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The profit impact of revenue heterogeneity and assortativity in the presence of negative word-of-mouth☆

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ABSTRACT

This study explores the adverse effects of customer disappointment after adoption accompanied by spreading negative word-of-mouth on firm profits. The study examines the effects of heterogeneity and assortativity of customer revenue on the profit impact of negative word-of-mouth that is initiated by three groups of consumers—revenue leaders, social hubs, and experts. The authors explore these effects using an agent-based simulation modeling approach and an in-depth computational experiment with empirical input data regarding social connectivity from 10 consumer social networks. The results indicate that negative word-of-mouth is more damaging in markets where there is a higher degree of heterogeneity. Moreover, assortativity may significantly affect the profit impact of disappointments, but this effect depends on the initial percentage of disappointed adopters. The study also finds an interaction between heterogeneity and assortativity, such that the effect of heterogeneity increases as assortativity increases up to a moderate level of assortativity, then the effect of heterogeneity on profits remains relatively constant. The implications from these results suggest that marketing managers should consider the heterogeneity and assortativity characteristics of their customer revenue streams to (a) better manage the adverse profit impacts of customer disappointments and negative word-of-mouth; (b) design more effective customer loyalty programs; and (c) more efficiently manage their customer equity portfolios.

1. Introduction

Firms' long-term survival depends on the success of their new products in the marketplace. About 25,000 innovations are introduced to the US market each year, a majority of which fail (Oreg & Goldenberg, 2015). In the US, Over 75% of new consumer packaged goods do not meet firms' minimum expectations, and only 3% of these products are highly successful (Schneider & Hall,

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2011). In the services industry, firms lose an estimated $6.2 trillion of revenue globally due to disappointed customers who switch to other service providers (Accenture, 2015).

Researchers have primarily associated innovation failure or slow diffusion with poor quality, high introductory prices, and network externalities (Goldenberg, Libai, & Muller, 2010; Golder & Tellis, 1998; Peres, Mahajan, & Muller, 2010). They have paid less attention to how negative word-of-mouth (WOM) initiated by disappointed customers can aggregate to adversely affect diffusion outcomes such as firm profits (Nejad, Sherrell, & Babakus, 2014). Moreover, such negative WOM is largely unobservable to firms except over the long term. Thus, the nature of the diffusion problem facing a firm may not be noticeable until it is too late to take any corrective action to combat the trend (Goldenberg et al., 2007).

The transference of customer disappointments and negative WOM to firm profits may have two primary components. The social influence process is one component which has been examined via negative WOM (Goldenberg et al., 2007; Hsu & Lawrence, 2015). Owing to the non-linear nature of negative WOM circulation, a few influential consumers may initiate a snowball effect that spreads across the market and eventually hampers the diffusion process (Moldovan & Goldenberg, 2004). A component of consumers' adverse reactions that has not been studied in the context of negative WOM is the elimination of the potential revenue stream from disappointed customers and those whom they may influence. For example, if an adopter of a new service such as a streaming TV program service via the Internet is disappointed with the service and terminates it, his/her decision may discourage his/her acquaintances from adopting the service. The acquaintances may or may not share common characteristics (e.g., similar job, income, education, or consumption patterns) with each other. There are multiple elements at work here that concern the service provider. One element is the foregone revenue of the disappointed customer's patronage. Another element is the social influence of the disappointed (lost) customer on other acquaintances' patronage decisions for the service. If the lost customer was a light user of the service, while the acquaintance would have made heavy use of the streaming service, the impact of the heavy user's decision will carry heightened consequences for the service provider compared to the initial lost customer. Both the revenue generated as well as the spread of social influence are of concern in this example. The missing piece of knowledge is how and under what conditions a small group of disappointed customers who may differ in revenue generation and/or social influence significantly reduce firm profits at the market level.

We suggest that heterogeneity and assortativity of customer revenue streams are important concerns when evaluating the adverse effect of consumer disappointment on firm profits. Heterogeneity captures the degree to which consumers are different in terms of a certain attribute regardless of whether they have a social tie with each other. Assortativity relates to the widely-held belief that ‘birds of a feather flock together,’ a phenomenon that has been observed by social network and sociology studies. Assortativity captures the degree to which two individuals who have a social tie with each other are similar in terms of certain attributes (Mcpherson, Smith-Lovin, & Cook, 2001; Newman, 2003). In this study, we focus on heterogeneity and assortativity in terms of customer revenue, so heterogeneity and assortativity hereafter refer to revenue heterogeneity and revenue assortativity.

We examine these effects for disappointments by different groups of individuals who play distinctive roles in innovation diffusion. These individuals are identified based on three primary traits: (a) heavy use, labeled revenue leaders or heavy users of a service or product category (Haenlein & Libai, 2013); (b) a large number of social ties within a social network, labeled social hubs or opinion leaders (Goldenberg et al., 2009); or (c) a strong influence on others who are in touch with them, often referred to as experts (Libai, Muller, & Peres, 2013). We also consider disappointments by a randomly-designated group of potential adopters for comparison purposes.

This study seeks to explore the following research question in the context of customer disappointment with innovations:

> What are the relative effects of revenue heterogeneity and assortativity on the profit impact of negative WOM following disappointments by revenue leaders, social hubs, expert, and average consumers?

We examine this research question in the context of a frequently-purchased service using Agent-Based Modeling and Simulation (ABMS). Given the challenges of data collection for negative WOM activity (Goldenberg et al., 2007; Rogers, 2003), simulation is a viable approach for the study. The ability to assess the *relative effects* of our study factors is a critical element in choosing ABMS as a methodology that can provide insights into the underlying mechanisms and deliver results that will guide managers in identifying the most critical factors that affect profits (Garcia, 2005; Kiesling et al., 2012). We carefully validated and verified the model to ensure its relevance to the real world, as recommended by ABMS and marketing researchers (North & Macal, 2007; Rand & Rust, 2011). The model assumptions as well as the parameter values and ranges used in computational experiments, are supported by existing empirical research which help provide a basis for validation of our model.

We simulate diffusion processes in 10 social network structures that are mapped from real-world social networks to represent various real-world contexts in which consumers may interact. Examples of the social networks include a consumer review website for products and services (ePinions), online social networking websites (Facebook, Google+, Anybeat, and Twitter), and a collaboration network among students. Each social network structure identifies individuals and the social ties among them (who is connected to whom). Use of these existing social networks as the context for our diffusion model ensures that the simulation results capture outcomes that resemble the real world, but may escape the notice of managers.

The outcome variable in this study is the NPV ratio (*NPVR*), which is the ratio of NPV of profits in a market where consumers are disappointed by the product to the NPV in the same market where no one is disappointed (i.e., base case). This operationalization captures both the size and timing effects of disappointments (Goldenberg et al., 2007; Libai, Muller, & Peres, 2013). The key findings of our study are as follows:

- Negative WOM following customer disappointments is more damaging in markets where there is a higher degree of heterogeneity. On average, this effect is over three times the effect of initial percentage of disappointed customers for revenue leaders, about twice for randomly designated groups, and about one third for experts and social hubs.
- Higher assortativity leads to stronger adverse effects of negative WOM when the percentage of disappointed customers is small (i.e., .5% of the market size). As the percentage of disappointed customers increases, the effect of assortativity becomes weaker. For revenue leaders, assortativity shows a disordinal interaction with the percentage of negative WOM initiators. Higher assortativity leads to stronger adverse effects when the percentage of disappointed customers is small (.5% of all potential adopters) and it leads to weaker adverse effects when the percentage is larger (i.e., 3%).
- The effect of heterogeneity increases as assortativity increases. However, the effect of heterogeneity on the adverse profit impact of negative WOM remains roughly constant after a moderate level of assortativity.
- Negative WOM significantly reduces firm profits. On average, disappointments by social hubs followed by initiation of negative WOM demonstrate *stronger* adverse effects on firm NPV of profits than the same reactions by experts, revenue leaders, and randomly-designated customers. These adverse effects mirror the positive effects found by previous studies on positive WOM, with stronger effects in the case of negative WOM (e.g. Haenlein & Libai, 2013; Libai, Muller, & Peres, 2013; Nejad, Amini, & Babakus, 2015).

We begin by reviewing the literature on consumers' adverse reactions to innovations, alternative consumer groups, and customer heterogeneity and assortativity. We then present the simulation model, the model parameters, and the analysis. The paper concludes with a discussion of the implications and limitations of the findings.

2. Innovation diffusion in the presence of negative WOM

Recent studies on innovation diffusion have examined how an innovation spreads across a social network. These studies assumed equal revenue contribution for all consumers by focusing on durables—one-time purchased products (Chandrasekaran & Tellis, 2007; Peres, Mahajan, and Muller, 2010). However, in the context of a service, customers generate revenue each time period and they are often heterogeneous in terms of the revenue they generate. Disappointed customers may terminate the service and spread negative WOM about it. This negative WOM may discourage others from adopting the service (Anderson, 1998; Chan & Cui, 2011; Richins, 1983). The length of time that a customer stays with the firm is a key determinant of his/her lifetime value for the business (Gupta & Zeithaml, 2006). Firms lose revenue when a disappointed customer terminates the service or when a potential adopter rejects the service due to receiving negative WOM. Negative WOM adversely affects firms' sales, cash flows, stock returns, and subscriber attrition (Chevalier & Mayzlin, 2006; Luo, 2009; Nitzan & Libai, 2011).

