



**Social Networks
in New Product Forecasts
and Marketing**

Christian Pescher

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Eingereicht bei:
Prof. Dr. Martin Spann

Zweitgutachter:
Prof. Dr. Rolf Bühner

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Index of Symbols

ActualValue _{xi}	realized value of group i's item x
C _B	betweenness centrality
C _C	closeness centrality
C _D	degree centrality
c _{jk}	extent to which consumer j's network is directly or indirectly invested in a relationship with contact k
Change _{FA}	change in forecasting accuracy
CONF _{xij}	stated confidence of informant j, member of group i, regarding item x
d(j)	degree of informant j = number of actor j's direct contacts
DIST _{xij}	distance between informant j's individual forecast of item x and the actual value of item x in group i
DS(j)	density in the egocentric network of actor j
f	index for informants within a network
g _{fl}	geodesic path (shortest distance) between two informants f and l
g	number of actors in an egocentric network excluding the informant = number of direct contacts of the informant
i	index for a group of informants
j	index for informants within a network
k	index for informants within a network
l	index for informants within a network
L	number of ties present between all direct contacts of informant j in her egocentric network
m	index for products
MAE	mean absolute error
MAPE	mean absolute percentage error
MS _s ^{forecast}	forecasted market share for product s
n _i	number of informants in group i
NC(j)	network constraint index of consumer j
NM _{xij}	network measure of informant j, which is used as a weight in the aggregated forecast of group i regarding item x
p _{jk}	proportion of consumer j's network time/energy invested in contact k
s	index for a product which is forecasted
t	index for a given time period
w _i	weight of informant i
WCOMPMEAN _{xi}	weighted competence based mean of item x for group i
WCONFMEAN _{xi}	weighted confidence based mean of item x for group i
WEIGHT _{xij}	weight, informant j's forecast receives in group i's aggregated forecast regarding item x
WSMEAN _{xi}	weighted information based mean of item x for group i
x	index for items that are subjects to forecasts
x _s	vector of the product attributes that form product s
X _{ij}	individual forecast of informant j, member of group i, regarding item x
Z _{jk}	intensity of consumer j's relationship with contact k
β _j	vector of the utilities consumer j assigns to the different product attributes

Index of Abbreviations

cf.	(latin: conferre) compare
CJF	combined judgmental forecasts
DV	dependent variable
e.g.	(latin: exempli gratia) for example
H	hypothesis
HP	Hewlett Packard
HBCBC	hierarchical Bayes choice-based conjoint analysis
i.e.	(latin: id est) that is
IS	information seeking
MBA	master of business administration
n.s.	not significant
no.	number
OL	opinion leadership
PK	product knowledge
R&D	research and development
SE	standard error
sig.	significance
SII	susceptibility to interpersonal influence
SNA	social network analysis
STD	standard deviation
VIF	variance inflation factor
WOM	word of mouth

1. Introduction

1.1 On the Relevance of Social Interaction in Forecasting and Marketing

The forecasting of market developments and the gathering of information, which is necessary to forecast these developments, are key problems in entrepreneurial planning (Lilien & Rangaswamy 2004; Spann, 2002). Inaccurate forecasts can have severe consequences for a company (Armstrong, 2001), which are based on two possible outcomes on the production level. The first outcome is overproduction. If companies produce too much of a good, they can store it, sell it with discounts or they can dispose it. All three options lead to higher costs or to lower revenues and thus lower the surplus compared to situations in which the forecasting is accurate. The second outcome is underproduction. If consumers cannot purchase the product they want to, the results can include lost sales or, if consumers purchase a competitor's product, lost customers. Once the customer is lost, it might be very difficult and costly to win her back.

There are two streams of literature in forecasting. The first stream uses econometric and statistical methods based on existing data to generate their forecasts. Examples include exponential smoothing or Box-Jenkins-models (Box, Jenkins & Reinsel, 2008; Gardner, 1985). They are useful in stable market conditions. The second stream deals with forecasting in conditions that include high uncertainty, e.g., unstable market conditions or when there is no data available, e.g., in case of new product introductions. In these forecasting situations researchers use alternative methods, which are mostly survey based (Armstrong, 2001). In those cases, researchers either survey experts or consumers. In the former case, they survey a limited number of experts and use methods like combined judgmental forecasts or the Delphi method to aggregate their responses (Dalkey & Helmer, 1963; Ferrell, 1985; Rowe & Wright, 1999; Schmidt, 1997; Van Bruggen, Lilien & Kacker, 2002). In the latter case, they can survey consumers using conjoint analysis (Green, Krieger & Wind, 2001; Green & Srinivasan, 1978; Green & Srinivasan, 1990). Especially in situations where information is scarce, such as forecasts regarding new products, every additional piece of information can help to improve the forecasting accuracy. One example that literature has not analyzed yet, is the consideration of data about social interaction between individuals, like experts or consumers, in forecasts.

Social interaction takes place within social networks. Social networks can be analyzed with social network analysis (Van den Bulte & Wuyts, 2007). Social networks are omnipresent, wherever humans are. In marketing literature, they have gained importance over the past decade.

The positions actors take within their social networks provide relevant information, e.g., on their information level or on their status. They can be considered in forecasts and thus improve them. To date, it is unclear how the patterns of interconnections between the individuals affect the quality of experts' individual forecasts. Social interaction can influence experts and consumers in a variety of ways. Experts in a given field tend to know each other and to exchange information (Borgatti & Cross, 2003). This can lead to information benefits of some experts. Two examples are hubs and brokers. Experts who talk to many people, the so-called hubs, are likely to possess more relevant information than experts who only talk to very few people. Experts whose position is between clusters, the so-called brokers, can combine information from different clusters and thus possess more non-redundant information than experts who are deeply involved in a single cluster. Similar mechanisms are at work among consumers. Consumers influence each other, e.g., in their purchase decisions (Burnkrant & Cousineau, 1975). Some consumers are more likely to influence other consumers in their purchase decisions than others. Again, hubs and brokers are potentially important. Whereas brokers can be helpful in the transmission of information about new products or trends from one cluster to others (Burt, 1992), hubs tend to have a high influence on other consumers that are related to them (Goldenberg, Han, Lehman & Hong, 2009).

Accounting for regular patterns of social interaction can help to improve forecasting accuracy. The development of approaches how this can be done is this thesis' main contribution to literature.

1.2 Goal of Thesis

The goal of this thesis is to show how social network analysis can help to improve new product success forecasts and other marketing-related activities. The approaches will be deduced from theory and tested in empirical studies.

This thesis answers the following research questions in detail:

1. What methods exist to collect social network data?

Before researchers can study new ideas and approaches related to social networks, they first have to measure the network. Chapter 2 provides an overview over existing methods to measure social networks as well as their advantages and disadvantages. The focus lies on the so-called egocentric networks, because this method is suitable in large scale survey based studies, where no data about the total network is available.

2. How can information from social networks be used to improve experts' forecasts?

Before companies develop new products, they often consult experts to generate the forecasts. But every expert is likely to make random errors in her or his forecasts. Thus, companies survey several experts and aggregate the individual forecasts. The reason is that random errors balance each other out. Thus, the aggregated forecast tends to be more accurate than individual forecasts. This is the key idea behind the concept of combined judgmental forecasts. Literature found out that forecasting accuracy improves if experts, who are likely to provide more accurate forecasts, receive a higher weight in the aggregated forecast (Van Bruggen, Lilien & Kacker 2002). The key task is to identify indicators that provide information about the forecasting accuracy. Social networks can provide these indicators, because experts tend to communicate with each other – for example within a company or in internet communities. Therefore the social network provides information about the level of information each expert has access to. Experts with a more solid information base tend to give more precise individual forecasts – and should thus receive higher weights in the aggregated forecast. Chapter 3 develops a procedure for the consideration of social network indicators in combined judgmental forecasts.

3. How can social network data help to consider the role of influentials in preference-based market forecasts and thus improve them?

Companies usually run conjoint analyses that analyze consumers' preferences in early stages of the new product development process, when they still have the option to alter the product according to the consumers' needs. Thus, conjoint analyses display consumers' preferences at the time of the survey. A longer time period can pass before the product is introduced into the market. In that time period, consumers' preferences are subject to change, e.g., due to interpersonal influence. This influence takes place within social networks, in which some users are more influential than others (Iyengar, Van den Bulte & Valente 2011; Van den Bulte & Joshi, 2007). Chapter 4 develops an approach that takes into account the important role of influentials and thus considers the changes in consumers' preferences, which occur between the conjoint analysis and the product's market introduction, in preference-based market forecasts.

4. Does the brokerage position provide information about the actor's role in social interaction and about the underlying preferences?

One of the main benefits of social networks is that they provide information about the consumers. Two important roles are hubs, who generally possess a lot of ties, and brokers, who

can be found in boundary-spanning position. Whereas the former one has received a lot of attention among marketing scholars (Goldenberg, Han, Lehmann & Hong, 2009), the latter one has not drawn a lot of attention among marketing scholars yet. This is surprising because for the success of seeding strategies it is very promising for companies to send information to a few brokers, who distribute this information into various parts of the network. Chapter 5 focuses on the role of brokers in the process of social interaction and analyzes, how brokers' preferences are different from the preferences of other actors.

5. What factors influence the success of viral marketing campaigns – psychographic constructs or social networks?

Viral marketing campaigns are interesting for companies because they offer the benefit that they can potentially be run with very low costs. In theory, companies only have to send a message to a small number of seeding points. The seeding points forward the message to their peers, who forward it to their peers, and so on (Godes & Mayzlin, 2009). Researchers have analyzed referral behavior with psychographic constructs (De Bruyn & Lilien, 2008; Okazaki, 2008) and with social network measures (Bampo, Ewing, Mather, Stewart & Wallace, 2008; Hinz, Skiera, Barrot & Becker, 2011). Chapter 6 develops a multi-stage model to analyze, what type of indicators significantly explains the campaigns' success on which stage of the process.

1.3 Structure of Thesis

Figure 1.1 illustrates the layout of this thesis and provides information about the key idea of each research project, the sample selection, and the group of subjects of each study. If a researcher plans to conduct a social network study, the first step is to measure the network. Chapter 2 compares different methods that researchers can use to collect social network data. The following chapters conduct empirical studies in the areas of forecasting and marketing. Chapter 3 shows how social network data can be used to improve combined judgmental forecasts of experts. Chapter 4 describes how social networks can help to consider the role of influentials in market forecasts. It uses consumer data. Chapters 5 and 6 focus on applications of social networks in marketing. Chapter 5 analyzes the role of brokers in the process of social interaction and whether they are good seeding points or not. Chapter 6 develops a multi-stage model of consumers' decision making process in viral marketing campaigns and assesses the influence of social network measures and psychographic constructs on each stage. This thesis ends with a summary and the implications of this thesis in chapter 7.

Figure 1.1: Layout of Thesis

Application of Social Network Analysis in Forecasting and Marketing				
Collection of Social Network Data (Chapter 2)				
Applications in New Product Success Forecasts		Applications in Marketing		
Chapter	Chapter 3	Chapter 4	Chapter 5	Chapter 6
Key Idea	Consideration of information from experts' social networks improves combined judgmental forecasts for new products	Consideration of information from consumers' social networks improves forecasts based on conjoint analyses	Analysis of brokers' role in the process of social interaction helps to determine whether they are suited for seeding strategies	Development of a multi stage model of consumers' decision making process to analyze forwarding behavior in referral campaigns
Data Collection	Students forecast key marketing indicators in a simulation game	Representative sample of consumers of the German mobile phone market provides information about psychographic constructs, social networks and carries out a conjoint analysis		Participants of a viral campaign provide information about stages in their decision making process, psychographic constructs, and their social network
Sample	Experts	Consumers	Consumers	Consumers
Summary and Implications (Chapter 7)				

2. A Comparison of Methods to Measure Social Networks

Summary

Social interaction has an influence on consumption decisions. Examples for related concepts from marketing literature include word-of-mouth and opinion leadership. Further, the analysis of existing research questions from the social network perspective can help to generate new and interesting insights. Usually, the networks in which consumers exchange their information are measured with survey-based methods and analyzed quantitatively. However, the measurement of total networks may not always be possible due to the size of a network. Instead, scientists use the concept of egocentric networks. They can be generated by interrogation of only one respondent and allow interesting insights in the respondent's relational structure. Egocentric networks can be measured in questionnaires and the related measures can be interpreted easily. That way, the relational level can be considered in future projects in empirical and research-oriented marketing projects.

2.1 Introduction

Social Interaction plays an important role in the development of consumers' preferences (Grewal, Mehta & Kardes, 2004; Woodside & Singer, 1994) and consumers' satisfaction (Bohlmann, Rosa, Bolton & Qualls, 2006). Further, social interaction can have an influence on consumers' choices (Brock & Durlau, 2001). Research dealing with social interaction and its consequences can be found in various academic disciplines, including psychology, sociology, and marketing. Examples from Marketing that deal with social interaction include word-of-mouth, diffusion models, opinion leadership, status consumption and brand congruence (Van den Bulte & Wuyts, 2007). Over the past years, researchers witnessed a strong increase in research activities in the area of social networks in marketing and other research areas (Borgatti, Mehra, Brass & Labianca, 2009; Goldenberg, Libai, Muller & Stremersch, 2010).

Social interaction takes place in networks of relationships. The analysis of these networks can offer new insights into existing problems. For example, it is possible to analyze opinion leaders using social network analysis. Iyengar, van den Bulte and Valente (2011) show that opinion leaders, that were identified within social networks (sociometric opinion leaders) and opinion leaders, that were identified with psychographic constructs (psychographic opinion leaders), tend to be different in their characteristics. Another advantage of social network analysis is that information from the networks can be used to develop new and innovative marketing strategies. Sociometric indicators can tell companies, which consumers should be contacted or informed in order to get their messages distributed to a high number of other consumers via word-of-mouth; i.e., they receive information on which seeding strategy is best suited for a viral campaign (Hinz, Skiera, Barrot & Becker, 2011). The main idea behind this approach is to use the marketing budget in a more efficient way (Watts, Peretti & Frumin, 2007). In that context, one important assumption is that consumers tend to consider information which stems from their peers as more reliable than information from sources they do not know.

Before one can analyze social networks and interpret the results, the networks first have to be measured. Whereas in sociology the units tend to be small and to have clearly defined boundaries, e.g., families or school classes, in marketing the situation is quite different: the entities tend to be large. They have too many members to survey each member of the resulting network, e.g., national consumer segments. Further, a high response rate is necessary to measure total networks. However, high response rates usually cannot be reached in large scale survey-based investigations. Thus, egocentric networks can help in these conditions: to measure egocentric networks, it is only necessary to survey single consumers within the network. In many

survey situations they are suited in a better way than alternative methods to measure networks. They form the basis to use the findings of social network analysis in surveys with a high number of respondents, which are common in marketing research.

Therefore, the goal of this section is to present the survey-based method to measure consumer networks, to describe it and compare it to alternative methods to gather network data: snowballing and the measure of total networks. A higher awareness among researchers of the method of egocentric networks can be helpful to analyze more interesting research questions and thus to gain more insights into existing problems.

This section is built up the following way: section 2.2 will display the relevance of the analysis of social networks in marketing. Section 2.3 will give a brief introduction in social network analysis and will display and compare common methods to measure social networks. The egocentric method will be in the focus. This section closes with a brief summary in section 2.4.

2.2 Social Networks

2.2.1 The Relevance of Social Networks in Marketing

Over the past years, there has been an increase in the number of publications that deal with social networks in the international marketing literature. According to van den Bulte and Wuyts (2007) one of the most important reasons is the decreasing effectiveness of traditional marketing expenditures, such as advertising. Therefore companies search for methods that can be helpful to use the existing marketing budget in a more efficient way. Consumers are more open for information they receive from other consumers, than for information they receive from impersonal sources (Gilly, Graham, Wolfinbarger & Yale, 1998; Herr, Kardes & Kim, 1991). In viral campaigns, the social network offers indicators, which clients should be targeted to increase the effectiveness of the campaign, i.e., which seeding strategy is best-suited (Hinz, Skiera, Barrot & Becker 2011). In marketing research, a detailed analysis of consumers' networks can lead to new insights in market segmentation, product positioning, and communication (Van den Bulte & Wuyts, 2007) or in the analysis of the impact of information diffusion on consumers' willingness to pay (Hinz & Spann, 2008).

2.2.2 Influence in Social Networks

The reasons why consumers can be influenced include uncertainty about a product they are planning to buy, as well as status issues within the consumer's reference group (Goldenberg, Lehmann, Shidlovski & Barak, 2006). The reference group consists of people who possess a

relevant influence on the consumer's consumption behavior (Amaldoss & Jain, 2008; Bearden & Etzel, 1982). The reference group's influence on individual consumption habits can be divided into two categories: informational and normative influence (Burnkrant & Cousineau, 1975; Deutsch & Gerard, 1955). Normative influence describes the tendency to act in a way that other people expect one to act in order to be accepted by the group (Bearden, Netemeyer & Teel, 1989). Informational influence describes the tendency to accept information obtained from other people to be correct. Both types of influence can work in an active or in a passive way. One example for passive influence would be, if consumers observe what types of mobile phones other consumers are using and unconsciously associate the person, or the person's status, with the brand. An example for active influence is to ask other people for their opinion about a certain mobile phone.

Informational Influence

Consumers exchange information about products. As a consequence, they develop or modify their preferences. This can lead to a number of consequences. First, informational influence can create awareness for a certain product among consumers (Liu, 2006). Second, informational influence can help to decrease uncertainty about product characteristics, if consumers are about to buy a new product (Nowlis & Simonson, 1996). The reason is that consumers often do not know how to judge specific product characteristics. Therefore, they are open to the information they receive from other consumers who know more about the product than themselves. For example, consumers talk to their peers before they purchase a new mobile phone. The importance of product attributes they considered to be little important before talking to their peers can increase in the perceived importance after talking to their peers. Third, information from a direct contact tends to have a strong influence on consumption decision. The reason is that the sender of the information tailors to the recipients needs, if they know each other (Gilly, Graham, Wolfenbarger & Yale, 1998).

