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The rise of electronic social networks and implications for advertisers

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ABSTRACT

The rise of modern digital communication technologies, most notably electronic social networks, transforms structures through which consumers interact with one another. In this paper we distinguish between two channels through which product promotion affects sales. The direct channel always positively affects consumers' pre-purchase valuation. The indirect channel goes through word-of-mouth (WoM) and can be either positive or negative. The sentiment contained in WoM is generated by the complex interaction process and depends on the aggressiveness of the advertising campaign. We investigate the implications of the current changes in social network architectures for the effectiveness of the indirect channel. We show that changes in social structures have increased the efficiency of WoM across a host of industries. Our results call for "smart" advertising policies.

1. Introduction

There is virtually no industry for which consumers' post-consumption satisfaction is unimportant. Consumer experience gets communicated through various channels and affects prospective sales of the product. The raise of modern digital telecommunication technologies has made the maintenance of large number of social contacts easier. As a consequence, a modern individual maintains larger number of links to the rest of the society. The shift of large part of communication from offline to online environments, which aids the proliferation of opinion leaders, and where conversation records stay for longer period, has also altered the conventional routs through which word-of-mouth circulates. Such social changes, brought by advances in electronic social networks, could potentially transform the economic system. The current paper investigates the implications of these changes in social structures for the link between advertising and sales.

Word-of-mouth (WoM hereafter) is particularly important in industries where consumers are not certain about the quality of the product they are purchasing. This collects service and information goods industries. In the case of the former, the quality of the service is largely affected by personal factors and, therefore, has large variance. In the case of the latter, the nature of the product on sale 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). There is an ample evidence that consumers in more conventional industries like electronics and apparel are also heavily influenced by WoM (Campbell, 2013). In fact, for a very large and diverse set of industries the information collected through interaction with other consumers is the most reliable piece of knowledge shoppers base their decisions on (Babutsidze, 2012).

Consumer satisfaction is believed to be particularly important for repetitive purchases as consumers base their decisions on past experience. However, sales of any product are stretched over time. This gives early adopters the opportunity to communicate their product reviews to consumers who have not made their choice yet. In this vain, negative experiences of early consumers might seriously damage producer's prospects even in the case of non-repetitive purchases.

Besides prices, consumers' purchase decisions are also affected by other factors. Advertising is arguably the most important of those (Nelson, 1974). Much like WoM, advertising is based on information transfer. Unlike WoM, however, advertising is a purposeful action with a clear aim to induce consumers to buy the product. In contrast, WoM has no clear aim and it can either increase or decrease sales.

Advertising usually takes the guise of broadcasting and can reach entire consumer population. On the other hand, WoM is decentralized and circulates through social networks. As a consequence, social network architectures will directly affect the efficiency of WoM. Hence, advertising is under direct control of producers, while WoM is user generated. However, producers can still influence WoM. This can be done, for example, by setting consumers' pre-purchase expectations about the product. Let's simplify the product and discuss it as having

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just one attribute – quality. If consumer's pre-consumption quality expectation is lower than her post-consumption quality evaluation – WoM generated by the consumer will be positive, and vice versa.

As a consequence, advertising is a double-edged sword. It can increase sales by raising consumers' pre-purchase product valuation (a direct channel). However, in the case of an aggressive advertising campaign it can also hurt (an indirect channel). In this paper we present a model of consumer behavior which allows for distinguishing these two channels. We study the dependence of the indirect channel on the topologies of the social network in order to evaluate the dangers of over-advertising in modern WoM environments.

The rest of the paper is structured as follows. Section 2 covers the prior literature, Section 3 introduces the model, Section 4 presents the methodology we use to analyze the model, Section 5 reports the results, Section 6 discusses the implications and concludes.

2. Literature

The main strand of literature that we build upon in this paper is the collection of diffusion models (Bass, 1969). These models discuss a monopolistic setup where a new product is introduced on the market and consumers have to take a decision whether to buy the product or to abstain from doing so. The diffusion setup has been fruitfully utilized to study the interaction between advertising and WoM in related environments (Dodson and Muller, 1978; Nerlove and Arrow, 1962).

Positive feedbacks, which are generated here through word-of-mouth, have been extensively studied in economics. The application particularly relevant to the current work is that of monopolistic firm's pricing behavior in presence of network effects. This strand of literature has had a recent surge (Fainmesser and Galeotti, 2016; Shin, 2017) thanks to the increased attention to consumer-side network effects (Ajorlou et al., 2016; Crapis et al., 2016). Our paper leaves the pricing question aside and concentrate on non-price-related factors.

Modeling advertising has a long tradition. It is usually seen as a signal of quality as the literature suggests the positive correlation between the quality of the product and incentives to advertise (Milgrom and Roberts, 1986). In this setup advertising is usually modeled as being content-free (Nelson, 1974).[1] In the current paper, advertising is content-free and induces the rise of pre-purchase product valuation in consumers. In order to avoid considerations concerning the optimal advertising campaign (Nerlove and Arrow, 1962), that is out of scope of this paper, we concentrate only on pre-release advertising.

A popular way to model WoM has been by using a random matching process (Dodson and Muller, 1978). In this environment consumers are randomly paired for interaction during every time period. Originally the interaction was aimed at persuasion of the uninitiated consumers by initiated ones. However, as the literature advanced, the possibility of negative WoM was incorporated into matching models (Mahajan et al., 1984). The implicit assumption in early models was that every consumer participated in WoM. Recent work, however, has acknowledged consumer heterogeneity in terms of willingness to engage in information exchange (Campbell et al., 2017; Lobel et al., 2016). In this respect a recent paper by Campbell (2013) is noteworthy. In the paper the author allows for consumers who might not be motivated sufficiently to engage in WoM. This introduces the difference between two types of networks – a social network and a WoM network. The latter is derived from the former by removing unmotivated consumers. In Campbell's setup WoM engagement status is constant over time: each shopper belongs to the group of either active or non-active WoM consumers.

However, consumers' incentives with respect to WoM engagement might change with time. For one, the act of consumption itself might alter the willingness of a consumer to interact with peers. If a person buys a laptop computer based on her quality expectations deduced from the information gathered, she might want to continue participating in information exchange in order to refine her choice of the same product in a couple of years. However, if a consumer sees a movie, she might not stay engaged in WoM (about this particular movie) long after seeing it. The first example concerns the setup with repeated purchases. In this case purchases will not affect the WoM circulation network. The second example concerns one-off purchases. In this case, purchases will erode the infrastructure for communication among consumers (Dwyer, 2007). This difference across groups of products could have significant effects on the relationship between social network structure and product sales. In order to account for this, we study two setups. In one the WoM network is static. In the other it changes with sales.

Besides allowing for WoM disengagement, Campbell (2013) pushes the literature in one more important way. Instead of modeling WoM using a standard matching protocol, the author explicitly models WoM on a social network. We follow the suit. We believe the random matching does not describe the forces at play behind WoM with sufficient granularity. This introduces difficulty as different network topologies might have starkly different implications. In this paper, we investigate two types of topologies that share properties with real-life social networks – small world and scale free. Small world networks have the features of high clustering and short path length between consumers (Watts and Strogatz, 1998). Scale free networks also have short path length, but instead of high clustering, they are characterized by immensely popular individuals that serve as connectors among different parts of the social network (Barabasi and Albert, 1999). For the sake of comparison, we add two other abstract topologies to this – a regular lattice and a random network. Representing the two extremes of the spectrum, these two topologies mostly serve as baselines for the comparison of the results for small world and scale free structures.

