in different terms, v_i^T is the utility that consumer i derives from the product. It contains two parts. One is the quality of the product x_i. The other is expectation-based $a(x_i - v_i^t)$. Recall that v_i^t is the expectation of quality that consumer holds just before consuming the product. This is the reference on which the actual enjoyment of the consumption act depends. In this context, a measures the degree of reference-dependence of the consumer preferences. If $a = 0$ consumers do not have reference-based preferences. If, on the other hand, $a > 0$ consumer preferences are expectation-based reference-dependent.

Once a person realizes the level of actual utility derived from the product, she communicates it to her friends, who update their beliefs according to

$$v_j^t = v_j^{t-1} + b(v_i^T - v_j^{t-1}), \tag{4}$$

where $b \in [0; 1]$ is a measure of how much people trust the judgement of their social contacts. Similar to a, we do not model b on a personal level. After updating their beliefs according to (4), buyer's friends communicate their new beliefs further to their contacts. Down the line people update their beliefs with

$$v_m^t = v_m^{t-1} + b^k(v_n^t - v_m^{t-1}), \tag{5}$$

where m receives the information from n, and k is the shortest (currently functional) path length from the person that purchased the product (i) to m. Modeling consumer interaction this way implies that weight that consumers put on each other's judgements is decreasing in social distance. After the information diffusion the node corresponding to the consumer i becomes dysfunctional. As a consequence functional social network changes (shrinks).

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 purchased the product and measure the success of the setup by the share of consumer population that has purchased the product. As time is not modeled in the system in a rigorous way, we do not take it into account when assessing the success of the product promotion effort (i.e. we do not discount the firm revenues/profits).

We employ the Monte-Carlo methodology. We run each setup 200 times for different random initial values and average them. Therefore, an (experimental) observation in our econometric analysis presents the mean of 200 numeric runs. Similarly, on graphical representations each point represents the average of 200 runs. Standard deviations in all the cases are extremely small, therefore we do not present them in plots and do not use them in econometric analysis. In what follows we concentrate on the effects of the level of trust in the society and the topology of social network.

Although our 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 (i.e. the strength of the reference-dependent); 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).

As each of these parameters enter the model in a non-linear manner, there is no obvious way to choose the exact values for low, medium and high levels for each of them. These levels have been chosen so that major effect is noticeable at least in one direction. That is to say that there is a significant difference in model behavior either in going from medium level of the parameter to high, or to low (or both). The chosen values are presented in Table 3 in appendix, although what matters is the relationships among the parameters, rather then values themselves. The setup is the same as used in plot in Figure 1.[2] As we are not interested in exact values of trust, strength of the mismatch effect or network density we shall simply treat them as dummy variables and refer to them as their level (low/medium/high) instead of the exact value of the parameter.

Every run of the economy has five parameters that specifies the characteristics of the society. These are the quality of the product (measured by the average subjective quality across population), the trust in the society (which can also be interpreted as the strength of the face-to-face interaction), the strength of the mismatch between expected and realized quality (the measure of the reference-dependence), social network architecture and its density.

For econometric analysis five parameters with three values each result in 10 dummy variables. In cases of each of four numeric variables (quality, trust, mismatch and density) we treat the medium level of the variable as base and create two dummies: one for low

[2]Which is $\sigma_x = \sigma_y = \sigma_v$.

value, another for high value. In case of the network topology, we treat random network as the base and create dummies for lattice and preferential attachment network structures.

Running full scale simulations with only three values of each parameter, with 11-point grid for the initial average valuation (belief), results over 5000 observations which we exploit in order to determine the effect of interesting variables.[3] Primary OLS regressions of the variables on total sales that pull all the observations together are presented in Figure 4 in the appendix.

As one can directly see from the figures, all the variables except the size of the mismatch effect and the network topology play a significant role on aggregate level. The average initial belief has positive and highly significant effect which points to the fact that, on aggregate, higher levels of advertising result in higher sales. Conforming with the expectations, high quality of the product also helps sales, while low quality presents a handicap. On the other hand, societies that highly trust information received through face-to-face communication result in lower sales. The effect of network density is somewhat similar - denser social networks result in lower sales.