2.1. On assortativity and heterogeneity of customer revenue

The marketing literature has long explored the implications of knowledge about the revenue that a customer generates, especially in the context of customer lifetime value (Gupta et al., 2006; Libai et al., 2010). However, previous research on innovation diffusion and viral marketing has primarily focused on the number of adopters, assuming equal revenue contribution for all adopters (Haenlein & Libai, 2013). Yet, service customers are often heterogeneous in terms of the revenue they generate.

Heterogeneity refers to the degree to which consumers in a market are different from each other in terms of a certain attribute (i.e., revenue in this study) regardless of whether they have a social tie. Greater heterogeneity in a market indicates that a revenue leader—customers who generate the highest revenue per time period—generates significantly higher revenue compared to an average consumer. Assortativity focuses on the similarity between individuals who have a social tie with each other in terms of certain attributes—customer revenue in this study (Haenlein & Libai, 2013; Newman, 2003). In a highly-assortative market, revenue leaders are likely to be in touch with other revenue leaders while a less-assortative market represents a market in which consumers who generate various degrees of revenue will be mixed (in touch) with each other. Heterogeneity and assortativity are two different dimensions of consumer revenue that have important research and managerial implications.

2.1.1. Heterogeneity of customer revenue

The degree of customer revenue heterogeneity depends on the type of product, the industry, and customer characteristics such as socioeconomic status and lifestyle (Gupta & Lehmann, 2005; Zeithaml, Lemon, & Rust, 2001). Hospitality, vacation, charitable donations, luxury goods, and books are highly heterogeneous markets while rental properties, tenant's insurance, tobacco, and used car purchases are less heterogeneous markets (Haenlein & Libai, 2013). The greater the difference between high and low revenue customers, the higher percentage of the firm revenue would be generated by the revenue leaders.

A customer's lifetime value, however, depends not only on the amount of revenue that a customer generates, but also on the duration of time that the customer remains with the firm (Gupta & Lehmann, 2005; Gupta & Zeithaml, 2006). Hence, revenue leaders of a service category who leave the firm are a considerable source of lost revenue for the business. Similarly, dissatisfaction by revenue leaders in a highly-heterogeneous market should have a stronger negative effect on firm profits compared to a less heterogeneous market.

Little research has been conducted on how the degree of heterogeneity of customer revenue affects diffusion outcomes such as firm revenue and profits. The only exception is a study by Haenlein and Libai (2013), which found that when markets are more heterogeneous in terms of customer revenue, revenue leaders become a more attractive target for marketing activities. However, there is a lack of research on the effect of heterogeneity on firm profits in the presence of customer disappointment and negative WOM.

2.1.2. Assortativity of customer revenue

Assortativity in a social network relates to the degree to which customers who have a social tie with each other are similar with regards to a certain attribute (Newman, 2003; Rogers, 2003). This concept closely relates to homophily as discussed in the marketing and sociology literature. For consistency and in line with recent research (Haenlein & Libai, 2013), we use the term assortativity (instead of homophily) in this paper and define assortativity in terms of the revenue that a customer generates. A study of a telecommunication company's customers found that high-revenue customers were connected to other high-revenue customers (Haenlein, 2011). Moreover, such observations have been indirectly supported by previous studies that found correlations between geographic location on one hand and customer profitability and customer satisfaction on the other hand (Mittal, Kamakura, & Govind, 2004; Reinartz & Kumar, 2000). Research in sociology has also found that people tend to associate with others like themselves (Lazarsfeld & Merton, 1954; Mcpherson, Smith-Lovin, & Cook, 2001). However, another group of researchers have argued that the degree of assortativity may vary across different consumer groups and markets due to proximity and availability. They suggest that individuals are not always able to find others who are like themselves and hence they connect to those who are around and available (Huang, Shen, & Contractor, 2013; Kleinbaum, Stuart, & Tushman, 2013). The two different types of findings suggest that the degree of assortativity may vary in different consumer groups and markets.

Previous studies have examined customer assortativity in terms of various attributes such as revenue or propensity to adopt a new product. They found that assortativity affects the diffusion process and the profit outcomes of targeted marketing activities (Aral, Muchnik, & Sundararajan, 2013; Haenlein & Libai, 2013; Nejad, Amini, & Babakus, 2015). Moreover, the probability of a customer's attrition following another customer's termination of a service is greater in an assortative market (Nitzan & Libai, 2011). So, assortativity should influence the adverse profit impact of customer disappointments. However, research is meager on the topic.

2.2. Alternative consumer groups

In this section we review three consumer groups who are likely to play critical roles with regards to the effect of negative WOM on firm profits.

2.2.1. Revenue leaders

Customer lifetime value entails two dimensions, the revenue that a customer generates during each time period and the duration that the customer stays with the firm (Gupta & Lehmann, 2005; Gupta et al., 2006). Recent studies found that targeting revenue leaders can significantly increase return on firm's marketing activities (Haenlein & Libai, 2013; Iyengar, Van Den Bulte, & Valente, 2011). Revenue leaders of a service category generate the highest revenue during each period, so they have the potential to generate the highest lifetime value if they remain a customer of the firm. Hence, firms lose a significant amount of potential revenue if such customers are disappointed with the service and terminate it.

2.2.2. Social Hubs

Social hubs, the most connected consumers in a social network, have the potential to spread information across their social networks and enhance the diffusion process (Barabasi, 2002; Goldenberg et al., 2009). The spread of negative WOM by social hubs may reach many potential adopters across the social network (Nejad, Sherrell, & Babakus, 2014). In this situation, their social ties will no longer be active in spreading positive WOM. They instead will block the spread of adoption chains and impede the diffusion by dividing the social network into sub-networks that have few or no communication channels with one another. Empirical and simulation studies have recently demonstrated that targeting social hubs has a stronger effect on sales than targeting other consumer groups (Hinz, Skiera, Barrot, & Becker, 2011; Libai, Muller, & Peres, 2013; Nejad, Amini, & Babakus, 2015). Their disappointments should have similar effects.

2.2.3. Experts

Experts exert influence owing to their persuasiveness or expertise on the topic (Weimann, 1994). They have a strong influence on others with whom they have a social tie as opposed to social hubs who have a high number of social ties (Libai, Muller, & Peres, 2013). Knowledge facilitates evaluation of a new product, and thus experts play an important role in innovation adoptions (Coulter, Feick, & Price, 2002). For the same reasons, negative WOM from an expert should have a strong adverse effect on others' adoptions. A study of dental products found that even for a successful product, about 20% of the market rejected the product without even trying it, owing to negative WOM received from experts (Leonard-Barton, 1985).

2.3. Negative WOM in the presence of heterogeneity and assortativity

2.3.1. Number of adopters versus customer revenue

The adverse effect of negative WOM on firm revenue and profits depends on two influential aspects. One aspect relates to the number of customers who reject the service due to negative WOM. The magnitude of this effect depends on the degree to which negative WOM spreads in the market and the number of potential adopters it influences. The more the negative WOM gets bounded in a certain part of a social network, the more isolated it will be from the rest of the social network. In such cases, negative WOM will have a limited adverse effect on firm profits. Goldenberg et al. (2007) demonstrated that the spread of negative WOM across the social network significantly intensifies the adverse effects it will have on firm profits.

The second aspect relates to the revenue potential of the rejecters (those who decided not to adopt the service due to negative WOM) or disappointed customers (who terminated their service if they were satisfied customers). Customers and potential adopters are typically heterogeneous in terms of their potential revenue. Hence, the potential lost revenue (direct revenue) is not the same for all rejecters and disappointed customers. While sparse studies have examined the social network aspect (Goldenberg et al., 2007), we are not aware of any diffusion study that has discussed the customer potential revenue aspect in the context of negative WOM. We use these two aspects simultaneously to explain why heterogeneity and assortativity play critical roles in the transference of negative WOM to firm profits.

2.3.2. Heterogeneity and negative WOM

In a homogeneous market, all potential customers have roughly the same amount of potential revenue. Thus, the effect of negative WOM in this market depends on how many potential adopters it reaches and influences. Negative WOM often spreads to a limited subset of a social network and may not reach many potential adopters. In a highly-heterogeneous market, revenue leaders are a significant source of revenue. Hence, the potential lost revenue following a revenue leader's disappointment and termination of the service is significant. The adverse profit impact of losing a potential revenue leader in such markets is equivalent to that of losing many average potential consumers. Negative WOM will reach some of the revenue leaders anyhow and the firm will lose significant revenue through their rejections.

Thus, we speculate that heterogeneity would increase the amount of lost potential revenue, leading to stronger adverse profit impact of disappointments followed by spreading negative WOM for all consumer groups. Since revenue leaders account for a higher percentage of firm revenue in a heterogeneous market, we speculate this effect to be stronger for revenue leaders compared to other groups.