Recent years have seen massive changes in social network architectures. The raise of modern telecommunication technologies and most prominently of electronic social media have made social networks denser (Donath and Boyd, 2004; Luarn et al., 2014; Sohn, 2009). There has also been a shift of consumer interaction toward an online space (Brown et al., 2007; Godes and Mayzlin, 2004). This has resulted in social networks looking more like scale free topologies with highly popular superstars (Backstrom et al., 2011; Bakshy et al., 2012; Ebel et al., 2002), instead of small world networks that are predominant in offline environments (Dellarocas, 2003; Granovetter, 1973; Travers and Milgram, 1969). The impact of these changes on the WoM efficiency, and hence on the link between product promotion and sales has not been studied as of today. This paper attempts to fill this void.[2]

3. The model

3.1. Setup

The economy consists of constant number (I) of consumers (indexed by i). A new product is placed on the market by a monopolistic producer. We assume that the price of the product is relatively small, so that the budget constraint is not binding.

The quality of the product is judged subjectively by each consumer. Thus, the perception of the quality is consumer specific. We denote the quality of the product as judged by consumer i with x_i. We assume that quality of the product is not known to a consumer prior to consumption. The variable x_i is randomly drown from distribution X. Realistically, X is also unknown to the public.

Each consumer has an internal quality requirement y_i for

[1] Recent advances have discussed non-content-free advertising (Anand and Shachar, 2011) which is built on the premise of improving consumer-product matching.

[2] There are other characteristics of social network topology that might also have an effect on the link between advertising and sales, like clustering (Katona et al., 2011). However, given that it is not clear how and whether average clustering levels have changes with the changes in social networks, we omit this characteristic from our discussions.

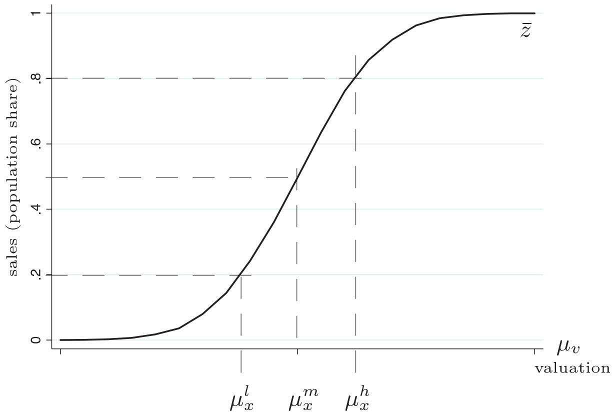

Fig. 1. Benchmark sales in absence of consumer interaction.

considering buying the product. She purchases the product only if her expectation for product's quality is no less than y_i. Similar to the variable x_i, y_i is drawn from distribution Y. The quality requirement is a private piece of information, and thus Y is not known to the public.

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

If there is no social interaction, we can calculate the expected sales of a given product. This will be the expected share of the people for whom initial belief about the quality of the product exceeds the quality requirement. The value is given by

$$\bar{z} = \int V^o(z)Y'(z)dz. \tag{1}$$

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 drawn from normal distributions: $X \sim N(\mu_x; \sigma_x^2)$, $Y \sim N(\mu_y; \sigma_y^2)$ and $V^0 \sim N(\mu_v; \sigma_v^2)$. In this case the expected share of the consumers that will buy the product is given by

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

Eq. (2) is plotted on Fig. 1 for the case when $\sigma_v^2 = \sigma_y^2$.[3] 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, the higher (average) belief about the quality of the product results in higher sales. Notice that due to the fact that consumers do not interact, the actual quality (μ_x) of the product does not affect sales. On Fig. 1 we also identify the average accepted quality in the population – μ_y. Quite intuitively, given that we are working with symmetric distributions, when average expectation is equal to average quality requirement – we can expect half of the society to buy the product.

To simplify the exposition, in what follows we work with three types of products. To define these products, consider a setup with no information uncertainty about the quality of the product, i.e. $v_i^0 = x_i \forall i$. In this setup we define a medium quality product as a product for which $\mu_x = \mu_y$. This means that 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 products are denoted by μ_x^l and μ_x^h, respectively. We define the low quality product as the one that will be purchased only by 1/5 of the population and the high quality product as the one that will be purchased by 4/5 of the population.[4] Similar to the definition of the medium quality product, both of these definitions subsume no informational uncertainty. Combining these definitions with the normality of X, Y and V^0 distributions, and further assuming $\sigma_x^2 = \sigma_y^2 = \sigma_v^2 \equiv \sigma^2$,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 Fig. 1.

3.2. Dynamics

Now we introduce two central forces in our morel that can affect consumer decisions – advertising and word-of-mouth.

3.3. Advertising

Producers can advertise. We assume that producers can advertise only before the product is placed on the market. Advertising increases μ_v - the average expected quality of the product.[5] However, it does not make expectations more (or less) homogenous, thus it does not affect σ_v. This does not imply that variance across valuations stays strictly the same after advertising, but rather that valuation now is drawn from a new distribution with a higher mean, but the same variation coefficient. Although we do not model the costs of averting explicitly, we assume that advertising is costly – all else being equal, driving μ_v to a higher level requires more spending. From the Fig. 1 we can readily see that in absence of consumer interaction higher advertising expenditures would result into higher sales.

3.4. Word-of-mouth

To model consumer interaction, we assume that there exists a static social network that specifies the potential interaction structure among consumers. Information about the product can stream through this social network. However, we consider the possibility of not every consumer engaging in WoM during all periods.

Following Campbell (2013), we distinguish the social network from the WoM network. We study two scenarios. One with the static WoM network which is the same as the social network. This scenario best fits products with repeated purchases. In this environment consumers still have incentive to engage in WoM and adapt their beliefs about the product following the information they receive from their social contacts.

The other scenario applies better to the environment with non-repeated purchases. In such a setting the consumer who has purchased the product has not further incentive to adapt her beliefs as she knows she will not have to make another choice about the same product anymore. In this setup consumers leave the WoM network once they have purchased the product. Thus, WoM network is dynamic. It departs from social network with time. This setting is different from Campbell (2013) environment where despite the different between WoM and social networks, both of the networks are static.

Fig. 2 demonstrates the difference between the social and WoM networks, as well as the difference between the setups with static and

[3] Throughout the whole paper we consider the arrangement when $\sigma_v^2 = \sigma_y^2 = \sigma_x^2$. Hence, we fix the variance coefficients of the three distributions. Although the existence of heterogeneity is crucial to the model, investigating the effects of the degree of heterogeneity is outside the scope of this paper. Therefore, we do not manipulate the values of standard deviations of three distributions. Rather, we put them to be all equal to each other. Hence, effectively we are left with setting only two parameters – the average quality of the product μ_x and the average initial quality expectation μ_v.

[4] Results are not sensitive to the definition of the high and low quality products. We have experimented with alternative definitions (e.g. 1/4 and 3/4; 1/3 and 2/3). Qualitatively the results are unchanged.

[5] This is in line with findings by Elberse and Anand (2007), who report that that prerelease advertising has a significant positive effect on expectations potential consumers hold about the product.