The remainder of this section is devoted to the in depth analysis of the effects of trust and network architecture on relation between product promotion and sales. In section 4 we elaborate on implications of the model concerning the level of advertising.

3.1 The effect of trust

We can expect that positive sentiment generated by the product will decrease as product promotion efforts increase. This will counteract the efforts of the product promotion to push the sales upward. To put it differently, at some point along the level of advertising, consumer sentiment will turn from positive to negative. Therefore, we should anticipate qualitatively different behavior for lower levels of advertising and for higher levels of advertising. Due to non-linearity of the model it is impossible to determine such a point analytically. It presents a great difficulty also numerically as its position depends on parameters of the model in a nontrivial way. However, we can argue that this point should be somewhere close to the point when initial average belief about the quality of the product, which measures the level of advertising, is equal to the actual quality of the product. If expectations are lower than product's actual quality, most of the consumers will be positively surprised and will generate positive WOM. However, high levels of advertising will guarantee a larger mass of disappointed consumers who will generate negative reviews.

To deal with this qualitative difference we split our dataset in two parts. In one part we collect observations corresponding to high levels of advertising, in another one we collect low levels of advertising. We call an economy to have low level of advertising when initial belief of the consumers about the quality of the product is below its quality. In contrast high level of advertising describes the setup where consumers' expectations are above the actual quality of the product. We are especially interested in high levels of advertising as

[3] These are derived from more than million Monte Carlo scenarios, averaging of which (over random initial-values) gives us 5103 experimental observations.

this is the part where the relationship between product promotion and consumer generated word-of-mouth becomes especially intricate.

Table 1 presents the results of regressing total sales on variables of interest. In the table the model 1A pools all observations, while models 1B and 1C collect observations with low and high levels of advertising respectively.[4] As it can be readily seen, the trust reduces the positive effect of product promotion on sales when the firm advertises heavily. Recall that in all regressions medium level trust is the baseline and effects of high and low trust variables depict the comparison to this baseline. This means that switching from moderate trust regime to high trust regime, all else equal, reduces returns to advertising (in absolute terms), while switching to low trust levels significantly increases sales. These results are straight forward to interpret. We know that the sentiment generated by face-to-face interaction in high advertising regime is negative. If consumers trust each other's opinion more, this word-of-mouth will induce more people to give up the idea of purchasing the product.

Contrasting models 1B and 1C, which run the same regression on the observations in low and high advertising regimes, we notice that the sign of the low trust dummy changes. This implies that in case of low levels of advertising, low trust level is disadvantageous for the producer. This is intuitive as in this case generated WOM is positive. However, we see a non-linearity in the effect as high trust dummy does not change the sign. To understand this non-linearity we have to understand the dual role of high trust and peculiar effect of sequentiality of consumption decisions. Clearly, high trust helps positive sentiment to diffuse faster in population, therefore we would expect that the sign for high trust dummy in regression 1B to be positive. However, high trust also amplifies the effect of negative sentiment which exists in every setup.

Sequentiality of consumption decisions has different implications for positive and negative sentiment propagation. Positive sentiment increases the likelyhood that other consumers will decide to buy the product. Making sentiment even more positive marginally increases this likelihood. However, due to disappointment aversion negative sentiment has a power of permanently halting product sales at any point in time. Mathemati-

[4]Note that all models in Table 1 include products of all three levels of quality.

variable	1A	1B	1C
valuation	0.060***	0.105***	0.067***
	(0.001)	(0.003)	(0.003)
high trust	-0.393***	-0.303***	-0.391***
	(0.010)	(0.012)	(0.011)
low trust	0.006	-0.337***	0.354***
	(0.010)	(0.012)	(0.011)
No of obs	5103	2430	2430
Adj R^2	0.290	0.231	0.222