2.3.3. Assortativity and negative WOM

The aforementioned two aspects—number of adopters and customer potential revenue—can explain the influence of assortativity on the adverse profit impact of negative WOM. In a highly-assortative market, revenue leaders are more likely to be connected to other revenue leaders. So, the negative WOM that they initiate reaches other revenue leaders. This negative WOM may influence them to reject the service and cause losses of significant revenue. Haenlein and Libai (2013) found that targeting revenue leaders in an assortative market is an effective strategy as they are more likely to be connected to other revenue leaders and hence generate more value for firms. We speculate that the opposite of this effect should occur in the case of negative WOM. In a highly-assortative market, negative WOM initiated by revenue leaders should have a strong adverse effect on firm revenue and profits since the negative WOM will reach other revenue leaders and discourage them from adopting the service.

Assortativity should have similar effects for disappointments by the other three groups—social hubs, experts, and randomly-designated—but perhaps with less strength. The negative WOM initiated by these targets will eventually reach some of the revenue leaders. With an increased assortativity, once negative WOM reaches a few revenue leaders, they will be more likely to influence other revenue leaders, leading to stronger adverse effects of negative WOM.

2.3.4. Assortativity and the percentage of disappointed customers

We speculate that increase in the percentage of disappointed customers would reduce the effect of assortativity. In a highly-assortative market, the negative WOM initiated by the higher percentage of disappointed revenue leaders will be bounded in a certain area of the social network—primarily among the revenue leaders who are mostly connected to each other. Hence, negative WOM will primarily and redundantly circulate between disappointed customers and those who may have already made their decisions to reject the service. In a less-assortative market, however, revenue leaders are spread across the social network, so the negative WOM initiated by the greater percentage of revenue leaders will reach more potential adopters in the social network, leading to a stronger adverse profit impact. Thus, assortativity increases the adverse profit impacts of disappointments by revenue leaders when the percentage is small and it reduces the adverse effects when the percentage of disappointed customers is larger.

Similarly, negative WOM initiated by other consumer groups eventually reaches revenue leaders and spreads among them. In a highly-assortative market, increase in the percentage of disappointed adopters will lead to redundant WOM reaching revenue leaders. In a less-assortative market, revenue leaders are spread across the social network so more disappointed customers leads to higher likelihood of negative WOM reaching more revenue leaders. Thus, for these groups, we expect the relationship between assortativity and percentage of disappointed customers to be similar to that for revenue leaders but demonstrate a less strong effect.

2.3.5. Summary

Research is sparse on the effect of customer revenue heterogeneity and assortativity on firm profits in the presence of negative WOM. We speculate that heterogeneity and assortativity intensify the adverse effects of negative WOM on firm profits. Moreover, for smaller percentages of disappointed adopters, negative WOM should have a stronger adverse profit impact in higher assortative markets. For higher percentages of disappointed adopters, however, we argue that negative WOM has a stronger adverse profit impact in less-assortative markets.

3. The ABMS model

An environment suitable for exploring the effect of study factors on NPV of a firm's profit must be capable of capturing a large number of consumer decisions over time. The adverse profit impact of negative WOM depends on the timing of initiation, the individual's attributes, and the social network structure as the environment in which the innovation diffuses. ABMS allows for longitudinal analysis of the diffusion process while offering the ability to study market outcomes by simulating consumers as agents with three essential characteristics—autonomy, interactivity, and bounded rationality (North & Macal, 2007). Previous studies have employed ABMS to offer important insights into the diffusion process (e.g. Delre et al., 2010; Goldenberg, Libai, & Muller, 2002; Goldenberg et al., 2007, 2010; Haenlein & Libai, 2013; Libai, Muller, & Peres, 2013; Nejad, 2013; Nejad et al., 2015). We present the development, validation, and verification of our model following the approach explained by Rand and Rust (2011).

3.1. Simulation model overview

The ABMS framework entails three stages. In stage 1 or the initialization stage, we create a virtual market comprising potential adopters as agents and the social network that exists among them. The virtual market mimics a marketplace at the time of service launch. In stage 2, we launch a new service to the virtual market that was created in stage 1. At the beginning of this stage, all agents are potential adopters who will make their adoption/rejection decisions through the diffusion process. The service gradually diffuses in the market over the simulation's discrete periods. Once the diffusion process is complete, in stage 3 we store the NPV of profits as well as the parameter values in a dataset that will be used in statistical analysis.

We compare two diffusion processes under the same market conditions (Goldenberg et al., 2007): The base case in which all adopters are satisfied; and a comparison case market with negative WOM in which we manipulate disappointments—the cause—by assuming that a certain group of adopters will be disappointed. We explain these two processes in Sections 3.4 and 3.5.

3.2. Agents' attributes

Panel A of Table 1 displays the key attributes of each agent, their definitions and relevant references. All agent attributes are assigned at the initialization stage (stage 1) of each simulation replication and remain intact until the simulation replication is completed. Attributes δ and q capture the effects of external influences (e.g., firm marketing activities) and internal influences

Table 1
Attributes (properties) of agents and consumer groups.

Panel A: Agents' attributes (properties)

	Attribute	Explanation	References
Agents' attributes (properties)	δ	The probability that an agent would adopt the new service at each time period owing to the influence of external influences (primarily marketing activities).	Goldenberg et al. (2002, 2007, 2010); Libai et al. (2013); Nejad et al. (2015)
	q	The influence that an agent has on others with whom it has social ties. It is the probability that the agent would influence another agent owing to social interaction with that agent at each time period.[a] Agents are heterogeneous with regards to this parameter.	
	r	The revenue that the agent generates during each period of being a customer. Agents are heterogeneous with regards to this parameter.	Haenlein and Libai (2013)
	Social Ties	The number of social ties of an agent with other agents in the social network. Agents are heterogeneous with regards to this parameter.	Goldenberg et al. (2009); Libai et al. (2013); Nejad et al. (2015)

Panel B: Consumer groups and their primary attribute

	Group	Primary attribute[b]	References
Consumer groups	Social hubs	The most connected agents; those who have the highest number of social ties	Goldenberg et al. (2009); Libai et al. (2013); Nejad et al. (2015); Watts and Dodds (2007)
	Experts	The agents with the highest values of influence on others (q)	Leonard-Barton (1985); Libai et al. (2013); Nejad et al. (2015)
	Revenue leaders	The agents with the highest value of revenue per period (r).[c]	Gupta and Lehmann (2005); Gupta and Zeithaml (2006); Haenlein and Libai (2013);
	Randomly-designated	Randomly-Chosen and representing average consumers	Libai et al. (2013); Nejad et al. (2015); Watts and Dodds (2007)

[a] We acknowledge that this attribute may be operationalized as incoming influence or outgoing influence or both. In line with Libai et al. (2013) and Nejad et al. (2015), parameter q relates to the influence that an agent has on other agents with whom it has a social tie (i.e., outgoing influence).

[b] We assume independence between different attributes of an agent and do not enforce any correlation between the attributes (Goldenberg et al., 2007; Libai et al., 2013; Nejad et al., 2015) but some agents may rank high in more than one attribute.

[c] Parameter r refers to the potential revenue that an agent will generate during each period in which he/she is a customer of the firm. Revenue leaders are heavy users of a service category.

(e.g., WOM) on a potential adopter, respectively.[3] In line with recent recommendations (Libai, Muller, & Peres, 2009), we focus on a service in which a customer generates certain revenue—attribute r in our model—during each period that he/she is a customer. If an agent terminates the service or rejects it, the value of r would be the lost potential revenue for the firm.

Agents are heterogeneous in terms of attributes q, r, and *social ties*. Consumers are heterogeneous in terms of the influence they have on others—parameter q—owing to differences in expertise and persuasiveness (Leonard-Barton, 1985; Nejad, Sherrell, & Babakus, 2014). We explained heterogeneity in revenue (attribute r) earlier and the empirical social network structures present heterogeneity in number of social ties. We operationalize experts as agents with the highest value of parameter q (Libai, Muller, & Peres, 2013), revenue leaders as agents who have the highest values of parameter r (Haenlein & Libai, 2013), and social hubs as the most connected agents (Goldenberg et al., 2009). See Panel B in Table 1 for further details.

We operationalize assortativity as the Pearson correlation between an agent's value of attribute r and the average value of its neighbors. The simulation executes an iterative process that implements a smoothing function on all agents. The process continues until the correlation between all agents' revenue and the average of their neighbors' revenue reaches the predefined value—the model parameter (Haenlein & Libai, 2013; Nejad, Amini, & Babakus, 2015). Section 3.2 in Web Appendix A provides the details of this algorithm.

3.3. Consumer social network structures

Consumers interact with each other and exchange information through their social ties, so the transference of disappointments to market-level diffusion depends on the social network in which consumers interact with each other. A social network comprises nodes—the consumers—and links—the social ties among them. The structure of a social network affects the diffusion process and it varies across markets depending on the nature of the service, the communication environment, and consumer motivations for adoption (Ghoreishi Nejad, 2011). However, owing to the challenges in mapping actual social networks, a majority of diffusion studies have assumed generic social network structures, such as random, small-world, and scale-free networks. Recent technological advances have provided opportunities to use real-world social network structures in diffusion studies (Libai, Muller, & Peres, 2013).

