International Journal of Research in Marketing 34 (2017) 536–552

Contents lists available at ScienceDirect

IJRM

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Full Length Article

Opinion leadership in small groups☆

Sarit Moldovan [a,*], Eitan Muller [b,c], Yossi Richter [d], Elad Yom-Tov [e]

[a] The Open University of Israel, Israel
[b] Interdisciplinary Center (IDC), Herzliya, Israel
[c] New York University, New York, NY, United States
[d] Google Israel R&D Center, Tel Aviv, Israel
[e] Microsoft Research, Tel Aviv, Israel

ARTICLE INFO

Article history:
First received on October 13, 2015 and was under review for 9 months
Senior Editor: Steven Shugan
Available online 25 November 2016

Senior Editor: Steven Shugan

Keywords:
Opinion leadership
Strong ties
Small groups
Churn

ABSTRACT

The role of opinion leaders in the diffusion of innovation has recently come under scrutiny: On the one hand, their central role in accelerating diffusion has been recognized in industry, academia, and the popular media. On the other hand, it has been argued that opinion leaders do not create contagion processes that differ significantly from those of other types of customers. We offer here a synthesis of these opposing theses: For many applications, opinion leadership should be studied in small groups rather than in an entire network.

Using data from two mobile operators, we show how our method of segmenting the market and defining local opinion leaders applies to churn. We show that opinion leaders are highly effective in small, strong-tie groups, and their effect considerably declines with larger groups and weaker ties. Opinion leaders are at the highest risk for churn compared with other group members, they are more likely to be the first to initiate churn, and when they churn, the probability of additional churners from their social group grows significantly, as compared to when non-leaders churn.

1. Introduction

The role of opinion leaders in diffusion of innovation has recently come under scrutiny (Hinz, Skiera, Barrot, & Becker, 2011). On the one hand, their central role in accelerating diffusion has been recognized in industry (Dunn, 2007; Marsden, 2006), academia (Goldenberg, Han, Lehmann, & Hong, 2009; Nair, Manchanda, & Bhatia, 2010) and the popular press (Gladwell, 2000; Keller & Berry, 2003). On the other hand, recent arguments claim that opinion leaders do not create contagion processes that differ significantly from those created by other types of customers (Watts & Dodds, 2007) and may even be less effective than non-leaders (Katona, Zubcsek, & Sarvary, 2011; Leskovec, Adamic, & Huberman, 2007; Libai, Muller, & Peres, 2013).

We suggest an explanation to the mixed findings regarding the effectiveness of opinion leaders: For many applications, opinion leaders are active and influential in small, strong-tie groups rather than throughout the network. In these situations, studies that explored opinion leaders' effect on the entire network may mistakenly find that leaders have no effect, while in fact they do affect their strong-tie group.

☆ Some of this research was conducted at IBM Haifa Research Labs. The authors would like to thank the editor, senior editor, and reviewer for their helpful review process, and Roni Shachar for a number of helpful comments and suggestions. The financial support of the following institutions is gratefully acknowledged: the Israel Science Foundation (grant No. 479/10), and the German–Israeli Foundation (GIF grant No. 1739/2007).

* Corresponding author.
E-mail addresses: saritmo@openu.ac.il (S. Moldovan), emuller@stern.nyu.edu (E. Muller), yrichter@google.com (Y. Richter), eladyt@microsoft.com (E. Yom-Tov).

http://dx.doi.org/10.1016/j.ijresmar.2016.11.004
0167-8116/

We develop a method to quantify connection strength and segment the market into small groups, and define opinion leaders therein. Using data from mobile operators in two countries, we show the application of this method to churning behavior and show how tie-strength and group size affect the power of opinion leaders.

Previous research has suggested that small groups or strong ties may be more conducive to social influence. For example, Leskovec et al. (2007) found that recommendations for expensive products are more effective in well-connected communities. Katona et al. (2011) found that groups that are more dense, or inter-connected, have more influence on their members. In an experiment, Duflo and Saez (2003) found that employees from small departments were more likely to attend a benefits fair after receiving an invitation, compared with employees from large departments who received the same invitation. While these studies present preliminary evidence of the strength of strong ties, they have not systematically explored this effect, nor the effect size. In this research we explore different dimensions of strong ties, such as comparing different group sizes, comparing strong and weak ties within the group, and manipulating different group sizes.

In addition, past research did not explore the effect of opinion leaders in small groups. As explained above, recent studies have questioned the role and strength of opinion leaders, as results were inconsistent. We suggest that opinion leaders' effect might fade when focusing on the entire market rather than on small groups. We find that opinion leaders have the strongest effect in small groups and strong ties: When increasing the size of the group or adding weaker ties to the group, the effect of the leader decreases considerably.

Thirdly, we explore the effect of opinion leaders, but using a different angle than most past literature: Churn rather than on adoption. We find that opinion leaders are at the highest risk of churn compared with other group members and they are more likely to be the first to initiate churn. Importantly, when opinion leaders churn, the probability of additional churners from their social group grows considerably, compared to when non-leaders churn.

With respect to churn prediction, past research traditionally used individual characteristics to predict churn (Kim & Yoon, 2004). More advanced models added social interactions to the traditional models and showed better prediction (Gruszczynski & Arabas, 2011; Nitzan & Libai, 2011). Other models used analysis of customers' calls to call centers to estimate their churn probability (Hadden, Tiwari, Roy, & Ruta, 2006). Our model allows for better prediction of churn with fewer variables. In addition, it can predict churn before any signs of churn appear, as it leans on the theory of finding leaders in their small groups and retaining them before churn begins and infects their group members. This has important applications as once the ripple of churn starts, especially through leaders, it might be much harder to stop it.

From a managerial point of view, past research questioned the effect of opinion leaders, thus generating calls for marketers to reconsider the use of viral marketing programs (Watts, 2007). Specifically, seeding strategies may be of little value if opinion leaders are not influential (Hinz et al., 2011). Understanding that opinion leaders may be highly effective although limited to their local group, means that seeding can be very successful if targeted at opinion leaders in separate groups.

We next discuss the relevant literature on opinion leadership, describe our model and data, and present new insights regarding opinion leadership in small groups.

2. Background

2.1. On opinion leadership

Opinion leaders are defined as consumers who influence other consumers' attitudes or behaviors, usually via word of mouth. Alternatively, in network analysis research, opinion leaders are often defined as those who have a high number of connections (Valente, 1995). In line with the first definition, the most common way of identifying opinion leaders in marketing research is via a self-report scale wherein people rate their own opinion leadership (e.g., Childers, 1986). This technique may suffer from a bias, as being an opinion leader is a desirable trait, and people may overestimate their opinion leadership. Indeed, the correlation between self-reported opinion leaders and nominated opinion leaders (the second technique) was found to be rather low (Iyengar, Van den Bulte, & Valente, 2011).

The second technique used to identify opinion leaders is a nomination technique, where people report which other individuals influence their decisions (e.g., Iyengar et al., 2011; Nair et al., 2010). While this technique appears to be the most reliable, it is the most complex to estimate, in research but mainly in practice, as it may be hard to locate the nominated opinion leaders.

The third technique used to identify opinion leaders, which is commonly used in network analysis research, is by computing *degree centrality* scores (Goldenberg et al., 2009). Using each node's in-degree (number of nodes connected thereto) and out-degree (number of nodes to which it is connected), it is possible to discover which individuals are connected to most others (frequently referred to as social hubs), and may therefore influence and be influenced by them purely via exposure. This technique is reliable and easy to measure when the data are available.

Yet, degree centrality scores may not be enough to capture opinion leadership. Trusov, Bodapati, and Bucklin (2010) developed a model for identifying influential users in a social network based on their activity therein. According to their findings, the opinion leaders were not necessarily those with the highest number of connections. Indeed, other studies suggested that occasionally the important individuals in a network are not those with the most connections, but rather those who bridge structural holes within a network or between groups, known as *brokers* (Burt, 1999; Venkatraman, 1989). It is therefore important to understand not only how many connections each individual has (volume of information transfer), but also the diversity of the connections (quality or redundancy of the information), as a broker can control the transfer of information in the network (Burt, 1999; Van den Bulte & Wuyts, 2007). Thus, another way to identify opinion leadership in networks is *betweenness centrality*, which is the number of shortest paths passing through a node. High betweenness means that the node connects between different groups (Hinz et al., 2011; Yan & Ding, 2009).

In this paper we define opinion leaders as the consumers who influence the decision-making of their followers. We therefore need to identify the consumers who exert most influence on the dissemination of information, yet we also need to identify the consumers who are responsible for high-quality information that influences others into action. We suggest that an efficient way to recognize the most influential consumers in the network is using a centrality score similar to PageRank, an algorithm that captures the most important webpages online (Page, Brin, Motwani, & Winograd, 1999).

PageRank was developed to allow for quick and efficient internet search. The score that the PageRank algorithm assigns to each node is its directed weighted degree centrality, which takes into account the degree centrality of the node's connections. PageRank therefore measures the importance of each webpage considering the number and importance of webpages that link to it. Going back to social networks, a node can get a high PageRank if it has high degree centrality, or if it has low degree centrality but its connections have high degree centrality. In a sense, PageRank captures both degree centrality and betweenness centrality (see also Dwyer, 2007). As degree centrality and betweenness centrality were already found to characterize opinion leaders, and considering that PageRank spots the most important nodes in the network, we believe that this measure is the most appropriate to recognize opinion leaders. The use of PageRank was also suggested by Libai et al. (2010) as a better measure of opinion leadership.

In this paper we therefore employ a method similar to PageRank to identify opinion leaders. We define relative leadership strength by computing not only the strength of each individual but weighing the relative leadership strength of the individual's connections. This is a recursive algorithm that converges to a single opinion leader. As explained, the advantage of our algorithm is that it does not capture opinion leaders only as the obvious social hubs, i.e., those with the highest number of connections, but it also captures leaders as brokers, i.e., those who bridge structural holes, although they may not necessarily have a high number of connections.