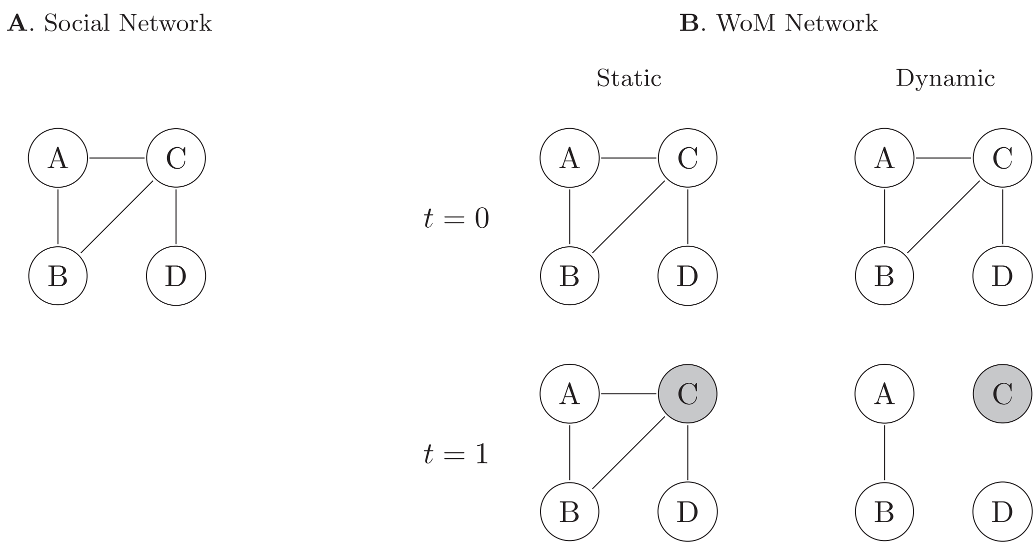

Fig. 2. The relationship between the social and WoM networks.

dynamic WoM networks. Panel A presents an example of a social network among four consumers. Panel B presents the corresponding WoM network at two time periods across two regimes. In this example the consumer C purchases the product at time $t = 0$. This is denoted by the node C turning grey in the subsequent ($t = 1$) period. This introduces the difference in WoM network across two scenarios. In the case of dynamic WoM network the consumer stops participating in WoM and thus information cannot stream through this node anymore. As consumers are leaving the WoM network randomly, the dynamic WoM scenario parallels the random attacks on networks studied by Albert et al. (2000). With time the WoM network disintegrates into the architecture that is hard to traverse. In this environment valuable information can get locked in remote parts of the social network and leave substantial part of consumers un-informed.

In contrast, in case of static WoM network consumer stays engaged in WoM and the information circulates on unaltered network architecture. In this setup the only constraint on information circulation is the social network itself.

To formalize the consumer reaction to WoM, consider people purchasing the product one by one (i.e. each time period only one person can purchase the good). Consumer making a purchase at time t is randomly selected from the people that are eligible.[6] Eligibility is based on two criteria. First, that this person has not already purchased the product in any of the previous time periods. And second, that she is willing to buy it ($v_i^t \geq y_i$). Once a person makes a purchase (we denote such a time period with *T*), she realizes the actual (idiosyncratic) quality of the product (x_i). Thus his impression about the product at the end of the period is

$$v_i^T = x_i. \tag{3}$$

After consumption, the consumer communicates v_i^T to her friends, who update their beliefs about the product 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. We do not model b on a personal level. Rather we assume that consumers are homogeneous in this respect. If $b = 0$ we are in the setup with the “cheap talk.” In this environment WoM does not affect consumer beliefs, and hence the model dynamics in unchanged. If, on the other hand, $b = 1$, consumers trust each other completely and disregard their previous information.

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 consumer m receives the information from consumer n, and k is the shortest path length between consumers n and m in the currently functional WoM network. Modeling consumer interaction this way implies that weight that consumers put on each other's judgements is decreasing in social distance, as long as $0 < b < 1$. This is reasonable in light of empirical findings pointing to the constantly altering information streams through WoM communication (Kozinets et al., 2010).

Notice that in our model consumers exchange information about the perceived value of the product in question. This is distinct from incarnations of observational learning that constitute the basis for revealed preferences. In case of observational learning the strength of the neighbor's recommendation cannot be deciphered. As a result, modeling of valence of WoM represents a challenge. In case of direct exchange of valuations among consumers the valence of WoM can be directly modeled. This paper follows the latter tradition. The notion of WoM valence is a cornerstone of much of work in consumer behavior in marketing and psychology disciplines (e.g. Hess and Ring, 2016; Roy and Naidoo, 2017). The distinction between observational learning and learning that allows for the communication of richer information (i.e. valuations) has been previously formalized as “showing” and “telling” respectively (Babutsidze and Cowan, 2014).

4. Methodology

The consideration of the social network architecture makes the model analytically intractable. Therefore, we resort to agent-based simulations. Simulation methodology is as follows. At the onset, we choose the environment – we set the values of model parameters. These are values associated to three distributions (X, Y and V^0),[7] plus the level of trust in the society (b) and the density of the social network. We also

[6] The alternative here would have been to allow consumers with the highest valuation to purchase the product first. However, as we are only modeling a part of the decision-making process, and various other aspects (i.e. availability of discretionary time and budget) might also affect the sequence of decision-making, such an assumption would have been unjustified.

[7] What matters for the results is the relation among these distributions, rather than actual parameter values. In this respect we have three sets of parameters – three means and three standard deviations. We can normalize the values of three means using one of them as a denominator. For interpretation purposes we choose this to be μ_y.

choose the nature of the WoM network (static or dynamic). We initiate 1000 consumers and randomly draw their characteristics (x_i, y_i and v_i^0) from corresponding distributions. We also generate the corresponding social network among our 1000 consumers. The network can be one of four types: regular lattice, random, small world, or scale free.[8]

At $t = 0$ we select consumers satisfying $y_i \leq v_i^0$ (the set of eligible consumers) and randomly draw one of them from this set. This is the agent who consumes the product at $t = 0$. She discovers x_i and communicates this information to her friends. They update their beliefs about the product quality according to (4) and communicate further so that others update their information using (5). The chosen consumer becomes ineligible for consumption in following periods. This constitutes the end of period $t = 0$ in case of static WoM network scenario. However, in dynamic WoM network scenario, after the acts of consumption and communication, the consumer (and all links associated with her) is also removed from the WoM network. This routine repeats at every consequent time period. Simulation stops when the set of eligible consumers is empty.

Given that our initial conditions fix only the distributions from which actual values are drawn (and not the values themselves) – two separate runs with same initial conditions will be (potentially) different. Therefore, in order not to allow random perturbations to skew the results we employ a Monte Carlo strategy. Namely, for every parameter setting we generate not one, but multiple (50) runs. Ultimately we sweep the relevant parameter space and run the model on 7560 different parameter settings.[9] This together with two information circulation network setups and 50 Monte Carlo iterations gives us the total of 756,000 runs of the economy which constitute the data for the analysis.