Table 1: Effect of trust on relationship between advertising and sales

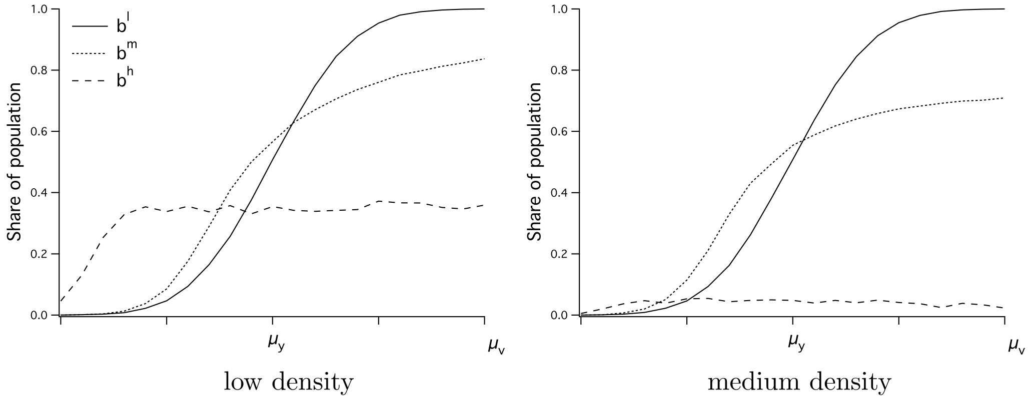

Figure 2: The demonstration of the effect of trust. Runs are performed on lattice network with low (left) and medium (right) densities, for medium quality product with low mismatch effect.

cally, negative sentiment can decrease every consumers' beliefs lower than their respective minimum-requirement thresholds. Therefore, potential effects of negative sentiment are much larger in size even if our consumers are updating their beliefs symmetrically with respect to the sentiment communicated to them.

To gain additional insight into results concerning the trust in the society we turn to graphical analysis. In what follows we compare the results of numerical simulations to the benchmark diffusion quantities given in Figure 1. This is due to the fact that no communication can be viewed as communication with zero trust. The difference between simulated and benchmark quantities is the measure of the effect of trust. However, this approach requires to separate different scenarios[5] rather than pulling the data as we have done in regressions above.

Figure 2 presents the total sales of an average quality movie in case of communication taking place on a structured lattice. The left panel presents results for the sparse social network, while the right panel uses a denser network. The sales in the benchmark case are given on both of the panels. Recall that for the product under discussion $\mu_x = \mu_y$.

As one can clearly see from Figure 2 the communication moderates the effects of advertising. For low levels of advertising, when μ_v^0 is low (compared to the actual quality of the product) communication complements the advertising and helps increase the sales. However, if advertising is too fierce, communication decreases the sales. This is intuitive as fierce advertising drives consumer expectations up and a typical consumer gets disappointed by the product. As a consequence negative word-of-mouth spreads and decreases the likelihood of other people making a purchase. The higher the level of trust between members of the society (b) the more pronounced is the communication effect.

Figure 2 depicts the scenarios where consumers' preferences are not reference-dependent ($a = 0$ and therefore $v_i^T = x_i$). When preferences are reference-dependent the variance in generated sentiment increases. This means that negative word-of-mouth becomes even more negative, while positive word of mouth becomes even more positive. Table 2 tests this conjecture. In the table we report the results of two regressions. The same model runs

[5]Different constellations of parameter values, network architecture etc.

on data pooling low levels of advertising (2A) and high levels of advertising (2B). As it can be anticipated, due to the polarization of the sentiments helping hand of WOM towards the advertising at low levels becomes stronger. For high values of mismatch the estimate becomes insignificant, but it carries the correct sign. For higher quantities of advertising WOM becomes more effective deterrent of the sales. Similarly, for high values of mismatch the effect is insignificant but with the correct sign. We can deduce the effect of the reference-dependence of consumer preferences by looking at the results reported in Table 2 from a different angle. The results imply that reference-dependent preferences benefit the producers that advertise moderately and harms the firms that advertise fiercely. This effect becomes especially pronounced certain types of network architectures. However, we do not go into the detailed discussion of this matter here as the next section is dedicated into the in-depth analysis of the dependence of sales/advertising relationship on network architecture.