Normative Influence

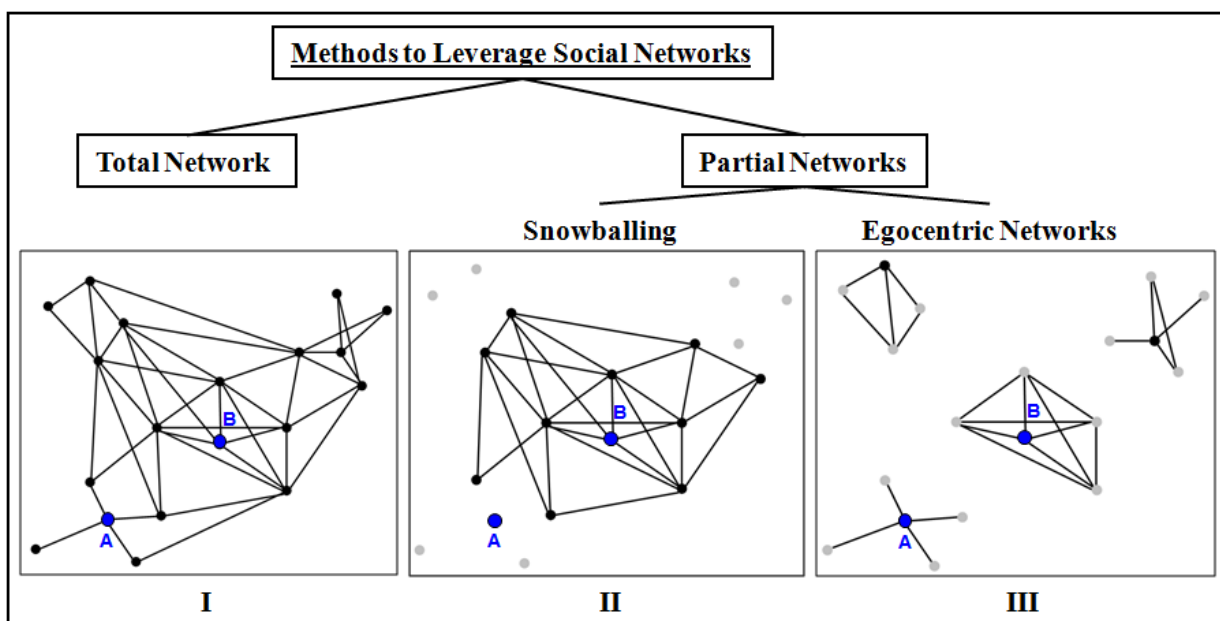
Consumers may alter their behavior due to normative pressure. The goal is to become or remain member of a group or to avoid sanctions by the reference group (Batra, Homer & Kahle, 2001; Rook & Fisher, 1995). The use of certain products can influence a consumer's status within the group (Burt, 1987); they are called status products. They influence the image other people have of them. As a consequence, consumers anticipate the reactions of their peers in their consumption behavior. They may become dissatisfied, if their peers within the reference group

possess certain “new” products which they do not possess themselves (Davis, Bagozzi & Warshaw, 1989; DiMaggio & Powell, 1983). Consumers in central roles tend to influence other consumers (Goldenberg, Lehmann, Shidlovski & Barak, 2006; Valente & Davis, 1999). Contrary, actors who are rather between than within reference groups, tend to be independent in their consumption decisions (Burt, Jannotta & Mahoney, 1998). Normative pressure tends to be higher for goods that are publically visible than for goods, which are used in private (Bearden & Etzel, 1982). If goods are consumed jointly, e.g., TV program or pizza, preferences of the consumers who share these products tend to be more homogeneous than for goods, which are consumed individually (Reingen, Johnson & Seidman, 1984).

2.3 Methods to Measure Consumers’ Networks

In a network of consumers, the consumers, which are called actors, are represented by dots, which are called nodes. The relationships between each pair of consumers are represented by lines, which are called edges. Nodes and edges are usually measured within boundaries, that are defined by the subject of research (Marsden, 1990). For example, the nodes can be members of a specific class of schoolchildren and the edges can represent friendship or communication (Kratzer & Lettl, 2009). Another example could be that the nodes are the employees of a company and the edges the information flow between them (Cross & Cummings, 2004). After the definition of the boundaries, researchers can choose between three methods to measure nodes and edges that exist within these boundaries. Figure 2.1 displays these three methods.

Figure 2.1: Three Methods to Measure Social Networks



2.3.1 Total Networks

Figure 2.1(I) displays a census of a total network, e.g., a school class. The steps to reach the network are the following. First, the researcher has to define the boundaries. Second, she has to identify all actors that exist within the boundaries before surveying them. This procedure is fairly easy within small networks like sport teams or small companies. Third, in order to measure the edges – which display the relationships between the actors - all actors receive a list which shows all other actors that exist within the network. They individually provide information about the strength of relationship to each of the other actors. In order to measure the total network, all actors have to be surveyed. As a consequence, the effort to measure the network tends to be high. Once the total network has been measured, researchers possess a wide variety of social network measures to analyze it in detail (Wasserman & Faust, 1994).

2.3.2 Snowballing

Figure 2.1(II) displays the snowballing procedure. Although it can be used to identify a total network, researchers usually use it to identify partial networks. In the snowballing procedure one first has to identify an actor, who is a member of the target network. Then, this actor is asked to name her direct contacts within the networks' boundaries. In the next step, the contacts are asked to name their contacts. This procedure is repeated until the total network or at least a sufficiently large proportion of the network has been mapped. Johnson Brown and Reingen (1987) used this procedure to reconstruct consumers' referral chains. Once the network has been measured, researchers possess the same network measures to analyze the network as total networks. But the quality of these measures decreases with an increasing number of network actors who were not identified.

2.3.3 Egocentric Networks

Another method to analyze partial networks is the use of egocentric networks (Burt, 1984; C. Fischer, 1982; Marsden, 1990, 2007). Egocentric networks can help to analyze the individual actor's network position with respect to personality (Burt, Yanotta & Mahoney 1998) or outcome related variables like salary, promotion (Burt, 1999) or the quality of ideas (Burt, 2004).

Each egocentric network analyzes a single actor of the total population, called "ego", and her contacts, the "alters". The information about this small network is obtained from only one respondent, ego. This includes information about the relationships between the alters. In order to identify an egocentric network, research uses two types of questions: "name generators" and "name interpreters" (Burt, 1984).

2.3.3.1 Name Generators

Name generators help to generate a list of alters. Usually, in the case of egocentric networks researchers use open questions to generate this list. In that context, the first question that has to be answered is how many name generators should be used. In the General Social Survey of 1985, Burt (1984) uses only one name generator, Fischer (1982) uses over 10 in the Northern California Communication Study, and the Social Support Questionnaire (Sarason, Levine, Basham & Sarason, 1983) has more than 20. In a study about job-related relationships of managers Burt (1997) recommends to use multiple name generators which should cover at least the dimensions “emotional closeness” and “activity”. The latter one can be measured in time units.

Whereas the use of only one generator helps to gain insights into a core network, a higher number of name generators can be helpful to display almost the entire network of a person (Marsden, 2007). With a single name generator Burt (1984) gained an average network size of three people, whereas the average network size of Fischer’s (1982) ten name generators was more than eighteen. In a marketing context, researchers should determine what part of the network is most likely to have an influence on the consumer. If it is likely to be a relatively small group of people, one or two name generators should be enough. For example, if a consumer plans to buy a tennis racket, it is likely that she will seek advice from her contacts in the tennis club. If the wider network is likely to influence the consumer in a certain way, a higher number of name generators can be appropriate. A typical objection against the use of egocentric networks is that respondents might forget to name contacts. Based on several recall-recognition (Brewer, 2000; Brewer & Webster, 2000; Sudman, 1988) and test-retest studies (Arnold, 1994; Barrera, 1980; Bell, Belli-McQueen & Haider, 2007; Schwarzenbacher & Baumann, 1990; Veiel, 1990) researchers came to the conclusion that the quality of egocentric network data decreases with decreasing strength of the relationship between ego and the alters.

2.3.3.2 Name Interpreters

Researchers use name interpreters for three different reasons (Marsden, 1990). First, they use them to measure attributes of ego and the alters, e.g., sex or age. Second, they can be used to describe the relationship between ego and the alters. Examples are indicators for the strength of a relationship, e.g., frequency of contact, duration of the relationship or intimacy of the relationship (Marsden & Campbell, 1984). Third, researchers use name interpreters to gain information about the relationship between pairs of alters. In this context, name interpreters form a fundamental basic for the construction of egocentric networks, which are used to calculate the

indicators. Once the list of alters has been measured with a name generator, it is generally recommended to analyze the relationship network between ego and three to five alters in depth. The main reason is that in this way, the effort of surveying remains at an acceptable level, but density can already be calculated with an acceptable level of reliability (Marsden, 1993).

2.3.4 Characteristics of Contexts of Network Studies and Suitable Methods to Identify Networks

Ideally, researchers can measure total networks with clearly defined borders and a manageable amount of actors. Examples include the marketing department of a medium-sized company or a class of schoolchildren.

However, in many settings which promise new insights the situation is quite different than described above. As a consequence, it is often impossible to measure total networks. In order to gain the insights social network analysis can provide, researchers developed the tools you can find in table 2.1.

Table 2.1: Overview over Methods to Measure Networks

		Number of Actors in a Network	
		Low	High
Informational Data about the Actors within the Boundaries of the Network	Partial	„Snowballing“	Depends on Research Question
	Full	Total Network	Egocentric Networks

If the database about the actors within the boundaries of a network is only partial, e.g., due to unclear boundaries of the network, the snowballing method is most suitable. The reason is that it is the only method, in which most of the actors within the network are identified during the study. This method is well-suited if the information flow should be analyzed in detail (Johnson Brown & Reingen 1987) or if there are privacy concerns in the subject of research (Heckathorn, 2002).

If the number of actors within the network is fairly high, for example all citizens of the United States of America, and if at least a part of the network participants are known to the researchers, they can use egocentric networks. Because the relevant information for the mapping and analysis of an egocentric network is obtained from a single actor, egocentric networks can be used for samples, too. Further, egocentric networks are useful when the response rate is expected to be low. If there is neither data available on the actors within the network nor information about the

numbers of actors within the network, generally it is not possible to measure the network. In this case, additional information has to be obtained.

2.3.5 A Comparison of the Methods to Measure Networks

Different methods to measure social networks possess different characteristics, which make each method more or less suitable for certain studies. There are three characteristics researchers should consider before they choose a specific method to measure and analyze their network.

The first aspect researchers should consider when choosing the method is the effort which is necessary to perform the study. For total networks, this effort is medium. Usually total networks are based on a solid database about the actors of a network – and almost all of them should participate in order to receive valid results. If single actors do not answer the questionnaire, the researcher can approach them systematically and ask them to fill it out. If there is no solid database about the actors within the boundaries of the network, researchers can use snowballing. As in the snowballing method, the actors of a (partial) network are identified with the help of an iterative process, this method tends to take a lot of effort. Compared to total networks and snowballing, egocentric networks require low response rates, because the participants of the study do not have to interact directly with each other. Thus, the effort to measure the network is fairly low. Figure 2.1 compares the methods directly. In all three methods, only the actors colored in black and blue have to answer the questionnaire. As you can see in figure 2.1, this number is lower for egocentric networks in (III) than for the total network (I) or the snowballing method (II). Therefore the effort the researcher has to put in to map the network is lower for egocentric networks than for both of the other methods.

The second aspect researchers should consider when choosing the method is the expected response rate. Due to the lower acceptable number of participants egocentric networks are appropriate in research situations where one can expect a low response rate – additional surveying rounds for non-responses, as in total networks, or iterative processes to increase the response rate, as it often can be observed in snowballing procedures, are not necessary. Therefore in situations with a low response rate, egocentric networks provide relevant benefits to the researcher.

The third aspect researchers should consider when choosing the method is the variety of social network measures that are available when analyzing the network. In total networks and snowballing, researchers usually possess a large, connected network in the end. This allows them to calculate a large number of indicators, which can be divided into local and global indicators.

Local indicators only analyze the relationship structure among the direct contacts of each individual. One example for a local indicator is degree centrality. The degree centrality is calculated based on the number of direct contacts of each person (Freeman, 1978). Global indicators are calculated based on the individual's position within the total network. One example for a global indicator is closeness centrality, because it is the average length of the shortest communication path to all other actors in the network. Its calculation requires information from direct and indirect contacts (Freeman, 1978). For details see Wasserman and Faust (1994). In the case of egocentric networks the data only allows to calculate the local indicators. Three important centrality measures in total networks are degree centrality, betweenness centrality and closeness centrality (Freeman, 1978). Degree centrality can be interpreted as measures for popularity or opinion leadership (Freeman, Roeder & Mulholland, 1979/80; Kratzer & Lettl, 2009; Stafford, 1966). Betweenness centrality describes the degree to which an actor lies between dispersed parts of a network (Freeman, 1978). These actors can access and pass on information from different parts of the network (Scott, 2005). Actors with a high closeness centrality can spread information efficiently due to their short communication paths (Freeman, 1978). Marsden (2002) compared the results of egocentric networks and total networks for these three measures using several well-known data sets and came to the conclusion, that egocentric degree centrality is a good indicator for degree centrality in total networks. Surprisingly, the same generally holds for betweenness centrality. However, in the case of closeness centrality, which clearly is a global measure, because it considers paths that include many steps, it is impossible to calculate it based on egocentric networks. When we take a closer look at figure 2.1 (I and III), this idea becomes clear. Egocentric networks display well the relationships among the direct contacts of consumers A and B. However, contrary to the total network (I) and snowballing (II), egocentric networks (III) do not contain any information that could explain that actor B is a central actor within the global network, whereas actor A can rather be found at the border of the network.

If we analyze the difference between total networks and snowballing, the same measures can be used to analyze these networks. However, as mentioned above, the quality of the measures decreases with an increasing number of nodes which are missing in the dataset. In this process respondents tend to forget the weak ties rather than the strong ties (Brewer, 2000; Brewer & Webster 2000). Since total networks usually are mapped with the help of existing lists of the network members, whereas snowballing works with name generators which can potentially be vulnerable to the forgetting of contacts, especially the measures that provide information about

the weak ties should be treated with caution. One example is the concept of key bridges between clusters (Friedkin, 1980). Table 2.2 displays the results of the comparison of different classification approaches to analyze networks.

Table 2.2: Comparison of Different Classification Approaches to Analyze Networks

Method of Leveraging the Network	Total Network	Snowballing	Egocentric Networks
Effort Needed to Measure Network	Medium	High	Low
Applicability if Response Rate is Low	Low	Low	High
Variety of Network Measures Available	High	Medium	Low

2.4 Discussion

Researchers can choose between different approaches to analyze social networks. The most common method is to use total networks. However, it might not always be possible to work with total networks. This can have a variety of reasons. First, the number of consumers might simply be too big to be measured in many large-scale empirical studies that are common in marketing – e.g., in the analysis of segments with thousands of consumers. Second, researchers need a very high response rate in order to generate the total network. Third, total networks cannot be measured if the information about the actors within the networks is limited.

In these cases researchers can use methods to measure partial networks. Two methods are available: snowballing and egocentric networks. First, in the case of snowballing, researchers use an iterative process until they reconstructed a part of the total network, which is large enough to analyze their subject of research. Second, they can use egocentric networks. Egocentric networks are generated based on the information of only a single consumer. They analyze only the direct contacts of each consumer. Thus, they are easy to measure and only require limited effort – and they are suitable for large scale empirical studies. However, the variety of network measures which can be calculated based on these is also limited.

The detailed discussion about egocentric networks in this section can help to provide access to a higher number of researchers. If more researchers were aware of this method, they could gain new insights in many existing and new researcher problems. They could develop more efficient viral marketing campaigns or analyze social networks to gain insights in consumers’ preferences. The networks, which will be analyzed in the following chapters, possess different characteristics.

In chapter 3, the data set consists of a relatively small number of students of a German university's marketing course. The boundaries are clearly defined and full information on the participants was available. Thus, the conditions allowed the measurement of a total network. Contrary, the data sets of chapters 4 and 5, which analyze the same data set, and chapter 6 possess different characteristics, which make the measurement of the total network almost impossible. The chapters 4 and 5 analyze a data set, which is a representative sample of German cell phone users. Clearly, measuring the total network of all German cell phone users is hardly possible, because there are several millions of them. Furthermore, if someone only takes a representative sample of a few hundreds of them, it is likely that the members of this sample are no direct contacts. Therefore, the measurement of the total network within the consumers who participate in the sample is of little use. To overcome these shortcomings, chapters 4 and 5 use egocentric network measures. Chapter 6 consists of a survey, which was a follow-up study of a large-scale viral marketing campaign which was conducted by a German telecommunication company with several thousand customers. The network was measured using a questionnaire. Given the high number of participants, high response rates and direct connections among the participants were unlikely. Thus, this data set also used egocentric networks to collect the participants' social networks. Details on the data sets will be provided within the chapters 3, 4, 5, and 6.

3. Social Network Based Judgmental Forecasting¹

Summary

Forecasting is especially challenging in high-uncertainty environments, e.g., due to unstable market conditions. A popular method to generate reliable forecasts in conditions of high uncertainty is judgmental forecasting, in which a number of informants is asked for their estimates. Improvements in forecasting accuracy can be gained by assigning weights to those forecasts that are likely to be more accurate. The structural position of each informant in a social network can be a good indicator for the informant's access to information, which has not been analyzed in literature yet. The authors show that in conditions of high uncertainty social network based weights can improve forecasting accuracy compared to weighting approaches discussed in recent literature. They find that informants in boundary-spanning positions, i.e., informants with a high betweenness centrality, should be assigned the highest weights.

¹ This study is based on the working paper:
Pescher, Christian; Spann, Martin (2010): Social Network Based Judgmental Forecasting. Working Paper, LMU München.

3.1 Introduction

The generation of reliable forecasts is especially challenging in situations of high uncertainty when they are most needed. Combined judgmental forecasts (CJF) (Armstrong, 2001; Ferrell, 1985) have been found to provide satisfying forecasts. Van Bruggen, Lilien, and Kacker (2002) demonstrate that assigning weights to informants' judgments can improve forecasting accuracy compared to the simple mean. Thus, a solid aggregation approach is a crucial step in order to reach a high forecasting accuracy.

Considering the informants' individual capability to provide reliable forecasts can help to improve combined forecasts' accuracy (Van Bruggen, Spann, Lilien & Skiera, 2010). However, they do not consider differences in informants' access to information, which may be relevant to the forecasting issue. An individual's position in a social network reveals his or her communication paths as well as potential access to (heterogeneous) information (Rodan & Galunic, 2004; Sammarra & Biggiero, 2008). Informants who are in central positions are likely to have access to more information than informants at the periphery of the network. Usually parts of this information are exclusive to the informant, because information tends to be sticky (Von Hippel, 1994). Social network analysis (SNA) (Wasserman & Faust, 1994) can help to analyze and visualize the information flows within the network (Cross & Parker, 2004). SNA provides a number of measures which can help to evaluate the level of information each informant possesses. Higher levels of information potentially lead to improved forecasts.

Therefore the goal of this paper is to consider the information access via informants' social networks in the aggregation of forecasts from multiple informants. Therefore, we analyze the accuracy of social network based weights in aggregating judgmental forecasts from multiple informants and compare the results to the existing informant-based weights in conditions of different degrees of uncertainty.

The key contribution of our paper is that we show that in situations of high uncertainty social network based weights yield the highest forecasting accuracy. In those cases informants in boundary-spanning positions, i.e., informants with a high betweenness centrality, should receive the highest weights. Contrary, in situations of low uncertainty, confidence-based weights perform best.

The remainder of this paper is structured as follows. In section 2, we will discuss different methods of pooling information. In section 3, we will show how to combine judgmental forecasts and we will determine how social network measures can help to improve forecasting

accuracy. In section 4, the aggregation based on social network measures is tested and compared to informant-based measures in a laboratory experiment. The article concludes with the discussion of the implications of our results in section 5.

3.2 Aggregation Information

3.2.1 Methods to Pool Information

Literature uses the term behavioral aggregation if informants have the option to interact (Garthwaite & Kadane, 2005). Informants share their information in groups and discuss them. That way the group can consider more information in their collective forecast than each informant could consider in her individual forecast (Dennis, Valacich, Connolly & Wynne, 1996). The formation of groups is useful when all members have partial and biased information but collectively can compose a less biased pool of information (Stasser & Titus, 1985). However, in discussions it cannot be assured that the relevant information is shared with the group (Hightower & Sayeed, 1996; Stasser, 1992). Often, groups tend to focus on the information which is shared by many members and not on sharing information which is exclusive to one or a few individuals. Other shortcomings are that group discussions cost a lot of time and that they are limited to a certain number of informants. Group discussions and other behavioral approaches face the problem that informants might fail to agree on a consensus. If they reach a consensus, it can be based on informants' status and personality instead of the information. Thus, forecasts stemming from a group of informants can be vulnerable to biases due to a selection of implausible decision criteria.

In order to overcome the deficits of methods that use direct interaction, researchers developed the Delphi Method (Dalkey & Helmer, 1963; Rowe & Wright, 1999; Schmidt, 1997). It is an iterative method in which experts share their knowledge anonymously for several rounds. It also suffers from drawbacks: the experts have to be chosen carefully and the iterative nature of the process takes a lot of time. In many cases, informants do not reach a consensus. In those cases other aggregation approaches have to be used.