Ultimately our aim is to relate the parameters of the model to the sales performance of the product. However, these relationships may be different across two WoM network settings. In order to see whether there are actual differences in outcomes across two scenarios recall that we have 7560 pairs of settings with 50 observations each. In other words, every parameter setting in dynamic WoM network scenario has its exact counterpart with static WoM network scenario, each of these alters having 50 Monte Carlo iterations. Therefore, we conduct a simple test of mean difference across the two corresponding sets of observations. Thus we can conduct 7560 tests. Statistically, if the two scenarios were similar, the likelihood of a test to result into rejection of the null hypothesis of mean equality is equal to 1 - level of confidence. Namely, if we are conducting a test with 90% confidence, the same data generation process across two sets of data will result in rejection of null hypothesis in 10% of the times. Therefore, if the static and dynamic WoM scenarios were the same, the share of statistically different means across the two pairs has to be about 10%. However, in our 7560 tests we can reject the mean equality in 27% of the cases. This implies that dynamic and static WoM scenarios are indeed statistically different.[10] The breakdown of the test results across the distribution of main variables is given in the Appendix A. As one can see, there is only one instance when the rate of rejection is close to 10%. That is for the 1st quantile of the trust variable, which effectively means when $b = 0$. This is intuitive as $b = 0$ is the "cheap talk" scenario. In this setup consumers ignore the information coming from their social contacts. Therefore, WoM has absolutely no effect on purchase decisions. Hence, differences in information circulation networks are irrelevant and static and dynamic WoM scenarios constitute the same data generating process.

In order to draw general conclusions regarding the implications of the model, we employ a regression analysis on the data generated from agent-based simulations. This is necessary to distill the effect of each parameter we are interested in, while controlling for the effect of all other parameters. Estimation of the econometric models on the artificial data produced by agent-based models is not usually a trivial issue (Grazzini and Richiardi, 2014). Major problems arise with time-series regressions because of open-endedness (and possible non-ergodicity) of the collected data. However, current methodological contributions (i.e. Guerini and Moneta, 2017) do contribute toward the popularization of this approach (i.e. D'Andria and Savin, 2018). The current application of Babutsudze and Valente (2018) is particularly close to the methodology employed in this paper (including the out-of-sample prediction power exercise described below). In the current paper, we run regressions on the data from the ergodic state of the system. We do not investigate the time series describing the convergence to the equilibrium. Therefore, there are no stationarity problems involved in our case.

As we want to see the relation between the model parameters and equilibrium sales, which is a bounded variable (expressed in shares it is bounded between zero and one), we have to run the generalized linear regressions relating all model parameters to sales. However, as we are dealing with the complex model (mostly due to the actual social network being explicitly modeled), it is unclear, a priori, which of the generalized linear shapes could describe the data the best. Therefore, we perform a model evaluation exercise using out-of-sample prediction power as a discriminant across the alternatives. We proceed as follows.

We take our 7560 scenarios and split them randomly in two parts: 80% of scenarios will be used to estimate the econometric model and the remaining 20% will be used to evaluate the out-of-sample fit of the model. As the split between the two groups is random we are running the risk of generating a spurious relationship if we do this just once. Therefore, we bootstrap the process 100 times – for each of the models evaluated we perform split- estimation-fitting procedure 100 times and average the results. After carrying out this exercise separately for static and dynamic WoM networks, we have sales calculated from the actual simulated data and predicted sales calculated from the estimated econometric model. We use the average mean squared error (AMSE) as the discriminant across the econometric models.

We contrast seven most popular generalized linear functions – Linear, Logit, Probit, Log, Log complement, Log-log and Negative binomial. Table 1 presents the results. As one can see three of the models (Logit, Probit and Log-log) significantly outperform the other four alternatives in case of the both types of WoM networks. Although the difference is small across the three best performing models, the exercise indicates the generalized linear regression with Logistic link function best describes the artificial data in dynamic, as well as static WoM environments. Thus, all the results presented in the following section come from such regressions.[11]

5. Results

Our data comprises 7560 distinct scenarios. Some of these scenarios are somewhat similar in terms of the environment. Others are quite different from one another. Our main concern is the impact of advertising on sales. There are two channels through which advertising affects sales. The first is the direct channel: advertising raises people's pre-purchase valuations of the product, and therefore more people pass the threshold of minimum quality requirement and are eligible to purchase the product. This channel is always positive. The second channel,

[8] An algorithm for generating a regular lattice is straight forward. We use the algorithm by Erdos and Renyi (1959) to generate random architectures, algorithm by Watts and Strogatz (1998) for small world and algorithm by Barabasi and Albert (1999) for scale free topologies.

[9] As mentioned in previous section for the demonstration purposes we use only three values of product quality (μ_x). We use five values for trust parameter $b \in \{0; 0.25; 0.5; 0.75; 1\}$. We investigate four types of networks. We use six values of network density (average degree being 4, 12, 20, 40, 60 and 100). And we use 21 equally spaced values for μ_v in range $\mu_v \in (\mu_y - 5\sigma; \mu_y + 5\sigma)$. $3 \times 5 \times 4 \times 6 \times 21 = 7560$.

[10] However, whether this difference affects the results qualitatively cannot be concluded from this test.

[11] The results are robust to the model choice across the three best alternatives. They are qualitatively identical across the three best performing models in both WoM environments.

Table 1
Statistical model evaluation.

Model	Dynamic WoM network			Static WoM network		
	Sales	Predicted sales	AMSE	Sales	Predicted sales	AMSE
Logit	0.5704	0.5780	0.0123	0.5692	0.5762	0.0123
	(0.012)	(0.012)		(0.011)	(0.011)	
Loglog	0.5704	0.5679	0.0125	0.5692	0.5660	0.0125
	(0.012)	(0.012)		(0.011)	(0.011)	
Probit	0.5704	0.5785	0.0126	0.5692	0.5767	0.0126
	(0.012)	(0.012)		(0.011)	(0.011)	
Log complement	0.5704	0.5647	0.0197	0.5692	0.5633	0.0197
	(0.012)	(0.011)		(0.011)	(0.010)	
Linear	0.5704	0.5711	0.0225	0.5692	0.5697	0.0226
	(0.012)	(0.012)		(0.011)	(0.011)	
Log	0.5704	0.5830	0.0359	0.5692	0.5815	0.0360
	(0.012)	(0.010)		(0.011)	(0.009)	
Negative binomial	0.5704	0.5831	0.0408	0.5692	0.5813	0.0409
	(0.012)	(0.010)		(0.011)	(0.009)	

Notes: Results obtained from out-of-sample prediction power of various models in synamic and static WoM settings. Sales are average sales calculated from the actual synthetic data. Predicted sales are obtained from generalized linear regressions with various link functions (given by column “Model” in the table). AMSE gives the average mean squared error between the respective sales and predicted sales.