2.2. Opinion leaders in small, strong-tie groups

While opinion leaders should be influential by definition, recent research found that opinion leaders are not more influential than non-leaders (Katona et al., 2011; Leskovec et al., 2007; Libai et al., 2013; Watts & Dodds, 2007; see Table 1). Yet, these studies, and research on opinion leaders in general, have not considered the effect of strong ties in small groups. The issue of small groups and clustering was found to be important to diffusion processes (Godes & Mayzlin, 2004; Katona et al., 2011; Libai et al., 2013; Reingen & Kernan, 1986), and may be critical for understanding interactions between consumers. We suggest and show in this paper that for some decisions, opinion leaders are more influential in their small, strong-tie group, thus their influence is less visible when exploring their effect on the entire network. Table 1 summarizes the inconsistent findings of past research on opinion leadership, while dividing the studies into studies that focused on small groups/strong ties and studies that focused on the entire network regardless of tie-strength. The table clearly shows that opinion leaders were found to be influential (marked in gray) more often when focusing on strong ties, as we discuss next.

2.2.1. Small, strong-tie groups

When two individuals (nodes) in the social network are connected, it means that they have a relationship with each other. However, this relationship can be of many forms starting from a random acquaintance (weak tie) to a very close friend or family member (strong tie). Tie-strength can be indicated by the amount of time the two individuals spend with each other, frequency of their interactions, importance attached to each other, type of relationship, emotional intensity, intimacy, or reciprocity (Brown & Reingen, 1987; Granovetter, 1973; Weimann, 1983). Importantly, strong ties exhibit in many cases transitivity such that if A is strongly related to B and B is strongly related to C, A is likely to be strongly related to C (Granovetter, 1973). This creates clusters or subgroups of strong-tie connections (Brown & Reingen, 1987; Granovetter, 1973). These strong-tie group members highly influence each other because of the high credibility among the members, and because they share multiple redundant paths of communication that lead to high availability of information (Brown & Reingen, 1987; Weimann, 1983).

Past research shows evidence for the existence of small, strong-tie groups, and for the strength of strong ties. First, individuals have more influence on their connections when the connections are inter-connected to each other (Katona et al., 2011), which implies that the members of small groups are highly influenced by their peers. Moreover, referrals from strong ties within small dense groups were found to be more effective (Leskovec et al., 2007; Reingen & Kernan, 1986), to include more relevant information (Weimann, 1983), and to influence decision making (Brown & Reingen, 1987). Consistently, Godes and Mayzlin (2004) showed that word of mouth is more informative when looking at small communities rather than total word of mouth spread. Research conducted by industry, e.g., Yahoo! (Watts, 2010), and Google (Adams, 2012, 2010) also showed the prevalence and importance of small groups, online as well as offline. A comprehensive review paper on the effect of social groups on adoption is given in Hill, Provost, and Volinsky (2006).

Thus, studies repeatedly show that in spite of the importance of weak ties in bridging between the groups, it is strong ties within the groups that are more influential when it comes to decision making, especially in the context of product consumption (Brown & Reingen, 1987; Duflo & Saez, 2003; Granovetter, 1973; Katona et al., 2011; Leskovec et al., 2007; Reingen & Kernan, 1986; Weimann, 1983). Yet, except for one simulation-based study (Valente & Davis, 1999) no research to our knowledge has explored the effect of opinion leaders in small groups. When considering the central role of opinion leaders in the diffusion process, and the strength of strong ties in facilitating decision making, it is reasonable that when we intend to understand how opinion leaders influence decision making, we need to focus on opinion leaders within these small groups. It should be noted that opinion leaders and their followers typically belong to the same primary group (Katz, 1957), thus it is possible to recognize leaders within groups.

Table 1
Studies on opinion leadership and tie-strength.

Source	Product	Sample and tie-strength	Type of opinion leaders	Findings
Studies that explored opinion leaders in small groups or strong ties				
Bhatia and Wang (2011)	Drug	Drugstore data of new physician to the same patient. Assuming that moving between primary care and specialist is due to referral.	Specialists	The prescriptions of specialists had a significant positive influence on the prescriptions of primary care physicians, but not the other way around.
Hinz et al. (2011)	Messages, video clip	Students' online social network	Hubs: members with the most connections Bridges: members who connect two parts of the network	Hubs and bridges outperformed random seeding.
	Mobile phone provider	Referrals by existing customers	Hubs: members with the most connections	
Iyengar, Van den Bulte, and Valente (2011)	Drug	Relevant physicians in three cities and those who influenced their decision	Self-designated and members with the most connections	Opinion leaders tend to be heavy users. Heavy users are more influential than light users in driving adoption.
Nair, Manchanda, and Bhatia (2010)	Drug	A sample of physicians and their paired, strong-tie, opinion leaders	Nominated	Opinion leaders who prescribe the drug influence their followers into prescribing the drug as well.
Reingen and Kernan (1986)	Piano tuning	66% of clients in the past two years divided into smaller strong-tie groups	Members with more than one connection (referred more than one person to the service)	Five opinion leaders were responsible for 60% of the clients.
Valente and Davis (1999)	No product – a simulation	Simulated network divided into small groups around the opinion leaders	Members with the most connections	When the diffusion starts with opinion leaders 100% adopts by time period 3, while in random diffusion only 30% adopts by time 3.
Weimann (1991)	Flow of information	All members of a kibbutz, a small, strong-tie, community	Self-designated	Compared with non-leaders, opinion leaders spread more news, consumer information and decision making information. However, opinion leaders did not spread more gossip than non-leaders.
Studies that explored opinion leaders in the entire market regardless of tie-strength				
Goldenberg et al. (2009)	Pictures and video clips in an online social network	A whole network	Members with the most connections	Opinion leaders have a stronger influence then non-leaders. They lead to more and faster adoption.
Katona, Zubcsek, and Sarvary (2011)	Joining a social network	A sample of users, their connections and interconnections	Members with the most connections	Opinion leaders are *less* influential. Individuals have more influence on their connections when the connections are interconnected.
Leskovec, Adamic, and Huberman (2007)	Books, DVDs, music and videos	All shoppers of an online retailer and their referrals	Shoppers that send a large number of recommendations	Beyond ten recommendations, the success rate of a recommendation decreases with the number of recommendations made.
Libai, Muller, and Peres (2012)	No product – a simulation on two competing brands	12 different simulated networks based on real networks	**Hubs**: members with the most connections	On average, a random seeding program increases firm value by 80%. Approaching hub opinion leaders increases the value by an additional 24%.
			Experts: members with the highest effect	Approaching expert opinion leaders increases the value by an additional 10% (compared with a random program).
Watts and Dodds (2007)	No product – a simulation	Simulated network	**Basic model**: members with the most connections (about four times more connections than the average individual)	Opinion leaders' effect is modest. The structure of the network seems more important than opinion leadership.
			Hyper-influentials model: Opinion leaders are defined as having about 40 times more connections than the average individual	Opinion leaders have a stronger effect than non-leaders.
			Group-based model: the population is divided into small groups	Opinion leaders have a similar effect as non-leaders.

Gray background marks studies that found that opinion leaders are highly influential compared withnon-leaders.

2.2.2. Opinion leaders in small, strong-tie groups

Although past research on opinion leadership did not divide the networks into small groups (except for the abovementioned simulation), some of the explored networks were small communities to begin with. Opinion leaders in these cliques (e.g., students' online social network, physicians, clients of piano tuner, and a kibbutz) were highly influential (Hinz et al., 2011; Nair et al., 2010; Bhatia & Wang, 2011; Reingen & Kernan, 1986; Weimann, 1991, respectively).

Going back to Table 1 that summarizes the main literature on opinion leadership while focusing on tie-strength, we can see that all the studies that focused on small, strong-tie groups found that opinion leaders are influential (marked in gray). However, when research focused on the entire network, the results were mixed. For example, when focusing on adoption of free pictures, opinion leaders influenced their connections regardless of tie-strength (Goldenberg et al., 2009). It is possible that the type of decision influences the strength of the opinion leader. When the decision is easy to make (downloading free pictures), opinion leaders may serve as a promotional tool in which more exposure is more effective. This is similar to the role of weak ties that are highly important in transmitting information, as they connect between groups (Granovetter, 1973; Weimann, 1983, 1991). However, we claim that when the decision is more difficult to make and involves higher customer engagement or higher risk, the effect of opinion leaders may be limited to their small, strong-tie group.

H1a. The influence of opinion leaders is negatively correlated with group size.

H1b. The influence of opinion leaders declines considerably when adding weaker ties.

2.3. Leading churn

In order to explore the effect of leaders in small groups, we focus on churn decisions. While opinion leaders have been vastly explored in the context of adoption, not much research has explored whether and how opinion leaders influence others into defection (Kumar et al., 2010). Customer retention is crucial to firm success over time, especially in highly competitive and saturated markets (Hadden et al., 2006; Prins, Verhoef, & Frances, 2009). Much research has therefore explored churn and its drivers. Yet, little research has explored the social effect of churn, and specifically how opinion leaders influence others into defection. The main drivers of churn explored traditionally are dissatisfaction with the product or service, a decrease in usage, and the time the customer is being served by the service provider (see a review in Nitzan & Libai, 2011).

However, churn also has a social aspect, as it is highly associated with negative word of mouth, which dissatisfied customers might spread and lead to further churn on the parts of those exposed thereto (Richins, 1983). Research has found that churn is affected by the number of connections who churned previously (Dasgupta et al., 2008; Nitzan & Libai, 2011). An individual who speaks more often with churned connections, shares more demographic and socioeconomic characteristics with them, or has more connections outside her network, is more likely to churn (Nitzan & Libai, 2011).