One such method are prediction markets (Forsythe, Nelson, Neumann & Wright, 1992; Spann & Skiera, 2003) which elicit and aggregate the information available to informants through the market mechanism of a virtual stock market in which participants trade their expectations about the future outcomes as shares of virtual stock. They work well for forecasting tasks that are interesting for a lot of participants, like new products, sports, or presidential elections. Recent

research has shown that they even work for small groups of as few as six participants (Van Bruggen, Spann, Lilien & Skiera 2010).

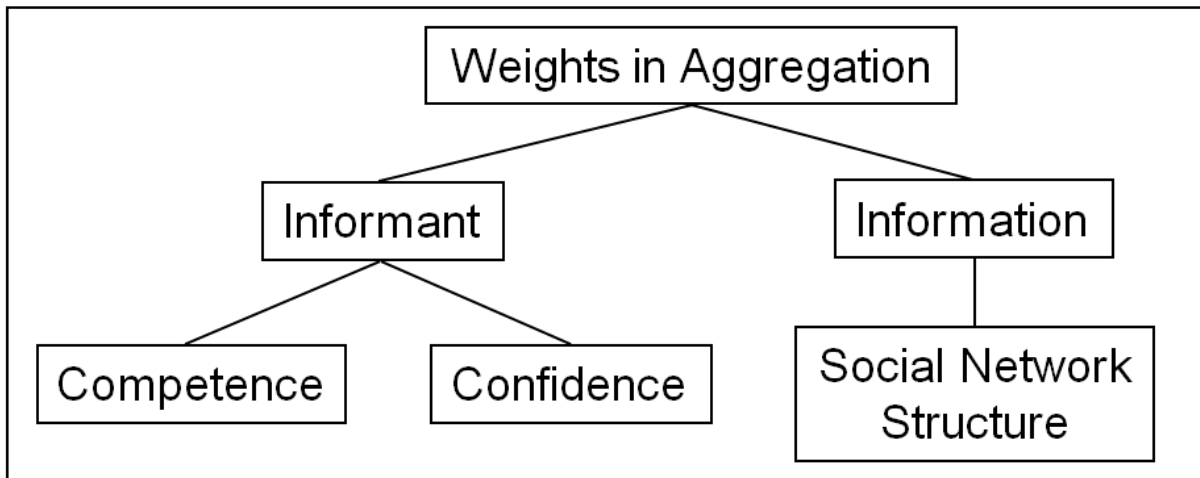
Another option is a mechanistic aggregation of individual forecasts without interaction of informants into a combined forecast (Garthwaite & Kadane, 2005). One type of mechanistic aggregation is to combine judgmental forecasts. The aggregation of individual forecasts lowers the error component in the combined forecast (Armstrong, 2001). A forecast's error component consists of a random error and a systematic error. The random error occurs because of the difficult task to transform the information presented into a forecast. In combined forecasts the random error can be assumed to be low because with a higher number of informants over- and underestimations balance out. The systematic error is the degree to which expectations of judgments do not equal the true value (Einhorn, Hogarth & Klemperer, 1977). In social networks possible sources of the systematic error include the informant herself, her personality characteristics, as well as organizational sources like the informant's hierarchical or functional position (Van Bruggen, Lilien & Kacker 2002). When an informant's estimate includes a systematic error, the aggregation by averaging estimates will not eliminate it (Ferrell, 1985). Therefore the simple average is only recommendable when there is no systematic error in the data. Instead, forecasters should try to identify the source of the systematic error and – if possible – identify the key informant who gives the most accurate estimates. If this is not possible, van Bruggen, Lilien and Kacker (2002) recommend the use of a weighted average of responses. Informants who are more likely to give accurate forecasts should receive higher weights in order to decrease the systematic error.

3.2.2 Weighting in Aggregation

In the process of weighting and aggregating judgmental forecasts, the crucial task is to choose the type of information which is appropriate to reduce the systematic error. Figure 3.1 lists the sources of information that can be used to aggregate responses in CJFs. They can be divided into informant-based sources (Van Bruggen, Lilien & Kacker, 2002) and into information-based sources. The former ones have been used in forecasting literature up to date. They focus on an informant's characteristics, i.e., competence and confidence. They represent the know-how and the expertise of the informant to make good forecasts, as well as the individual ability to estimate the quality of the forecasts. However, even great forecasters will neither be able to generate reliable forecasts nor to judge the quality of their forecast, if the information they rely on is of poor quality. Therefore our approach is to base the aggregation on the social network structure of

informants. The network describes who is talking to whom and thus can reveal who is likely to have access to a wide range of heterogeneous information.

Figure 3.1: Sources of Information for the Aggregation of Combined Judgmental Forecasts



Competence-based weights. Competence-based weights measure the individual's competence in tasks related to the forecasting task, e.g., how well they recall measures related to the forecasting task. This weighting approach assumes that when the related task is performed well, the forecasting accuracy will be higher. However, there are reasonable doubts that a good performance in recall-tasks automatically leads to a higher forecasting accuracy.

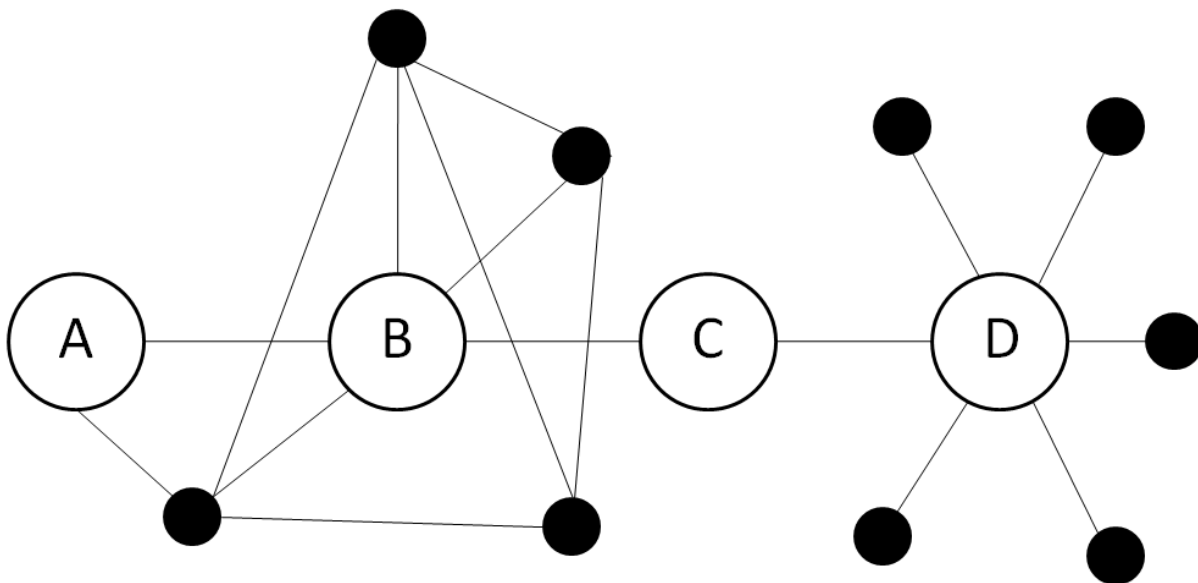
Confidence-based weights. Confidence-based weights assume that the informant can judge best the accuracy of one's own forecast. Shortcomings of this method include that it is hard to judge the accuracy of one's own forecast compared to the colleagues' forecasts and that whenever individuals have to judge their own performance there is a risk of a bias. For each forecast informants generate, they state their confidence in the forecast. Forecasts given by informants that state a higher confidence receive higher weights.

Information-based weights. We use social network measures to generate the information-based weights. They provide information about the informant's relational characteristics and thus about the strategic location in the overall information flow (Granovetter, 1973).

Forecasting accuracy improves with the quantity and quality of information which is available to the informant at the point of generating the forecast. Studies in organizational research have shown that when informants need information they turn to their peers to obtain it (Cross & Parker, 2004). Networks in working groups and organizations show who is talking to whom and how the information travels within the network. Social network measures provide information

about an informant's access to information. Figure 3.2 illustrates the different social network measures discussed below.

Figure 3.2: Example to Illustrate different Social Network Measures



Degree centrality. Degree Centrality is equivalent to the number of contacts an informant possesses. Informants with a high degree centrality, e.g., actors B and D in figure 3.2 have a lot of contacts and thus a higher potential communication activity (Freeman, 1978) than other actors, e.g., the actors A and C. Informants who have a lot of contacts are perceived to be influential and popular (Van den Bulte & Wuyts, 2007). They play an active role in the communication process (Freeman, Roeder & Mulholland 1979/80) and thus know what is going on within the organization (Cross & Parker, 2004). In the absence of more detailed information about someone, others use the number of contacts as an indicator for someone's status (Ball, Eckel, Grossman & Zame, 2001). When other informants need help, they approach them first. Therefore informants with a high degree centrality may be aware of critical factors in the organization and able to obtain a lot of information (Hansen, 2002). Because they have a lot of contacts to choose from, they can demand little information from each individual contact (Van den Bulte & Wuyts, 2007). If they need information and do not get it from one informant, they simply ask another informant. Thus, informants with a high degree centrality possess information benefits. Therefore they give more accurate forecasts than informants with a low degree centrality.

Betweenness Centrality. Within the organizational network, a variety of studies stress the importance of informants being in the position of bridging groups or clusters; they lie between diverse parts of the network (Freeman, 1978). Bridging positions are associated with better ideas (Allen, 1977; Burt, 2004; Hutt, Reingen & Ronchetto, 1988), a better work performance (Cross & Cummings, 2004), earlier promotion and a higher compensation (Burt, 1999). The reason is that they generally have access to heterogeneous information from different clusters. Granovetter (1973) shows that weak ties give access to relevant information, because they allow information to travel between parts of the network, that are otherwise not connected. Burt (1992) demonstrates that informants in bridging positions have information benefits and can control the information by passing it on or not. Broad networks increase people's perspective (Reagans & McEvily, 2003) and the probability that informants understand how to use relevant information from socially distant regions of a network (Cross & Cummings, 2004). The access to heterogeneous information from different groups gives the informant a solid base to generate reliable forecasts.

Figure 3.2 illustrates the concept of betweenness centrality. Although the informants A and C have an equal degree centrality, informant A is involved with the group around informant B and only receives information from that group. When she receives information, it is likely that her contacts already communicated. Therefore part of this information is redundant. Contrary, informant C receives information from two different sources who do not communicate: B and D. It is likely that information from different sources will have different contents; therefore a lot of this information is not redundant, because informant C lies between the groups. When information travels from any member of the group around B to any member around the group around D it has to pass through C. Therefore informant C is likely to have information benefits compared to informant A. To illustrate the idea consider the informants B and D. Their degree centrality is equal. Informant B could be a member of the finance department and is deeply involved there. All of her contacts are members of the finance department that talk with each other as well. When she talks to either one of her contacts it is very likely that she mainly receives information she already has, because the information circulates within the department. Thus, she receives a lot of redundant information. Informant D is a member of the same department. But instead of talking exclusively to members from the same department, her communication partners work in other departments: e.g., production, R&D, sales and accounting, and do not communicate with each other. In the information flow she also rather stands between the departments. Each time she talks to someone it is very likely that she receives information

circulating in other departments. A lot of the information she receives is new to her, i.e., non-redundant. Thus, she can base her individual forecast on diverse information, which increases the likelihood of an accurate forecast.

Closeness Centrality. Closeness Centrality is associated with short communication paths within the network. Within a network actors control each other. Someone with short communication paths to all other actors cannot be controlled by one or a few (Van den Bulte & Wuyts, 2007; Wasserman & Faust, 1994). She quickly reaches other actors and is easily reachable for others. If she wants to spread or search for information available within the network, she can do it efficiently. Thus, actors with a high closeness centrality are considered to be independent in the communication process. They have several ways to access the information they need. This means that if one path to the access of information needed is blocked, the actor can quickly find another one. When new, relevant information enters the network, these actors obtain it sooner than the average. Taking into account that information generally is considered valuable when it is new, actors with a high closeness centrality receive it when the information still has a high value (Borgatti, 2005). When making forecasts, the latest information is probably the most useful, enabling the informant possessing it to make accurate forecasts.

3.3 Empirical Study

The goal of the empirical study is to compare informant-based and information-based weights in the aggregation of judgmental forecasts in forecasting situations with varying degrees of uncertainty. The laboratory study was performed at a European University with a course of 24 students who served as informants using the MARKSTRAT simulation.

3.3.1 Methodology

We chose the MARKSTRAT simulation (Larréché & Gatignon, 1997) as research environment because of its benefit to take place in a realistic organizational setting. Informants' individual forecasts can be compared to the values provided by the simulation. This benefit makes MARKSTRAT popular among researchers (Glazer, Steckel & Winer, 1992; Glazer & Weiss, 1993; Kilduff, Angelmar & Mehra, 2000; Kinnear & Klammer, 1987). In our study, we extended the research design of van Bruggen, Lilien, and Kacker (2002) by social network based measures and their use in forecasting.

The informants were in their last year of undergraduate studies and participated in the game as part of their advanced marketing course. 24 informants were divided into six groups of four students. In the MARKSTRAT simulation, each group of informants is responsible for one

company which they manage for a variety of periods. The groups compete against each other in one industry whose characteristics resemble those of consumer durables. They have to take a range of decisions, e.g., what products should be introduced into or withdrawn from the market and decisions concerning the marketing mix for each product. Within the groups all members had the same tasks – we did not assign any positions or specific responsibilities in order to avoid biases in the information available. Before each period the teams have to take a series of strategic decisions. All six teams started with exactly the same products in the same markets. Thus, company success only depended on their decisions and not on different starting positions in the market (Ross, 1987). In order to take their decisions, teams have the opportunity to study the results of the past rounds of every company and also have the opportunity to purchase between zero and all of fifteen market research studies. To give the teams the chance to get familiar with the game, they played two rounds over a period of one week; the other eight rounds were played during two full days when students had two hours to take the decisions for one period, followed by breaks after the rounds. To assure that all teams had the same conditions and to avoid biases, all teams had to take their decisions simultaneously and had the same time available. Communication in which students had the opportunity to exchange information between teams could take place during the breaks.

After period three of the simulation game, the students were asked to individually fill out questionnaires. Students were provided a list with the names of all the participants of the course. They were asked to give information about the perceived strength of the relationship to the other participants of the course ranging from 5 (best friend) to 1 (don't know the person) in order to generate the social network within the course. Further, the questionnaire included a recall of the values of eight items (the levels of marketing mix items, such as advertising, price, and sales effort) concerning decisions they had just made, and forecasts for relevant items (marketing budget available next period, stock price index of their company in the next period, brand awareness for brand 1 and brand 2 of the own team as well as the sales for both brands) whose actual values would be provided by MARKSTRAT in the next round. They also provided information about their confidence in the accuracy of their responses. This confidence had to be given on a scale from 1 (not certain at all) to 9 (completely certain). After period seven and again after period ten, students were asked to answer the questionnaires again, this time without the questions about their social network. The students filled out the questionnaire simultaneously in the classroom. It was not allowed to communicate while filling out the questionnaire. This is important because differences in the time available or differences in the time period between the

last set of decisions and filling out the questionnaire could potentially have an influence on forecasting accuracy. A voucher served as incentive to provide the most accurate answers possible. Unfortunately, one group of four was observed to collude while filling out the questionnaire. Therefore we eliminated their answers from the data set. In order not to affect the quality of the social network measures they remained part of the network which was used to calculate the social network measures.

3.3.2 Forecasting Tasks

At the point of filling out the questionnaires, informants were aware of the market situation in past periods until $t-1$ and of their own decisions in the current period t . They did not know the decisions of the other teams in t and they did not know the results of period t . Informants had to forecast four measures for their own company: “budget available next period”, “stock price index next period”, and the “brand awareness”-levels of the two brands. The results of the measures “budget available next period” and “stock price index” heavily depend on the success of the company in t , which means that the forecasts are subject to a high uncertainty. The brand awareness levels are less vulnerable to sudden changes. When a consumer is aware of a brand in one period, it is likely that this will not change in the next period. The different degrees of uncertainty become visible when we analyze the average forecasting errors for each set of measures measure. The forecasting error’s coefficients of variation for the measures with high uncertainty is at .924 and thus a lot higher than for the measures that are associated with low uncertainty, which is at a level of .652.

3.3.3 Weights

We calculate the individual weights for each informant in the combined judgmental forecasts according to the methods suggested by van Bruggen, Lilien, and Kacker (2002). We followed their selection of items to calculate confidence- and competence-based means. The information-based means were calculated using social network measures. Table 3.1 gives a short overview over details of the weighting approaches.

Table 3.1: Description of Weighting Approaches

Indicator	Detail	Explanation
Confidence	item-specific	indicates informant’s confidence in specific measure
	average	average confidence across the four measures
Competence	recall	Reflects informant’s accuracy in recalling items from the previous MARKSTRAT period (eight items concerning the marketing mix such as advertising, price, and sales effort)
	forecasting	Reflects informant’s accuracy in providing forecasts on two

		other MARKSTRAT items (sales for brand 1 and sales for brand 2)
Structure	degree	Calculated from self-stated social network data (see text for details)
	betweenness	
	closeness	

Confidence-based Mean. Equation 3.1 shows that in order to calculate the weighted confidence-based mean of item X for group i, $WCONFMEAN_{xi}$, the estimates of each informant j receive the weight congruent with the stated confidence $CONF_{xij}$ in the response accuracy:

$$(3.1) \quad WCONFMEAN_{xi} = \sum_{j=1}^{n_i} \left[\frac{CONF_{xij}}{\sum_{j=1}^{n_i} CONF_{xij}} \times X_{ij} \right]$$

Competence-based Mean. Equations (3.2)-(3.4) depict the calculation of weights for the competence-based mean, $WCOMPMEAN_{xi}$, of group i. In a first step we calculate the distance $DIST_{xij}$ of informant j's estimate on item X to the actual value of item X of group i. Keep in mind that informant j belongs to group i and that the actual observed values are group specific.

$$(3.2) \quad DIST_{xij} = |X_{ij} - ActualValue_{xi}|$$

In a second step we use individual j's estimate's distance to the actual value of item X to calculate her weight $WEIGHT_{xij}$ within group i. The weight assigned to an informant should be inversely related to the distance between individual j's estimate and the observed value; e.g., informants with accurate estimates receive higher weights and informants with less accurate estimates receive lower weights.

$$(3.3) \quad WEIGHT_{xij} = \left[\frac{\left(\sum_{j=1}^{n_i} DIST_{xij} \right)}{DIST_{xij}} \right]$$

In a third step we use the weights calculated based on the distance between each individual j's estimate and the real value to compute the weighted mean based on competence $WCOMPMEAN_{xi}$ of item X for each group i.

$$(3.4) \quad WCOMPMEAN_{xi} = \sum_{j=1}^{n_i} \left[\frac{WEIGHT_{xij}}{\sum_{j=1}^{n_i} WEIGHT_{xij}} \times X_{ij} \right]$$

Information-based Means. Equation (3.5) shows that group i 's weighted mean on item X using information-based weights, $WSMEAN_{xi}$, is calculated in analogy with the procedure used for the confidence-based weights. Informant j 's network measure NM_{xij} is used as weight.

$$(3.5) \quad WSMEAN_{xi} = \sum_{j=1}^{n_i} \left[\frac{NM_{xij}}{\sum_{j=1}^{n_i} NM_{xij}} \times X_{ij} \right]$$

Degree Centrality. The degree centrality of the informant j , $C_D(j)$, is equal to the sum of all relations z between the informant j and all of its direct contacts k .

$$(3.6) \quad C_D(j) = d(j) = \sum_k z_{jk}$$

Betweenness Centrality. The calculation of betweenness centrality is based on the concept of the geodesic path between two informants f and l , g_{fl} : a geodesic path is the shortest connection possible between the two informants. Suppose informants f and l were not directly connected, but there are two paths possible to get from informant f to informant l , one including two other actors and another path including three other actors. In that case the geodesic path is the path that includes two other actors. The idea behind that concept is that information generally travels on the shortest path possible between two informants. Equation (3.7) shows that in order to calculate the betweenness centrality of informant j , $C_B(j)$, we first count the number of geodesic paths that exist between any two pairs of informants in the network. Second, we count how many of these geodesic paths pass through informant j . The last step includes dividing the number of geodesic paths passing through j by the total number of geodesic paths within the network.

$$(3.7) \quad C_B(j) = \sum_{f < l} \sum \frac{g_{fl}(j)}{g_{fl}}$$

Closeness Centrality. Equation (3.8) shows that closeness is the informant j 's graph-theoretic distance from all other actors in the network. If $d(j,l)$ is the number of links in the shortest paths between informant j and all other actors k , then closeness centrality is its inverse.

$$(3.8) \quad C_c(j) = \left[\sum_{k=1}^n d(j,l) \right]^{-1}$$

Before calculating the network measures, we first dichotomized the network data using the symmax method. When two participants disagreed on the strength of their relationship, we chose the stronger one of the strengths stated. Then we binarized the data using a cut-off value of zero which means that when informants stated that they did not know each other, they were coded as

0, otherwise they were coded as one. The binarization simplifies the interpretation of the network measures.