We examine our research question using 10 real-world social networks (see Table 2). These existing social networks capture a diverse set of social relationship types and network attributes including size, clustering, connectivity, and diameter. Using these social network structures allows us to explore the study research question various market conditions reflecting real-world settings. We acquired data for these social networks from the SNAP library at Stanford University, the Social Computing Data Repository at Arizona State University, and the Ben-Gurion University Social Networks Security Research Group (Leskovec & Krevl, 2014; Zafarani & Liu, 2009). We thank these centers for providing public access to the data.

3.4. The base case

The base case scenarios represent a market in which every adopter is satisfied with the adoption. Following previous ABMS models, we adopt a stochastic cascade model in which an agent may adopt due to parameters δ and q during each period (see Table 1). In the base cases, an agent may have one of two states: potential adopter or satisfied adopter. Potential adopters do not engage in WOM and satisfied adopters initiate positive WOM. At the beginning of the simulation execution, stage 1, all agents are potential adopters. Gradually, some agents adopt the service as a result of external influences. Satisfied adopters spread positive WOM through their social ties and encourage further adoptions. Hence, the probability that potential adopter i adopts at period t is calculated as follows (Goldenberg, Libai, & Muller, 2002):

$$P^{+}_{(i,t)} \leftarrow 1-(1-\delta_i)\prod_{j=1}^{S_i^{+}(t)}\left(1-q_j\right) \tag{1}$$

where δ_i represents the effect of external influences on agent i; $S_i^{+}(t)$ captures the total number of satisfied adopters at period t who have direct links with agent i; q_j represents the probability that agent j may influence the potential adopter i at time period t. For each potential adopter, the simulation program calculates the probabilities and then generates a uniform random number between 0 and 1 to determine the potential adopter's new status—adopts or remains undecided.

3.5. A market with negative WOM

The scenarios of 'a market with negative WOM' seek to capture the effects of negative WOM. In these scenarios, an agent may have one of four states at the beginning of each time period: potential adopter, satisfied adopter, disappointed adopter, or rejecter (see Fig. 1). Potential adopters and satisfied adopters behave similarly to those in the base cases. Disappointed adopters, however, only generate revenue for one period and will then terminate the service and spread negative WOM about it through their social ties. An agent's decision to terminate the service is in line with a majority of previous literature on the effect of customer dissatisfaction on using a service and future purchases (Bolton, 1998; Cronin, Brady, & Hult, 2000; Nitzan & Libai, 2011; Oliver, 2010).

[3] Parameter q in the agent-based model that we use is not exactly the same as parameter q in the Bass model (which is a hazard rate model). For information on how the values of parameter q in an ABMS model can be calculated from previous aggregate models, see Goldenberg et al. (2002, 2007).

Table 2
Social networks used in this study and their attributes.

Social network	Description[a]	Size[b]	Average degree	Average degree top 10%	Clustering coefficient	Average separation	Network diameter
Epinions	Trusting online reviews	75879	10.7	81.6	0.567	4.2	15
Anybeat	Online social network	12645	7.8	55.3	0.699	3.2	10
Emails (Enron)	Email communications - Enron	36692	10	66.07	0.802	3.4	13
Blog Catalog	Connections between blogs	10312	64.8	386.1	0.489	2.4	5
Wikipedia Vote	Voting on Wikipedia	7115	28.3	161.5	0.465	3.2	7
Google+	Online social network	4712	160.4	537.4	0.39	2.3	6
Facebook	Online social network	747	80.4	196.1	0.64	2.5	7
Twitter-2	Online social network	235	92.4	181.5	0.637	1.6	3
Students	Collaboration among students	185	3.4	5.8	0.697	3.8	See below[c]
Twitter-1	Online social network	217	112.2	180.6	0.784	1.3	3

[a] Epinions is an online consumer review website that captures data from consumers who trust each other's reviews (Richardson, Agarwal, & Domingos, 2003). Anybeat, which is no longer operational, was an anonymous online social networking website that operated without collecting any personal data about its users (Fire, Puzis, & Elovici, 2013). The Enron email network captures over half a million email communications sent and received by Enron company employees (Leskovec, Lang, Dasgupta, & Mahoney, 2009). Data from Blogcatalog—a social blog directory that manages bloggers and their personal blogs—reflect friendship ties on that site (Agarwal et al., 2009). The Wikipedia network comprises the voting of Wikipedia users on who should be promoted to become an administrator (Leskovec, Huttenlocher, & Kleinberg, 2010). Google+, Facebook, and Twitter datasets comprise friendship or followers' lists of users of the social networking websites (Mcauley & Leskovec, 2012). The students' co-operation network at Ben-Gurion University is a network of collaborations among college students engaged in completing their assignments (Fire et al., 2012).

[b] Size of a network is the number of nodes (individuals) in the social network. Average degree is the average number of social ties of nodes. Average Degree Top 10% are the average number of social ties that the top 10% most connected consumers have. Clustering coefficient captures the degree to which nodes are clustered to each other or are sparse. Average separation represents the average degrees of separation in the social network. Degree of separation between two nodes (i.e., individuals) is the number of nodes that stand between them. Network diameter represents the furthest degree of separation between two nodes in the social network.

[c] The network includes nodes or isolated clusters.

Similarly, the decision to spread negative WOM is supported by the literature and previous ABMS studies (Anderson, 1998; East, Hammond, & Wright, 2007; Goldenberg et al., 2007; Mahajan, Muller, & Kerin, 1984; Richins, 1983). We acknowledge that customer satisfaction or dissatisfaction might evolve over time leading to a cumulative satisfaction/dissatisfaction, which may potentially result in spreading negative WOM or changes in the usage of a service (Bolton & Lemon, 1999). However, in order to keep the scope of the study manageable, we followed the assumption regarding customer's immediate satisfaction/dissatisfaction suggested by Goldenberg et al. (2007) and discuss this alternative behavior as a consideration in the limitations and future research section.

Some potential adopters may reject the service due to the negative WOM that they receive from disappointed adopters or from other rejecters. Rejecters do not consider the service any longer and they transfer the negative WOM that they have received to others (Goldenberg et al., 2007; Moldovan & Goldenberg, 2004). These two assumptions are supported by the literature on consumer resistance to innovations (Oreg & Goldenberg, 2015; Szmigin & Foxall, 1998) and by previous diffusion studies and research on negative WOM (Chan & Cui, 2011; Luo, 2009; Mahajan, Muller, and Kerin, 1984). Moreover, a majority of negative WOM is passed on by non-users of a service, product, or brand (East, Hammond, and Wright, 2007). In line with Goldenberg et al. (2007) and in order to account for the decay of negative WOM as it spreads from one person to another, we assume that negative WOM only travels two degrees of separation

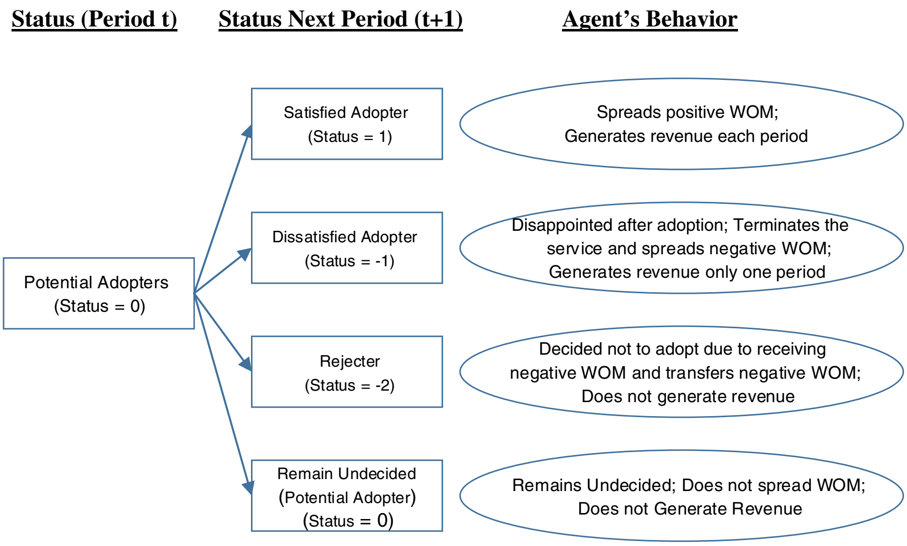

Fig. 1. Agent adoption status and decisions. Status (period t), status next period (t + 1), agent's behavior.

(i.e., disappointed adopter ➔ rejecter ➔ potential adopter), that is 'third-hand negative' WOM is not considered. This is a conservative assumption as negative WOM may travel across the social network from one receiver to another (Peres, Mahajan, and Muller, 2010).

At the beginning of each simulation experiment replication, we chose a certain percentage of agents comprising one of the four groups—revenue leaders, social hubs, experts, or randomly—designated—and assumed that these agents will be disappointed after adoption. For example, in a simulation experiment that examines the effect of disappointment by 1% of the market comprising social hubs, we picked the top 1% of the most connected agents. This approach allows for capturing the net effect of disappointments by each group compared to the base case (the same parameter values, where every adopter is a satisfied one).