These studies treated all customers as having equal influence, thus did not explore the effect of opinion leaders. However, some consumers, such as opinion leaders, have more influence on others. Opinion leaders are highly involved with the product, they are pleased to share information about it, and they have the knowledge and means to affect others' adoption decisions (Van den Bulte & Wuyts, 2007; Venkatraman, 1989; Weimann, 1991). Therefore, there is no reason to believe that opinion leaders will not affect others' defection decisions as well, considering that churn is a social phenomenon.

Opinion leaders are not only highly influential; research shows that opinion leaders have two important characteristics. First, opinion leaders are more likely to adopt new products and tend to adopt more products (Goldenberg et al., 2009; Katona et al., 2011). Second, opinion leaders tend to adopt earlier than non-leaders (Feick & Price, 1987; Goldenberg et al., 2009; Iyengar et al., 2011; Venkatraman, 1989). These characteristics demonstrate opinion leaders' significance to the diffusion process, by means of igniting it and influencing others. While there is evidence for the importance of opinion leaders for *adoption*, little research has explored whether opinion leaders are more likely to discontinue use, are the first to do so, and to influence others into discontinuing as well. Nitzan and Libai (2011), for example, found that opinion leaders (high degree centrality) are more likely to churn compared with non-leaders, implying that leaders have similar behavior in churn as in adoption. If we look at churn as early adoption of an alternative product (or early adoption of no product if they leave the category), we may find that opinion leaders are commensurately more likely to churn, churn sooner than others, and influence others into churning as well.

We previously claimed that for important decisions, such as churn, the effect of opinion leaders is limited to their small, strong-tie groups. We therefore focus on leaders in small groups to explore our hypotheses. We suggest that compared with non-leaders from their small group:

H2. Opinion leaders are at the highest risk for churn.

H3. Opinion leaders are more likely to be the first to initiate churn.

H4. When opinion leaders churn, the probability of additional churners from their small, strong-tie group grows considerably.

To summarize, our model explores diffusion of churn in a network, while focusing on opinion leaders in small groups. We employ an innovative method that first divides the network into small, strong-tie groups and then assigns an opinion leader for each group using a system similar to PageRank (Page et al., 1999). We then explore how opinion leaders affect churn of other members of their group. The analysis provides a theoretical understanding of opinion leaders in small groups, as well the effect of opinion leaders on churn.

3. The model

3.1. Data

We test our hypotheses on data from two mobile telephony carriers. The advantage of these datasets is that they provide an entire network of individuals who are actually in touch with each other, unlike a sampling and snowball technique that provides limited truncated data or online networks that can easily connect between strangers. These kinds of datasets are in common use in social network analysis (Iyengar, Ansari, & Gupta, 2007; Landsman & Nitzan, 2015; Nitzan & Libai, 2011; Onnela et al., 2007; Risselada, Verhoef, & Bijmolt, 2014) and were recently shown to provide a good representation of actual social networks (Eagle, Pentland, & Lazer, 2009). Yet, the data contains records of calls made by or to the carriers' subscribers (inside or outside the network), thus, it provides a somewhat incomplete view of the network, but one which is a realistic picture of the network as seen by the carrier.

The first carrier is located in a Mediterranean country where three main carriers operate in a mature, saturated market. The carrier we focus on has a market share of approximately 25% with three million subscribers. For this carrier we have information on its entire network with an average of 31 million call data records per day. Call data records (CDRs) provide an indication of which subscriber called (or text-messaged) which other subscriber(s), as well as when that occurred. We also received information on churn in the ensuing three months. The monthly churn rate was approximately 1% for both carriers. The carrier supplied us with information on individual subscriber churn (as opposed to commercial subscribers), thereby enabling us to conduct the analysis on individual subscribers only, where the churn effects are cleaner.

The second carrier differs in that it is a large North American carrier with approximately 19% market share. However, we obtained data from a limited geographic area with approximately 1.6 million subscribers and an average of 48 million CDRs per day. We also received churn information for the entire customer base, for three months. For this carrier, because of the nature of the truncated data, only 22% of the opinion leaders, as recognized by our model, are from its own subscriber base (as compared with 91% of the first carrier), while the other opinion leaders are customers of other carriers. The fact that our results are similar for both carriers, despite their differing widely (the second is from a much larger country, focuses on a smaller geographical area, and uses truncated networks), expands the model's applicability to various types of data, validates our results beyond a specific country or network, and shows that our model can also be useful for truncated or missing data.

For each carrier, we built the social networks based on just two weeks' worth of call data records (CDRs). While previous studies used three months' worth of data to construct the social network (Nitzan & Libai, 2011; Onnela et al., 2007), we offer a model that is more parsimonious both in the length and quantity of the required data.

3.2. Identifying social groups and their opinion leaders

Our model for identifying small, strong-tie groups and their opinion leaders is comprised of four main steps.

a) First, we construct a weighted, directed graph that represents the mobile network. Similar to other methods, nodes correspond to customers, and edge weights capture the strength of the social relations. We employ a novel, information theory-based measure to quantify the tie-strength between each pair of subscribers in the network. Unlike previous approaches, our measure takes into account second-order social factors when quantifying the tie-strength between each pair of users. This is done by considering the overlap between their social ties.
b) Once the weighted graph is constructed, we retain only the strongest ties (namely, the edges with the largest weights), and partition the network into a collection of small, disjoint clusters, each representing the core of a dense social group.
c) We then augment the core social clusters with customers who were not covered by the process thus far.
d) Finally, we consider each cluster separately, analyzing its social structure while establishing the relative social status of each of its members.

The following sections provide a more technical description of each step (more details of the algorithm can be found in Richter, Yom-Tov, & Slonim, 2010).

a) *The underlying graph: quantifying social connections*. We represent the mobile network as a weighted, directed graph, wherein nodes correspond to customers, and edge weights represent the strength of their social ties. Note that any given mobile operator's data includes all communication directed from or to its subscribers. Therefore, the node set of the graph will include both subscribers of the given operator as well as those of competing operators.

Each subscriber is associated with the list of subscribers she called (or texted—we treat voice or non-voice CDRs similarly throughout the paper) during the past two weeks. If >100 calls were made by a subscriber, only the last 100 calls are considered.[1] Previous work (Dasgupta et al., 2008) has considered the duration of calls between subscribers as a measure of similarity between them. However, we found that the number of calls between pairs of subscribers and their durations are highly correlated (Spearman $\rho = 0.94$, $p < 10^{-10}$). Additionally, the use of simple indicators of a call (i.e., whether it occurred or not) bears several advantages: First, it allows the simple use of other call types (SMS, MMS, etc.). Second, the application of the similarity measure described below is straightforward.

[1] Keeping a buffer of the of the last 100 calls is required to make the algorithm computationally feasible for large networks, as it allows us to find the strength of connection between two subscribers using a relatively reasonable (and bounded) order of computation of $Nlog(N)$, where N is the size of the buffer.

In order to quantify the social relatedness of a pair of subscribers, we rely on the intuitive notion that if two subscribers call each other, as well as relatively similar individuals, they should be considered strongly socially related (Adamic & Adar, 2003). This is similar to the idea of transitivity made by Granovetter (1973), in which two individuals have a stronger tie if both are connected to the same third individual. To formally capture this intuition, we use a similarity measure based on the concept of Mutual Information (MI) (Cover & Thomas, 2006).

Formally, given customers i and j, we define the binary vectors v_i and v_j of dimensions equal to the number of customers in the network, to have value 1 in position k if customer i (respectively, j) has customer k on the list of subscribers she called. We now define a 2×2 count matrix C_{ij}, out of v_i and v_j. Specifically, $C_{ij}(0, 0)$ counts the number of entries wherein both v_i and v_j equal zero; $C_{ij}(0, 1)$ counts the number of entries wherein v_i equals zero and v_j equals one; $C_{ij}(1, 0)$ counts the number of entries wherein v_i equals one and v_j equals zero; and $C_{ij}(1, 1)$ counts the number of entries wherein both v_i and v_j equal one. Normalizing C_{ij} by the total number of entries (subscribers), we obtain a joint bivariate distribution, denoted P_{ij}. For example, $P_{ij}(1, 1)$ is the probability of the event that both v_i and v_j equal one, namely the probability that both the ith subscriber and the jth subscriber have called a subscriber that is picked uniformly at random. Given this joint distribution, we quantify the similarity of subscribers i and j via the Mutual Information (MI) contained in P_{ij} (Cover & Thomas, 2006) and given by Eq.(1):

$$S(i,j) = \left\{ \begin{array}{ll} \sum\limits_{0 \le k,l \le 1} P_{ij}(k,l) \log \dfrac{P_{ij}(k,l)}{P_i(k) \cdot P_j(l)} & \textit{if i called j} \\ 0 & \textit{otherwise} \end{array} \right\} \tag{1}$$

Note that P_i and P_j represent the marginal distributions of P_{ij}. Due to the mutual information properties, $S(i, j)$ is symmetric and non-negative, and is bounded by the maximum of the entropies of P_i and P_j. If both subscribers have called precisely the same set of individuals in their 100 most recent calls, then $S(i, j)$ is maximal. As the overlap between the set of individuals called by the ith subscriber and those called by the jth subscriber decreases, $S(i, j)$ will decrease accordingly, and if these two sets do not overlap, then $S(i, j)$ will tend toward 0.