3.3.4 Results and Discussion

Table 3.2 shows that the application of the weighting procedure leads to different results for the measures with low and with high uncertainty. The main difference is that in case of the forecasting situation of low uncertainty, changes in forecasting accuracy are not significant, whereas in forecasting situations with high-uncertainty, increases in forecasting accuracy are significant.

Table 3.2: MAPEs and Coefficient of Variation of Forecasting Tasks in Laboratory Study

Class of Measure	Indicator	MAPEs low uncertainty (Brand Awareness of brand 1 and brand 2)			MAPEs high uncertainty (Budget available, Stock Price Index)		
		MAPE	t-value	sig.	MAPE	t-value	sig.
	unweighted group mean	16.15			23.44		
Confidence	item-specific	13.46	1.747	n.s.	22.52	.537	n.s.
	average	13.99	1.595	n.s.	22.89	.320	n.s.
Competence	recall	20.66	-1.163	n.s.	26.64	-.679	n.s.
	forecasting	19.73	-1.248	n.s.	26.03	-.924	n.s.
Social Network	degree	16.75	-.527	n.s.	21.65	2.463	p<.05
	betweenness	21.24	-1.447	n.s.	19.73	2.671	p<.05
	closeness	15.99	.394	n.s.	23.01	1.886	p<.1
Coefficient of Variation of MAPE		.652			.924		

With respect to the quality of existing weighting approaches in aggregated forecasts, our findings partly confirm the results of previous studies. Van Bruggen, Lilien, and Kacker (2002) found that all types of weights outperform the unweighted mean and that the confidence-based mean outperform the competence-based mean. Our results show that the confidence-based mean improves forecasting accuracy, whereas the competence-based mean leads to a lower forecasting accuracy. However, none of the changes in forecasting accuracy is significant.

With respect to the information-based forecasts, our findings are mixed. In case of the low-uncertainty forecasting situations, results were not significant. However, in case of the forecasting situations with high uncertainty, the use of information-based weights leads to significant improvements in forecasting accuracy. When informants meet during breaks, it is likely that they exchanged information about their decisions. In those cases the informants in central network positions possess information benefits. These information benefits are more

important in situations of high uncertainty than in situations of low uncertainty, because the latter provide less relevant information from other sources for informants' judgments.

Table 3.1: Differences in Forecasting Accuracy between Network Measures

Measure 1	Aggregated forecast 1	Measure 2	Aggregated forecast 2	Difference in MAPE	t-value	sig.
betweenness	19.73	degree	21.65	1.923	1.822	p<0.1
betweenness	19.73	closeness	23.01	3.281	2.644	p<0.05
degree	21.65	closeness	23.01	1.358	2.589	p<0.05

Table 3.3 shows that within the group of information-based measures, assigning weights based on betweenness centrality leads to results that are significantly better than the results of other network measures. Informants with a high betweenness centrality can usually be found in boundary-spanning positions. Those positions give them access to heterogeneous information from various groups. Informants use these information benefits to generate more accurate forecasts than others. Assigning weights based on a high number of direct contacts, i.e., a high degree centrality, also leads to significantly better forecasts than the short average communication paths that are considered by closeness centrality. But it leads to less accurate forecasts than forecasts that used weights that were assigned based on betweenness centrality. This indicates that having access to non-redundant heterogeneous information is more important to generate solid forecasts than having access to a lot of information. This is in line with the literature that associates boundary-spanning positions and the resulting information benefits with a better work performance and other benefits (Burt, 1992).

3.5 Implications and General Discussion

The study presented in this paper analyzes if social network measures should be used to assign weights in CJF in forecasting conditions with different degrees of uncertainty. Our results show that forecasters should rather rely on weights that consider the informant, especially confidence-based measures, when uncertainty is low. However, when uncertainty is high, it is useful to assign weights that account for informants' access to information, i.e., social network measures. Within the group of social network measures, weights assigned based on betweenness centrality significantly outperform other centrality measures. Informants who possess a high betweenness centrality generally have access to non-redundant information from different parts of the network. The information benefits allow them to make more accurate forecasts.

The findings of our study are relevant for practitioners, because they show how to consider potential information benefits available to informants in forecasts with an easy-to-apply method.

This study also has some limitations which provide avenues for future research. Future studies should focus on the generalizability of the results. The results of this study indicate that in situations of low uncertainty the informant tends to be the source of the systematic error, whereas in situations of high uncertainty the quality of the information available to the informants seems to play a more important role. This finding could inspire other studies that tend to focus on the elimination of the source of the systematic error in forecasts. An efficient identification of the systematic error's source would allow to develop methods to reduce it and thus to improve forecast accuracy – not only in CJF, but also when forecasters use other methods. In order to do that, it is useful to replicate this study for different products and organizations, as well as to develop schemes that give practitioners indicators how to reduce the error term in different forecasting situations.

4. Considering Influentials in Market Forecasts²

Summary

Consumers interact with each other and within their social networks. Influentials have an overproportional influence on other consumers' preferences and choices, thus having relevant implications for product development, marketing planning and strategic marketing. An important question that previous research has not analyzed yet, is whether and how to capture their influence on other consumers in preference-based market forecasts. The authors study these aspects for a representative sample of 364 consumers in the mobile phone market of a large European country. They find that assigning higher weights to the preferences of influentials significantly increases forecast accuracy. Thus, ignoring the importance of influentials in market forecasts may cause inaccurate predictions. The authors further test different measures of social interaction and find that social network measures outperform psychographic constructs when it comes to account for the effects of social interaction in the forecasts.

² This study is based on the working paper:
Pescher, Christian; Spann, Martin (2010): Considering Social Interaction in Market Forecasts. Marketing Science Conference, Cologne.

4.1 Introduction

Market forecasts based on consumers' preferences can be available before a product's market introduction and thus provide several benefits. They offer the opportunity to redesign a product, to alter its characteristics, as well as to plan or readjust production levels. However, consumers' preferences may not be stable. They can change in the time period between the market forecast and consumers' purchase decisions. Given their peers' influence, consumers may alter their preferences and thus their product choices (Brock & Durlau, 2001; Woodside & Singer, 1994). Influentials have an overproportional influence on others in the process of social influence (Van den Bulte & Joshi, 2007). This influence is especially important for products which are used or consumed in public and therefore visible to other consumers, e.g., mobile phones, apparel, sports equipment or cars (Bearden & Etzel, 1982). These products are often also associated with status considerations.

Thus, marketing managers need to account for the relevance of influentials in the process of social interaction in many core marketing decisions: product development (e.g., correctly measure preferences), pricing (e.g., determine consumers' willingness-to-pay) and promotion strategy (e.g., promote word-of-mouth). For most of these decisions, managers need accurate forecasts of product success. Therefore, market success forecasts of products may need to account for the relevance of influentials or, put differently, if it is neglected, market success forecast may be inaccurate.

Previous research has quantified the influence of social interaction on sales (Chevalier & Mayzlin, 2006; Godes & Mayzlin, 2009; Trusov, Bucklin & Pauwels, 2009), shown that it has an influence on brand switching behavior (Iacobucci, Hernderson, Marcati & Chang, 1996), demonstrated the effects of social interaction on preferences at an aggregate level (Valente, 2005) and in the diffusion process (Peres, Muller & Mahajan, 2010; Van den Bulte & Joshi, 2007). However, there is little research that deals with the consideration of social interaction in market forecasts. One notable exception is the study of Toubia, Goldenberg, and Garcia (2009) who forecast the diffusion of packaged consumer goods on an aggregate level. We differ from their approach in two ways. First, our forecasts use data on a disaggregated level based on individual purchase probability estimates. Second, by incorporating individual indicators in market forecasts we explicitly consider the importance of influentials in the aggregated market forecast.

For anyone wishing to consider the role of influentials in market forecasts based on individual-level data, the crucial task is to efficiently identify indicators for consumers whose preferences are likely to be dominant in the market (Iyengar, Van den Bulte & Valente 2011). One option is to use psychographic constructs such as opinion leadership (Childers, 1986; Reynolds & Darden, 1971) and susceptibility to interpersonal influence (Bearden, Netemeyer & Teel 1989). Alternatively, influentials can be identified via sociometric measures, i.e., based on their position in their social networks. Burt (1999) has shown that opinion leaders can be found in boundary-spanning positions and that they influence others by passing on information between groups. Kratzer and Lettl's (2009) results indicate that opinion leaders can rather be found within groups in central positions. Goldenberg, Han, Lehmann, and Hong (2009) stress the importance of hubs (i.e., actors with a lot of contacts) in the adoption process.

Iyengar, van den Bulte, and Valente (2011) show that psychographic and sociometric measures are only moderately correlated, even if they are traditionally interpreted in similar ways. In order to be useful for forecasters who want to consider the role of influentials, an adequate measure should be able to capture and predict the effects of social interaction on consumers' preferences and choices.

It is this research gap that we aim to fill in the present paper. The goal of this article is to analyze the accuracy of preference-based market forecasting models that account for social interaction on a disaggregated level. To do that, we build a model to forecast market shares and analyze the forecasting accuracy of different measures for the effects of social interaction.

The unique contribution of our work is that we show that considering the role of influentials in the process of social interaction improves the accuracy of preference-based market forecasts. We develop a model for considering social interaction in market forecasts based on a weighting procedure for consumers' individual choice probabilities. Contrary to previous research which mainly builds on sales or diffusion data (Trusov, Bucklin & Pauwels 2009), this paper uses conjoint analysis. One major benefit of this approach is that it can provide valuable information before the launch of a product and therefore also help to evaluate decisions during the product development process. Further, we show that sociometric measures lead to a higher forecasting accuracy than psychographic measures.

The remainder of this article is build up as follows: In section 2, we provide theoretical background about the impact of social interaction on the accuracy of market forecasts. In section

3, we outline our methodological approach. In section 4, we describe our empirical study and its results. In section 5, we discuss the implications and limitations of this study.

4.2 Influentials' Impact on Purchase Decisions

4.2.1 Drivers of Social Influence

If social interaction is based on the product, it occurs because consumers face uncertainty about product characteristics before they purchase a new product. Consumers turn to knowledgeable peers in order to obtain relevant information about the product. This information helps them to decrease the uncertainty and thus to make better-informed purchase decisions. In many cases the information which is passed on will be influenced by the preferences of the knowledgeable peer. To clarify this idea, imagine a consumer who is planning to buy a new compact class car. After doing some search, his or her consideration set contains the following cars: a Ford Focus, a Honda Civic and a Volkswagen Golf. Being indifferent between the three cars, the consumer turns to a knowledgeable friend for advice. She might tell you that Honda recently had some quality problems and, thus, recommends you not to buy the Honda and rather purchase the Ford instead. Although the consumer only spoke to one person, she would probably avoid buying the Honda and rather choose the Ford over the Volkswagen. The preferences of the knowledgeable consumer were passed on to another consumer. Although it may certainly be heroic to assume that a consumer takes such an important purchase decision based on the recommendation of only one expert, it is reasonable to assume that the tendency to be influenced by peers' preferences is present in the marketplace.

Status and popularity can also be the source for the effects of social interaction. Publicly consumed products have an influence on status or social location within the reference group (Amaldoss & Jain, 2010; McCracken & Roth, 1989). Consumers with a lower status tend to emulate the consumption decisions of consumers with higher status (Amaldoss & Jain, 2010; Bryson, 1996; Simmel, 1957). Imagine a clique of young people. Within the clique some members have a higher status than others. One of the high-status individuals buys a shirt from the latest Nike collection. Group members of "lower" status see this shirt and think that it is fashionable to use exactly that shirt. Therefore they may buy it as well in order to fit in the group. They might even buy this shirt if it was not their preferred choice. Thus, the preferences of the high-status consumer can become more visible in the market.

Both types of influence have similar outcomes. The preferences of the influential – whether it is the knowledgeable or the high-status influential – become more dominant in the market and affect the product choice of others.

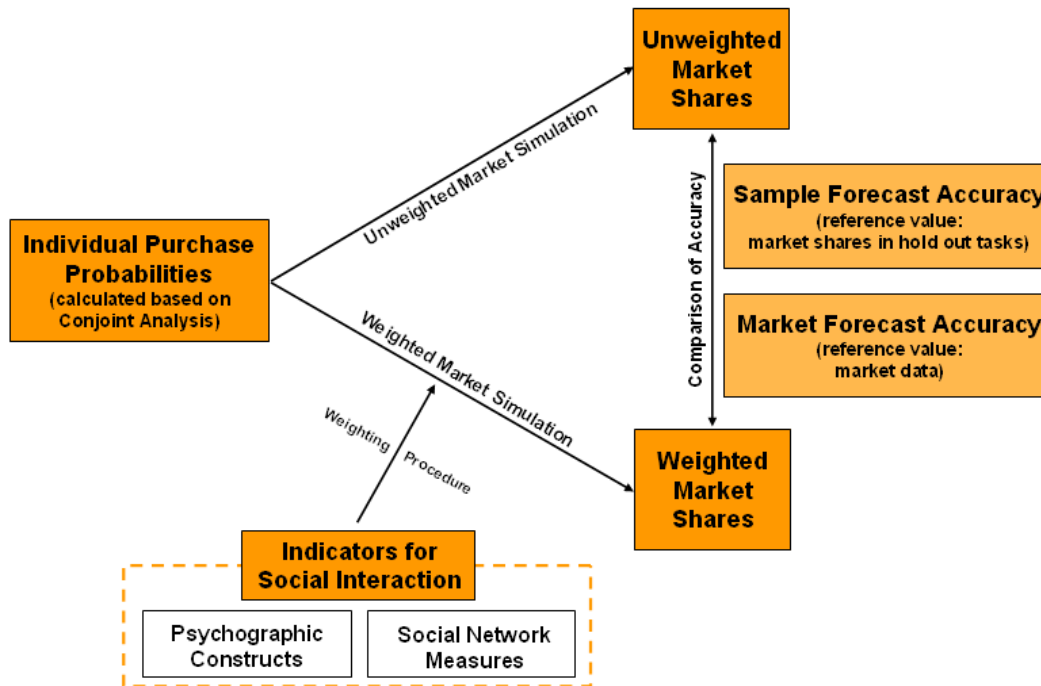
4.2.2 Considering the Role of Influentials in Market Forecasts

Market forecasts based on individual preferences display consumers' preferences at the point when consumers' preferences were measured. In many cases, a certain time period passes between the market forecast and the actual event, e.g., the market introduction of a product. It is likely that consumers influence one another during this time period. Previous research on the role of influentials, as discussed above, indicates that this influence appears to occur via relatively stable mechanisms, in which they exert influence on other consumers. Therefore it is likely that influentials' preferences will become more dominant in the market in the time period following the preference measurement. This aspect enables researchers to account for future social influence and to anticipate some of the changes in individual consumers' preferences by assigning higher weights to the preferences of influentials in the market forecast.

4.3 Methodological Approach

Figure 4.1 shows our methodological approach. The methodology applied in our empirical study consists of four steps. First, we estimate individual-level preferences and choice probabilities via a Hierarchical Bayes Choice-Based Conjoint Analysis (HBCBC). Second, we assign weights to individual choice probabilities in order to capture the influence of influentials on other consumers' product choices. In market simulations and forecasts, individual purchase probabilities are usually given equal weights. Instead, we draw on research from the area of combined judgmental forecasts and assign weights to individuals (van Bruggen, Lilien & Kacker 2002). The weights are assigned based on psychographic constructs or social network measures. Individuals who are likely to influence others receive a higher weight on their purchase probability. Third, we aggregate these purchase probabilities and receive a weighted market share forecast. Fourth, the weighted market share forecasts are compared to a benchmark, the unweighted market share forecasts. In order to calculate the forecast accuracy, we used actual market data for the products presented in the holdouts until three months after the conjoint study.

Figure 4.1: Methodological Approach



Measures of social interaction. Consumer-related indicators for influentials can be measured in a variety of ways (Rogers & Cartano, 1962). Two of the most common types of measures include psychographic constructs and sociometric indicators, i.e., social network measures. Although the interpretations can be similar, the resulting measures have shown only weak correlations in previous research. Thus, it is likely that they measure different constructs (Iyengar, Van den Bulte & Valente, 2011). Further, Iyengar, van den Bulte, and Valente (2011) have shown that psychographic opinion leaders are less sensitive to social contagion than nonleaders, whereas sociometric leaders are not differentially sensitive. As a consequence, sociometric leaders adopt earlier than psychographic opinion leaders. Goldenberg, Han, Lehmann, and Hong (2009) show that early adoption of hubs, a concept closely related to the sociometric leader, speeds up the diffusion process among all actors. Based on these findings it might be hypothesized that sociometric leaders influence the preferences of other consumers in a stronger way than psychographic leaders. However, this question has never been addressed in an empirical study before, but will be tested in our study.

4.4 Empirical Study

4.4.1 Goal and Research Design

The goal of this empirical study is to test the performance of our methodological approach to consider social interaction in market share forecasts. Additionally, we analyze how

psychographic constructs and sociometric indicators correlate and which measures serve best to improve market forecasts.

In our study, we estimate consumers' preferences with a choice-based conjoint design as well as gather different psychographic constructs and social network measures from survey participants. We chose mobile phones as product category because previous research found that the important role of influentials is higher for products that are consumed in public, e.g., mobile phones, than for privately consumed products (Childers & Rao, 1992; Ratner & Kahn, 2002). We therefore chose mobile phones as the product category due to their public visibility, substantial variation in product characteristics and the potential status effects of cell phone possession.

The study was conducted as an online survey in cooperation with a leading market research institute in a large European country in early 2009. The sample is representative for the national market of this country. It consists of 364 consumers, of which 235 bought a cell phone with a 24-month contract within the last six months and another 129 were planning to buy a cell phone with a 24-month contract within the next three months. A 24-month contract is the standard contract length in this country. The time interval was selected based on the recommendations of the market research institute because those consumers are most likely to be activated and thus possess actual information about the cell phone market.