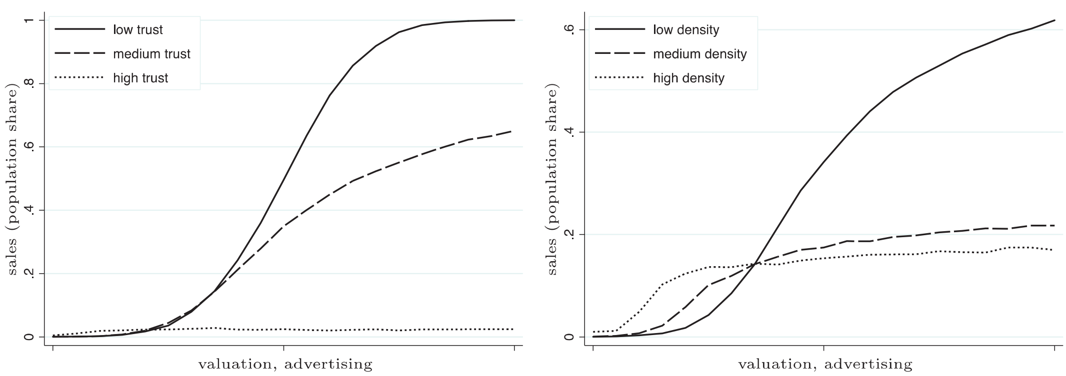

Fig. 3. The effects of trust and social network density.
Notes: The left panel depicts averages of Monte Carlo results for the low quality product with dynamic WoM and a sparse (average degree equal to 4) lattice as a social network. The right panel depicts averages of Monte Carlo results for the low quality product with dynamic WoM, with medium size trust (b = 0.5) and lattice as a social network.

however, goes through WoM. Advertising affects the valence of the sentiment contained in WoM and the latter, on its own, affects consumer's likelihood to purchase the product.

How can advertising affect the sentiment contained in word-of-mouth? Consider the producer that heavily advertises its product. So much so, that the average expected quality is above the actual quality of the product at t = 0. Then as consumers start purchasing the product, expectations of majority of the people will not be met. This will induce negative (compared to the average initial belief) WoM which, all else equal, will decrease future consumers' likelihood of buying the product, and thus hurt sales. However, if the producer advertises moderately, so that the average expected quality at the onset of dynamics is below actual (average) quality, then generated word-of-mouth will be positive and will push the sales upward. Therefore, the indirect channel might be positive or negative depending on the producers advertising level.

Before going into regressions demonstrating general results, we present plots demonstrating some of the effects present in the model. Fig. 3 plots average sales across 50 Monte Carlo runs for few of the model settings. Plots on both panels of the figure show the positive relationship between advertising and sales. This confirms the direct chan- nel. The left panel on the figure demonstrates the effect of increasing trust in WoM in the society, while the right panel demonstrates the effect of increasing density of social network. Higher values of both, trust and network density, have similar effects: they help sales in low advertising environments (left portion of each panel) and hurt them in high advertising scenarios (right portion of each panel). This is due to the indirect channel.

To demonstrate the presence of two channels statistically we switch to regressions. The direct channel is straight forward as advertising represents the parameter of the model and has to be included in the regression as an explanatory variable. In order to accurately detect the presence of the indirect channel in our data, we separate scenarios when $\mu_v < \mu_y$ and the ones when $\mu_v > \mu_y$. We refer to the former as scenarios when producers “underadvertise” and to the latter as scenarios when producers “overadvertise”. Notice here that these references are not completely accurate. In a sense that as we do not model advertising costs we cannot talk about the optimal level of advertising. Thus, underadvertising in our context does not mean to the advertising

Table 2
Regression results.

	Dynamic WoM network		Static WoM network	
	Underadvertise	Overadvertise	Underadvertise	Overadvertise
Valuation	+	+	+	+
Valuation squared	−	−	−	−
High quality	+	+	+	+
Low quality	−	−	−	−
Trust	+	−	+	−
Density	+	−	+	−
Network controls	Included	Included	Included	Included
Number of observations	186,000	186,000	186,000	186,000

Notes: Reported results are the coefficient signs from the generalized linear regression with Logistic link function and robust standard errors. All the coefficients are statistically significant with 99% confidence. Network controls include three (out of four possible) dummy variables corresponding to the network topology (random, lattice, scale free and small world).

levels below optimal one and consequently overadvertising does not mean advertising levels above the optimal. Rather, with those terms we refer to the comparison between consumers' initial expectations and the (average) quality of the product.[12]

Thus, as we expect qualitatively different response of sales to WoM in cases of “underadvertising” compared to the cases of “overadvertising”, in what follows we concentrate on results obtained with regressions ran on collection scenarios that qualify for one of the two groups.

Table 2 presents the results obtained from the regressions. The share of consumers who have bought the product (sales) is the dependent variable. Valuation in the list of independent variables refers to the average initial expected quality μv, or how much consumers value the product at the onset of the dynamics. This is the measure of the advertising effort by the producer. Regressors also include two dummies for high and low quality products. Scenarios with medium-quality products serve as the baseline. The list of explanatory variables includes: trust in society (b), density of the social network and three dummy variables to control for the effects of varying network topology.

Given that our model is not calibrated with real data and that we sweep a large parameter space with agent-based regressions, the actual values of the regression coefficients are less important. What are important are the signs of these coefficients as we seek to draw qualitative conclusions.[13] Therefore, in the table we report only the signs of statistically significant coefficients. The complete report on the regression results (i.e. coefficients, standard errors, significance levels) is presented in the Table 4 in the Appendix A. For reader's reference, in Table 4 we also present the regression results on pulled data, which collects observations from underadvertising and overadvertising scenarios, as well as the scenarios that do not qualify for any of the two definitions (i.e. when $\mu_v = \mu_y$).

For each WoM network setting there are two separate scenarios: one when producers overadvertise and the other when they underadvertise. Firstly, it is obvious from the results that the product quality has a pretty direct and straight forward effect – better products sell better. This is true in all scenarios except when consumers don't trust each other at all (b = 0). In this case sales are governed by initial quality expectations and the model behaves exactly as the model without interaction as presented in Fig. 1.

The direct effect of advertising on sales can be read from the coefficients for the variable “valuation”. Recall higher valuation (initial quality expectation) is interpreted as higher advertising. As one can readily see, in both types of regimes (over and underadvertising) higher advertising results in higher sales, all else equal. This is the direct channel.

More interesting are the results for the indirect channel. We can infer the behavior of the model in this respect by looking at coefficients for consumer trust in WoM and density of the social network. The coefficients are starkly different across the two regimes in dynamic as well as static WoM scenarios. In case of under advertising both higher trust and higher density increase sales, while in case of overadvertising the opposite is true.

In the case of underadvertising generated word-of-mouth is positive. It is helping increasing sales. Higher consumer trust boosts sales because people are easily persuaded that the product is of a high quality. On the other hand, denser network facilitates the positive word-of-mouth reaching all corners of social network. On the contrary, the WoM's persuasion power and its speed to traverse the social space is hurtful for sales in case of overadvertising as in this case generated WoM is negative.

We have identified two channels of influence from product promotion to sales. The direct is always positive. However, the indirect channel is initially positive, but turns into negative when advertising reaches high levels. Hence, even though we are not modeling the advertising costs and therefore cannot identify the optimal level of advertising, we can still ask a question whether the negative effect of the second channel can dominate the positive effect of the first channel. For this we have included valuation squared in the regression. As you can see its coefficient is negative and significant all four setups. This means that the dependence of sales on valuation is concave. Thus, sales are bound to start decreasing in advertising, if the campaign is aggressive”. This means that returns on an extra dollar in advertising will turn negative (not simply less than one). This is effectively due to the fact that the indirect channel dominates the direct one, for sufficiently high intensity of advertising. Thus, the model points to the trap of overadvertising in case of ignoring the effects of the indirect channel.