3.2 The effect of network architecture

In this section we analyze the effects of social network density and of its topology. Simple demonstration of the effect is the contrast between left and right panels of Figure 2. The only difference between the panels is the density of the underlying social network. As it can be readily seen higher density of the network amplifies the consumption-discouraging effect of word-of-mouth in presence of fierce advertising. To test this implication in a general setup we run regressions on data that pools all the scenarios. The results are presented in table 5 in the appendix. From the coefficients estimated by the model 5A we can conclude that higher network density indeed discourages consumption.

In order to understand the reason behind this result, 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 a social network might get disconnected. In this environment higher density means that for any given number of viewers larger part of the network

variable	2A	2B
valuation	0.105***	0.067***
	(0.003)	(0.003)
high trust	-0.303***	-0.391***
	(0.011)	(0.011)
low trust	-0.338***	0.354***
	(0.011)	(0.011)
high mismatch	0.006	-0.005
	(0.011)	(0.011)
low mismatch	-0.042***	0.030***
	(0.011)	(0.011)
No of obs	2430	2430
Adj R^2	0.231	0.221

Table 2: Moderation of the trust effect by size of the mismatch.

stays connected. If network is disconnected in two subnetworks the information coming from any given consumer cannot reach individuals 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. To sum up, the reason why sales stay at low for any level of advertising in setups with denser networks is that in these setups word-of-mouth from dissatisfied customers can reach larger parts of the network.

The present model implies that higher quality products can capitalize on overly positive word-of-mouth at low levels of advertising. This is clear from the results of models 4B and 5B. However, the density of the underlying social network moderates this effect. Consider the estimation of the model 5C which includes cross multiplied variables of density and quality. It is clear that lower density networks push the effects of quality significantly further. The additional effects of higher density networks have correct signs but are insignificant. All in all, the density of the network affects the returns to product promotion in complex and not-so-obvious ways.

Another topic of interest is the topology of the social network. Recall that we have used three topologies: lattice, preferential attachment and random.[6] In general, the effect of topology is not very strong. Model 6A that pools the data to regresses the sales on initial valuation and topology dummies identifies no significant effect. The same is true when data is split for two regimes, low and high levels of advertising, results of which are presented in 6B and 6C respectively.

However, once we start analyzing more specific setups the effect of the topology appears. Models 6D and 6E exclude high quality products and concentrate on the low advertising. They run the same regression, the only difference is the reference group in definition of dummy variables. The results suggest that in such environments preferential attachment and lattice networks are significantly different from each other, however none of them is significantly different from random social network. Model 6F distills the set of observations by dropping setups with high levels of trust and concentrating only on low levels of mismatch effect. In this setup all three topologies are significantly different from each other.

Figure 3 reduces the set of observations even further and demonstrates the main implication of the model with respect to the network topology. For 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 smallest average shortest path length out of all three architectures tested here. 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

[6]Another obvious candidate for analyzing the topology effect is the Small World networks. It is true that these networks have substantial similarities to real world networks. However, their major drawback is that the known algorithm for generating them (Watts and Strogatz, 1998) produces graphs with very unrealistic degree distributions. This of course is true for lattice and random networks too, but in case of Small World networks we have to deal with one more parameter, which would greatly complicate the comparison of the results across network topologies. This is the reason for not including Small World networks in the analysis.

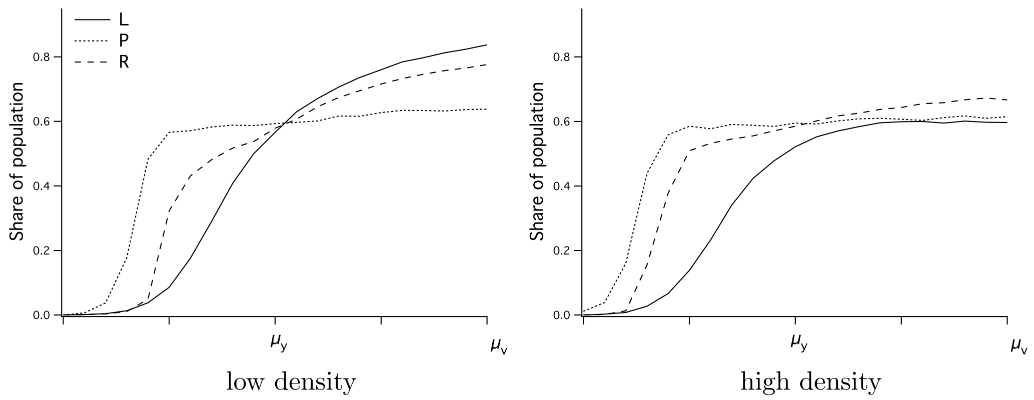

Figure 3: The demonstration of the effect of network topology. Runs are performed on networks with low (left) and high (right) densities, for medium quality product, medium level of trust and low mismatch effect.