Survey and choice tasks. After some initial questions respondents were asked to perform 12 choice tasks. Each choice task consists of three cell phones and a no-choice-option. Following, they provided information about their social networks and responded to items of the psychographic construct scales. At the end of the questionnaire respondents performed three hold-out-tasks.³ Each hold-out-task consisted of three cell phones and a no-choice-option. The cell phones presented in the two hold-out tasks and their characteristics can be found in figure 4.2. Please note that we did not include the iPhone in our study because it represents a category of its own.

³ One of the mobile phones in the hold-out task achieved hardly any sales, potentially due to lack of distribution. Therefore, we used only the remaining two hold-out task. However, including it would not change our general results.

Figure 4.2: Hold-Out-Tasks of Conjoint Analysis (no-choice-option not displayed)

	Hold-Out 1			Hold-Out 2		
Cell Phone	Nokia 6300	Sony Ericsson W595	LG KF 750	Sony Ericsson K770I	Nokia E71	Motorola RAZR2 V9
						
Design	Bar	Slider	Slider/Touch	Bar	QWERTY	Clam
Brand	Nokia	Sony Ericsson	LG	Sony Ericsson	Nokia	Motorola
Camera	2 mp	3.2 mp	5 mp	3.2 mp	3.2 mp	2 mp
Music	Radio+MP3	Radio+MP3	Radio+MP3	Radio+MP3	Radio+MP3	MP3
E-Mail	Push	Push	None	Push	Push	Client
Organizer	Sync	Sync	Yes	Sync	Sync	Yes
W-LAN	No	No	No	No	Yes	No
GPS	No	No	No	No	Yes	No
Price	Low	Medium	High	Low	High	Medium

4.4.2 Measures

Social network measures. In order to measure consumers' social networks, we asked the consumers for their egocentric network (Burt, 1984; Fischer, 1982; McCallister & Fischer, 1978; Straits, 2000). Egocentric networks are defined as the direct relationships between an individual consumer (or ego) and her relationships to other people (or alters) and the relationships that exist between the alters. They are small networks of one focal actor called the "ego," the participant in the survey, and the people with whom she has contacts, called "alters." The difference between a regular network and an egocentric network is that in egocentric networks all of the information necessary is obtained from one actor, which makes it a feasible method for samples that are representative for a large-scale population. To gain respondent's core network (Marsden, 2007), we used the name generator, which was taken from Burt (1984) and adapted it to the specific characteristics of this study. After generating the list of alters, in which the participants of the study stated their most frequent contacts, participants were asked a series of name interpreters. Note that each egocentric network is calculated based on the information from one single respondent. Therefore egocentric networks are usually treated as undirected. Based on this information we calculated the following network measures: 1) degree centrality, 2) brokerage, and 3) density (see table 4.1). Marsden (2002) showed that the egocentric centrality measures are generally good proxies for the sociocentric centrality measures.

Table 4.1: Social Network Measures – Descriptions and Interpretations

Measure	Description	Interpretation	References
Degree Centrality	Given number of contacts	<ul style="list-style-type: none"> - provides information about activeness in communication process - indicator for popularity and influence 	Freeman (1978/79) Goldenberg, Han, Lehmann, and Hong (2009) Newman (2005)
Brokerage	Number of pairs of direct contacts, that are not directly connected	<ul style="list-style-type: none"> - indicator for control of information flow - indicator for uniqueness of information 	Burt (1992) Burt (2004)
Density	No. of ties present relative to no. of ties possible	<ul style="list-style-type: none"> - indicator for efficiency of information flow and uniqueness of information - indicator for level of peer pressure → independent decisions possible when density is low 	Van den Bulte & Wuyts (2007)

1) *Degree Centrality*. Within their communication networks, opinion leaders tend to have a central position (Stafford, 1966) and many contacts; i.e., high degree centrality (Kratzer & Lettl, 2009). Degree centrality is equivalent to the number of contacts someone possesses. Actors with high degree centrality have many social contacts and thus high potential communication activity (Freeman, 1978). Equation (4.1) shows that the degree centrality of consumer j , $C_D(j)$, is equal to the sum of all relationships z between the consumer j and all direct contacts k .

$$(4.1) \quad C_D(j) = d(j) = \sum_k z_{jk}$$

One of the reasons for the important role of influentials lies in their ability to exchange information with many others. Acting in this way increases other consumers' awareness of their views. A high number of contacts helps them to gain and to pass on information (Venkatraman, 1989). Influentials have more people to ask them for information, and, second, they are more likely to acquire the desired information due to a high number of direct contacts. On a normative level, influentials are more likely to be in the position of setting the rules the group follows, and they are at less risk of being excluded from a group when they do not comply with the rules. On an aggregate level, consumers with high degree centrality, also called hubs, have been found to

play an important role in the adoption (Goldenberg, Han, Lehmann & Hong 2009) and diffusion processes (Shapira, Goldenberg & Lowegart, 2009).

2) *Brokerage*. Brokers tend to be between rather than within groups. Brokerage counts the number of pairs of alters that are not directly connected within the egocentric network. In egocentric networks all actors are direct alters to ego, by definition. Actors with a high brokerage can benefit from the information benefits provided by structural holes (Burt, 1992, 2004). It is closely related to the popular concept of betweenness centrality and can be interpreted similarly.

A consumer with a high brokerage invests relatively little network time in the information or resources of one contact because her contacts are not highly involved with one another. Thus, normative pressure is low, and much of the information is non-redundant. Brokers are familiar with different kinds of thinking and are aware of different points of view of a product and its characteristics.

3) *Density*. The density of the ego-centered network of consumer j , $DS(j)$, can be described as the percentage of ties present in the ego-centered network divided by the percentage of ties possible in the ego-centered networks. In an egocentric network j is adjacent to all alters by definition; because she named them, she is excluded in the calculation of the density. In an ego-centered network, there are g consumers, excluding the respondent of our questionnaire j . The maximum number of ties within the network – if all alters were connected with each other – is $(g(g-1)/2)$. L is equal to the number of ties that are present between all possible pairs of actors l (excluding j) and k within the ego-centered network (see equation (4.2)). Note that in this case we treat z_{lk} as binary.

$$(4.2) \quad DS(j) = \frac{L}{g(g-1)/2} = \frac{\sum_k z_{lk}}{g(g-1)/2} \quad \text{with } j \notin l$$

Norms are more firmly held and easier to enforce in networks with high density than in networks with low density (Granovetter, 2005). In order to avoid sanctions by the group or to be popular, consumers with dense networks are usually willing to act according to the rules of that group and also to purchase products that are generally accepted by that group. When the density is very high, information travels fast within the group (Van den Bulte & Wuyts, 2007). Contrary, low density indicates that a consumer rather tends not to be deeply involved in one group but has contacts with different groups. Thus, consumers with low density receive a lot of new, non-

redundant information from different groups (Granovetter, 1973). Normative pressure tends to be lower in less dense networks.

Psychographic measures. To measure individual characteristics, we used established scales for the constructs of opinion leadership, information seeking, susceptibility to interpersonal influence, and self-stated product knowledge.

We captured opinion leadership and information seeking constructs developed by Reynolds and Darden (1971). In our context, they are more appropriate than alternative scales (Childers, 1986; Flynn, Goldsmith & Eastman, 1996), because they were developed in a context analyzing interpersonal communication. The susceptibility to interpersonal influence was measured on a scale developed by Boush, Friestad, and Rose (1994), which consists of items based on the scale developed by Bearden, Netemeyer, and Teel (1989). In order to measure the self-stated product knowledge we used a scale developed by Lichtenstein, Netemeyer, and Burton (1990). See the Appendix for details. All items were measured on a five-point Likert scale using scale points from “do not agree at all” to “totally agree.” The items were rotated and randomized to avoid biases.

Calculation of weights. Equation (4.3) shows the calculation of the market share forecast for product s (where s is one of m products) by assigning a weight w to each consumer j . x_s is a vector of the product attributes that form product s and β_j is the vector of utilities consumer j assigns to the different product attributes.

$$(4.3) \quad MS_s^{forecast} = \sum_i \frac{\exp(x_s' \beta_j)}{\sum_m \exp(x_m' \beta_j)} w_j$$

Equation (4.4) depicts how the weights are calculated. Accordingly, each of the n consumers j with higher score levels of the measure receives higher weights in the market share forecast calculation (exposition below for $C_D(j)$ and equivalent for the other indicators used for weighting):

$$(4.4) \quad w_i = \frac{C_D(j)}{\sum_{i=1}^n C_D(j)}$$

4.4.3 Results

The sample consists of 364 consumers, 157 female and 207 male. Descriptive statistics can be found in table 4.2.

Table 4.2: Demographics

Age	No.	%	Cell Phone Possession	No.	%
14-19	36	9.9%	< 1 year	6	1.6%
20-29	82	22.5%	1-2 years	6	1.6%
30-39	76	20.9%	2-5 years	35	9.6%
40-49	86	23.6%	5-10 years	152	41.8%
50-64	68	18.7%	> 10 years	165	45.3%
65+	16	4.4%			
Σ	364	100%	Σ	364	100%

4.4.3.1 Relationship between Psychographic Constructs and Sociometric Indicators

The reliability of the constructs opinion leadership (OL), information seeking (IS), susceptibility to interpersonal influence (SII), and product knowledge (PK) is satisfactory with Cronbach's alphas of .889 (OL), .716 (IS), .764 (SII), and .787 (PK). The validity of the conjoint analysis is good, with the hit rate across the three hold-out tasks being 66.27% and thus significantly higher than chance (25% for four-choice tasks including the no-choice option). Table 4.3 shows the relationship between psychographic constructs and sociometric measures for both segments. Analyzing each segment independently leads to similar results.

As shown in table 4.3, there tend to be high values of correlation within the group of psychographic constructs and within the group of sociometric indicators. Within the group of correlations between psychographic measures three results deserve being discussed in detail. First, there is a positive correlation between opinion leadership, which describes the influence on others, and information seeking and susceptibility to interpersonal influence, which describe the tendency of being influenced in an active (information seeking) or passive (susceptibility to interpersonal influence) way. This finding is in line with previous literature (Flynn, Goldsmith & Eastman, 1996). Second, there is a very strong positive correlation between opinion leadership and product knowledge, but the correlation between susceptibility to interpersonal influence and product knowledge is not significant. This indicates that a central aspect that differentiates opinion leaders from actors that are likely to be influenced is the product knowledge. Third, there is a very high correlation between information seeking and susceptibility to interpersonal

influence. This indicates that the observable behavior of consumers (e.g., information seeking) also provides relevant information about the non-observable likelihood of being influenced.

Table 4.3: Correlations between Psychographic Constructs and Social Network Measures

	Mean	STD	Psychographic Constructs				Social Network Measures	
			1.	2.	3.	4.	5.	6.
1. Opinion Leadership	2.81	1.08						
2. Information Seeking	2.43	.93	.39**					
3. Susceptibility to Interpersonal Influence	2.32	.97	.29**	.79**				
4. Product Knowledge	3.03	1.07	.68**	.14**	.08			
5. Degree Centrality	4.20	1.17	-.04	-.06	-.07	-.06		
6. Brokerage	4.70	2.56	-.10	-.10	-.12*	-.08	.88**	
7. Density	.40	.19	.13*	.16**	.20**	.07	-.44**	-.61**

Within the group of sociometric indicators the interpretation of correlations is somewhat problematic, because only ego and the direct alters are included in the calculation of the values. Brokerage increases directly with higher degree centrality, because the number of alters rises. It also decreases with higher density within the ego-network, because if the alters are directly connected, they do not have to communicate through the ego.

The analysis of the correlations between psychographic constructs and sociometric indicators offer a series of interesting insights in the role of influentials. First, the levels of correlation between the psychographic constructs and sociometric indicators tend to be low. This finding is consistent with the results of previous research. Iyengar, van den Bulte, and Valente (2011) stated that that the correlations between sociometric opinion leaders and psychographic opinion leaders is low – and that it is likely that they form different constructs. In our study, opinion leadership is neither significantly correlated with degree centrality nor with any other of the psychographic constructs. Thus, these results confirms the finding of Iyengar, van den Bulte, and Valente (2011). Second, brokerage is correlated significantly negative with susceptibility to interpersonal influence. This result is plausible, because brokers tend to be between, rather than within groups. Thus peer pressure on them is lower than on other actors. Third, density plays an important role in the correlation analysis. A higher density in the social network is associated with higher degrees of opinion leadership, as well as with higher levels of information seeking

and susceptibility for interpersonal influence. Previous research shows that within dense groups it is easier to reach the information needed (Van den Bulte & Wuyts, 2007). Therefore information seeking increases with increasing density. It also shows that it is likely that normative pressure is higher in densely connected subgroups (Burt, 1984). Therefore susceptibility to interpersonal influence is positively related with higher density, too.

4.4.3.2 Effect of Weighting on Forecasting Accuracy

Before consumers purchase a product, they face uncertainty concerning the product characteristics and the reaction of their peers. Once they buy and use the product, they know the reactions of their peers as well as how to value the product and its characteristics. In order to account for this decrease in uncertainty through purchase, we divided the sample of 364 consumers into the two segments of 235 consumers who already bought the products and the 129 consumers who did not buy the product yet. We find that weighting of influentials' in market forecasts only improves the accuracy if consumers have not yet bought the product.

Before the purchase decision, consumers face uncertainty with respect to product characteristics and the reactions of peers. Under these conditions, they are more likely to approach influentials. Once the product is bought, preferences and choices tend to be consistent. Consumers who have already bought a cell phone have gained experience with the product. These consumers know precisely the characteristics of the product and the reactions of their peers, whether they be negative or positive. Thus, we now report the results for the application of the weighting procedure to consumers who did not purchase the product yet.

For each mobile phone presented in the hold out tasks, we calculate the unweighted market share according to equation (4.3), in which each consumer receives an equal weight. Next, we calculate the weighted market shares according to equations (4.3) and (4.4). Market data serves as reference value and we calculate the MAE. Then we compare the forecasting errors of the weighted market shares to the forecasting errors of the unweighted market shares via paired t-test across the mobile phones presented in the hold out tasks. We calculated the changes in the forecasting accuracy, $Change_{FA}$, for the MAE according to equation (4.5), with higher forecasting accuracy is indicated by a positive value and lower forecasting accuracy by a negative value:

$$(4.5) \quad Change_{FA} = \frac{MAE_{unweighted} - MAE_{weighted}}{MAE_{unweighted}}$$

Table 4.4 shows that the application of the weighting procedure significantly improves forecast accuracy, if we incorporate information from the sociometric indicators degree centrality (+8.3%, $p < .1$), and brokerage (+14.5%, $p < .05$). Density does not lead to significant improvements in forecasting accuracy, which may be explained by opposite effects resulting from density: In networks with high density normative pressure is higher and information can travel faster – but some of the information might be redundant (Granovetter, 2005). In networks with low density normative pressure tends to be low, but information tends to be non-redundant (Burt, 1992, 2004). It remains subject to future research, whether a fast information diffusion or non redundant information is more relevant for influentials. Accounting for information which was obtained from psychographic constructs does not lead to significant improvements in forecasting accuracy. We conclude that the weighting procedure helps to account for the role of influentials and thus leads to an improved forecasting accuracy.

Table 4.4: Results

Changes In MAE (in %) by Application of Weighting Procedure	
	Consumers who will purchase the product within next three months
Opinion Leadership	5.81
Information Seeking	5.29
Susceptibility to Interpersonal Influence	8.65
Product Knowledge	-6.45
Degree Centrality	8.26*
Brokerage	14.45**
Density	-1.80

* $p < .1$ ** $p < .05$

One possible confound that could question the influence of influentials on other consumers' product choices might stem from the fact that influentials are often associated with different characteristics than other consumers. Previous has shown that influentials tend to be early adopters (Coulter, Feick & Price, 2002). As a consequence, increases in forecasting accuracy might stem from the fact that opinion leaders simply buy new cell phones earlier than other consumers. However, the characteristics of the mobile phone market and the consumer segment we study make this problem unlikely. We analyze consumers who buy a cell phone with a 24-months contract, which is the standard contract length in our focal country. Whenever consumer sign or renew a contract in the focal country, a new cell phone is heavily subsidized. Thus,

consumers rather decide about a new phone then their contract is up for renewal and not when a new phone is introduced into the market.

4.4.3.3 Relationship between consumer characteristics and preferences.

A deeper analysis of the conjoint analysis' results can provide further insights in the relationship between the indicators that characterize influentials and consumers' preferences. Importance weights indicate the relevance of one product attribute, e.g., brand, compared to all other product attributes for each consumer. Table 4.5 shows the correlations between the important weights for the most relevant product features and the indicators that characterize influentials.

Table 4.5: Correlations between Measures of Social Influence and Importance Weights of Selected Product Features

Importance Weight	Design	Brand	Price
Opinion Leadership	.11*	.00	-.24**
Information Seeking	-.02	-.03	.03
Susceptibility to Interpersonal Influence	-.04	-.02	.07
Product Knowledge	.14**	.03	-.26**
Degree Centrality	.05	-.13*	.01
Brokerage	.06	-.14**	.02
Density	-.06	.08	.06

* $p < .05$ ** $p < .01$

Whereas the design is more important for opinion leaders and product experts, the price is less important for them. These findings are relevant, because these consumers are likely to possess relevant information that allows them to make realistic assumptions about the quality of a product. They do not need price as an indicator for quality, like other consumers do. Actors with smaller social networks, e.g., with a lower degree centrality, put more emphasis on the brand of each product. This finding makes sense because consumers who socially interact with few people regularly are likely to put more emphasis on the brand of a cell phone. This might help them to indicate status if they interact with other people, the do not know. For consumers with a high brokerage, the brand is less relevant than for other consumers. This can be explained by an increased normative pressure within groups (Burnkrant & Cousineau, 1975). Brokers tend to be between groups in network regions, where normative pressure low.

4.5 Discussion

The results of this paper show that it is possible to account for the characteristics of influentials and thus to improve market success forecasts with a method applicable for researchers and practitioners. Indicators from social network analysis are best suited to account for the higher weights that influentials should receive and can be used to increase sample and market forecast accuracy. One relevant advantage of the procedure presented in this paper is that it is not based on sales or diffusion data (Toubia, Garcia & Goldenberg, 2009; Trusov, Bucklin & Pauwels, 2009), which are available after the market introduction of a product. Instead, it uses conjoint data, which is available before the market introduction of a new product. This offers a wider range of possible applications. Especially, it can be applied to evaluate new product concepts before they are introduced into the market and thus help companies to choose the product configuration which is likely to perform best. In fact, whereas a rich stream of literature proposes to identify and contact users who are ahead of the market trend, to contact them, and to let them evaluate different product concepts (Spann, Skiera & Soll, 2009), the method presented in this paper allows to assign different weights to the preferences of a large sample of consumers.

The fact that sociometric indicators have the ability to account for effects of influentials also has implications for seeding strategies. One key condition for viral marketing campaigns is the ability to identify influentials (Iyengar, Van den Bulte & Valente, 2011). Measures that allow this identification therefore are of great help. The identification of influentials should be performed using social network measures, especially focusing on actors with a lot of contacts and actors in bridging positions.

Although the psychographic constructs in our study were apparently of limited use to account for the effects of influentials, the comparison with the importance weights, however, indicates their importance. We find that the price of a status good like a cell phone is significantly less important for psychographic opinion leaders than for other consumers. This aspect may be used for the pricing of products targeted at psychographic opinion leaders – which is likely to be profitable.

This study has some limitations, which provide additional avenues for future research. We used sales data to calculate the market shares, but had no information available on marketing efforts such as advertising. Although this creates additional noise, it should not alter the direction of our results. Furthermore, we conducted our study for one specific product category, a publicly used product with product characteristics that are already known to the market. It is less likely to hold

for products that are only used in private; examples of this include mattresses and refrigerators. Future studies could test whether the procedure presented here is generalizable to cases where the benefits of the product are less known to the market.