5.1. Effects of network topology

Because advertising in our model works as broadcasting – it reaches (and affects) every consumer – its effect does not depend on the topology of the social network. Direct channel of influence is therefore

[12] Notice that if product quality can be inferred from its appearance then higher expected product quality might be achieved with lower amounts of advertising. Therefore, higher initial expected product quality implies higher advertising costs only in case of the products of similar quality.

[13] What are also important are the significance levels of corresponding parameters. However, given the agent-based modeling approach the level of significance is somewhat artificial. In principle, there can only be two outcomes – significant or insignificant. By generating sufficiently large set of synthetic data any statistically significant relationship can be driven to 99% confidence level (as standard errors shrink with increasing sample size). Thus, highly significant coefficients in our regressions as reported in Tables 4 and 5 in the Appendix A are not surprising. An extensive bootstrapping exercise to generate alternative standard errors from smaller samples generates very similar results: no single statistically significant coefficient in non-bootstrapped regressions is insignificant in bootstrapped counterpart, and no single statistically insignificant coefficient in non-bootstrapped regressions is significant in bootstrapped alternative.

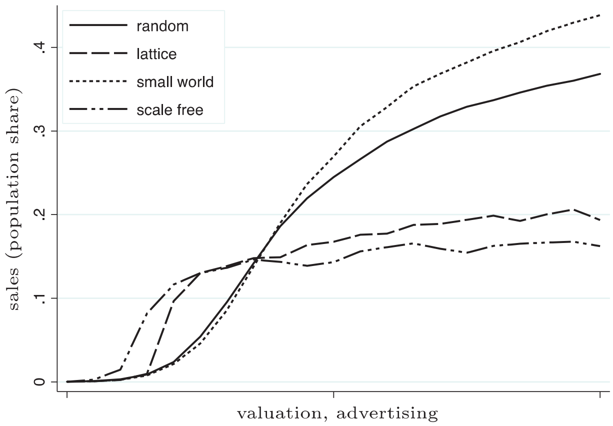

Fig. 4. The effect of social network topology.
Notes: The figure depicts the averages of Monte Carlo results for the low quality product with static WoM, medium level trust ($b = 0.5$) and a sparse (average degree equal to 12) social network.

not affected by network topology. However, word-of-mouth is generated through local interactions. As a result, its effects are bound to depend not only on the density of the social network but also its topological structure. In principle, WoM efficiency might be very different across different social network topologies.

Recall that we are comparing four network architectures to each other: lattice, random, small world and scale free. Before going into the statistical analysis, we present a graphical demonstration of the relationship. Fig. 4 demonstrates the effect of topology difference for a limited number of settings. In this example it is clearly visible that for high values of advertising, sales are the highest for the small world network architecture and the lowest for the scale free topology. Recall that high values of advertising imply an un-favorable WoM sentiment. Therefore, in this particular example the scale free topology seems to be more conducive for the WoM.

For the thorough investigation of the topological effects we resort to the regression analysis. In the runs presented in Table 2 we have included only three out of four network dummy variables. For the sake of controlling for the topology (in order to get effects of model's other settings) it clearly does not matter which of the three dummies were included.

However, if we want to understand the differences across the topologies we have to study the regressions coefficients for network dummies themselves. Clearly coefficients of each of three included dummies have to be read as the differential effect from the baseline (omitted) topology. Therefore, in any regression we can only judge statistical difference between three included topologies vis-a-vis the omitted one. We cannot say anything about statistical significance of the difference between any pairs of two included topologies. Therefore, we estimate the same regressions as in Table 2 four different times. Each time one of the four topologies serves as the baseline and other three are included in the regression. In Table 3 we present the regression results and concentrate on coefficients of network dummies (all other coefficients are of course the same as presented in Table 2 and are pulled in this table under "Controls"). In this table each box presents the result of a single regression. We again concentrate on reporting the signs of the statistically significant coefficients. The full report is given in the Table 5 in the Appendix A.

We find that all four topologies are statistically significantly different from one another in both of the scenarios – when producers overadvertise and when they underadvertise. This is true for settings with static as well as dynamic WoM networks. Somewhat more

Table 3
Regression results with respect to network topology.

	Dynamic WoM Network		Static WoM Network	
	Underadvertise	Overadvertise	Underadvertise	Overadvertise
Random	base	base	base	base
Lattice	-	+	-	+
Scale free	+	-	+	-
Small World	-	+	-	+
Random	+	-	+	-
Lattice	base	base	base	base
Scale free	+	-	+	-
Small World	-	+	-	+
Random	-	+	-	+
Lattice	-	+	-	+
Scale free	base	base	base	base
Small World	-	+	-	+
Random	+	-	+	-
Lattice	+	-	+	-
Scale free	+	-	+	-
Small World	base	base	base	base
Controls	included	included	included	included
Number of observations	186 000	186 000	186 000	186 000

Notes: Reported results are the coefficient signs from the generalized linear regression with Logistic link function and robust standard errors. All the coefficients are statistically significant with 99% confidence. Each box corresponds to a separate regression. In each regression we omit one of the network dummies and mark it in the table as "base". Controls include all parameters of the model, including valuation and valuation squared.

surprisingly, we detect a clear ranking among the four topologies in terms of their effectiveness in facilitating the link between advertising and sales. Namely, the network effectiveness increases as we go from small worlds to regular lattice, further to random and to scale free networks. This result does not depend on the nature of the WoM network.

In order to understand the intuition behind the ranking note that, there are two important factors at play here. One is the average shortest path length within the WoM network. The other is the existence of heavily connected individuals – opinion leaders. The interplay between these two factors is complex. Opinion leaders can reach large masses and directly influence them. Shorter path length also facilitates information diffusion. However, in essence, opinion leaders play an important additional role verifying the consistency of WoM across multiple closed neighborhoods. Without such opinion leaders contrasting information can spread (at least locally) in remote neighborhoods.

Varying the number of highly connected individuals in the network also varies other characteristics of the network, most importantly the clustering coefficient. Therefore, there is no clean methodology in this framework to test our intuition about the moderating effect of highly connected individuals on path length in terms of information diffusion. However, Appendix B does present the exercise that is fairly clean. We follow the methodology of Cowan and Jonard (2007) and generate two sets of networks by varying rewiring probability in Watts and Strogatz (1998) model. In the first set the initial network is a regular lattice, where every note has the same number of connections and therefore the network does not have highly connected individuals. In the second set – the initial network is a modification of a regular lattice that allows for opinion leaders (“stars” in language of Cowan and Jonard (2007)). The exercise demonstrates the rate of increase in sales with the falling average path length is higher under the network with opinion leaders (i.e. “stars”), compared to the network without opinion leaders.[14]

As a result, we can conclude that without the presence of opinion leaders shorter path length also facilitates diffusion of the “false”, or in our case different from mass WoM, information.[15] As a result, in absence of highly connected individuals, shorter path length does not necessarily result into higher WoM effectiveness. This is the reason why regular lattice ranks above small world architecture.

6. Discussion

The findings concerning the effects of network density and topology in previous section have an important implication. Our results imply that changing social network architectures from sparse small worlds to dense scale free structures has increased the efficiency of WoM. In modern days a single overly negative review (which can be induced by super-high pre-purchase expectations) can hurt product sales. With time, the indirect channel gets to dominate the direct (positive) channel for lower levels of advertising efforts. Recent literature does indeed point toward the large power of WoM (Hewett et al., 2015; Trusov et al., 2009).