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 advertising levels the sentiment is positive and in high levels it is negative, there is another important 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 dysfunctional - it does not pass WOM any further. Therefore, higher sales result higher number of dysfunctional nodes. As sales are random in our model, each act of consumption 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 clustering is low, 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, which is in line with the findings by Albert et al. (2000).

4 Returns to advertising

Heavy advertising practices in certain information goods industries (e.g. motion pictures, publishing etc.) raise the question of the optimality of these expenditures. As we can see from the results of this paper (e.g. the left panel of Figure 2) sales stop increasing with advertising after a certain threshold is passed. This means that after this threshold

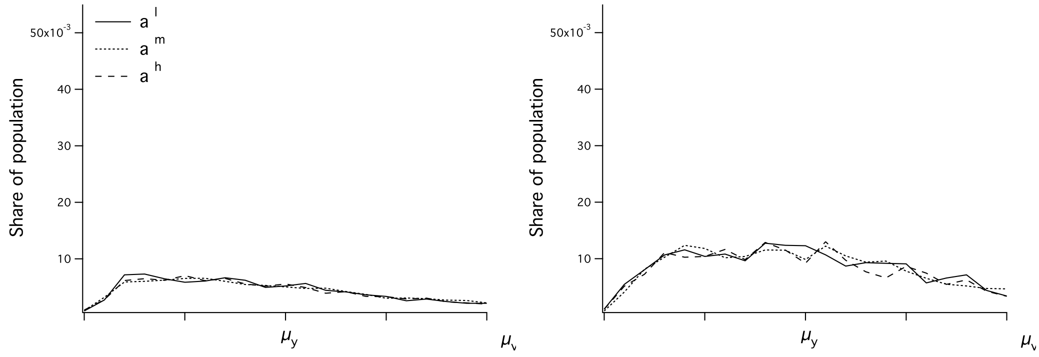

Figure 4: The demonstration of the effect of advertising on sales. Runs are performed on low (left) and medium (right) quality products, high level of trust with dense lattices.

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 not be optimal. It will be a 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.

In this respect, 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 4 demonstrates the finding that after certain threshold 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 latecomers from consuming.

There are environments that facilitate kind of behavior demonstrated on Figure 4. The higher density of social network increases the reach of information. As we have discussed above, denser networks help spread WOM in the consumer population. Therefore, the density is important for spread of negative sentiment. High trust levels work in the same direction. High trust guarantees that consumers will act on the negative sentiment communicated to them. Last, but not least the quality of the product matters. If the quality is very high, its sales will not generate sufficient number of disappointed customers that could produce substantial negative word-of-mouth. Therefore, low quality products are more likely to suffer from this phenomenon. This goes in line with the vast literature that regards advertising as the signal of quality (Nelson, 1970, 1974; Milgrom and Roberts, 1986).

Recall that what we are talking here is only over-advertising (i.e. high levels of advertising) and the general relationship between advertising and sales is still positive (models 4A, 4G etc.). As also seen from the Figure 4, for sufficiently low levels of advertising the relationship is always positive. Therefore, to test for inverse relationship in more general setup we drop the observations that fall in the lower quantile of initial valuation distribution. We restrict ourselves to environments with high trust, exclude high quality products and sparse networks, which leaves us with 576 observations. Ordinary least squares regression of sales on initial valuation indeed results into negative coefficient that is small (-0.001) but significant at 1% significance level.