5. Brokers in Social Networks – Importance for Marketing Research?⁴

Summary

Research in marketing examines concepts that deal with social interaction, for example opinion leadership and word-of-mouth. Two types of actors play key roles in social networks where social interaction takes place: actors who have a lot of contacts (so called hubs) and actors in bridging positions, so called brokers. Given their importance in social networks, the lack of studies in marketing literature that focus on brokers is surprising. Information on brokers' roles in information and product diffusion on a micro-level is important for companies and marketing research. The goal of this paper is to study brokers' characteristics in a representative study of consumers in the mobile phone market of a large European country. The study shows that brokers significantly differ from other consumers regarding their role in social interaction. They are less susceptible to normative influence and therefore, although in central positions, less suited to be used in seeding strategies.

⁴ This study is based on the working paper:
Pescher, Christian; Spann, Martin (2010): Brokers in Social Networks, Importance for Marketing Research?
Working Paper, LMU München.

5.1 Introduction

Social interaction plays a substantial role in the formation of consumers' preferences (Woodside & Singer, 1994). Given their peers' influence, consumers may form or alter their preferences and thus their product choices (Brock & Durlau, 2001; Kuenzel & Musters, 2007; Woodside & Singer, 1994). Further, status considerations in the social interaction process may influence consumers in their choice of products (Bryson, 1996; Simmel, 1957). Thus, marketing managers need to account for social interaction in many core marketing decisions: product development (e.g., correctly measuring preferences), pricing (e.g., determining consumers' willingness-to-pay), promotion strategy (e.g., promoting word-of-mouth) and distribution strategy (e.g., via an exclusive channel).

Social interaction takes place in social networks. Thanks to the progression of the Internet, social network data become increasingly available to researchers and practitioners. As a result, marketers experiment with different forms of network marketing (Iyengar, Van den Bulte & Valente, 2011). A detailed analysis of consumers' networks concerning bidding behavior (Hinz & Spann, 2008) and seeding strategies (Bampo, Ewing, Mather, Stewart & Wallace, 2008) may lead to new approaches and findings in the fields of market segmentation, product positioning or communication (Van den Bulte & Wuyts, 2007).

On a macro-level, researchers from many disciplines such as sociology, organization science, and marketing study the influence of the social network and its structures, for example on adoption and diffusion processes (Iyengar, Van den Bulte & Valente, 2011; Newman, 2005). Literature also relates the network structure to the outcomes of interpersonal influence. For example, Reingen, Johnson and Seidman (1984) find out that social cohesion is likely to lead to brand congruence. Consumers in structurally equivalent positions tend to have similar brand preferences (Ward & Reingen, 1990).

On a micro-level, research relates network positions to personality traits (Burt, Jannotta & Mahoney, 1998) and psychographic constructs (Iyengar, Van den Bulte & Valente, 2011; Kratzer & Lettl, 2009). Two network positions in particular are more important than others: those with a lot of contacts (i.e., hubs) and those who are in bridging positions (i.e., brokers). Brokers connect actors that otherwise would be unconnected. Marketing literature studies hubs (or influentials) extensively. They have a higher degree of opinion leadership and influence the adoption process (Goldenberg, Han, Lehmann & Hong, 2009). Actors in bridging positions play important roles in sociological studies (Burt, 1992, 1999; Granovetter, 1973, 2005) and

organizational science (Allen, 1977; Burt, 2004). But despite their significance in the aggregated diffusion process (Granovetter, 1973, 2005), marketing studies do not describe these actors on a micro level yet. A detailed analysis of actors in bridging positions could help to target them more efficiently because they are able to transport the information provided to them into different groups.

This study has two goals. The first one is to test whether brokers differ from other consumers regarding their role in the process of social influence. The second goal is to compare the importance brokers attribute to product characteristics relative to other consumers. In order to do so the study contains a representative sample of consumers who bought a mobile phone within the last six months or who will buy a mobile phone within the next three months.

The paper proceeds as follows: Section 2 provides a literature overview on social interaction and consumers in brokerage positions and develops hypotheses about personality constructs of consumers in bridging positions and how they relate to social influence, as well as the importance brokers put on price and brand. Section 3 describes the empirical study and hypotheses tests, as well as a linear regression. Section 4 concludes with a general discussion.

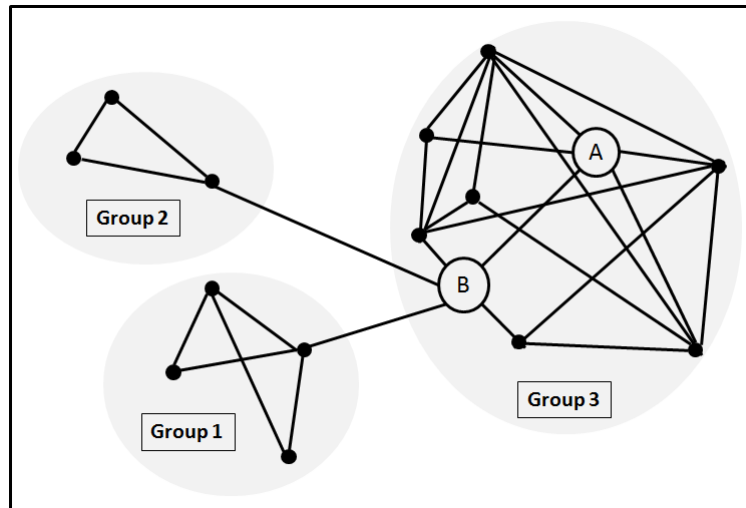
5.2 Concept of Brokers

In dense subgroups of a network, norms and rules have a higher value and are easier to enforce than in subgroups with low density (Granovetter, 2005). However, dense networks also enable the transfer of information and other resources, for example complex knowledge (Nahapiet & Ghoshal, 1998). There is also a downside of density in networks: no one possesses unique information, when everyone talks to everyone else (Van den Bulte & Wuyts, 2007). Information benefits of individual actors occur, when they serve as a bridge between otherwise unconnected actors (Granovetter, 1973).

This coherence is the idea behind Burt's concept of the so-called broker (1992). Brokers are less constrained than other actors in their networks. To illustrate the concept of brokerage in a network, see figure 5.1. Actors A and actor B are two marked actors within the network. Both of them have the same number of contacts. However, actor A's contacts are all members of the same group, group 3. It is not relevant which of her contacts she talks to, a lot of the information she receives will be redundant. The reason is that her contacts also talk to one another. Contrary, actor B is in a brokerage position. The majority of her contacts does not communicate with each other. Although three of her contacts are also members of group 3, they do not communicate directly. Therefore actor B receives information from different parts of group 3, as well as

information from group 1 and group 2. Information that travels between the groups has to pass through B. She can decide what type of information to pass on and what type of information to withhold. She possesses control benefits.

Figure 5.1: Brokerage Position in a Network (cf. Burt (1992))



In a series of studies that follow the introduction of the broker's concept, Burt analyzes actors in brokerage positions in detail (Burt, 1992, 1999, 2004; Burt, Jannotta & Mahoney 1998). He associates brokerage with opinion leadership, because they brokers control the information that is passed on between groups (Burt, 1999). In a company, brokers receive a higher compensation, better job evaluations and tend to have good ideas (Burt, 2004). Allen (1977) confirms the positive influence of bridging positions on innovation quality. In a study with 51 MBA students and 252 personality statements, Burt, Jannotta and Mahoney (1998) find out that brokers state that they like to be in positions of authority and that they are able to create an aura of excitement. Further, they do not prefer to take the safe approach and they do not closely follow the original mandate of the group. Having identified these regularities, the network position provides information on the actor. However, all of Burt's studies focus on organizational networks. Whether the results hold for private networks or not remains subject to future research.

5.2.1 Brokers and Social Influence: Hypotheses

Brokers play a decisive role in the aggregated information diffusion process. They often determine whether information about a new product travels from one group to another. However, the role of brokers in the process of social interaction on a micro level remains largely unclear. Further, marketers are increasingly experimenting with different forms of network marketing (Iyengar, Van den Bulte & Valente, 2011). The understanding of the relationship between the

network position and consumer characteristics is a key necessity. Therefore the goal of the development of hypotheses is to clarify the relationship between the brokerage position, psychological constructs of social interaction and the importance consumers assign to brand and price.

5.2.1.1 Normative Influence

The term normative influence describes the influence to conform to the expectations of another person or group and serves as an indicator for peer pressure (Deutsch & Gerard, 1955). The degree to which consumers behave according to the expectations of the group depends on the number of groups they can turn to as well as on the ability of the group to enforce the norms. In dense subgroups of a network, norms and rules have a higher value and are easier to enforce than in subgroups with lower density (Granovetter, 2005).

Figure 5.1 shows that brokers take boundary-spanning positions within groups or even tend to be between groups in regions with low density. If one group rejected them because they do not behave according to the norms or because they do not use the products accepted in that group, they could simply turn to another group. Peer pressure on them tends to be low. This line of argumentation leads to hypothesis 1:

H1: Brokers are less susceptible to normative influence than other consumers.

5.2.1.2 Information Seeking

Brokers generally have access to heterogeneous information (Burt, 1992). Heterogeneous information from different sources allows consumers to take more objective purchase decisions (Hinz & Spann, 2008). In order to turn heterogeneous information into information benefits, brokers have to actively approach others.

Information seeking describes the tendency of consumers to actively search for information which is relevant for the purchase decision (Reynolds & Darden, 1971). Whereas Burt (1992) shows that brokers use their information control to gain entrepreneurial benefits, other authors indicate that boundary-spanners rather mediate the information (Obstfeld, 2005; Tushman & Katz, 1980). These findings indicate a rather passive approach that does not include active information seeking. It is likely that as they receive a lot of information, brokers do not have to approach others actively. As a consequence hypothesis 2 states that:

H2: Brokers show a lower degree of information seeking than other consumers.

5.2.1.3 Opinion Leadership

Burt (1999) associates brokers with opinion leadership, because they control the flow of information and thus decide what information enters another group and what type of information does not. The findings of other researchers raise doubt about brokers' degree of opinion leadership. Brokers hold bridging positions and tend to be rather between than within groups (Burt, 1999). Contrary to Burt's finding, literature on consumption in social networks suggests that opinion leaders tend to be in the center of their local groups rather than at the borders (Kratzer & Lettl, 2009). This finding makes sense because within dense subgroups leaders enforce the existing norms more easily. The normative influence is higher in the center of the group than at the borders. Therefore opinion leaders, who tend to exert a lot of normative influence, hold central positions in densely connected groups, whereas brokers tend to connect a higher number of otherwise unconnected groups. Since they are not able to enforce the norms of a single group, for publically consumed goods H3 states:

H3: Brokers display a lower degree of opinion leadership than other consumers.

5.2.1.4 Status Consumption

Brokers strive to be in positions of authority and they are connected to different groups (Burt, Jannotta & Mahoney, 1998). Positions of authority generally lead to a high status. Possessing access to more groups implies that people have access to a wider range of resources than others. In social capital research, access to a wide range of resources is positively related to status (Lin, 2001). However, the consumption of status goods closely relates to the concept of social circles. Only few products represent a high status globally. Products that provide status are likely to differ within subgroups. Take for example the smartphone market. Whereas business people tend to signal status with the latest version of a Blackberry, many IT-specialists tend to prefer HTC or Samsung smartphones with an Android operating system – and lifestyle segments purchase the iPhone. Since brokers usually have contacts to different subgroups, it is difficult for them to buy products that provide status for him among most of his/her contacts. As a consequence, H4 states that:

H4: Brokers perceive status products to be less important than other consumers.

5.2.1.5 Importance of Brand and Price

Brand. The functions of brands include social demonstration, which describes consumers' tendency to display their self image by using a brand, and the reduction of risk (Fischer, Völckner & Sattler, 2010). In the context of social interaction, the social demonstration seems to

be the more important one, because the use of certain brands directly relates to the reference group (Bearden & Etzel, 1982; Childers & Rao, 1992). One or a few brands are likely to be dominant in the group and form part of the group's social identity (Berger & Heath, 2007). If someone is deeply involved with that reference group, he tends to purchase the brands that are accepted within the group. Brokers tend to be between the groups. This finding indicates that they do not have one densely connected reference group which could lead them to consume certain brands. They get in touch with different brand preferences from different groups. Probably the preferences between the groups diverge. Therefore, brokers are exposed to heterogeneous preferences from different groups. As a consequence, brokers do not have a reason to value a single brand over others – and to assign a high importance to the brand. This argumentation line leads to H5:

H5: Brokers display lower importance weights for brand than other consumers.

Price. Actors in brokerage positions of social networks tend to be very innovative. This finding holds for job networks (Burt, 2004; Obstfeld, 2005) as well as for friendship networks (Kratzer & Lettl, 2009). Brokers know better what products are up to date than other consumers. Modern, state-of-the art products are more expensive than others. Only consumers that earn higher salaries can afford to buy them. Burt (2004) shows that brokers tend to earn higher salaries than other consumers. Therefore, the price is most likely less important for brokers than for other consumers. H6 states that:

H6: Brokers display lower importance weights for price than other consumers.

5.2.2 Overview

Table 5.1 gives an overview of the hypotheses tested in this paper.

Table 5.1: Overview Over Hypotheses

No.	Hypothesis
1	<i>Brokers are less susceptible to normative influence than other consumers.</i>
2	<i>Brokers show a lower degree of information seeking than other consumers.</i>
3	<i>Brokers display a lower degree of opinion leadership than other consumers.</i>
4	<i>Brokers perceive status products to be less important than other consumers.</i>
5	<i>Brokers display lower importance weights for the brand than other consumers.</i>
6	<i>Brokers display lower importance weights for the price than other consumers.</i>

5.3 Empirical Study

5.3.1 Research Design

The goal of the empirical study is to test the hypotheses developed in the theoretical part of the paper. The study collects data with an online survey in cooperation with a leading market research institute in a large European country (Pescher & Spann, 2010). Mobile phones serve as the product category because social influence is higher for goods that are visible in public, for example mobile phones, than for privately consumed goods (Ariely & Levav, 2000; Bearden & Etzel, 1982; Childers & Rao, 1992; Ratner & Kahn, 2002). The sample is representative for the national market and consists of 364 consumers who bought a mobile phone with a 24-month contract within the last six months or who plan to buy a mobile phone with 24-month contract within the next 3 months. 24 months is the standard length of contracts in this country. The market research institute recommends this 3-months-time period because those consumers tend to possess actual information about the mobile phone market.

After a short introduction consumers perform a series of choice tasks. A Hierarchical Bayes Choice-Based Conjoint design helps to analyze consumers' preferences. The conjoint design includes nine product characteristics. Further, consumers provide their egocentric network as well as the psychographic constructs. The questionnaire ends with three hold-out tasks to assess the quality of the conjoint analysis.

5.3.2 Measures

Network Constraint. Burt (1984) defines egocentric networks are defined as the direct relationships between individual consumers (ego) and their relationships to other people (alters)

as well as the relationships that exist between the alters. In order to construct each consumer's egocentric network (Burt, 1984; Campbell & Lee, 1991; Fischer, 1982; McCallister & Fischer, 1978; Straits, 2000), this study contains one name generator and a series of name interpreters. In the name generator, respondents specify the people they meet most frequently in social activities over the last six months. In the name interpreter, the respondents provide pairwise information about the relationship between each pair of ego's contacts, the so-called alter-alter relationships.

The network constraint, as you can find in equation (5.1), describes the network time and energy a network actor invests in the resources of one contact. Two measures may lead to low network constraints. The first one is the number of network contacts, degree centrality. The more contacts someone possesses, the lower the effort invested in each contact. The second one is density. The lower the density, the less effort someone invests indirectly in the resources of one contact. A low density also leads to a low network constraint. Actors with a low network constraint are brokers. Burt (1992) developed the concept of the broker and identifies them by calculating the network constraint as follows.

$$(5.1) \quad NC(j) = \sum_k c_{jk} \text{ with } c_{jk} = (p_{jk} + \sum_q p_{jq} p_{qk})^2 \text{ and } p_{jk} = \frac{z_{jk}}{\sum_q z_{jq}}$$

where:

NC(j) = Network constraint index of consumer j

c_{jk} = extent to which consumer j's network is directly or indirectly invested in a relationship with contact k

p_{jk} = proportion of consumer j's network time and energy invested in contact k

z_{jk} = intensity of j's relationship with contact k

Figure 5.1 illustrates the network constraint as in equation (5.1). Actors A and B both possess five direct contacts. But most of actor A's contacts are directly connected as well, whereas broker B's contact do not interact with each other directly. Therefore A indirectly invests a relevant part of her network time in the information of one contact, whereas broker B does not. Assuming that each contact provides access to resources like information, B invests less network

time in the resources of one. Thus, the network constraint in equation (1) accounts for primary structural holes, i.e., whether your friends are friends as well. However, it cannot account for secondary structural holes, i.e., whether the friends of your friends are friends as well (Burt (1992). Please note that the network constraint is an egocentric measure for the sociocentric betweenness centrality. Marsden (2002) empirically shows that egocentric and sociocentric versions of Freeman's betweenness centrality lead to very close results and concludes that a betweenness measure based on egocentric network data can be a reliable substitute for Freeman's betweenness centrality. The network constraint has been used in several studies for an in-depth analysis of brokers (Burt, 1992, 1999, 2004).

Psychographic constructs. Hypotheses 1 to 4 use established scales. Opinion leadership (H3) and information seeking (H2) use Reynolds and Darden's (1971) constructs which is more appropriate than alternative scales (Childers, 1986; Flynn, Goldsmith & Eastman, 1996) in the context of this study, because it refers to a context analyzing interpersonal communication. To measure the susceptibility to normative influence (H1) Boush, Friestad and Rose (1994; Bristol & Mangleburg, 2005) take items from a scale developed by Bearden, Netemeyer and Teel (1989). To measure the importance of status consumption (H4), this study uses three items of a materialism-scale developed by Richins and Dawson (1992) that directly focus on status consumption. All of the constructs use a five-point Likert scale with scale points from (1) do not agree at all to (5) totally agree.

5.3.3 Results

Brokers' possess positions with a low network constraint, which describes network time and energy they invest in the resources of one contact. The mean network constraint is at .68, the standard deviation is at .19 (min: .20, max: 1.13). Brokers are the consumers whose network constraint is lower than the mean minus one standard deviation. This characteristic applies to 35 consumers (9.6% of sample). A series of t-tests shows whether brokers and non-brokers vary significantly. Table 5.2 shows the results. Hypotheses 1 to 4 analyze psychographic constructs, hypotheses 5 and 6 compare the importance weights for the product characteristics brand and price based on conjoint analysis between brokers and non-brokers.

Table 5.2: Relationship Between Constructs and Brokerage Position

	Brokers		Other Consumers		Difference
	<i>mean</i>	<i>STD</i>	<i>mean</i>	<i>STD</i>	<i>t-value</i>
Susceptibility to normative influence	1.86	1.01	2.31	1.03	2.46**
Information Seeking	2.14	.97	2.47	.93	1.96*
Opinion Leadership	2.62	1.14	2.83	1.07	1.06
Importance of status goods (perceived)	1.88	.91	2.43	1.08	2.94***
Brand (Importance)	19.00%	7.54	18.84%	9.37	.10
Price (Importance)	21.86%	14.20	26.34%	15.27	1.66*
Age	40.06	12.06	38.24	14.00	-.74

***p<.01; **p<.05; *p<.10; items were measured on a scale from 5 to 1 where 5 indicates a high and 1 a low level of the construct.
Brand and Price:

Results show support for H1 which states that Brokers display a lower susceptibility to interpersonal influence than other consumers. Brokers tend to be between groups rather than within groups. They are not susceptible to social norms. As hypothesized above, brokers are less active in information seeking than other consumers. Therefore, our results indicate that H2 can be supported as well. H3 hypothesizes that brokers show lower values of opinion leadership than other consumers. However, the differences are not significant. Therefore this study does not show support for H3. H4 states that brokers perceive status products to be less important than other consumers. This result is supported on a 1%-level.