This insight does not depend on whether we use dynamic or static WoM network. Even though have found that dynamic and static WoM network scenarios are statistically different,[16] there is no qualitative differences across the two. Thus, we can conclude that over-advertising trap is universal and exists for wide range of products – products with repetitive, as well as with non-repetitive purchases. This universal trend has complicated product innovation processes for modern companies. Today's companies cannot quietly try out their product on small scale in order to elicit important feedback for perfecting them. Companies are forced to look out remote geographical areas in order to carry out this task (Economist, 2015). Some of the products are too hot even for a great geographical distance. Even very powerful companies cannot pull off bringing such products prematurely on the market, as demonstrated by cases of Fire Phone (Amazon), Maps (Apple) or Google Glass (Google).

This highlights the power of the negative WoM in our model. It is well-documented that negative word-of-mouth has effects of larger size than its positive counterpart. A large number of studies have found that negative WoM reduces perceived credibility of advertising as well as brand attitudes and purchase intensions (Chevalier and Mayzlin, 2006; Lou, 2007; Park and Lee, 2009; Singh, 1990; Smith and Vogt, 1995; Yang and Mai, 2010). This points to the fact that the consumers have asymmetric response to positive vs. negative sentiment contains in WoM. However, this is not the mechanism that stands behind the power of the negative WoM in our model. Here we do not allow for the difference in intensity of WoM depending on its valence. Effectively there is no *ex ante* difference in positive and negative WoM. This allows us to shed light on a novel danger of the negative WoM: it is able to halt sales at early stages of sales dynamics (by pushing everybody's valuations below their respective thresholds) and shield the society from further (possibly positive) information. Therefore, even though ex ante positive and negative WoM are similar, ex post negative WoM is more powerful.

In this respect, our results highlight the increasing importance of the well-known managerial advice to “underpromise and overdeliver” (Dixon et al., 2010; Parasuraman et al., 1991). With the rise of electronic social media that empowers consumers together with marketers (Ya et al., 2015), the danger of over-advertising trap is ever increasing. As a result, our findings call for the “smart” advertising policies, which would involve economizing on product promotion spending and riding the wave of the positive word-of-mouth. There is indeed an empirical support for the optimality of moderately-toned media strategy. Bolton et al. (2006) has found such evidence in a standard communication setting, while the recent study by Hewett et al. (2015) has reached a similar conclusion in an online communication setting. Yet, judging from the dynamics of the product quality expectations, which are usually decreasing over time (Yong, 2006), a number of producers still get into an over-advertising trap. Over-advertising firms fail in two respects. Firstly, they waste their money on advertising. And secondly, their campaigns turn WoM from the force that can help sales (positive) into the one that ultimately hurts performance figures.

Besides, a strong performance of scale free architectures also points to another way advertisers might want to make their efforts “smart”. This is by relying on star individuals for promoting the brand. The transformation of social networks to scale free structures that are dominated by highly connected individuals presents another opportunity for advertisers to save on advertising costs by relying on these opinion leaders. Many advertisers have already seizes the opportunity by jumping into sponsoring YouTube stars or Twitter mavens.[17]

However, a caveat has to be pointed out here. Our model only considers a monopolistic setup. In this setup producers are shielded from the effects of the competitors' advertising campaigns. Once we include competition in the setup it might very well happen that advertising becomes an arms race. A moderately-toned advertising campaign might not be an optimal response to competitor's product promotion efforts. In such environments strategic advantages of the direct channel between averting and sales might well out-weight the costs of the indirect channel identified in the paper.

Acknowledgements

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[14] Also notice that, despite the fact that for a given average shortest path length the clustering coefficient is different for the two networks, this feature does not seem to be driving the results (hence the relative cleanliness of this exercise). Given the difference between static and dynamic WoM network implementations, clustering would likely explain the differences across the two setups as dynamic WoM would imply a rapid fall in clustering as we progress into the dynamics of interaction. However, we see no visible difference in two panels of Fig. 6 in the Appendix B.

[15] Notice that this results highlights the importance of the integrity of highly connected individuals in social networks to counter-act the diffusion of “fake news”. These “stars” seem to have the power to counteract the generic effect of decreasing shortest path length that electronic social media have. However, this hinges on their motivation to contribute to finding the truth which (implicitly) exists in our model, but might not exist in the field.

[16] This is confirmed by the regression analysis too: if we run the any of the regressions presented in the paper on data combining static and dynamic WoM network setups and include a dummy variable for one of the scenarios, say static WoM, the coefficient of this dummy is always significant.

[17] I thank an anonymous referee for pointing out this insight.

Appendix A

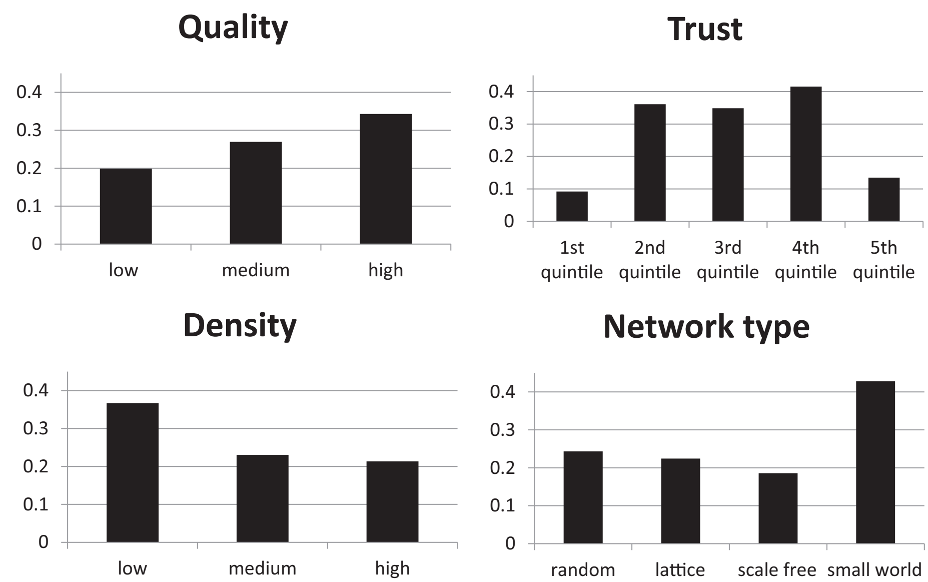

Fig. 5. The distributional breakdown of the difference in outcomes of scenarios with static and dynamic WoM networks across parameters of the model.
Notes: The height of the bars corresponds to the share of scenarios with statistically distinct outcomes at 90% level of confidence.

Table 4
Complete report on regression in Table 2.