The use of Mutual Information (MI) has an additional advantage in that call centers and other service providers will have a low MI for all subscribers. The reason for this is that because a call center contacts many people, the overlap between its most recently called subscribers and those of any other subscriber will be very low, and thus the MI will be low. Consequently, the weights on edges adjacent to call centers and service providers will be relatively low, and those edges will later be pruned from the graph, as the next section explains.

b) *Clustering: finding social clusters' cores*. Once the weighted, directed graph has been constructed, we retain only a fraction (for example, the top 10%) of the heaviest edges, and focus on the induced graph. This naturally forms islands of subscribers who are tightly connected to one another. These are the cores of social groups we use for our study. Algorithmically, this stage is performed by treating the resulting graph as undirected, and partitioning it into its connected components, an operation that can be performed quickly, even for very large networks. Instead of retaining tightly connected edges, it is possible to remove edges with the highest betweenness (Girvan & Newman, 2002). However, this algorithm is iterative and much more complex computationally, which makes it impractical for very large graphs, such as the one we use here (see a review of the two methods in Girvan & Newman, 2002).

The fraction of strongest links retained represents a tradeoff between two desired outcomes: On the one hand, while a high threshold (namely a large fraction), which retains many connections, will place many people into groups, the connections between individuals will have less significance. On the other hand, a low threshold will form very tightly connected groups, yet at the cost of neglecting large sections of the network. We have found empirically that a 10% threshold covers approximately 75% of the network subscribers, while maintaining strong social effects. We discuss the effect of this threshold in the results below.

c) *Augmenting the core social clusters*. After constructing the core clusters in the network, we examine all subscribers who were not linked to any group, and consider adding them to one of the existing clusters. To this end, we compute the connectivity of each "uncovered" subscriber to each of the clusters based on the number of that subscriber's calls to cluster members. The subscriber is connected to the cluster to which she made the most calls, but marked as having joined at a later stage. We term these subscribers "stragglers". By definition, stragglers are connected to their groups via weaker ties, and we expect them to be less influenced by the group. However, as we later show, this influence is not negligible. An additional incentive for adding stragglers is to increase the size of the population for which a predictive model—which uses social attributes—can be used. The process described above places each subscriber in no more than one group, and essentially creates a partition of a subset of the original network. A future research direction will examine the possibility of using soft clustering, which allows each subscriber to be a member of more than one group.

d) *Clusters' social analyses*. Once the social clusters have been identified, they are analyzed separately. For each cluster, we wish to establish the relative social influence of each of its members. We represent each group by the directed graph induced by its members, and initiate a standard random walk with restarts over this graph. Specifically, we consider a Markov chain whose states are the nodes in the cluster with the following transition matrix: at each node v with probability p (tunable parameter; we used $p = 0.15$, a commonly used value, see Page et al., 1999), we move to a random node (restart). The remaining probability mass (1-p) is evenly divided between the neighbors of v in the group. Note that since the resulting Markov chain is irreducible and aperiodic, it has a unique stationary distribution that is attainable (inside the limit) from any initial distribution. We continue the random walk until convergence to the stationary distribution (or sufficiently close thereto). The social strength assigned to each member is her corresponding probability in the distribution obtained. We define leadership strength as the stationary probability of the opinion leader, divided by the minimal probability in her group. When leadership strength equals at least two, this group is defined as having an opinion leader. While other measures of strength, such as ratio of the highest to second highest, could be considered, we found this measure indicative of leadership strength, as shown below. Note that the opinion leadership is local in the sense that the opinion leader influences only others in her social group.

As discussed above, the opinion leaders' selection method is similar to that of PageRank (Page et al., 1999). The advantage of this method is that it does not capture opinion leaders only as the obvious social hubs. We also capture opinion leaders as brokers, i.e., those who bridge structural holes, although they may not necessarily have a high number of connections (Burt, 1999). PageRank scores were already found to be highly correlated with degree centrality scores, the common measure of opinion leaders as social hubs ($r = 0.95$), and also with betweenness centrality, a measure of leaders as those who bridge structural holes ($r = 0.73$, Yan & Ding, 2009). In addition, Haenlein and Libai (2013) suggested a revenue measure of leaders as those who generate the most revenue to the firm, as opposed to the previous measures that compute the customer's position in the social network. We compared our measure of local leadership to the measure of revenue leader as well, using the data of the first carrier. The correlation between our leader strength and the revenue each customer generates is 0.40 ($p < 0.01$). Moreover, when comparing local leaders to revenue leaders, we see that 89% of the customers are classified into the same type: a leader or non-leader (the other 11% are classified as leaders using one method but as non-leaders using the other method).

Note that our social analysis can be performed in two directions along the call graph: from the caller to the called subscribers, or from the called to the caller (namely by reversing the original edge orientations). We term the opinion leader computed in the first instance a *disseminating opinion leader* (sometimes called outgoing opinion leader), and the opinion leader computed according to the reversed links, an *authority opinion leader* (incoming opinion leader).

4. Results

4.1. Linkage between opinion leadership and churn

Before beginning the analysis, we present the various variables that we include in the model, and initial results that demonstrate the linkage between opinion leadership and churn. The results are presented in Table 2 and are statistically significant ($p < 10^{-5}$).

First, note that although the two carriers and the data they provided differ widely, their descriptives and churn mechanisms are similar. The main difference is that for Carrier 2, a large percentage of the opinion leaders are subscribers of another carrier, which is a result of the truncated data this carrier provided. The initial analysis confirms that opinion leaders are at the highest risk for churn compared with other group members (H2): The opinion leader's likelihood of leaving is 1.2 that of any other group member. Opinion leaders are also more likely to be the first to churn (H3). Consider the fact that the average number of churners in groups where (a) the opinion leader churned and (b) not all churn occurred on the same date, was 4.6 for Carrier 1. Therefore, the likelihood of any churner of churning first is 1/(4.6), or 22%. The actual share of groups where the opinion leader churned first is 54%, thus opinion leaders are about 2.5 times more likely to churn before other group members. Furthermore, when opinion leaders churn, the probability of additional churners from their social group grows about 50-fold, compared to when a non-leader churns (H4). This effect is even stronger when the opinion leader belongs to another carrier.

Lastly, for many subscribers of the first carrier, we were able to determine the new carrier choice for churners. For those customers, we can track the tendency to match their new carrier of choice. Specifically, we track churning subscribers' tendency to defect to the same new carrier together. In groups that suffered opinion leader churn in addition to at least three churning members, we found that 91.6% of subscribers switched to the same new carrier. This is another indication of the immense effect of the opinion leader and the strength of our model.

Table 2
Model variables and relationship between opinion leadership and churn.

Model variables	Carrier 1	Carrier 2
% of groups with an opinion leader	88%	82%
% of opinion leaders who are subscribers to the same carrier	91%	22%
% of group members who subscribe to the same carrier	70%	37%
Average group size	15	15
% of groups whose opinion leader churned	1%	2%
Relationship between opinion leadership and churn		
How much more likely is the opinion leader to leave than are other group members?	1.2	1.1
% of groups where the opinion leader churned first	56%	46%
If an opinion leader leaves, how much more likely is another churner?	57.1	47.3
If an opinion leader leaves, how much more likely are two or more other churners?	38.4	87.3
How much more likely is churn when the opinion leader is not from the carrier?	1.8	1.5
When opinion leader plus three or more members churned, how many switched to the same new carrier?	91.6%	–

The initial results confirm what we hypothesized in H2–H4, opinion leaders are more likely to churn and are the first to do so in their social groups. Once they churn, they are likely to influence others to churn as well.

4.2. The defection hazard model

In order to quantify the effect of opinion leadership and the group on the likelihood of churn, we used a Cox regression model (Allison, 1995) to measure the churn hazard for group members. We computed the following attributes for each (non-leader) group member:

1. Group size in terms of the number of subscribers in the social group.
2. Disseminating/Authority leader churned—a binary indicator of whether the opinion leader in the group churned or not.
3. Disseminating/Authority leader rank—ratio of opinion leader's strength to the minimal social strength in the group.

The time variable was synchronized to the day that the first individual in the group churned (whether opinion leader or not), i.e., the time variable was the number of days that passed between the first individual to churn from the group and a given individual's date of churn.[2] We removed all churners that left on day zero, to reduce the risk of a confounding influence whereby multiple subscribers of the same account churn on the same day. While this measure does not completely alleviate this problem, it minimizes its effect. In addition, we reanalyzed the data of Carrier 1 while excluding accounts of multiple subscribers (families) and the results were similar. We can therefore conclude that the effects are not a result of families churn together or due to financial benefits (free calls within the account).

The regression coefficients are presented in Table 3, Model A.

Results reconfirmed that the churn of an opinion leader increased the likelihood of other members' churn (H4). Group size has an inverse effect: The smaller the group, the higher the likelihood of churn, controlling for leader churn. Importantly, the interaction term of group size and leader churning is negative, which implies that for groups whose opinion leader churns, churn probability was much higher in smaller groups, confirming H1a. This clearly demonstrates the local aspects of opinion leadership in this case: While opinion leaders have an effect on the groups they lead, that effect weakens considerably as their group size grows.

An interesting result is the effect of leader rank on the probably of other members' churn. Leader rank is the ratio of the leader's strength to the strength of weakest member of the group. A higher ratio implies that the opinion leader is stronger. For Carrier 1, this ratio has a negative effect on the likelihood of other members' churn. If the opinion leader is strong, she is more likely to prevent churn (controlling for cases in which the opinion leader churns). This is a result of the fact that >90% of the opinion leaders belong to the same carrier and prevent churn, unless they themselves churn. For Carrier 2, however, the result is reversed as 80% of opinion leaders belong to another carrier. In this case, a stronger opinion leader influences others to churn. This result strengthens our claim that retaining opinion leaders may lead to high overall customer retention. Together with the finding that when opinion leaders churn with additional three or more group members, almost 92% of subscribers switch to the same new carrier (Table 2), we can see the substantial managerial implications of retaining opinion leaders, as we discuss later.