As a general conclusion of H1-H4 which analyze brokers in the context of social interaction, this study's results indicate that brokers tend not to play key roles in the process of social interaction. They are less susceptible to normative influence than other consumers, display a lower degree of information seeking and perceive status products as less important than other consumers. According to these results, they turn out to be very independent consumers.

The difference between brokers and non-brokers in the importance weights of the brand is not significant. However, brokers perceive the price to be less important than other consumers. This finding is potentially relevant for companies: by analyzing network data, they can gain additional information about the consumer by taking the network position into account. Table 5.3 gives an overview of the results of the hypotheses tested in this paper.

Table 5.3: Results of Hypotheses Regarding Psychographic Constructs

No.	Hypothesis	Result
1	<i>Brokers are less susceptible to normative influence than other consumers.</i>	<i>supported</i>
2	<i>Brokers show a lower degree of information seeking than other consumers.</i>	<i>supported</i>
3	<i>Brokers display a lower degree of opinion leadership than other consumers.</i>	<i>not significant</i>
4	<i>Brokers perceive status products to be less important than other consumers.</i>	<i>supported</i>
5	<i>Brokers display lower importance weights for the brand than other consumers.</i>	<i>not significant</i>
6	<i>Brokers display lower importance weights for the price than other consumers.</i>	<i>supported</i>

Linear regression tests the relation between the psychographic constructs related to social interaction influence and the network position. The network constraint is the dependent variable and the constructs related to social interaction serve as independent variables. Table 5.4 shows the regression results. The overall fit is significant and R^2 is low but acceptable for such cross sectional data. All variance inflation factors (VIFs) are well below 3, therefore multicollinearity does not pose a problem.

Table 5.4: Regression Results (DV: Network Constraint)

Independent Variables	Coefficient	t-value
Susceptibility to Normative Influence	2.95×10^{-2}	2.08**
Information Seeking	-1.13×10^{-2}	-.74
Opinion Leadership	0.38×10^{-2}	.38
Importance of Status Products	2.08×10^{-2}	2.00**
Intercept	.58	17.58***
F	4.32***	
R^2	.05	

*** $p < .01$; ** $p < .05$; * $p < .10$; items were measured on a scale from 5 to 1 where 5 indicates a high and 1 a low level of the construct

In order to interpret the results, remember that brokers display low values of the network constraint. Results show that only the susceptibility to normative influence and the importance of status products have a significant influence on brokerage. In both cases the coefficient is positive. These results indicate that brokers are less susceptible to normative influence and that status products are not important to them.

5.4 Discussion

Given the amount of social network data and the high expectations researchers have when analyzing this data, gaining additional knowledge on how to interpret the network data is

important. Researchers frequently use social networks to analyze important aspects of social interaction, for example the flow of information and normative influence. Two positions are important to consider: actors with a lot of ties (i.e., hubs) and actors in bridging positions (i.e., brokers). This article focuses on the latter ones.

Important characteristics that describe social interaction vary with the social network position. Brokers display lower levels of information seeking and susceptibility to normative influence than other consumers. These results indicate that the reference groups' influence is lower on them than on other consumers (Bearden & Etzel, 1982; Childers & Rao, 1992). The fact that within dense groups social norms are easier to enforce supports this finding (Granovetter, 2005). Thus, brokers tend to take their purchase decisions independently of other consumers. Those who tend to stress the importance of consumers in bridging positions should take this finding as a call to gain additional insights.

One important aspect where researchers and practitioners expect promising results from the analysis of social networks are seeding strategies. The results of this paper indicate that targeting actors in brokerage positions may not be fruitful. The effect that the actors in boundary spanning positions tend to be very independent – and thus not likely to influence others – potentially contradicts the advantage that they may spread information in different groups. Additional research should focus on the analysis which of these two effects is stronger.

The findings of this article also indicate that the social network provides some information about the consumers' underlying preferences. Therefore this study serves as an additional call to develop segmentation and targeting approaches based on social network measures, like van den Bulte and Wuyts (2007) propose.

The present study also has some limitations that provide avenues for future research. One limitation is the use of the method of egocentric networks to capture the consumers' egocentric networks. Egocentric networks allow capturing the network structure of the focal actor and the immediate contacts. However, they do not allow the calculation of other social network measures that are also interesting to analyze in the context of preferences, but that take into account more than the immediate neighbors of an actor. Structural equivalence is one example that associates with similar preferences in group settings (Ward & Reingen, 1990). Another limitation comprises the fact that this study only contains one product category, mobile phones. Mobile phones are visible in public and associate with status consumption. But additional studies need to examine whether or not these findings hold for other products as well.

6. Consumers' Forwarding Behavior in Mobile Marketing Campaigns – A Decision-Model⁵

Summary

The mobile market is undergoing a transition process. Technological advancements and the diffusion of smart phones offer a wide range of possible applications in the near future. A very promising application in the area of mobile marketing is viral marketing campaigns. The success of these campaigns crucially depends on the willingness of the consumers to actively forward the messages they receive from companies. Therefore it is important to gain insights in the consumer's decision making process in a mobile context and to analyze the factors that influence the consumer's likelihood to forward a message to a high number of contacts.

In this paper the authors conduct a mobile viral marketing campaign and survey study participants. They build a three stage model of the consumer's decision making process from awareness to the number of referrals. Sociometric and psychographic indicators are incorporated into the model. Results indicate that psychographic indicators play a substantial role until consumers take the decision to forward the message, whereas sociometric indicators determine to how many other consumers the message is forwarded. Within the group of sociometric indicators the likelihood to actively participate in a viral campaign increases with the quantity of contacts, but decreases with their quality. Within the group of psychographic indicators the hedonic entertainment value is less important than the utilitarian purposive value.

⁵ This paper is an early version of the following working paper:

Pescher, Christian; Reichhart, Philipp; Spann, Martin (2011): Analyzing Consumers Referral Behavior in Mobile Markets – A Model of their Decision-Making Process. Working Paper, LMU München.

The version presented here was written in single authorship by Christian Pescher, data was collected jointly with Philipp Reichhart. Later versions were improved by Martin Spann.

6.1 Introduction

There is indication of the effectiveness of traditional marketing tools diminishing (Van den Bulte & Wuyts, 2007). More than a half of the consumers feel that advertising has nothing relevant to offer them or that they receive too much advertising (L. Porter & Golan, 2006). Companies hope that viral marketing can be an alternative way to efficiently transmit their messages to the consumers. This finding is supported by the fact that there is an increasing number of viral campaigns which have been successful in recent years. One famous example for a viral campaign is Hotmail. The company acquired more than 12 million clients in a year and a half with average acquisition costs per customer cut to 4 cents. Their main source of gaining customers was an attached small message at the end of each outgoing mail from a hotmail account, informing consumers about the costless hotmail-service (Krishnamurthy, 2000). Other examples for successful campaigns that are mentioned in marketing literature include high-tech companies such as Microsoft, HP, Hotmail, ICQ, but also traditional blue chips like Hasbro, Toyota, BMW, Volkswagen, Ford, Burger King, Unilever and Anheuser Busch (De Bruyn & Lilien, 2008; Godes & Mayzlin, 2009; Libai, Muller & Peres, 2009; Porter & Golan, 2006; Van der Lans, Van Bruggen, Eliashberg & Wierenga, 2010).

However, all of these papers mainly focus on the online perspective. They fail to consider the opportunities the transitions in the mobile setting offer. Every generation of mobile phones has more capabilities than the previous one. Large segments of the market already own a technologically advanced Smartphone or will buy one the next time they purchase a mobile device. Mobile phones and smart phones further enhance consumers' ability to quickly and electronically exchange information about products independently of their physical location. Mobile Data Services are adopted by more and more consumers in large parts of the world and enrich mobile business models (Bina & Giaglis, 2007; Hong & Tam, 2006). Considering these changes which lead to promising business opportunities, it is surprising that researchers on viral marketing largely ignored mobile communication to date (Okazaki, 2008).

In viral marketing campaigns companies first set a stimulus to selected customers and then rely on peer-to-peer communications to accelerate the purchases of consumers who would have bought the product anyway or to acquire new consumers (Libai, Muller & Peres, 2009). Since consumers may spread most of the messages after receiving an initial stimulus, viral marketing campaigns can be less costly than traditional mass media advertising (Hinz, Skiera, Barrot & Becker, 2011). Viral marketing campaigns rely on the classic assumption of word-of-mouth (WOM) that consumers assign a high credibility on informal sources (Godes & Mayzlin, 2005).

Consumers acquired via referrals can be more valuable to the company than other consumers (Schmitt, Skiera & Van den Bulte, 2011). Although previous research also considers viral marketing to be random and unmanageable (Bampo, Ewing, Matter, Stewart & Wallace, 2008).

A crucial aspect for the success of viral marketing campaigns is consumers' forwarding behavior if they receive unsolicited advertising by companies on their mobile phones. Although there is a wide body of research on interpersonal influence, it remains largely unclear what factors influence the process from reading the message to the decisions whether and to how many contacts they forward the message – especially in the dynamic setting of mobile viral marketing campaigns.

The main contribution of this work is that we build a model of the consumers' forwarding behavior in response to unsolicited mobile advertising via text messages. Findings from analyses of decision literature suggest that consumers undergo a multi stage process from receiving a stimulus, like a short message, until taking an action, like forwarding the message to their friends (Bettman, 1979). Within this process, different factors influence consumers' behavior on different stages of the process (De Bruyn & Lilien, 2008). These factors can be analyzed by psychographic and sociometric indicators (Iyengar, Van den Bulte & Valente, 2011). Both have been studied extensively in two important streams of literature and both of them have significantly helped to explain diffusion and adoption processes. However, they have never been analyzed jointly in a viral marketing study – so until now it remains unclear which factors have a stronger influence on consumers' referral behavior in viral marketing campaigns and thus determine their success. Answering this research question can help companies to set up their viral campaigns more efficiently. The analysis of this research question is the second contribution of this paper to literature.

In order to make these contributions to literature this study and the remainder of this article is built up as follows: section 3.2 presents related literature, develops the model and outlines the hypotheses presented in this paper. Section 3.3 describes our empirical study, its design and the results. Section 3.4 discusses the implications of this study for referral campaigns for researchers and practitioners.

6.2 Related Literature and Development of Hypotheses

6.2.1 Word-of-Mouth in Viral Campaigns

Since the study of Katz and Lazarsfeld in the 1950's, marketing literature has developed a rich body of research on WOM (Katz & Lazarsfeld, 1955). Literature has identified several reasons why consumers participate in WOM. Satisfaction and dissatisfaction are among the most important ones (Bowman & Narayandas, 2001; Maxham & Netemeyer, 2002). WOM has an influence on consumers' preferences and purchase decisions (Brock & Durlau, 2001; Woodside & Singer, 1994), the pre-purchase attitude (Herr, Kardes & Kim, 1991), the post-usage perception of a product (Bone, 1995) and it is considered an important factor for driving sales (Chevalier & Mayzlin, 2006; Coleman, Katz & Menzel, 1966). Systematic viral campaigns can have a positive influence on the performance of a company (Godes & Mayzlin, 2009). WOM referrals lead to the acquisition of new customers that are likely to churn less, to be more loyal and therefore to be more profitable than customers acquired through regular marketing investments (Schmitt, Skiera & Van den Bulte 2011; Trusov, Bucklin & Pauweils, 2009; Villanueva, Yoo & Hanssens, 2008).

After the development of a sophisticated marketing message the company sends the message to the consumers and stimulates the consumers to forward the message to their contacts (Van der Lans, Van Bruggen, Eliashberg & Wierenga, 2010). Then the company benefits from referrals between consumers (Porter & Golan, 2006). Companies only communicate with a limited number of consumers. Therefore gaining insights in their decision-making in the referral process and an identification of the factors that drive them to forward a message is important.

6.2.2 Factors that Influence Consumers' Decision-Making

Two streams of literature provide important insights in the referral process from a consumer's point of view. The first stream analyzes why consumers participate in viral campaigns and make referrals using psychographic constructs. Consumers participate and refer products to their friends due to intrinsic motives, i.e., to generate fun or value for others (Dholakia, Bagozzi & Pearo, 2004) or due to extrinsic motives like financial incentives (Ryu & Feick, 2007). Verhoef, Franses and Hoekstra (2002) show that relational constructs like commitment and trust play an important role in the referral process and thus highlight the relevance of the relationship. The second stream focuses on the relationship between the consumer's position within her social network and WOM-related aspects. The network structure is important in viral campaigns (Bampo, Ewing, Mather, Stewart & Wallace, 2008). Within their network consumers are more

likely to activate strong ties than weak ties when they actively search for information (Johnson Brown & Reingen, 1987). Tie strength can therefore be associated with the quality of the relationship. Targeting consumers with a high quantity of relationships, i.e., consumers who possess a high degree centrality, leads to a higher number of visible actions, like page visits, than random seeding strategies (Hinz, Skiera, Barrot & Becker, 2011). However, both streams of research are rarely analyzed jointly. The authors are only aware of one study of Iyengar, van den Bulte, and Valente (2011) in recent years who analyze psychographic and sociographic constructs for opinion leadership jointly in the context of referrals for new drugs between specialists. They conclude that correlations between both are low and that they are likely to form different constructs. But this study neither takes place in an electronic, nor in a mobile context.

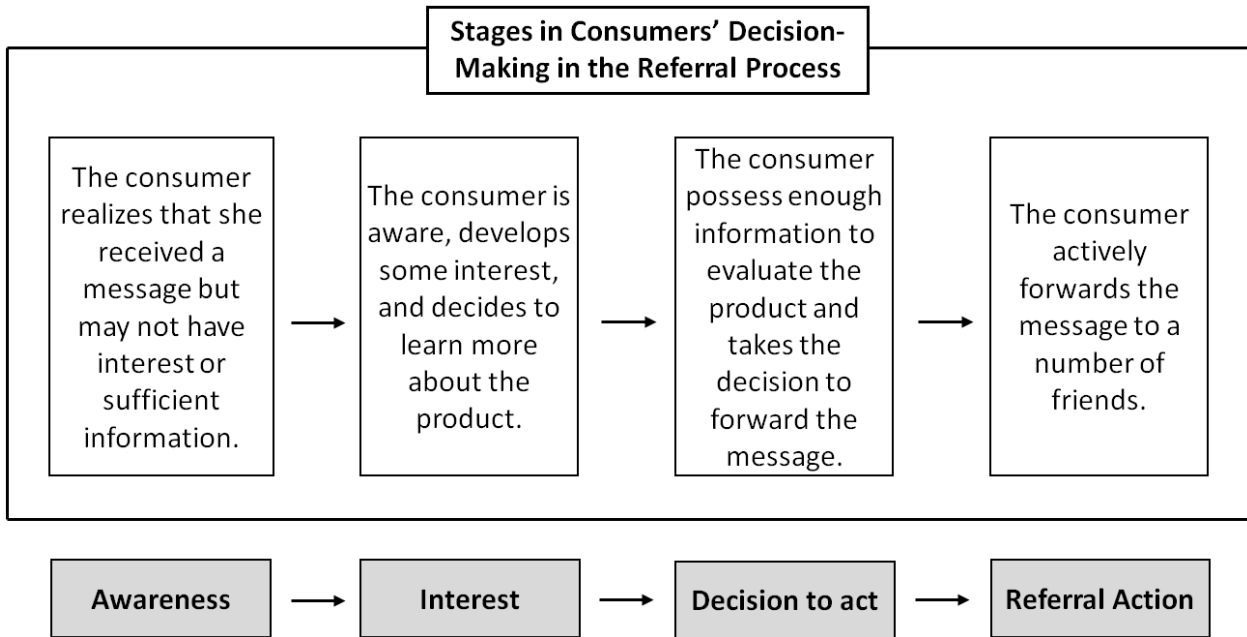
6.2.3 Stages of Consumers' Decision-Making in the Referral Process

Consumers' decision making processes consist of multiple stages (Bettman, 1979; De Bruyn & Lilien, 2008). However, the models described in literature analyze decision making processes that end in a visible action, usually in a binary 0/1 decision, like buy/no buy. In a referral context, the final goal is to generate a high number of referrals. Therefore our model of consumers' forwarding behavior is built according to the specific situation of referral campaigns.

Once consumers receive and read a text message, they enter the awareness stage. In this stage, they are aware of the message itself and of the product which is advertised. If the consumer develops more interest, she enters the interest stage. In this stage the consumer decides to learn more about the product. If the consumer perceives the product to be interesting after learning about it, she takes the decision to act and forwards the message. However, after taking the decision to forward the message, the consumer has to decide to how many of her contacts she will forward the message to; we call it referral action stage. This step is important for the success of a campaign, in which higher numbers of referrals are better than lower number of referrals.

Figure 6.1 displays our model, summarizes the steps and provides an individual description.

Figure 6.1: Stages of Consumers' Decision-Making in the Referral Process



6.2.4 Development of Hypotheses

The factors that influence the stages in the decision-making process can be divided into two groups. The first group consists of psychographic indicators that focus on the consumers' individual motivation to participate in the campaign as well as on her usage behavior. The second group of factors are sociometric indicators. They provide information about the type of relationship the consumer has with her contacts and about the resulting social structure.

6.2.4.1 Constructs of Individual Motivation and Usage Intensity

When it comes to consumers' motives to participate in referral programs, research has focused primarily on financial incentives. Some researchers even consider them as an essential characteristic of referral campaigns (Schmitt, Skiera, Barrot & Becker, 2011). Other researchers take a broader approach. Okazaki (2008) defines purposive value and entertainment value as primary value dimensions for consumers in referral campaigns. They are based on the finding that consumers obtain two different benefits of participating in sales promotions: hedonic and utilitarian benefits (Chandon, Wansink & Laurent, 2000). Hedonic benefits are primarily intrinsic and can be associated with entertainment value. Due to legal restrictions companies have to get the permission of their consumers before contacting them. Consumers participate voluntarily and derive value from the fun and relaxation through interacting with peers by forwarding a referral (Dholakia, Bagozzi & Pearo, 2004). For example, a consumer might forward a message to signal to someone: I am thinking of you and obtain value from a funny response.

Utilitarian benefits are instrumental and functional and can be associated with the purposive value (Okazaki, 2008). For some consumers forwarding a message in a referral campaign can have personal and social meaning. For example, if a consumer receives a 2for1 offer for a meal at Applebee's on her mobile and knows that one of her friends goes there with a friend regularly, she would know that she is doing something good to her friend by forwarding it to her.

For both motives it is likely that they apply to each of the stages. If a consumer assigns higher levels of entertainment value or purposive value to a message, it is more likely that the message draws her interest and that she takes the decision to pass it on to other consumers. Further, it is likely that the one who assigns higher levels of purposive value or entertainment value to the message forwards it to a higher number of people.

H1a: Higher levels of entertainment value increase the likelihood of entering the interest stage.

H1b: Higher levels of entertainment value increase the likelihood of entering the decision to act stage.

H1c: Higher levels of entertainment value increase the number of referrals.

H2a: Higher levels of purposive value increase the likelihood of entering the interest stage.

H2b: Higher levels of purposive value increase the likelihood of entering the decision to act stage.

H2c: Higher levels of purposive value increase the number of referrals.