As we can see in our model aggressive advertising might become consumption-deterrent due to the exceedingly negative sentiment that it generates. Anand and Shachar (2011) provide a different reason for consumption-deterrent advertising. They study the information provision role of the advertising on proliferated markets. Unlike our setup, in that model advertising is not content free. It provides information about the characteristics of the product. Therefore, in the presence of multiple options advertising increases the likelihood of better match between a consumer and a product. As a consequence, (non-content-free) advertising might reduce sales if consumers realize that the product is not what they would like to buy. In the setup of Anand and Shachar (2011) advertising can be consumption-deterring 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-deterring due to the mismatch between the two pieces of information: one received from producers through advertising, the other received from consumers through face-to-face interaction.

5 Conclusion

In this paper we have presented a simple computational model of consumer behavior in order to analyze the interaction between advertising and word-of-mouth that diffuses through social interactions. Our consumers possess expectation-based reference-dependent preferences and they make choices about the purchase of an information product that is supplied by the monopolistic firm. As is common in information goods industries, the consumers are not sure about the actual quality of the product prior to the consumption and try to use the information coming from the producer and peers in order to make an informed decision about the non-repetitive purchase.

The most striking result is that if advertising is too intensive, marginal return to product promotion becomes negative. This effectively means that more advertising leads to smaller number of consumers. This effect is somewhat stronger manifestation of the over-advertising effect ("underpromise and overdeliver") derived by the marketing literature. This is due to the fact that advertising drives consumer expectations high and as a consequence leaves large number of them disappointed due to the mismatch between their expectations and realized product quality. This triggers negative word-of-mouth that affects consumption intensions of following (potential) customers.

Empirical research on the subject has indeed found that in some information goods industries marginal returns to advertising are very low. For example, 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 lens of the model discussed in this paper, we can argue that advertising is at inefficiently high levels. However, we can conclude that the industry has no surpassed the threshold where returns would become negative.

Besides the negativity of the marginal returns to product promotion for very high advertising levels, our model results in several other empirically testable propositions. For example, the model implies that denser social networks decrease returns to advertising. It also implies that the relation between the sales and the trust in the society are highly non-linear. Furthermore, the model suggests that if an industry is selling to consumers with expectation-based reference-dependent preferences should be characterized by the larger drop in marginal return to product promotion as they go from low advertising levels to high advertising levels compared to those who are selling to consumers whose preferences are not reference-dependent.

However, the model presented in this paper has an important shortcoming. It is that it analyzes the monopolistic setup. Therefore, strategic considerations of competition are absent from the framework. Advertising in our framework works only for creation of the market. In the real world, however, advertising is heavily used as a competition tool. 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. We leave the discussion of competitive environments and empirical testing of above-mentioned propositions for the future research and suffice here with the presentation of the parsimonious model of consumer behavior that warns that overly aggressive advertising campaigns can reduce not only the market share of a product, but also the size of the market itself.

References

Albert, R., H. Jeong, and A.-L. Barabasi (2000). Error and attack tollerance of complex networks. *Nature 406*, 378–382.

Anand, B. and R. Shachar (2011). Advertising, the matchmaker. *RAND Journal of Economics 42*, 205–245.

Anderson, E. W. (1998). Customer satisfaction and word of mouth. *Journal of Service Research 1*, 5–17.

Bechwati, N. N. and M. Morrin (2003). Outraged consumers: Getting even at the expense of getting a good deal. *Journal of Consumer Psychology 13*, 440–453.

Bell, D. E. (1985). Dissapointment in decision making under unvertainty. *Operations Research 33*, 1–27.

Bolton, R. N., L. N. Lemon, and M. D. Bramlett (2006). The effect of service experiences over time on a supplier's retention of business customers. *Management Science 52*, 1811–1823.

Brocas, I. (2012). Information processing and decision-making: Evidence from the brain sciences and implications for economics. *Journal of Economic Behavior and Organization 83*(3), 292 – 310.

Brock, W. A. and S. N. Durlauf (2000). Interaction-based models. technical working paper 258, NBER.

Brown, J., A. J. Broderick, and N. Lee (2007). Word of mouth communication within online communities: Conceptualizing the online social network. *Journal of Interactive Marketing 21*, 2–20.