Fig. 1 shows the cumulative hazard of churn over time, where day zero is the day that the leader (green line) or the non-leader (blue line) churned. As the figure shows, the defection hazard over time is much higher when the leader churns, yet not when non-leaders churn. The figure emphasizes the crucial role of leaders compared with non-leaders in inducing churn.

4.3. Robustness checks

While trying to understand the effect of opinion leaders' churn on the churn of other group members, we need to consider several alternative explanations, or identification issues (Manski, 2000, 1993). It is possible that group members appear to follow opinion leaders, while in fact they experience similar influences at the same time as the opinion leader that lead both to churn. Moreover, it is possible that leaders may experience an influence that affects them and their followers, yet non-leaders are less influenced by these effects. The two main unobserved effects that can lead to a mass churn are (a) internal effects, for example, the carrier raised prices or has a service malfunction, and (b) external effects, such as competitors' marketing activities or other environmental effects (such as a crisis). In addition, similarity and simultaneity can also lead to churning together.

We could not access the data to control for these possible effects, a problem service providers usually face when analyzing their own customer base without collecting additional data. However, in order to rule out these alternative explanations we ran additional tests.

First, we added the effect of a non-leader churn to the hazard model. A non-leader that churned with proximity to her opinion leader could have been affected by the opinion leader (as we claim), or by any of the other internal or external effects that affected both the opinion leader and non-leaders in the group. If the focal (non-leader) customer churned as a result of internal/external effects or similarity/simultaneity (as did the other non-leader), the non-leader's effect should be strong and the opinion leader's effect should weaken or disappear. However, if the focal customer was influenced by the opinion leader, than the opinion leader's effect should remain the same as in Model A. Model B in Table 3 presents the coefficients of the same Cox regression model as presented in Model A, but with an additional variable: A non-leader churned, a binary indicator of whether a non-leader in the group churned before the focal customer.

[2] The advantage of using the hazard approach is that it is well suited with dealing with right-censored data and thus individuals that had not yet churned in their groups were not truncated.

Table 3
Cox regression results.

Carrier 1	Authority opinion leader			Disseminating opinion leader		
	Model A Parameter (Z)	Model B Parameter (Z)	Model C Parameter (Z)	Model A Parameter (Z)	Model B Parameter (Z)	Model C Parameter (Z)
Group size	−0.0009 (−18.63)	−0.0009 (−19.51)	−0.0009 (−19.37)	−0.0007 (−13.15)	−0.0007 (−13.17)	−0.0007 (−13.26)
Authority/disseminating leader churned	2.42 (48.67)	2.54 (51.08)	2.53 (50.91)	2.86 (61.99)	2.86 (62.03)	2.87 (62.44)
Interaction between size and leader churn	−0.0036 (−10.51)	−0.0040 (−10.80)	−0.0040 (−10.82)	−0.0042 (−17.66)	−0.0042 (−17.66)	−0.0043 (−17.82)
Authority/disseminating leader rank	−0.015 (−4.4)	−0.015 (−4.43)	−0.014 (−4.09)	−0.016 (−3.38)	−0.016 (−3.41)	−0.013 (−2.69)
A non-leader churned	–	0.8870 (9.07)	0.8625 (8.80)	–	−0.00980[NS] (0.78)	−0.0154[NS] (−0.12)
Homophily score	–	–	0.3523 (6.86)	–	–	0.4537 (8.83)

Carrier 2	Authority opinion leader			Disseminating opinion leader		
	Model A Parameter (Z)	Model B Parameter (Z)	– –	Model A Parameter (Z)	Model B Parameter (Z)	– –
Group size	−0.0003 (−6.88)	−0.0003 (−7.59)	–	−0.0002 (−3.91)	−0.0002 (−3.90)	–
Authority/disseminating leader churned	2.23 (68.24)	2.27 (68.89)	–	2.46 (78.58)	2.46 (78.57)	–
Interaction between size and leader churn	−0.0059 (−12.53)	−0.0062 (−12.71)	–	−0.0074 (−16.71)	−0.0074 (−16.69)	–
Authority/disseminating leader rank	0.0733 (10.88)	0.0755 (11.53)	–	0.1508 (2.94)	0.1507 (2.93)	–
A non-leader churned	–	0.644 (7.74)	–	–	−0.0139[NS] (−0.12)	–
Homophily score (N/A)	–	–	–	–	–	–

All values are significant at the $p < 0.05$ level except those that are marked by NS.

As the results clearly show, the non-leader's having churned is only significant for authority opinion leaders, and does not significantly affect the coefficient of the effect of leader churn. This suggests that the opinion leader has an effect beyond other effects — internal, external, or similarity—that affects all customers, thus ruling out the alternative explanations.

In addition to the model controlling for non-leader churn, we ran a third model, Model C, for Carrier 1 only, in which we controlled for similarity by adding scores based on observed homophily that we received from the carrier. Carrier 1 provided us with homophily scores that it collected for each subscriber. The carrier, as most other carriers, extracts for each subscriber a set of Key Performance Indicators (KPIs) such as usage level, debts, complaints, and demographic information (the exact set of parameters the carrier uses is confidential). These KPIs are collected over a year and are compared to previous churners in order to predict the churn of current subscribers. We added these scores to our hazard model to explore the effect of opinion leader churn on churn of her group members regardless of similarity. As Model C in Table 3 clearly shows, although similarity has an extensive effect on churn, the opinion leader's effect is by far stronger.

Lastly, we explored churn over calendar time, for leaders and non-leaders (for Carrier 1, authority leaders only). If all customers, or just leaders, were affected by common unobserved shocks, it would be visible in an increase in churn on a specific point in time. Fig. 2 shows that churn over time changes daily (specifically there is no churn on the weekend), but no common shocks are observed. We ran two regression analyses of churn over time for leaders and non-leaders, while controlling for the days of the week (six dummy variables), and explored the distribution of the residuals. A non-normal distribution of the residuals would suggest extreme amounts of churn on specific days that may indicate common shocks. There is no churn on weekends we therefore removed the weekends from the analysis. The residuals for both leaders and non-leaders are normally distributed (χ^2_{leaders} $(3) = 5.9$, *NS*, $\chi^2_{\text{non-leaders}}$ $(3) = 8$, $p = 0.07$) suggesting that no unobserved effects have affected leaders or non-leaders, to churn at the same time.

4.4. The weakness of weak ties

In H1a and H1b we claimed that opinion leaders have stronger influence in their small, strong-tie groups. The previous analyses suggested a strong influence of leaders on their followers, and that this influence is greater in small groups. In order to accumulate more evidence as to the effect of small groups, and show the strength of strong ties within these groups, we ran additional three tests on the data. First, we compared between different group sizes within the analysis we made. Second, we compared between core group members and stragglers (subscribers who were linked to a group at a later stage as they have weaker ties), again within our results. Finally, we compared between various models by manipulating the percentage of heaviest edges used in the analysis. Since the effects of authority and disseminating leaders are very similar, we hereafter focus on authority

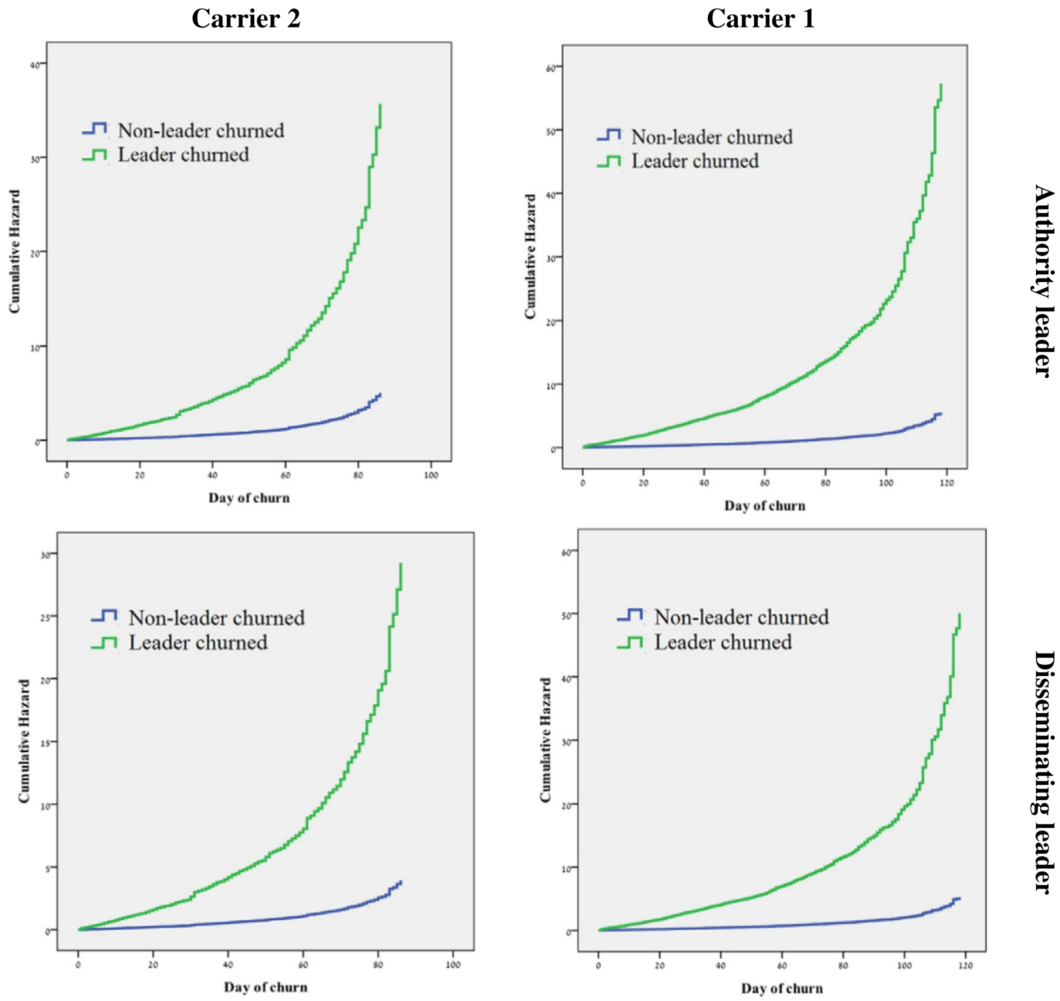

Fig. 1. Cumulative hazard rates. "Non-leader churned" denotes groups where the leader did not churn, yet at least one other member churned.