Fig. 2 presents the process of creating agents in the initialization stage of each simulation replication. Agents remain undecided until they have received adequate information via WOM and marketing activities to make their decisions. In line with previous studies (Goldenberg et al., 2007; Moldovan & Goldenberg, 2004), the decision making process for disappointed agents will be similar to those of other potential adopters but they become disappointed after adoption. This approach is necessary to manipulate the 'cause' in our research question for which we seek to examine the 'effects.' All agents make a one-time decision and they do not change status after making their decision (Goldenberg et al., 2002, 2007, 2010).

At every simulation period, the effect of positive (negative) WOM on each potential adopter agent is calculated based on the total number of satisfied adopters (disappointed adopters and rejecters) who have direct links with the agent. We capture the influence of positive and negative WOM on potential adopter i at period t as follows (Amini et al., 2012):

$$P^{+}_{(i,t)} \leftarrow 1-(1-\delta_i)\prod_{j=1}^{S_i^{+1}(t)}\left(1-q_j\right) \tag{2}$$

$$P^{-}_{(i,t)} \leftarrow 1-(1-\delta_i)\prod_{j=1}^{S_i^{-1}(t)}\left(1-\omega q_j\right)\prod_{j=1}^{S_i^{-2}(t)}\left(1-\omega q_j\right) \tag{3}$$

where δ_i represents the effect of external influence (i.e., marketing activities) on potential adopter i, q_j represents the probability that potential adopter i is influenced by social interaction with agent j at time period t, and ω is the relative effect of negative to positive WOM; $S_i^{+1}(t)$,$S_i^{-1}(t)$ and $S_i^{-2}(t)$ capture the total number of satisfied adopters, disappointed adopters and rejecters (respectively) at period t who have direct links with agent i.

A normalization factor ($\alpha_i = \frac{p^{+}_{(i,t)}}{(p^{+}_{(i,t)}+p^{-}_{(i,t)})}$) is then calculated as the ratio of positive WOM influence over the total WOM influence on potential adopter i. The probabilities of the potential decisions for agent i at period t are calculated as follows (Goldenberg et al., 2007):

$$P^{adopt}_{(i,t)} \leftarrow \left(1-P^{-}_{(i,t)}\right)P^{+}_{(i,t)} + \alpha_i p^{+}_{(i,t)}\ p^{-}_{(i,t)}, \tag{4}$$

$$p^{rejection}_{(i,t)} \leftarrow \left(1-p^{+}_{(i,t)}\right)p^{-}_{(i,t)} + (1-\alpha_i)p^{+}_{(i,t)}\ p^{-}_{(i,t)}, \tag{5}$$

$$p^{undecided}_{(i,t)} \leftarrow \left(1-p^{+}_{(i,t)}\right)\left(1-p^{-}_{(i,t)}\right). \tag{6}$$

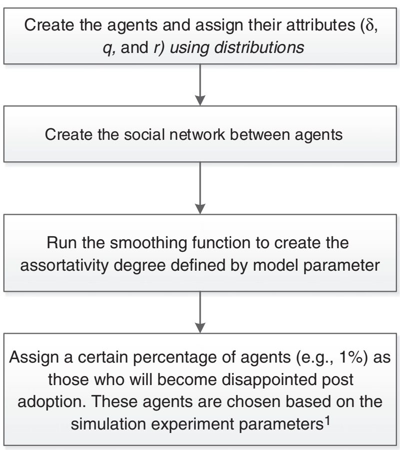

Fig. 2. Creating agents and assigning their attributes (properties) prior to the beginning of the diffusion process (stage 1). 1—The simulation program chooses a certain percentage of agents and assigns them as those who will be disappointed post adoption. These agents are chosen based on a certain attribute depending on the model parameter (see Tables 1, 2, and 4). For example, if the experiment seeks to examine effects of disappointments by 1% of the market comprising social hubs, then the top 1% of the most connected agents will be chosen.

The sum of the above three equations is equal to 1. After calculating the above probabilities for each potential adopter, a uniform random number between 0 and 1 is generated to determine the potential adopter's new status.

3.6. Performance measurement

We chose NPV of profits as an effective performance measure of diffusion outcome for comparing the effects of disappointments. NPV captures both the number of adopters and the discounted value of profits over time. We calculated the relative effect of disappointments as the ratio of the NPV of two diffusion processes: the diffusion in a market where disappointments exist ($NPV_{Disappointment}$) and the diffusion under the same parameter combinations without disappointments (NPV_{Base}). The computation is as follows (Goldenberg et al., 2007):

$$NPVR = \frac{NPV_{Disappointment}}{NPV_{Base}}$$

Lower values of *NPVR* denote stronger adverse effects on NPV. For instance, a diffusion process with an *NPVR* of .80 generates an NPV that is 20% less than that in the same conditions if no one is disappointed. Disappointments may reduce NPV in three ways: (a) loss of revenue, (b) blocking the spread of positive WOM, and (c) spreading negative WOM. *NPVR* captures all these effects. The variable and the fixed costs associated with offering the service are out of the context of this study. Hence, in line with previous studies (Haenlein & Libai, 2013; Libai, Muller, & Peres, 2013), we assume that the revenue that an adopter generates at each period, attribute r, is equal to the value or the profit. Disappointed customers who terminate their services only generate revenue during the first period after adoption and they do not generate profit after terminating the service. We calculated NPV based on the total profits that all adopters generate during each period using a discount rate of 10% (Goldenberg et al., 2007).

3.7. Model parameters and the effect of negative WOM relative to positive WOM

Table 3 displays the simulation multi-value parameters and Table A-1 in Web Appendix B depicts the fixed parameters. In line with previous research, the simulation continues until 30 time periods have completed (Goldenberg et al., 2010; Libai, Muller, & Peres, 2013). The results indicated that on average across all simulation runs, 84.7% of the market adopted in scenarios with only positive WOM (i.e., the base cases) and 68.6% of the market had adopted (satisfied or dissatisfied) in the markets with both negative and positive WOM.

One parameter that requires further explanation is the relative effect of negative WOM over positive WOM. Consumers assign more weight to negative WOM than positive WOM, as they find negative information more useful and enlightening than positive information (Herr, Kardes, & Kim, 1991; Mizerski, 1982). This perception specifically applies to potential adopters who are unfamiliar with the offering and are concerned with adoption risks (Ahluwalia, 2002). Moreover, disappointed adopters communicate with more individuals than do satisfied customers (Anderson, 1998; Richins, 1983). A field study found that negative WOM has a stronger effect on sales than positive WOM (Chen, Wang, & Xie, 2011). Another study found that negative WOM arising from low quality of a video-on-demand service was more than twice as effective as positive WOM arising from excellent quality (Nam, Manchanda, & Chintagunta, 2010). Hence, we fixed the relative effect of negative WOM over positive WOM to 2 and assumed that disappointed adopters and rejecters influence others to the same degree (Amini et al., 2012; Goldenberg et al., 2007). The decay of the effect of negative WOM is already captured through our conservative approach that negative WOM only travels two degrees of separation.

Table 3
ABMS simulation multi-value parameters.[a]

Parameter	No. of levels	Parameter value or range	References
Disappointed consumer groups	4	Revenue leaders, social hubs, experts, and randomly designated	Goldenberg et al. (2009); Haenlein and Libai (2013); Libai et al. (2013); Nejad et al. (2015)
Percentage of disappointed customers	6	.5%, 1%, 1.5%, 2%, 2.5%, 3%	Libai et al. (2013); Haenlein and Libai (2013); Moldovan and Goldenberg (2004);
Mean value of δ	5	.001, .006, .011, .016, .021	Goldenberg et al. (2002, 2007, 2010); Libai et al. (2013); Jiang, Bass, and
Mean value of q	5	.01, .03, .05, .07, .09	Bass (2006); Nejad et al. (2015); Sultan, Farley, and Lehmann (1990)
Assortativity of r	6	.10, .25, .40, .55, .70, .85	Haenlein and Libai (2013); Nejad et al. (2015)
Standard deviation of the distribution of r[b]	6	.10, .45, .80, 1.15, 1.50, 1.85	Haenlein and Libai (2013)
Consumer social network structures	10	Please see Table 3	

[a] The fixed parameters are reported in Web Appendix B, Section 1.
[b] The reported value in the table is the standard deviation of the underlying normal distribution for the lognormal distribution that was used to create the values of r (see Section 3.7 Heterogeneity of q and r). The standard deviation of the resulting lognormal distribution was between .005 and 4.980 with a mean of .973. These numbers are in line with those reported by Haenlein and Libai (2013).

With regards to the distributions for individual-level diffusion parameters, Haenlein and Libai (2013) examined the revenue generated by various customers of a cell phone carrier and used a lognormal distribution which captured the empirical distributions of the customer attributes. We adopted the same approach and used lognormal distributions for parameters q and r. A lognormal distribution captures the highly-skewed distributions that have been found for customer attributes (Fader, Hardie, & Lee, 2005). The mean revenue was fixed at 1 for model parameter r. For parameter q, however, we examined various values of the parameter (see Table 3) and fixed the measure of variability (as opposed to the standard deviations) by keeping the ratio of the standard deviation over the mean of the distribution constant. This approach ensured that experiments with different mean values of q have similar heterogeneity and the results will not be confounded (Goldenberg et al., 2010; Snedecor & Cochran, 1989).