Card, D. and G. B. Dahl (2011). Family violance and football: The effect of unexpected emotional cues on violent behavior. *Quarterly Journal of Economics 126*, 103–143.

Caves, R. E. (2001). *Creative Industries: Contracts between Arts and Commerce*. Harvard University Press, Cambridge, MA.

Chevalier, J. and D. Mayzlin (2006). The effect of word of mouth on sales: online book reviews. *Journal of Marketing Research 43*, 345–354.

Choi, S., R. Fishman, D. Gale, and S. Kariv (2007). Consistency and heterogeneity of individual behavior under uncertainty. *American Economic Review 97*, 1921–1938.

Crawford, V. P. and J. Meng (2011). New york city cab drivers' labor supply revisited: Reference-dependent preferences with rational ecpectations target for hours and income. *American Economic Review 101*, 1912–1932.

Dixon, M., K. Freeman, and N. Tolman (2010). Stop trying to delight your customers. *Harvard Business Review 88*, 116–122.

Elberse, A. and B. Anand (2007). The effectiveness of pre-release advertising for motion pictures: An empirical investigation using a simulated market. *Information Economics and Policy 19*, 319–343.

Ferguson, J. L. and W. J. Johnston (2011). Customer response to dissatisfaction: A synthesis of literature and conceptual framework. *Industrial Marketing Management 40*, 118–127.

Gill, D. and V. Prowse (2012). A structural analysis of dissapointment aversion in a real effort competition. *American Economic Review 102*, 469–503.

Godes, D. and D. Mayzlin (2004). Using online conversations to study word-of-mouth communication. *Marketing Science 23*, 545–560.

Gul, F. (1991). A theory of disappointment aversion. *Econometrica 59*, 667–86.

Ho, T. H. and Y.-S. Zheng (2004). Setting customer expectations in service delivery. *Management Science 50*, 479–488.

Holbrook, M. B. (1999). Popular appeal versus expert judgements of motion pictures. *Journal of Consumer Research 26*, 144–155.

Johansson-Stenman, O. and P. Martinsson (2006). Honestly, why are you driving a bmw? *Journal of Economic Behavior and Organization 60*(2), 129 – 146.

Joshi, Y. V. and A. Musalem (2012). Underpromising and overdelivering: Strategic implications of word of mouth. Research Paper RHS-06-142, Robert H. Smith School of Business, University of Maryland.

Knetsch, J. L. and W.-K. Wong (2009). The endowment effect and the reference state: Evidence and manipulations. *Journal of Economic Behavior and Organization 71*(2), 407 – 413.

Koszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics 121*, 1047–1073.

Koszegi, B. and M. Rabin (2007). Reference-dependent risk attitudes. *American Economic Review 97*, 1047–1073.

Lau, G. T. and S. Ng (2001). Individual and situational factors influencing negative word-of-mouth behaviour. *Canadian Journal of Administrative Science 18*, 63–178.

Loomes, G. and R. Sugden (1987). Testing for regret and disappointment in choice under uncertainty. *Economic Journal* (118–129).

Lou, X. (2007). Consumer negative voice and firm idiosyncratic stock returns. *Journal of Marketing 71*, 75–88.

Mahajan, V., E. Muller, and R. Kerin (1984). Introduction strategy for new products with positive and negative word-of-mouth. *Management Science 30*, 1389–1404.

Milgrom, P. and J. Roberts (1986). Price and advertising signals of product quality. *Journal of Political Economy 94*(4), pp. 796–821.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy 78*(2), pp. 311–329.

Nelson, P. (1974). Advertising as information. *Journal of Political Economy 82*(4), pp. 729–754.

Parasuraman, A., L. Berry, and V. A. Zeithaml (1991). Understanding custormer expectation of service. *Sloan Management Review 32*, 39–48.

Park, C. and T. M. Lee (2009). Information direction, website reputation and ewom effect: A moderating role of product type. *Journal of Business Research 62*, 61–67.

Pope, D. G. and M. Schweitzer (2011). Is tiger woods loss averse? persistent biase in the face of experience, competition, and high stakes. *American Economic Review 101*, 129–157.

Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of Marketing 47*, 68–78.