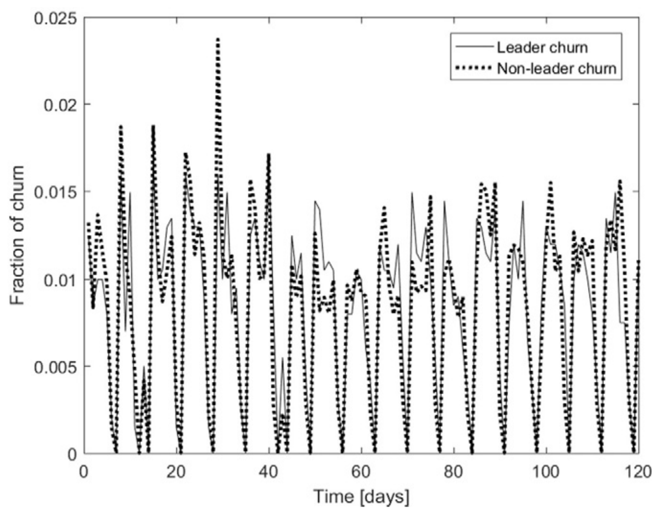

Fig. 2. Leaders and non-leaders churn over time (Carrier 1).

leaders only. Authority leaders are the more interesting, as they are leaders because of their followers (incoming calls), and not due to their being socially active (outgoing calls).

4.4.1. Group sizes

We have partitioned the social network into relatively small social groups and defined the opinion leader in each. Fig. 3 shows the percentages of groups for various size ranges. As the figure shows, there are many small groups and few large groups. In fact, group sizes are power-law distributed ($r = 0.93$, $p < 10^{-5}$), a common distribution for many social behaviors. In order to explore the effect of group size on leadership strength, we compared the churn rate for various group sizes. For each group size, we divided the groups into three types:

1. Opinion leader churned: Groups where the opinion leader churned.
2. Opinion leader did not churn: Groups where the opinion leader **did not** churn (other members may or may not have churned).
3. Non-leader churned: Groups where the opinion leader **did not** churn, but at least one group member churned.

As Fig. 4 clearly shows, the fact that the opinion leader churned has an immense effect on churn rates. Likelihood of churn is as high as 50% in groups where the opinion leader churned. Results also confirmed that group size is negatively correlated with the opinion leader's influence, i.e., the smaller the group, the larger the percentage of churn that occurs when the opinion leader churns. This is consistent with the results of the Cox model presented above.

Moreover, by comparing the first and third types of groups, we reconfirm that the effect of the opinion leader goes beyond a social one (friends churning as a group) or other internal or external effects (service problems or a deal from a competing carrier leading to massive churn). If one of these alternative explanations were true, we would see a similar churn rate in groups where the opinion leader did not churn, but other group members did. The fact that the churn rate is rather low for groups in which the opinion leader did not churn, regardless of whether other members churned or not, shows the importance of recognizing the opinion leader.

4.4.2. Core group members and stragglers

Another way to demonstrate the importance of small groups, and specifically strong ties, is to consider the stragglers in our setting. Recall that following the construction of the core clusters in the network, we examined all subscribers who were not linked to any group, and added them to one of the existing clusters. These subscribers are the stragglers. By definition, stragglers are connected to their groups through weaker ties, and we expect them to be influenced by the group to a lesser extent. A comparison of the opinion leader's effect on the core members of the group (strong ties) compared with that on stragglers (weak ties) is shown in Fig. 5: Core members, who are connected to the opinion leader by strong ties, are highly influenced by the opinion leader, with their churn probability increasing by an order of 13–17 if the opinion leader churned. The stragglers, on the other hand, are also influenced by the opinion leader, yet to a lesser degree, i.e., their likelihood of churn increases by less than fourfold if the opinion leader churns.

4.4.3. Comparing various models

A third way to demonstrate the strength of strong ties is by comparing various models that use different weights of ties. Recall that in the process of defining the groups, we retained only 10% of the heaviest edges, and focus on the induced graph. This naturally forms islands of subscribers who are tightly connected to each other. These are the cores of social groups we use for our study. Clearly, we can manipulate this threshold percentage to discover the effect of adding or deleting weaker ties. For example, if we retain only the top 2.5% of heaviest edges, only very strong ties are retained, while when we increase this threshold to 20%, we add a considerable number of much weaker ties. Fig. 6 shows the results: Opinion leaders' effectiveness declines when we add weaker ties. When

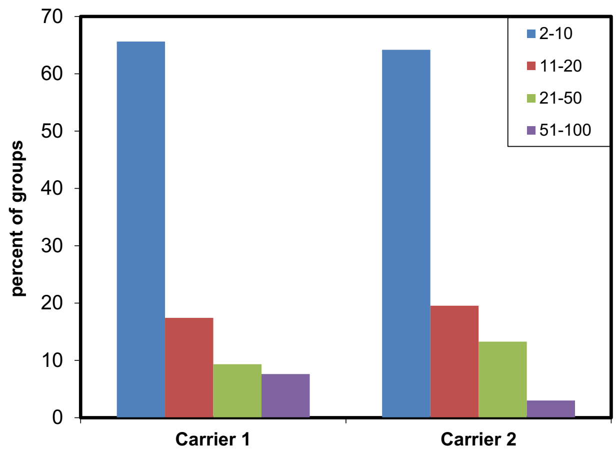

Fig. 3. Distribution of groups by group size.

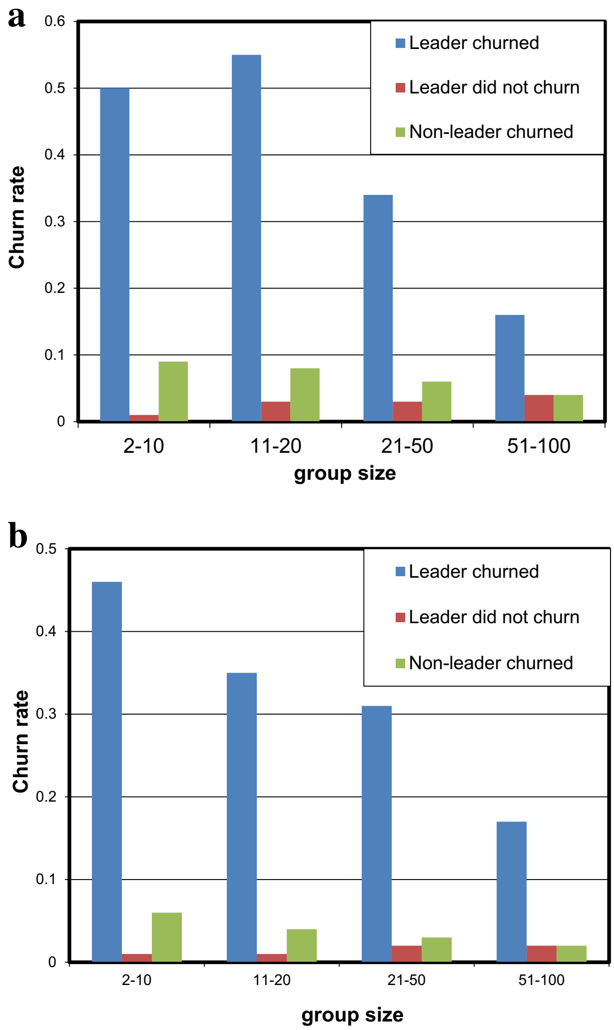

Fig. 4. a Churn as a function of group size and group churn: Carrier 1. b Churn as a function of group size and group churn: Carrier 2.

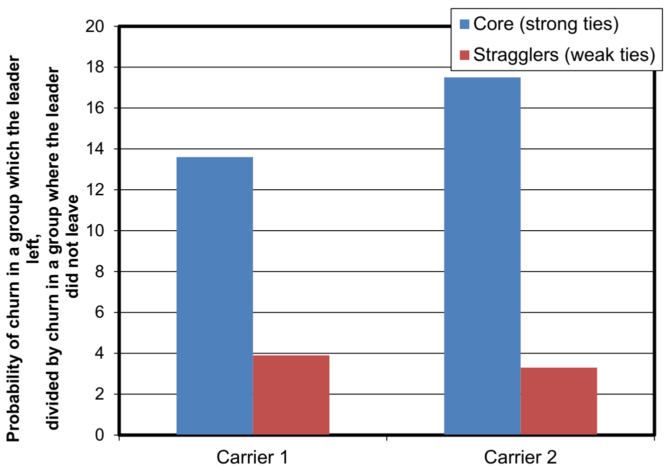

Fig. 5. The impact of the opinion leader's strong and weak ties.

restricting ties to the top 2.5%, the probability of churn from a group from which an opinion leader has churned is about 17 times that of a group from which the opinion leader did not churn. This ratio is reduced to about 10 times when 20% of the ties are retained.

The results show that opinion leaders are more influential in smaller groups. While previous research explored opinion leaders among the entire social network (and in some cases found little effect of opinion leaders), here we show that for some decisions, such as changing mobile carriers, the opinion leader has stronger influence in her strong-tie immediate group, and loses influence as approaching more distant group members.