	Dynamic WoM network			Static WoM network		
	Pulled	Underadvertise	Overadvertise	Pulled	Underadvertise	Overadvertise
Valuation	2.548***	4.294***	3.746***	2.568***	4.450***	3.674***
	(0.018)	(0.050)	(0.034)	(0.019)	(0.051)	(0.034)
Valuation squared	−0.054***	−0.105***	−0.079***	−0.055***	−0.109***	−0.078***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
High quality	2.030***	1.723***	2.961***	2.079***	1.734***	3.014***
	(0.013)	(0.008)	(0.008)	(0.013)	(0.008)	(0.008)
Low quality	−1.109***	−2.633***	−1.527***	−1.122***	−2.622***	−1.537***
	(0.004)	(0.018)	(0.005)	(0.004)	(0.018)	(0.005)
Trust	−0.961***	2.233***	−3.533***	−0.977***	2.199***	−3.533***
	(0.011)	(0.015)	(0.008)	(0.012)	(0.015)	(0.008)
Density	−0.000	0.005***	−0.004***	−0.000	0.004***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network controls	included	included	included	included	included	included
Number of Observations	378,000	186,000	186,000	378,000	186,000	186,000

Notes: "Pulled" regressions are performed on the data combining under- and overadvertising scenarios, as well as the scenarios that do not fall under any of the two definitions. They are not present in Table 2 in the text and are given here only for reader's reference. Reported results are the coefficients from the generalized linear regression with Logistic link function and robust standard errors. Standard errors are reported in parentheses. Statistical significance levels correspond to: * −90% confidence; ** −95% confidence; *** −99% confidence. Network controls include three (out of four possible) dummy variables corresponding to the network topology (random, lattice, scale free and small world).

Table 5
Complete report on regressions in Table 3.

	Dynamic WoM Network			Static WoM Network		
	Pulled	Underadvertise	Overadvertise	Pulled	Underadvertise	Overadvertise
Random	base	base	base	base	base	base
Lattice	0.054 ***	- 0.083 ***	0.176 ***	0.049 ***	- 0.119 ***	0.194 ***
	(0.007)	(0.012)	(0.006)	(0.007)	(0.013)	(0.006)
Scale free	- 0.022 ***	0.082 ***	- 0.117 ***	- 0.024 ***	0.061 ***	- 0.104 ***
	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)
Small World	0.055 ***	- 0.390 ***	0.444 ***	0.082 ***	- 0.350 ***	0.471 ***
	(0.007)	(0.012)	(0.005)	(0.007)	(0.012)	(0.006)
Random	- 0.054 ***	0.083 ***	- 0.176 ***	- 0.049 ***	0.119 ***	- 0.194 ***
	(0.007)	(0.012)	(0.006)	(0.007)	(0.013)	(0.006)
Lattice	base	base	base	base	base	base
Scale free	- 0.076 ***	0.165 ***	- 0.293 ***	- 0.073 ***	0.180 ***	- 0.297 ***
	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)
Small World	0.001	- 0.307 ***	0.268 ***	0.032 ***	- 0.231 ***	0.278 ***
	(0.007)	(0.011)	(0.005)	(0.007)	(0.012)	(0.006)
Random	0.022 ***	- 0.082 ***	0.117 ***	0.024 ***	- 0.061 ***	0.104 ***
	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)
Lattice	0.076 ***	- 0.165 ***	0.293 ***	0.073 ***	- 0.180 ***	0.297 ***
	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)
Scale free	base	base	base	base	base	base
Small World	0.077 ***	- 0.472 ***	0.561 ***	0.106 ***	- 0.411 ***	0.575 ***
	(0.007)	(0.012)	(0.006)	(0.007)	(0.012)	(0.006)
Random	- 0.055 ***	0.390 ***	- 0.444 ***	- 0.082 ***	0.350 ***	- 0.471 ***
	(0.007)	(0.012)	(0.005)	(0.007)	(0.012)	(0.006)
Lattice	- 0.001	0.307 ***	- 0.268 ***	- 0.032 ***	0.231 ***	- 0.278 ***
	(0.007)	(0.011)	(0.005)	(0.007)	(0.012)	(0.006)
Scale free	- 0.077 ***	0.472 ***	- 0.561 ***	- 0.106 ***	0.411 ***	- 0.575 ***
	(0.007)	(0.012)	(0.006)	(0.007)	(0.012)	(0.006)
Small World	base	base	base	base	base	base
Controls	included	included	included	included	included	included
Number of observations	378 000	186 000	186 000	378 000	186 000	186 000

Notes: “Pulled” regressions are performed on the data combining under- and overadvertising scenarios, as well as the scenarios that do not fall under any of the two definitions. They are not present in Table 3 in the text and are given here only for reader's reference. Reported results are the coefficients from the generalized linear regression with Logistic link function and robust standard errors. Standard errors are reported in parentheses. Statistical significance levels correspond to: * −90% confidence; ** −95% confidence; *** −99% confidence. Each box corresponds to a separate regression. In each regression we omit one of the network dummies and mark it in the table as “base”. Controls include all parameters of the model, including valuation and valuation squared.

Appendix B

In order to pin down the effect of highly connected individuals on efficiency of social networks we adapt the methodology from Cowan and Jonard (2007). We compare two scenarios for generating networks using Watts and Strogatz (1998) methodology. One starts with the regular lattice (1000 nodes being located on a circle and each node being connected to 7 nearest neighbors on each side, in total 14,000 links) and varies the rewiring probability in order to generate networks with varying average shortest path length. The other has a different starting network than a regular lattice. Here we also start with the 1000 nodes located on the network. Then we randomly identify 100 stars and connect with 25 closest neighbors on each side. This allocates 5000 links. Then we distribute 9000 remaining links across the remaining nodes (on average 5 links on each side) to make the lattice as regular as possible. Then we vary the rewiring probability to generate different networks

It is worth noting that across the two treatments (networks with stars and without stars) one needs to use different values of rewiring probability in order to generate networks with comparable average shortest path lengths. Also note, that clustering coefficients are different across the networks of comparable average shortest path length with stars and without stars.

Fig. 6 presents the results of this exercise for an under-advertising scenario of a medium quality product on two panels. Left panel concentrates on static WoM networks, while the right panel illustrates the results for the dynamic WoM network. Results in both panels highlight the importance of stars in efficiency of social network. No noticeable difference across the two panels also points to the fact that difference in clustering coefficients across networks is not driving these results.

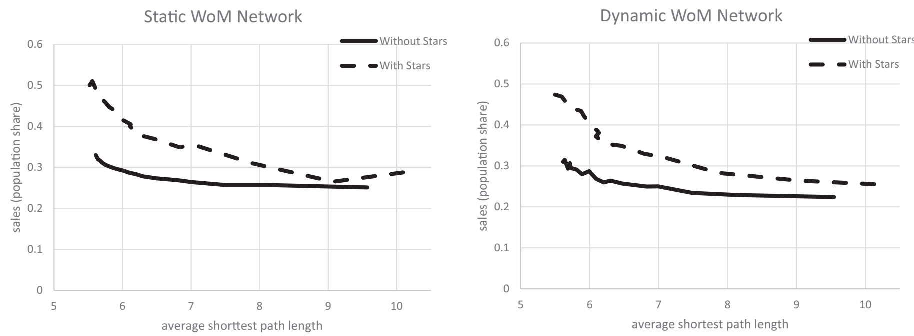

Fig. 6. The difference in sales for small world networks with and without opinion leaders ("stars") across static (left) and dynamic (right) WoM networks.
Notes: The graphs are generated for the medium quality product under the under-advertising scenario. Presented data are averages across 100 Monte Carlo simulations. Each Monte Carlo simulation results in potentially (slightly) different average shortest path length compared to other 99 simulations generated from the same initial conditions. In these graphs average shortest path lengths are averaged across 100 simulations for plotting.

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