3.8. Model verification and validation

In validating and verifying the ABMS model, we followed recommendations by previous research (North & Macal, 2007; Rand & Rust, 2011). We verified the software and the model using documentation, software unit testing, and software integration testing by tracing the codes and running test cases. We have also prepared a technical document (see Web Appendix A), which presents details of the steps taken for verifying and validating the model. The ABMS simulation platform was implemented using Java programming language and the Repast agent-based modeling toolkit, which can be found on http://repast.sourceforge.net (North et al., 2013).

The model assumptions, processes, and parameter values and ranges used in the simulation experiments are based on empirical findings in current literature and thus provide basis for validation of the model and its results (North & Macal, 2007; Rand & Rust, 2011). See Web Appendix A, Section 1.5 for details of these basis for model validation. The shape of diffusion curves resulting from the simulation models is in line with those of extensive classic and ABMS diffusion studies. Moreover, with the exception of two studies (Libai, Muller, & Peres, 2013; Nejad, Amini, & Babakus, 2015), previous ABMS studies in the Marketing literature research have relied on theoretical social networks among consumers. We conducted our simulations on 10 real-world social networks that have been mapped from various social networks and hence represent alternative settings that may occur in the real world (see Table 3). For each network, we first executed the base cases in which all adopters would be satisfied. Then, using a between-subjects design employing the same model parameters and social networks, we explored how much the NPV would change if certain consumers were disappointed post adoptions. Hence, the results provide insights into a phenomenon that is difficult to capture with other methodologies but may very well occur in the real world and escape the notice of managers.

4. The ABMS computational experiments, analysis, and results

The ABMS computational experimental design included a full factorial design of different values for all six parameters (see Table 3) using 10 real-world social network structures (see Table 2). To capture variations that may be due to stochastic effects of simulation runs, we replicated each simulation experiment 10 times, each time using a different random number seed (Goldenberg et al., 2007), resulting in 2,160,000 different simulation runs (i.e., observations).[4] This section presents the results and analyses. To examine the research questions, we conduct regression analyses and expand the key findings of the regression analysis as necessary.

We examined the effects of customer revenue heterogeneity and assortativity in the presence of negative WOM using regression models with *NPVR* as the dependent variable. The independent variables in the regression models were Heterogeneity, Assortativity, Initial Percentage and all two-way interaction effects between the three factors.[5] The analysis found that the patterns of *NPVR* results for revenue leaders were different compared to the other three groups—social hubs, experts, and randomly-designated customers—who demonstrated more or less similar patterns. Thus, we report the results of two separate regression models in this section, one for revenue leaders and another one for the other three consumer groups. The details of separate regression results for each group are presented in Table A-2 in Web Appendix B, Section 2. In the second regression model, we coded social hubs and experts as separate dummy variables. To avoid multicollinearity issues due to having both the main and interaction factors in the regression model, we first mean centered the three independent variables and then used the centered terms for calculating the interaction factors. The centered terms were included in each regression model (Farrar & Glauber, 1967). On the basis of stringent criteria (Hair, Black, Babin, & Anderson, 2009), multicollinearity was not an issue for the regression models (VIF ≤ 1.00).

Table 4 presents the results of the two regression analyses. As this table indicates, the coefficient of heterogeneity is negative for both revenue leaders as well as for other consumer groups. For revenue leaders, heterogeneity is the strongest predictor among all study factors. This factor is over three times stronger than the effect of percentage of disappointed customers. For all other consumer groups, on average, heterogeneity shows a strong negative effect on *NPVR*, slightly over half that of percentage of disappointed customers. The results of separate regression models for each consumer group demonstrated that the effect of heterogeneity on *NPVR* is twice the effect of initial percentage of disappointed consumers for the randomly-designated group (the strongest predictor among all study factors) and is about one third for social hubs and experts (see Table A-2 and

[4] 2,160,000 = 4 (disappointed consumer groups) × 6 (initial percentage of disappointed customers) × 6 (revenue assortativity) × 6 (revenue heterogeneity) × 5 (mean value of δ) × 5 (mean value of q) × 10 (consumer social network structures) × 10 (simulation replications).

[5] We tested the regression analyses by including the variables δ and q and the key findings did not change. However, keeping the δ and q in the simulation factorial design is necessary in order to ensure that we capture various market conditions. The results of regression analysis including δ and q are available from the authors.

Table 4
The effect of heterogeneity, assortativity and percentage of disappointed adopters on *NPVR*: Regression model results.

Variable	Revenue leaders				Other consumer groups			
	Coefficient	Standardized coefficient	Standard error	t-Value	Coefficient	Standardized coefficient	Standard error	t-Value
Heterogeneity	−.179	−.867	.000	−508.11	−.032	−.087	.001	−46.17
Assortativity	.014	.029	.001	16.18	−.031	−.036	.002	−19.26
Initial Percentage	−4.102	−.284	.025	−166.66	−4.074	−.157	.049	−83.35
Heterogeneity × Assortativity	−.036	-.045	.001	−26.59	−.038	−.026	.003	−13.89
Heterogeneity × Initial Percentage	−1.031	−.043	.041	−25.05	2.115	.049	.082	25.86
Assortativity × Initial Percentage	4.457	.079	.096	46.40	2.376	.023	.191	12.45
HubsDummy					−.341	−.722	.001	−333.07
ExpertDummy					−.173	−.366	.001	−168.85
Adjusted R^2	.843				.428			

Note: All coefficients are standardized with $p < .001$. Moreover, for the regression model for revenue leaders, $F_{(6,53,993)} = 48{,}286.99$, $p < .001$; and for the other groups, $F_{(8,161,991)} = 15{,}175.72$, $p < .001$.

Figure A-3 in Web Appendix B for more details). The results conclusively support our earlier speculations by highlighting the importance of heterogeneity in determining the adverse profit impact of disappointments on *NPVR*.

Insight 1. Higher revenue heterogeneity in the market will lead to stronger adverse effects of negative WOM generated by disappointed customers for all customer groups. This effect is over three times the effect of initial percentage of disappointed customers for revenue leaders, about twice for randomly-designated group, and about one third for experts and social hubs.

The coefficient of assortativity is negative for social hubs, experts, and randomly-designated adopters. The effect, however, is positive for revenue leaders which requires further attention. We speculated that there may be an interaction effect between the percentage of disappointed customers and *NPVR*. To examine this, we executed a separate regression model only for an initial percentage of disappointed adopters of .5% The coefficient of assortativity and the interaction between heterogeneity and assortativity were −.129 and −.115 respectively. Separate analysis for each consumer group demonstrated the same effects (see Figure A-4 in Web Appendix B for further details).

Insight 2. Revenue assortativity has a negative relationship with the adverse profit impact of negative WOM for all consumer groups when the percentage of disappointed customers is small (i.e., .5%).

The interaction effect between assortativity and percentage of disappointed customers is reflected in the positive sign of the interaction between assortativity and percentage (both for revenue leaders and the other three groups). For revenue leaders, the standardized coefficient of the interaction term (.079) is greater than that of the main effect (.029). This indicates that

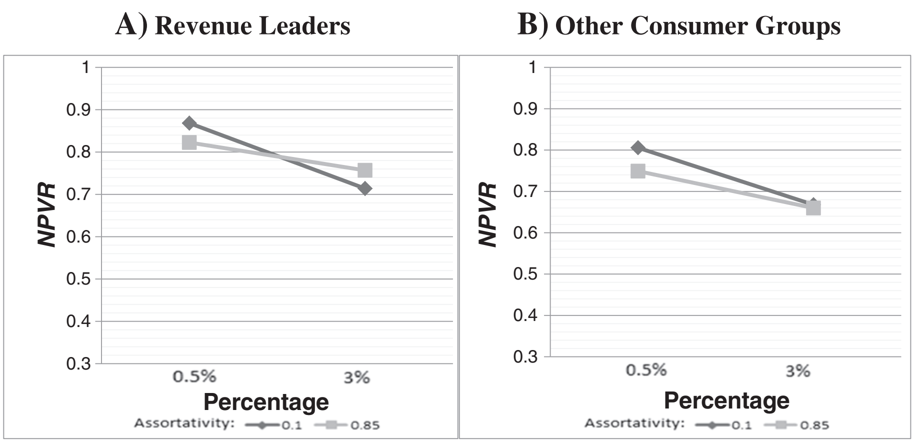

Fig. 3. The interaction between assortativity and percentage of disappointed customers*. Panel A: Revenue leaders. Panel B: Other consumer groups. * *NPVR* is the ratio of the NPV that two diffusion processes generate: the diffusion process in a market where some consumers adversely react to the innovation ($NPV_{Disappointment}$), and the one under the same conditions without adverse reactions (NPV_{Base}). NPV Ratio (*NPVR*) may be stated as follows: $NPVR = \frac{NPV_{Disappointment}}{NPV_{Base}}$. Thus, smaller values of *NPVR* indicate stronger negative effects (see Section 3.6 "Performance Measurement"). Assortativity is operationalized as the Pearson correlation between the revenue attribute of an agent and the average of its neighbors' revenue attributes.

when assortativity and percentage of disappointed customers are both high, *NPVR* will be higher, indicating a weaker effect of disappointments.