4.5. The predictive power of the model

The results so far contributed to the understanding of leaders in small groups. Yet, a more accurate model should allow for better prediction of churn. Better prediction strengthens our theory of leaders in small groups, but also has important theoretical and managerial implications. In many industries the cost of winning a new customer is far greater than the cost of retaining an existing one (Hadden et al., 2006). An efficient churn prediction system should not only pinpoint potential churners successfully, but also provide a sufficiently long horizon forecast in its predictions because it is easier and cheaper to prevent churn if a potential churner is recognized before making the churn decision. In this section we show that our model improves the forecasting ability of homophily-based models commonly used by most companies, but moreover it can be used to recognize and retain leaders *before* making a churn decision.

Carrier 1 provided us with the churn scores derived from a homophily-based model, as we presented in Table 3, Model C. In addition, we extracted other Key Performance Indicators (KPIs) from the groups identified above, which were built using only two weeks' worth of CDR data. The KPIs included (1) number of group members, (2) numbers of group members who are subscribers of the analyzed carrier, (3) maximal and (4) minimal social strength in the group, and (5) the ratio between them, (6) number of calls made and (7) received by the leader, (8) average number of calls made and (9) received by group members. KPIs 2–9 were measured for each type of leader (authority and disseminating), and were further expanded by normalizing them by group size. This led to a total of 33 variables. A decision tree was then trained using the first two weeks of the data, and applied to the subsequent data periods. Note that logistic and linear regression models' performance was inferior to that of decision trees, and we are thus reporting the results of the latter.

We ran three models. Our model—the social model—made use of the 33 KPIs that we collected. The second is the carrier's homophily model, made use of the homophily-based churn scores that we received from Carrier 1. Although for reasons of confidentiality we were not privy to the KPIs themselves, the churn scores represent the best model that could be obtained by the carrier, using only individual subscriber attributes, collected over a period of over 12 months. The third model is a combined model created by taking the carrier models' churn scores and our model's churn scores, and training a meta-model (another decision tree) to combine the scores. All three models output a churn score for each subscriber at each time period. The fact that variables such as usage, adoption time, and demographics do affect churn and disadoption is well documented (e.g., Prins et al., 2009) and so that their inclusion in predicting churn would benefit the prediction is not surprising. What we wish to show is the marginal benefit of our approach over and above the well-established state-of-the-art methods.

Recall that once the prediction system produces its churn scores, the retention department makes contact with the subscribers most likely to churn, in an attempt to retain each customer determined to be at churn risk. Naturally, only a fraction of the subscriber pool can be contacted at any given time, and the subscribers with the highest churn likelihood scores are assigned top priority. Therefore, a churn prediction system should be measured by its ability to identify churners within its top predictions. Formally, performance is measured using the lift metric (Richter et al., 2010), where for any given fraction $0 < T < 1$, lift is defined as the ratio between the number of churners among the fraction of T subscribers ranked highest by the proposed system, and the expected number of churners in a random sample from the general subscriber pool of equal size. For example, a lift of 3 at a

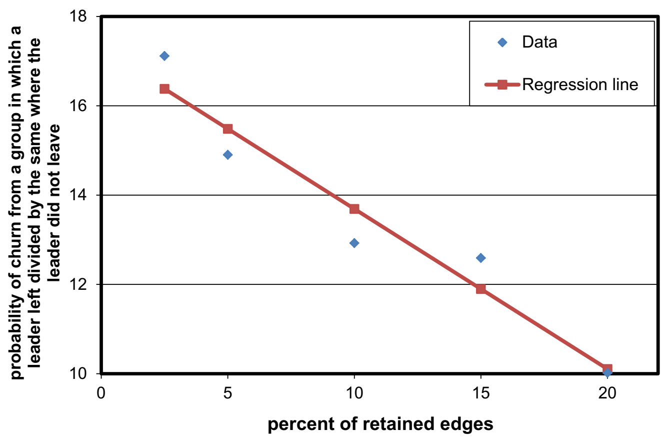

Fig. 6. The impact of adding weak ties on opinion leader effectiveness (Carrier 2).

fraction $T = 0.01$ means that if we contact the 1% of subscribers ranked highest (most likely to defect) by the proposed system, we expect to see three times more subscribers who plan to churn in this population than we do in a random 1% sample.

A churn prediction system's performance is characterized solely by its derived lift curve, which maps each fraction $0 < T < 1$ (horizontal axis) of the lift (vertical axis) obtained by the system. In general, the lift curve is monotonically decreasing, since it is usually harder to provide a substantial lift for larger fractions (note that by definition, for $T = 1$ the lift equals 1).

Fig. 7 shows the lift reached by our social model (using two weeks' worth of data), the current homophily-based carrier model (based on one year's worth of data), and a combined model. We note that the combined model was applied to the entire population of the carrier, not only to those subscribers who were part of a group. As can be seen from the figure, the carrier's homophily-based model is superior to our social model. This is not surprising given that the former encompasses data collected over an entire year (as opposed to two weeks in our model), and encompasses much more information on various facets of each user, as well as the experience in typical subscriber behavior that the carrier gained over many years. However, the combined model is by far superior to either of the other two models, especially when prediction is measured for the top 10% of the population or less (which is the typical operating point of carriers).

Beyond the practical use of the combined model, we claim that the improvement in churn prediction is another indication that the proposed model does not identify proxies for homophily. If this were the case, correlation between the score obtained by the social model and the homophily-based model would be high, and the improvement in lift negligible. If both models identified the same information, they would err on the same subscribers, and lift would not improve. Fig. 7 clearly demonstrates that the social model provides new information, which is utilized by the combined model.

5. Discussion

In this paper we try to solve the disagreement in past literature regarding how influential opinion leaders are. We suggest that for major decisions opinion leaders are most effective in their small, strong-tie groups. We therefore segmented the market into small, highly dense groups, and defined opinion leaders for those groups using an algorithm similar to PageRank. Using data from mobile operators in two countries, we showed this method's application to churning behavior and demonstrated the effect of leadership strength and group size on churn.

Our results suggest that opinion leaders are at highest risk for churn compared with other group members, and they are more likely to be the first to churn in their group. When opinion leaders churn, the probability of additional churners from their social group grows considerably compared to when a non-leader churns. Importantly, our results show that opinion leaders are influential in small, strong-tie groups. Group size is highly negatively correlated with the opinion leader's influence: The smaller the group, the larger the percentage of churn that occurs when the opinion leader churns. Similarly, the effect of opinion leaders is stronger for strong ties compared with weak ties with group members. Our results also suggest that not only do opinion leaders lead churn, but they can also influence their followers to stay with the current provider or switch to another one, depending upon where they go. These results change the way we perceive the effect of opinion leaders and the implications of retaining them.

We also discuss identification issues and repeatedly rule out alternative explanations. Yet, there are still limitations to the model: There are different effects that can explain mass-churn, such as internal and external effects that influence the whole market, similarity, simultaneously, unobserved effects, and other effects that influence group members together (such as family or local plans that provide discount to calls between family members or calls within the networks). Although we tried to control for these effects by showing that the leader has a greater effect compared with non-leaders or when controlling for other effects,

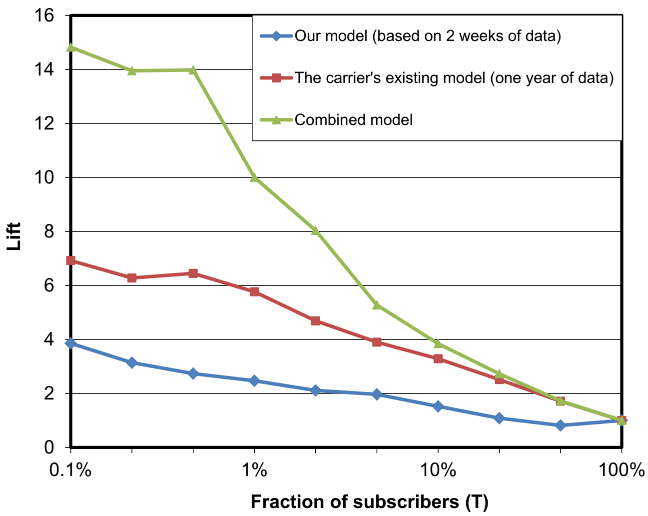

Fig. 7. Comparison of three models for prediction of churn (Carrier 1). Lift is defined as the ratio of the number of correctly recognized churners using each model to the expected random number of correctly recognized churners for each sample size.

we did not have the data to fully control for these effects. In addition, the model is based on descriptive data, and cannot be used to infer causality. It would be interesting to manipulate group sized and leaders, or use propensity score matching (Aral, Muchnik, & Sundararajan, 2009) in future research, to see more conclusive results.

The influential hypothesis, as advanced by Watts and Dodds (2007), comprises two fundamental claims regarding interpersonal influence: First, that some people are more influential than others; and second, that these same people are also important because they exert a disproportionately strong indirect influence on the much larger community. In this paper, we lend credence to Watts and Dodds' critique of the second claim of the influential hypothesis. While we do find that some individuals are more influential than others—some considerably so—their influence is greatly limited by two factors: It is limited to a rather small group of individuals; and it decays rapidly due to weaker ties. These limitations suggest that we should think of these opinion leaders as “local opinion leaders”.

The “local opinion leaders” theory also helps resolve the disagreement between the theory and findings of opinion leaders as influentials (e.g., Goldenberg et al., 2009; Nair et al., 2010) and the findings that opinion leaders do not show a stronger influence than the average or random consumer (Katona et al., 2011; Leskovec et al., 2007; Libai et al., 2013; Watts & Dodds, 2007).