Singh, J. (1990). Voice, Exit, and Negative Word-of-Mouth Behaviors: An Investigation Across Three Service Categories. *Journal of the Academy of Marketing Science 18*, 1–15.

Smith, R. E. and C. A. Vogt (1995). The effects of integrating advertising and negative word-of-mouth communications on message processing and response. *Journal of Consumer Psychology 4*, 133–151.

Watts, D. J. and S. H. Strogatz (1998). Collective dynamics of 'small-world' networks. *Nature 393*, 440–442.

Yang, J. and E. S. Mai (2010). Experiential goods with network externalities effects: An empirical study of online rating system. *Journal of Business Research 63*, 1050–1057.

Appendix

A Parameter values for numerical analysis

parameter	description	value
μ_y	The average accepted quality	20
μ_x^l	The average quality of a poor movie	18.74
μ_x^m	The average quality of a moderate movie	20
μ_x^h	The average quality of a good movie	21.26
σ_y	The variance of the accepted quality	1
$\sigma_x^l = \sigma_x^m = \sigma_x^h$	The variance of the quality	1
σ_v	The variance of initial quality expectations	1
a^l	Low effect of mismatch	0
a^m	Medium-size effect of mismatch	0.5
a^h	High effect of mismatch	1
b^l	Low level of trust	0
b^m	Medium level of trust	0.5
b^h	High level of trust	1
d^l	Low density (measured by average degree)	4
d^m	Medium density (measured by average degree)	20
d^h	High density (measured by average degree)	60
I	The number of consumers	1 000

Table 3: Parameter values for the numerical analysis.

B Primary runs

variable	4A	4B	4C	4D	4E	4F	4G
valuation	0.060***						0.060***
	(0.002)						(0.001)
high quality		0.183***					0.183***
		(0.012)					(0.009)
low quality		-0.146***					-0.146***
		(0.012)					(0.009)
high trust			-0.349***				-0.349***
			(0.012)				(0.009)
low trust			0.006				0.006
			(0.012)				(0.009)
high mismatch				0.000			0.000
				(0.013)			(0.009)
low mismatch				-0.006			-0.006
				(0.013)			(0.009)
high density					-0.025**		-0.025***
					(0.013)		(0.009)
low density					0.097***		0.097***
					(0.013)		(0.009)
lattice						-0.007	-0.007
						(0.013)	(0.009)
preferential attachment						-0.003	-0.003
						(0.013)	(0.009)
No of obs	5103	5103	5103	5103	5103	5103	5103
Adj R^2	0.226	0.126	0.191	0.000	0.019	0.000	0.562

Table 4: General runs

C Network density

variable	5A	5B	5C
valuation	0.060***	0.060***	0.060***
	(0.002)	(0.001)	(0.001)
high density	-0.025**	-0.025**	-0.127
	(0.011)	(0.010)	(0.018)
low density	0.097***	0.097***	0.068***
	(0.011)	(0.010)	(0.018)
high quality		0.183***	0.150***
		(0.010)	(0.018)
low quality		-0.146***	-0.130***
		(0.010)	(0.018)
low density × low quality			-0.053**
			(0.025)
low density × high quality			0.141***
			(0.025)
high density × low quality			0.004
			(0.025)
high density × high quality			-0.041
			(0.025)
No of obs	5103	5103	5103
Adj R^2	0.330	0.301	0.298

Table 5: Effect of network density on returns to advertising

D Network topology

variable	6A	6B	6C	6D	6E	6F
valuation	0.060***	0.105***	0.067***	0.072***	0.072***	0.099***
	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
lattice	-0.007	-0.018	0.004	-0.016	-0.023**	-0.035**
	(0.011)	(0.014)	(0.019)	(0.011)	(0.011)	(0.017)
preferential attachment	-0.003	0.006	-0.012	0.007		0.035**
	(0.011)	(0.014)	(0.019)	(0.011)		(0.017)
random					-0.007	
					(0.011)	
No of obs	5103	2430	2430	1377	1377	306
Adj R^2	0.334	0.285	0.081	0.261	0.261	0.534

Table 6: Effect of network topology on returns to advertising