Fig. 3 demonstrates that higher assortativity has a significantly stronger adverse effect on *NPVR* for smaller percentages (e.g., .5%) than for larger percentages (e.g., 3%). For revenue leaders, this effect presents a disordinal interaction effect and for the other groups the interaction effect is observed but it is ordinal (see Fig. 3). For smaller percentages of disappointed revenue leaders (i.e., .5%) higher assortativity increases the adverse effects of negative WOM ($M_{.1}$ = .868, $M_{.85}$ = .823), while for higher percentages (i.e., 3%), higher assortativity weakens the effect of negative WOM ($M_{.1}$ = .714, $M_{.85}$ = .757). For other groups, higher assortativity leads to significantly-stronger adverse effects of negative WOM (lower *NPVR*) when the percentage is small (M = .806 to .749) and it leads to slightly-stronger adverse effects when the percentage is larger (M = .668 to .660). These findings are in line with our speculations earlier and they are different from the previously observed effects found in the context of positive WOM (Haenlein & Libai, 2013; Nejad, Amini, & Babakus, 2015).

Insight 3. Higher assortativity leads to stronger adverse effects of disappointments by all consumer groups when the percentage of disappointed customers is small (.5%). When the percentage is larger (3%), lower assortativity leads to stronger effects only for revenue leaders.

The results also demonstrate a significant interaction between assortativity and heterogeneity (see Table 4 and Fig. 4). When assortativity is small, the difference between *NPVR* resulting from different levels of heterogeneity is relatively small especially for social hubs, experts, and randomly-designated group. As assortativity increases, the difference between various levels of heterogeneity increases. Once assortativity passes an average level (around .55), the difference between various levels of heterogeneity remain roughly constant afterwards. We remind our readers that assortativity is operationalized as the Pearson correlation between the revenue attribute of an agent and the average of its neighbors' revenue attributes.

Insight 4. The effect of heterogeneity on the adverse profit impact of negative WOM increases as assortativity increases up to a moderate level, after which the impact of heterogeneity remains roughly constant.

We also observed that the interaction effects between heterogeneity and percentage are different for revenue leaders compared to the other three groups. The interaction effect has a negative sign for revenue leaders, but it has a positive sign for other groups. For revenue leaders, the effect of heterogeneity remains significant for both small and large percentages of disappointed adopters, while for other groups, higher heterogeneity has a significantly stronger adverse effect on *NPVR* for smaller percentages than for larger percentages.

Finally, we compared the effects of disappointments by alternative consumer groups. Disappointment by social hubs on average has a stronger adverse effect on *NPVR* (M = .538) than does disappointment conclusions by experts (M = .706), revenue leaders (M = .777), or randomly-designated consumers (M = .878). This finding is in line with previous findings in the context of positive WOM, even though the magnitude of this effect is stronger in the case of negative WOM compared to positive WOM that previous studies found (Hinz et al., 2011; Libai, Muller, & Peres, 2013; Nejad, Amini, & Babakus, 2015).

Insight 5. On average, disappointment by social hubs presents the strongest adverse effects on the adverse effect of negative WOM compared to experts, revenue leaders, and randomly-designated group.

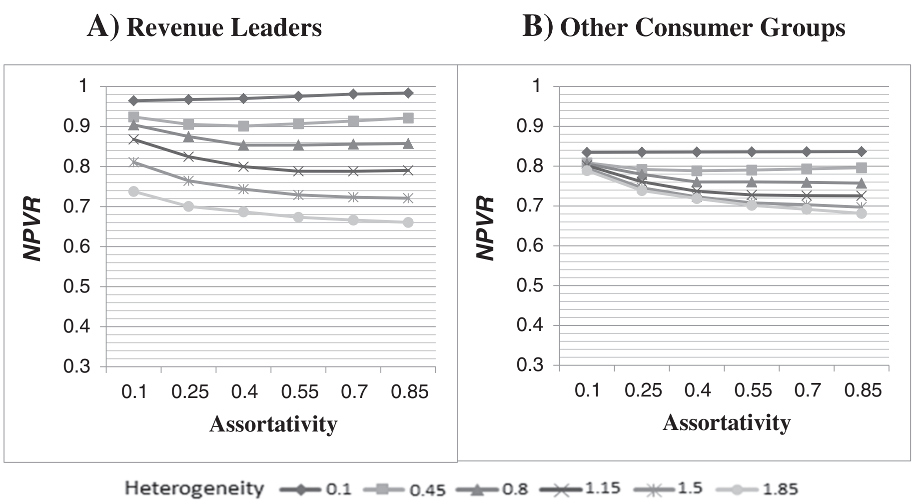

Fig. 4. The interaction effect between revenue heterogeneity and assortativity. Panel A: Revenue leaders, Panel B: Other consumer groups. * Heterogeneity is operationalized as the standard deviation of the distribution of revenue (i.e., a Log-normal distribution). A value of .1 represents a homogenous market and a value of 1.85 creates a group of customers who generate a lot of revenue.

5. Discussion

Extensive agent-based simulation experiments conclusively demonstrate that customer revenue heterogeneity and assortativity are important factors in determining the adverse effects of negative WOM on firm NPV of profits. The results present novel insights on how disappointments by a small group of adopters accompanied by negative WOM may reduce firm profits. We first discuss the implications for research followed by the managerial implications.

5.1. Implications for research

We proposed two different aspects through which negative WOM may adversely influence diffusion outcomes such as firm profits. The social networks aspect suggests that the adverse profit impact of negative WOM depends on the degree to which it spreads across the social network. The more negative WOM reaches different parts of the social network, the stronger adverse effects on firm profits (Goldenberg et al., 2007). The other aspect considers the effect of negative WOM based on the revenue potential of consumers who terminate the service or reject it. A customer's lifetime value for the firm depends on the value that he/she generates each period and the number of time periods the customer stays with the firm (Gupta & Zeithaml, 2006). Hence, a customer's lost potential value due to rejection or termination of the service depends on both dimensions of lifetime value. The social networks and customer lifetime aspects help us explain how customer revenue heterogeneity and assortativity influence the adverse profit impact of negative WOM.

Heterogeneity intensifies the adverse effects of negative WOM as captured by *NPVR*. In highly-heterogeneous markets, the revenue that revenue leaders generate is significantly greater than an average consumer. Therefore, termination of a service due to disappointment by revenue leaders will lead to the loss of significant direct revenue. In a homogenous market, however, all consumers generate roughly the same amount of revenue. Hence, the effect of negative WOM on *NPVR* depends on the degree to which it spreads in the market. The negative WOM that other consumer groups initiate will reach some revenue leaders anyways, leading to significant losses for the firm in heterogeneous markets. Revenue leaders may also be connected to other revenue leaders and may influence them to reject the service.

Assortativity also leads to stronger adverse effects of negative WOM on *NPVR*. This is due to the fact that in an assortative market, revenue leaders are connected to each other. Once the negative WOM reaches a few revenue leaders, they will communicate it to other revenue leaders. In a less-assortative market, however, revenue leaders are located at different areas of the social network. So, it is less likely that they hear negative WOM from other revenue leaders and decide to reject the service. Moreover, these effects depend on the percentage of disappointed adopters in the market. For smaller percentages of disappointed customers (i.e., .5%), higher assortativity leads to stronger adverse effect of negative WOM (i.e., smaller *NPVR*) for all groups. As the percentage increases, revenue leaders will redundantly hear negative WOM that they had already learned. Thus, increase in the percentage of disappointed adopters does not proportionally affect *NPVR*. These effects are stronger for revenue leaders compared to other consumer groups.

An important question is whether there is a degree of assortativity which is required for the effect of heterogeneity to kick in? The results indicate that the difference between *NPVR* of various degrees of heterogeneity is relatively small for the less-assortative markets compared to highly-assortativity markets. As assortativity increases, the effects become larger and once the degree of assortativity passes a moderate level (assortativity of .55), then the slope of the heterogeneity graph reduces and it becomes less steep and gradually flattens.

Finally, we examined the diffusion of a service in contrast to the previous research that focused on diffusion of durables or one-time purchased products. Services differ from products since service customers generate revenue each period and they may terminate the service at any time, leading to lost revenue. Diffusion of services is an under-researched area that offers opportunities for research (Libai et al., 2009). We modeled customer revenue heterogeneity and assortativity based on the revenue they generate each period. This approach expands agent-based models of customer's lifetime value based on the revenue that a customer generates during each period and the number of periods that he/she is a customer of the firm.