This paper also adds to past literature by focusing on opinion leaders' churn, rather than adoption, and showing that leaders are the first to initiate churn and influence other customers into churning as well. Our model improves the prediction power of current models and allows to recognize and retain leaders before churn begins. It can therefore help retain the most profitable customers—we found that opinion leaders are likely to be revenue leaders—and their followers.

The managerial implications of these local opinion leaders are pronounced not only for customer retention but also for seeding programs, which are becoming more and more prevalent. Consider for example Philips's seeding campaign of 2006 that gave away power toothbrushes (Sonicare Essence) to 33,000 North Americans together with five $10 rebates to give to others; or the Ford campaign that gave away 100 Ford Fiestas. Should these companies make the additional effort in terms of time and money to target influential consumers? The answer depends on how local these potential opinion leaders are. In cases such as the ones presented herein, the local nature of opinion leadership coupled with the rapid decay of its influence, renders such efforts less profitable, as these local opinion leaders are not likely to generate an epidemic of adoptions. On the other hand, identifying these local opinion leaders for retention purposes might prove effective.

References

Adamic, L. A., & Adar, E. (2003). Friends and neighbors on the Web. *Social Networks*, *25*, 211–230.

Adams, P. (2010). The real-life social network. available online at http://www.slideshare.net/padday/the-real-life-social-network-v2.

Adams, P. (2012). *Grouped: How small groups of friends are the key to influence on the social web.* Berkeley: New Riders.

Allison, P. D. (1995). *Survival analysis using the SAS system: A practical guide.* Cary, NC: SAS Institute.

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, *106*(51), 21544–21549.

Bhatia, T., & Wang, L. (2011). Identifying physician peer-to-peer effects using patient movement data. *International Journal of Research in Marketing*, *28*(1), 51–61.

Brown, J. J., & Reingen, P. H. (1987). Social ties and word-of-mouth referral behavior. *Journal of Consumer Research*, *14*(3), 350–362.

Burt, R. S. (1999). The social capital of opinion leaders. *The Annals of the American Academy of Political and Social Science*, *566*(1), 37–54.

Childers, T. L. (1986). Assessment of the psychometric properties of an opinion leadership scale. *Journal of Marketing Research*, *23*(2), 184–188.

Cover, T. A., & Thomas, J. A. (2006). *Elements of information theory* (2nd ed.). New York: John Wiley and Sons.

Dasgupta, K., Singh, R., Viswanathan, B., Chakraborty, D., Mukherjea, S., Nanavati, A. A., & Joshi, A. (2008). Social ties and their relevance to churn in mobile telecom networks. *ACM Proceedings of the 11th International Conference on Extending Database Technology* (pp. 668–677).

Duflo, E., & Saez, E. (2003). The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. *The Quarterly Journal of Economics*, 815–842.

Dunn, L. (2007). Identifying influencers in the digital age: The uploader research. In W. J. Carl (Ed.), *Measuring Word of Mouth*, *Vol. 3*.Chicago: Word of Mouth Marketing Association.

Dwyer, P. (2007). Measuring the value of electronic word of mouth and its impact in consumer communities. *Journal of Interactive Marketing*, *21*(2), 63–79.

Eagle, N., Pentland, A., & Lazer, D. (2009). Inferring social network structure using mobile phone data. *Proceedings of the National Academy of Sciences*, *106*(36), 15274–15278.

Feick, L. F., & Price, L. L. (1987). The market maven: A diffuser of marketplace information. *Journal of Marketing*, *51*(1), 83–97.

Girvan, M., & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821–7826.

Gladwell, M. (2000). *The tipping point.* New York: Little, Brown and Co.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, *23*(4), 545–560.

Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing*, *73*(2), 1–13.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Gruszczynski, W., & Arabas, P. (2011). Application of social network to improve effectiveness of classifiers in churn modeling. *2011 International Conference on Computational Aspects of Social Networks (CASoN)* (pp. 217–222).

Hadden, J., Tiwari, A., Roy, R., & Ruta, D. (2006). Churn prediction: Does technology matter? *International Journal of Intelligent Systems Technologies and Applications*, *1*(2), 104–110.

Haenlein, M., & Libai, B. (2013). Targeting revenue leaders for a new product. *Journal of Marketing*, *77*(3), 65–80.

Hill, S., Provost, F., & Volinsky, C. (2006). Network-based marketing: Identifying likely adopters via consumer networks. *Statistical Science*, *21*(2), 256–276.

Hinz, O., Skiera, B., Barrot, C., & Becker, J. U. (2011). Seeding strategies for viral marketing: An empirical comparison. *Journal of Marketing*, *75*(6), 55–71.

Iyengar, R., Ansari, A., & Gupta, S. (2007). A model of consumer learning for service quality and usage. *Journal of Marketing Research*, *44*(4), 529–544.

Iyengar, R., Van den Bulte, C., & Valente, T. (2011). Opinion leadership and social contagion in new product diffusion. *Marketing Science*, *30*(2), 195–211.

Katona, Z., Zubcsek, P. P., & Sarvary, M. (2011). Network effects and personal influences: The diffusion of an online social network. *Journal of Marketing Research*, *48*(3), 425–443.

Katz, E. (1957). The two-step flow of communication: An up-to-date report on an hypothesis. *Public Opinion Quarterly*, *21*(1), 61–78.

Keller, E., & Berry, J. (2003). *The influentials.* New York: Free Press.

Kim, H. S., & Yoon, C. H. (2004). Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market. *Telecommunications policy*, *28*(9), 751–765.

Kumar, V., Aksoy, L., Donkers, B., Venkatesan, R., Wiesel, T., & Tillmanns, S. (2010). Undervalued or overvalued customers: Capturing total customer engagement value. *Journal of Service Research*, *13*(3), 297–310.

Landsman, V., & Nitzan, I. (2015). Service adoption and defection decisions: Understanding cross- and within-process effects of social influences in consumers' social networks. *Working paper*.
Leskovec, J., Adamic, L. A., & Huberman, B. A. (2007). The dynamics of viral marketing. *ACM Transactions on the Web*, *1*(1), 228–237.
Libai, B., Bolton, R., Bügel, M. S., de Ruyter, K., Götz, O., Risselada, H., & Stephen, A. T. (2010). Customer-to-customer interactions: Broadening the scope of word of mouth research. *Journal of Service Research*, *13*(3), 267–282.
Libai, B., Muller, E., & Peres, R. (2013). Decomposing the value of word-of-mouth seeding programs: Acceleration vs. expansion. *Journal of Marketing Research*, *50*(2), 161–176.
Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, *60*, 531–542.
Manski, C. F. (2000). Economic analysis of social interactions. *Journal of Economic Perspectives*, *14*(3), 131.
Marsden, P. (2006). Seed to spread: How seeding trials ignite epidemics of demand. In J. Kirby, & P. Marsden (Eds.), *Connected marketing: The viral, buzz, and word of mouth revolution* (pp. 3–23). Oxford, UK: Butterworth-Heinemann.
Nair, H., Manchanda, P., & Bhatia, T. (2010). Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *Journal of Marketing Research*, *47*(5), 883–895.
Nitzan, I., & Libai, B. (2011). Social effects on customer retention. *Journal of Marketing*, *75*(6), 24–38.
Onnela, J. -P., Saramaki, J., Hyvonen, J., Szabo, G., Lazer, D., Kashi, K., ... Barabasi, A. -L. (2007). Structure and tie strength in mobile communication networks. *Proceedings of the National Academy of Sciences*, *104*, 7332–7336.
Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). The PageRank citation ranking: Bringing order to the Web. *Stanford Infolab working paper* (available at: http://ilpubs.stanford.edu:8090/422/1/1999-66.pdf).
Prins, R., Verhoef, P. C., & Frances, P. H. (2009). The impact of adoption timing on new service usage and early disadoption. *International Journal of Research in Marketing*, *26*, 304–313.
Reingen, P. H., & Kernan, J. B. (1986). Analysis of referral networks in marketing: Methods and illustration. *Journal of Marketing Research*, *23*(4), 370–378.
Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of Marketing*, *47*(1), 68–78.
Richter, Y., Yom-Tov, E., & Slonim, N. (2010). Predicting customer churn in mobile networks through analysis of social groups. *Proceedings of the 2010 SIAM International Conference on Data Mining, Columbus, OH* (pp. 732–741).
Risselada, H., Verhoef, P. C., & Bijmolt, T. H. A. (2014). Dynamic effects of social influence and direct marketing on the adoption of high-technology products. *Journal of Marketing*, *78*(2), 52–68.
Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining influential users in internet social networks. *Journal of Marketing Research*, *47*(4), 643–658.
Valente, T. W. (1995). *Network models of the diffusion of innovations.* Cresskill, NJ: Hampton Press.
Valente, T. W., & Davis, R. L. (1999). Accelerating the diffusion of innovations using opinion leaders. *The Annals of the American Academy of Political and Social Science*, *566*(1), 55–67.
Van den Bulte, C., & Wuyts, S. (2007). *Social networks and marketing.* Cambridge, MA: Marketing Science Institute.
Venkatraman, M. P. (1989). Opinion leaders, adopters, and communicative adopters: A role analysis. *Psychology and Marketing*, *6*(1), 51–68.
Watts, D. J. (2007). The accidental influentials. *Harvard Business Review*, *85*(2), 22–23.
Watts, D. J. (2010). *Private communications.*
Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. *Journal of Consumer Research*, *34*(4), 441–458.
Weimann, G. (1983). The strength of weak conversational ties in the flow of information and influence. *Social Networks*, *5*(3), 245–267.
Weimann, G. (1991). The influentials: Back to the concept of opinion leaders? *Public Opinion Quarterly*, *55*(2), 267–279.
Yan, E., & Ding, Y. (2009). Applying centrality measures to impact analysis: A coauthorship network analysis. *Journal of the American Society for Information Science and Technology*, *60*(10), 2107–2118.