5.2. Managerial implications

5.2.1. Heterogeneity and assortativity

The introductory decisions for new products and services play a crucial role in their success or failure. Firms need to understand and estimate how consumers may react to their innovation and plan accordingly (Oreg & Goldenberg, 2015). Our results demonstrate that firms must consider customer revenue heterogeneity and assortativity in estimating the adverse effect of negative WOM on their profits. The findings indicate that negative WOM will have a stronger negative effect on *NPVR* in a heterogeneous market compared to a homogeneous market. On average, the effect of customer revenue heterogeneity on *NPVR* is over three times the effect of initial percentage of disappointed customers for revenue leaders, about twice for randomly designated group, and about one third for experts and social hubs. Without considering these factors, managers will not be able to accurately estimate the adverse profit impact of negative WOM and plan for remedies. Importantly, these effects are significantly stronger for smaller percentages of disappointed customers than for larger groups of disappointed customers. So, firms should not overlook disappointments by even a small percentage of customers as they may lose significant profits in a highly-heterogeneous and moderately to highly-assortative market.

Most service firms can estimate revenue heterogeneity using customer revenue data from their internal sales, service usage, and loyalty databases. Estimating revenue assortativity, however, entails more challenges. Certain service providers such as telecommunication companies can estimate revenue assortativity by enriching customer usage and sales data with social network data that can be mapped using the communications between consumers (Nitzan & Libai, 2011). Alternatively, service firms often store referral data about their customers (who referred who). Managers can use this data to map consumer social network and couple it with customer usage/purchase data to estimate assortativity. Even though this method will likely map a subset of the social network, it serves the purpose well. Partial mapping of a social network effectively identifies many attributes as long as data is collected for at least 20% of the customers (Van Den Bulte, 2010). Firms can also enrich their CRM databases using surveys or secondary data such as social media or mobile data to estimate assortativity in their markets (Nejad, Amini, & Babakus, 2015). In the absence of granulated data, managers can analyze consumption patterns across geographical areas to estimate revenue assortativity (Haenlein & Libai, 2013).

Alternatively, firms can use general guidelines from previous research. Markets for products and services that are more visible and related to one's identity are more likely to be susceptible to assortativity effects than others. Customers adopt these services and products as a way to conform to their own social group. Thus, markets for high involvement and visible services and products such as music, cars, and clothing are more likely to be assortative. In contrast, markets for less visible and low-involvement services and products such as consumer packaged goods are less-assortative (Berger & Heath, 2007; Nejad, Sherrell, & Babakus, 2014). Customers in individualist cultures make their decision more independently than those in collectivist cultures. Thus, markets in collectivist cultures are more likely to be assortative than in those in individualist cultures (Nejad, Amini, & Babakus, 2015). This information can also be used to choose the most promising market for introducing a new service or product, a factor that plays crucial role in the success of innovations (Oreg & Goldenberg, 2015).

5.2.2. A comparison of different consumer groups

The results demonstrate that disappointed social hubs reduce *NPVR* more than others. We suggest three reasons for this observation. First, such negative WOM will spread quickly across the social network, whereas negative WOM from other consumer groups may take a while to spread in the social network. Second, social hubs play a major role in the flow of positive WOM (Hinz et al., 2011), so the flow of positive WOM would be hampered when social hubs are disappointed with an innovation or reject it. Disappointments and rejections by social hubs will divide a social network into a number of isolated network clusters that have few or no communication channels with one another, and thus impede the flow of positive WOM. Finally, social hubs receive information about an innovation and adopt it sooner than average consumers (Goldenberg et al., 2009). Thus, their negative WOM would likely be initiated early.

Compared to other groups, revenue leaders primarily influence firm profits because of the revenue they generate. While this revenue is critical to firm profits, the degree to which their negative WOM spreads across the social network is also important. Experts, on the other hand, affect the diffusion process primarily through their ability to strongly influence their neighbors to adopt the service or product and spread WOM about it. So significant losses following an experts' disappointments depends on the characteristics of their second-degree neighbors.

Nonetheless, firms should not underestimate the destructive power that negative WOM initiated by average consumers may have on *NPVR*. A majority of firms' customers do not generate high revenue, but the large number of these customers makes the overall revenue from average customers considerable, and negative WOM can significantly reduce this revenue. Moreover, negative WOM among the less revenue-generating customers may make it difficult for the innovation to pass its tipping point which could lead to its failure.

5.2.3. Implications for negative WOM in general

Our findings support the conventional wisdom that “bad news travels fast” (Goldenberg et al., 2007). Regardless of the type of innovation and the type of market, some adopters may become disappointed with their adoption choices. Our results can help managers design remedies for limiting the adverse profit impact of negative WOM. First, managers can use our findings to design more effective marketing activities. The benefits of targeting social hubs are not limited to their greater influence on the overall diffusion process or to the high likelihood of their participation (Goldenberg et al., 2009; Hinz et al., 2011; Libai, Muller, & Peres, 2013). Such targeting, especially with a higher degree of customer service, will also reduce the likelihood of social hubs' disappointments and resulting adverse effects on the diffusion process.

Second, our results have implications for designing more effective loyalty programs. Loyal customers are less likely to be influenced by negative WOM (Nitzan & Libai, 2011). Moreover, consumers are more likely to speak positively about a brand they like or own and spread negative WOM about a brand they dislike or do not own (East, Hammond, and Wright, 2007). They are also more likely to be influenced by positive WOM about a brand they like and by negative WOM about a brand they dislike (East, Hammond, & Lomax, 2008). Thus, firms need to spend more resources on their loyalty programs and on their customer services in heterogeneous and assortative markets and on the consumers who are more likely to reduce profits if they react negatively to the firm's offerings such as the social hubs and revenue leaders.

Third, brands with a smaller market share are more likely to receive negative WOM (East, Hammond, and Wright, 2007). The literature on the concept of double jeopardy indicates that brands with a smaller market share not only have fewer customers but also have less loyal customers (e.g., Ehrenberg, Uncles, & Goodhardt, 2004). Thus, weaker brands may be more likely to be hurt by rejections and disappointments and they would need to pay more attention to the satisfaction of their customers in order to prevent adverse reactions and manage the effects.

Fourth, firms need to monitor those who do not use their brand. Notably, current users of a brand generate 78% of the positive WOM about it, while non-users of a brand and those who have never used it initiate 49% and 30% of the negative WOM about the brand respectively (East, Hammond, and Wright, 2007). Consumers are also more likely to spread negative WOM about a service that they previously used but do not use any more (Wangenheim, 2005).

5.3. Limitations and future research

This study investigated a complex phenomenon in an under-researched area. While the study has certain limitations, the findings suggest a number of future research directions. First, we rely on assumptions that are in line with a majority of relevant research as listed throughout the paper. We only capture WOM via social ties and do not examine other means of social influence such as observational learning, status, or social norms (Nejad, Sherrell, & Babakus, 2014). An agent has the same degree of influence on all its neighbors and ties are bi-directional. Future work can investigate how relaxing these assumptions may generate further insights. Nonetheless, we adopted conservative assumptions. For example, assortativity between two individuals increases the chances of their defection due to social influence (Nitzan & Libai, 2011). We did not incorporate this effect which increases the effect of assortativity. Moreover, we assumed that negative WOM travels only two degrees of separation, while it may travel much further.

In this study we focused on customer disappointments. Future research can examine other forms of adverse reactions such as resistance to innovations due to various types of risks associated with the adoptions—physical, economic, functional, and social (Oreg & Goldenberg, 2015; Ram & Sheth, 1989). Alternatively, some disappointed customers may not spread negative WOM (silent disappointed customer). We assume that customer dissatisfaction and changes in behavior happen one period after adoption (Goldenberg et al., 2007). In certain cases, customer dissatisfaction and the behavioral consequences such as spreading negative WOM and changes in level of a service usage may evolve over time (e.g., Bolton & Lemon, 1999). Changing these assumptions should not change our findings but relaxing them may generate further insights.

One important future research question raised from our study concerns the emphasis placed in the services literature on customer equity management in recent years (i.e., targeting heavy users explicitly). Managing customer base profiles to move customers from average to heavy users would seem to predict a direct effect on increasing the heterogeneity of a firm's customer base. If so, such activities would accentuate the negative effects of customer disappointments. Another issue is the impact of increasing customer revenue heterogeneity on the assortativity of a customer group. If heavy users have similar characteristics (i.e., demographics or psychographic profiles), then the impact of revenue leader's disappointments on other revenue leaders with similar characteristics could accelerate the drop in *NVPR*. These issues could benefit from further research in different service or product contexts.

Future studies can also advance our findings by exploring the relationships between potential consumers' characteristics, social network position, individual attributes, and new service's attributes. These effects may also depend on the investments a consumer has in the relationship in terms of time and effort. Research has also found that the group to which potential adopters will turn for information about an innovation may depend on the type of innovation—radical versus incremental—and on the risks attached to the adoption (Godes & Mayzlin, 2009; Goldenberg et al., 2006; Iyengar, Van den Bulte, and Valente, 2011). Investigating these dynamics in the context of this study seems to be a fruitful avenue for future research. The research question this study considered may also be extended to different generations of an innovation. Furthermore, future research may examine the variable cost of each customer and the fixed costs associated with offering the service. Finally, researchers can investigate how different policies for handling disappointment may affect these different groups, and the resulting effects on *NPVR*. We hope that this work will further enhance the growing interest in a promising area of innovation diffusion research.

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