Consumers with a high usage intensity are more likely to participate in a mobile viral campaign than other consumers due to two reasons. First, if a consumer does not have a lot of experience with mobile viral campaigns, usage intensity is an antecedent of the probability of trial and adoption (Steenkamp & Gielens, 2003). Since mobile viral campaigns are a fairly new of advertising, it is likely that consumers with high usage intensity are more likely to forward messages than other consumers. Second, consumers with high usage intensity are used to communicate via cell phone and they are used to write messages. Therefore it is likely, that the threshold to forward a message is lower for them than for other consumers. This effect is likely to hold for all stages of the decision process.

H3a: Higher levels of usage intensity increase the likelihood of entering the interest stage.

H3b: Higher levels of usage intensity increase the likelihood of entering the decision to act stage.

H3c: Higher levels of usage intensity increase the number of referrals.

6.2.4.2 Sociometric Indicators

Sociometric indicators describe the interaction structure of an individual consumer with her surroundings. Once consumers receive an interesting message with a link, it is likely that they want to find out more about the link. The interest is mainly product related. Therefore sociometric indicators are not relevant in entering the interest stage. Once the consumer has visited the homepage and verified that the offer is interesting, she starts to think whether the message is worth forwarding, and if yes to whom. Sociometric indicators provide information about the social structure of each individual consumer. This structure influences the likelihood of knowing someone who might be interested in the offered product. Whether and to how many people the message is forwarded, depends on two aspects: the quality and the quantity of relations.

Tie strength is an important factor in WOM. It increases with the amount of time spent together and emotional intensity (Marsden & Campbell, 1984). When consumers actively search for information, they tend to turn to strong ties instead of weak ties to receive referrals and they perceive strong ties to be more influential, too (Johnson Brown & Reingen, 1987). The main reason for this is that strong ties are perceived to be more trustworthy and credible than weak ties (Rogers, 1995). Therefore, tie strength is an indicator for the quality of a relationship. In an e-mail context, De Bruyn and Lilien (2008) argue that trust reduces the perceived risk which follows the advent of spam and e-mail based worms and viruses. In a mobile context, this argumentation is not likely to hold because aspects like worms and viruses are not a major issue. Instead, the perceived risk for the consumer – if she forwards the referral and becomes a sender – rather lies in the fact that the receiver is already overwhelmed by advertising and therefore is not too happy about receiving additional messages. As a consequence the message's receiver could ask the sender not to forward messages anymore. Or the receiver could possibly simply decide to block messages from the sender; in other words: they would sanction the consumer. Consumers generally perceive sanctions to be worse if they are imposed by strong ties like good friends as if by weak ties like acquaintances - simply because the weak tie is less important to her. Thus, the perceived risk of forwarding a message decreases with decreasing tie strength.

On the information level consumers that are connected via strong ties tend to share the same information which is rarely new to them. Contrary, consumers rather obtain important information via weak ties, because those tend to possess information which is “new” to them (Granovetter, 1973). Given that consumers are more likely to send a message to someone if the

content is new to the receiver, this argumentation makes it more likely that consumers forward the message to a weak tie than to a strong tie.

Both lines of argumentation point to the same direction and lead to the conclusion that

H4a: Lower levels of tie strength increase the likelihood of taking the decision to act.

H4b: Lower levels of tie strength increase the total number of referrals.

Hubs are actors who possess a high number of direct contacts, e.g., they possess a high quantity of contacts (Goldenberg, Han, Lehmann & Hong, 2009). They know more people to forward the message to – thus they can influence more people (Hinz, Skiera, Barrot & Becker, 2011). Hubs adopt early, increase the speed of the adoption process and have an influence on the size of the total market (Goldenberg, Han, Lehmann & Hong, 2009). They also tend to be opinion leaders (Kratzer & Lettl, 2009; Rogers & Cartano, 1962). They possess a high status and serve as reference points in the process of information diffusion. Small groups of opinion leaders often initiate the diffusion process of innovations (Van den Bulte & Joshi, 2007). All of these arguments indicate that targeting a hub with a message leads to a higher number of referrals.

Other scholars argue that if many companies focus on actors with one special characteristic, i.e., on hubs, this could potentially lead to an information overload (Porter & Donthu, 2008). This information load could lead to a lower level of attention they can pay to messages – and thus to a lower number of referrals.

However, in the case of mobile marketing it is not likely that single actors suffer from information overload at the moment because the entire area of mobile marketing is still at the beginning its growth phase. Thus, we hypothesize

H5a: Higher levels of degree centrality increase the likelihood of taking the decision to act.

H5b: Higher levels of degree centrality increase the number of total referrals.

6.3. Empirical Study

6.3.1 Goal and Research Design

The goal of the empirical study is to test the hypotheses presented above with a three stage sample-selection model that represents the stages of a consumer's decision-making process in a referral context.

In our study we conduct a mobile viral campaign in cooperation with a large European telecommunication company. The participants had declared that they would accept to receive advertising messages on their cell phones. A text message was sent to randomly chosen customers of the company, which included a link and the notice that they could download a lately introduced piece of music from the charts for free. In this text message, they were also asked to forward the message. One week later we sent another text message to all participants who received the first link which includes a link to the online survey/questionnaire. This questionnaire was sent to 26137 consumers. We provided 1 x 100 Euro and 2 x 50 Euro as an incentive to participate in the survey. The winners were drawn in a lottery. In the questionnaire, participants provided information about their behavior in different steps of the referral process, as well as about psychological constructs and about their egocentric network (Burt, 1984). 634 consumers recalled the message (attention), 440 visited the homepage (interest), 144 consumers forwarded the message (decision to act) to a total of 606 contacts (referral action).

We implement a three stage sample selection model with two selection stages. We model the interest stage with a binary variable I_i , which states whether the consumer i visited the homepage via the link she received via short message, using a Probit model. For the action stage we use a Tobit II specification (Amemiya, 1984) which consists of the binary variable A_i providing information about whether consumer i forwarded the message to her friends or not. R_i captures the number of people consumer i forwarded the message to, i.e., the number of referrals made. I_i^* and A_i^* are the latent variables related to I_i and A_i , R_i^* is the censored variable related to R_i . Our resulting model can be found in equations (6.1)-(6.6):

$$(6.1) \quad I_i = \begin{cases} 1 & \text{if } I_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$(6.2) \quad A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$(6.3) \quad R_i = \begin{cases} R_i^* & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

with

$$(6.4) \quad I_i^* = \beta_{I0i} + \beta_{Iij} * X_{Iij} + \varepsilon_{Ii}$$

$$(6.5) \quad A_i^* = \beta_{A0i} + \beta_{Aij} * X_{Aij} + \varepsilon_{Ai}$$

and

$$(6.6) \quad R_i^* = \beta_{R0i} + \beta_{Rij} * X_{Rij} + \varepsilon_{Ri}$$

In this model X_{ij} is the vector of the explanatory variables j (entertainment value, purposive value, usage intensity, degree centrality and tie strength); ε_{Ii} , ε_{Ai} and ε_{Ri} represent unobserved factors that influence the individuals' referral decision and its extent. The subscripts I, A, and R show that the parameters are equation specific. All equations are estimated simultaneously using a conditional recursive mixed process estimator in Stata 11. Note that the model specification requires that the variables which enter the regression stage are not identical to the ones in the selection stages. Therefore we added the sex in the selection stages, but not in the regression stage.

6.3.2 Measures

Psychographic Constructs. The psychographic constructs “purposive value” and “entertainment value” originally stem from Dholakia, Bagozzi and Pears (2004) and were operationalized according to Okazaki (2008). See Appendix for details. All items were measured on a five-point Likert scale using scale points from “do not agree at all” to “totally agree”. We operationalized the “usage intensity” by the number of text messages each participant writes per day. Sex is coded with 0 for male and a 1 for female.

Sociometric Indicators. In order to measure consumers' social networks, we surveyed their egocentric network (Burt, 1984; Fischer, 1982; McCallister & Fischer, 1978; Straits, 2000). Egocentric networks are defined as the direct relationships between an individual consumer (or

ego) and her relationships to other people (or alters) and the relationships that exist between the alters. They are small networks of one focal actor called the “ego,” the participant in the survey, and her contacts, called “alters.” The difference between a regular network and an egocentric network is that in the latter all of the necessary information is obtained from one actor, which makes it a feasible method for samples that are representative for a large-scale population. To gain respondents’ core network, we used the name generator, which was taken from Burt (1984) and adapted it to the specific characteristics of this study. After generating the list of alters, in which the participants of the study stated their most frequent contacts, participants were asked a series of name interpreters, including the strength of relationship with each contact. Note that each egocentric network is calculated based on the information from one single respondent. Therefore egocentric networks are usually treated as undirected. Based on this information we calculated the degree centrality and the average tie strength. Marsden (2002) shows that the egocentric centrality measures are generally good proxies for the sociocentric centrality measures.

6.3.3 Results and Implications

6.3.3.1 Relationship between Psychographic Constructs and Sociometric Indicators

Table 6.1 shows the correlations among the variables in this study. The entertainment value is weakly correlated with both sociometric indicators, degree centrality and tie strength as well as with the usage intensity, and strongly correlated with the purposive value of a message. However, in our sample selection model multicollinearity is not a problem. All variance inflation factors (VIFs) are below 2.

Table 6.1: Correlations Among Variables in Study

	Mean	STD	1.	2.	3.	4.
1. Entertainment Value	4.179	1.536				
2. Purposive Value	3.786	1.645	.524*			
3. Usage Intensity	7.520	19.679	.136*	.045		
4. Degree Centrality	3.040	1.459	.080*	.022	.047	
5. Tie Strength	3.102	.795	.110*	.062	.008	.024

*p<.05

6.3.3.2 Results of Three-Stage Sample Selection Model

Table 6.2 shows the results of our sample selection model. The likelihood ratio test supports the model at a significance level of .01 percent.

Table 6.2: Results of Sample Selection Model

		No. of observations		634			
		Wald chi ²		21,18			
Log likelihood		-983,138		Prob>chi ²			
				<.001			
		Selection Stage Awareness-Interest		Selection Stage Interest – Decision to Act		Regression Stage Decision to Act – Referral Action	
		Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept		-.055	.272	-2.409*	.317	2.705	1.667
Entertainment Value		.078	.041	.089	.051	-.007	.297
Purposive Value		.173*	.039	.431*	.050	.369	.320
Usage Intensity		.004	.003	.006*	.003	.063*	.020
Degree Centrality		.005	.038	.049	.043	.572*	.243
Tie Strength		-.123	.068	-.257*	.077	-.980*	.415
Sex		-.254*	.108	-.094	.130		

*p<.05

Entertainment Value and Purposive Value (H1a, H1b, H1c, H2a, H2b, H2c). Our model does not show support for the hypotheses 1a-c, which are related to entertainment value. However, it does show support for H2a and H2b, but not for H2c which is related to the number of referrals. This finding leads to two relevant insights. First, in the context of mobile viral marketing campaigns the effects of purposive value are a lot stronger than the effects of entertainment value. This finding can potentially be mobile-specific because the mobile setting is different from the internet for example. In text messages, there is only space for a limited content which mainly consists of text features. As a consequence, in this setting consumers rather deal with information than with entertainment. This is different from an online setting, where consumers have the option to attach links to videos or pictures to the e-mail – which can be used to entertain the receiver of the message. Further, usage patterns differ between mobile devices and

computers. Whereas consumers are usually used to spend longer time periods on the internet, mobile devices are more often used in settings when consumers are hurried – for example on the way to or during work. Thus, quick reactions based on impulsive behavior play a more important role. After taking a close look at the contact, consumers are likely to decide rather quickly if they forward the message or not. In an online context, it is likely that consumers possess more time to think whether they will forward a mail or not. Therefore, companies which are planning to conduct mobile viral campaign should consider the specific characteristics of the mobile setting and rather focus on the usefulness of a product or on the unique feature of the specific offer than on entertaining the consumers.

Usage Intensity (H3a, H3b, H3c). Our model provides support for H3b and H3c, but not for H3a. These results indicate that the usage intensity does not play a relevant role when it comes to the point when consumers enter the interest stage of the model. However, when the consumer takes the decisions whether to forward the message or not and to the number of referrals, then the usage intensity provides relevant insights. This finding indicates that consumers who are used to write text messages are more likely to forward the messages to other consumers. The benefit of the usage intensity for companies is it being an observable variable.

Relevance of Sociometric Indicators. The quality and quantity of relationships do not have any influence on the interest stage, in which the consumer mainly focuses on the message and its content. However, when the consumer thinks about her contacts in the decision to act stage and especially to how many contacts she should forward the message, sociometric indicators become relevant. This finding is especially interesting in the context of the renewed interest on social interaction. Iyengar, van den Bulte and Valente (2011) found out that sociometric and psychographic opinion leaders are likely to form different constructs although they are traditionally interpreted in similar ways.

Tie Strength (H4a, H4b). Our model shows support for H4a and H4b. Low tie strengths significantly increase the likelihood that the consumers take the decision to forward the message. Low tie strengths have a positive influence on the total number of referrals, too. This finding seems to contradict previous results from literature, namely the results of Johnson Brown and Reingen (1987), who found out that consumers tend to turn to strong ties when they actively search for information. However, in their study they focused on consumers who are actively searching for relevant information and who are thus receivers of information. Contrary, in the present study we deal with messages that are sent from the consumer to her contacts without

being solicited. Thus we focus on the sender of the message. The same argumentation holds for a comparison between the study of De Bruyn and Lilien (2008) and the present study. They find out that receivers of unsolicited e-mails tend to be more aware if the mails stem from close contacts – e.g., contacts with a high quality. This finding is plausible. In this study we focus on the sender of unsolicited messages. They are more likely to pass the message on to weak ties, i.e., low quality contacts. Although on the first view these results seem to be contradictive, on the second view they provide insights into a possible explanation why some viral campaigns might fail although they are carefully planned. On the one hand, the consumers with weaker ties tend to forward the message to a higher number of contacts, because the perceived risk of forwarding a message is lower for them than for strong ties. On the other hand, the receivers of the message tend to become aware mainly through the messages from strong ties, because they trust them more than they trust the weak ties (Rogers, 1995) – which in turn are unlikely to be the senders of the messages. This might lead to a high number of referrals who are performed by the consumers but ignored by the receivers of the messages. This finding can be seen as a call for further research when it comes to conditions for the success of mobile referral campaigns.

Degree Centrality (H5a, H5b). Our model does not support H3a, but it supports H3b. This means that the quantity of relationships does not influence whether someone takes the decision to forward the message. But it does influence to how many people a consumer forwards a message. The positive influence of degree centrality on the number of referrals is in line with previous research that found out that actors with a high degree centrality tend to forward the message to more contacts (Hinz, Skiera, Barrot & Becker 2011). Further, the non-significance of degree centrality on the interest and the decision to act stages of the model helps to gain insights on the usefulness of sociometric indicators in the context of social interaction. Sociometric opinion leadership which is characterized by a high degree centrality does not have a high influence on decision processes which take place within each consumer. But it does have an influence on the outcome of social interaction due to information flow via referrals. This finding is in line with previous research which states that observable differences between sociometric opinion leaders and other consumers are mainly based on different levels of information that stem from differences in the network structure (Goldenberg, Han, Lehmann & Hong, 2009).

Table 6.3 gives an overview of the results of this paper.

Table 6.3: Results

	Awareness	→	Interest	→	Decision to Act	→	Referral Action
Entertainment Value			H1a		H1b		H1c
Purposive Value			H2a		H2b		H2c
Usage Intensity			H3a		H3b		H3c
Tie Strength					H4a		H4b
Degree Centrality					H5a		H5b

6.4 Discussion

On a theoretical level this paper develops a multi-stage model to analyze the decision-making process of consumers in mobile viral campaigns. This is of crucial importance because in viral campaigns only few consumers are actively approached by the company. Therefore, gaining additional knowledge on these consumers and their decision-making process, as well as on the factors that influence it, may decide over success or failure of viral campaigns.

The multi-step approach allows us to gain a deeper understanding of consumer's decision-making process in referral campaigns. We have three key findings in this paper. The first key finding is the important role of the purposive value in early stages of the decision-making process contrary to the entertainment value. This finding is relevant for the design of mobile viral campaigns. When using text messages as an advertising tool in viral campaigns, managers should take into account two specific characteristics of the mobile setting. First, it is a setting in which consumers are more often hurried and tend to show more impulse behavior than in an online setting, in which they tend to spend more time. Second, in text messages they have limited space and few graphical options that can help to entertain the consumer. As a consequence of both, they should highlight the usefulness of the product or special offer, whereas the entertainment aspect is less relevant in mobile viral campaigns. The second key finding is that characteristics that are observable for mobile marketing companies, like sociometric indicators and the usage intensity, play an important role in the late, but not in the early phases of the decision-making process. They influence the final number of referrals made by each consumer. When choosing the seeding points for a viral campaign, managers should focus on consumers with those characteristics. The third key finding of this paper can be seen as a call for future research with respect to the success of viral marketing campaigns. Consumers with low quality contacts tend to forward the message more frequently, because the perceived risk, which

includes social sanctions for example, of forwarding a message is low. Contrary, the message's receivers are mainly interested in content they receive from high quality contacts, because they are perceived to be more trustworthy (Rogers, 1995). But those are unlikely to be the senders of the messages. This process might lead to a high number of referrals who are ignored by the receivers of the messages.

Our study possesses some limitations which provide avenues for future research. First, it is not clear whether our findings are generalizable to the viral marketing campaigns on the internet. Take for example the weak results of the entertainment value. Whereas text messages in mobile settings offer limited space to entertain consumers, on the internet there is a wide variety of features available which can be used to entertain consumers. In this context it remains interesting how things will change once a large part of the population will possess technologically advanced smart phones which provide easier access to the internet than current mobile- and smart phones do. Second, the participants of this study were members of an opt-in program of a large phone company. They had declared they accept to receive messages by the company. Due to legal restrictions in Europe this was the only way this study could be realized in the focal country. Therefore it remains unclear how consumers who did not give their permission to receive messages would react to unsolicited messages. Third, in the focal country mobile marketing is still an emerging field. There are very few campaigns compared to other countries. Therefore it is likely that consumers pay attention to those they become aware of. It is not clear how results will change when growth rates of mobile viral marketing campaigns continue to increase.

7. Conclusion

7.1 Summary

Social networks describe patterns of human interactions, e.g., communication or friendship. The goal of this thesis was to develop approaches how social network analysis can help to improve new product success forecasts based on information obtained from experts or consumers, and to find out how information about social networks can provide relevant information for marketing applications like targeting or seeding strategies in viral marketing campaigns.

This thesis started with an introduction which was followed by a theoretical chapter on how to measure social networks. Chapters 3 to 6 conducted four empirical studies that helped to analyze this thesis' goals. The key results will be presented briefly on the following pages.

1. What methods exist to collect social network data?

The best and most common approach to analyze social networks are total networks. Under certain circumstances, which are common in marketing, it is not possible to measure them: (1) the number of consumers in the network might be too large to be measured, for example market segments with thousands of consumers; (2) high response rates are necessary in order to generate the total network; (3) total networks cannot be measured if there is no or only little information about the network's actors.

For those cases researchers developed alternative methods to gather network data; the most important ones are snowballing or egocentric networks. The snowballing method is useful in case (3). In case (1) and (2) researchers can use egocentric networks. They can be generated based on the information of an individual consumer, because they only take into consideration the consumers' direct contacts. Benefits include that they are easy to measure and only require limited effort. A limitation is that the variety of network measures available for egocentric measures is fairly low.

2. How can information from social networks be used to improve experts' forecasts?

Chapter 3 shows that information from social networks can help to improve the forecasting accuracy of combined judgmental forecasts for variables which are hard to predict, but not for those which are easy to predict. For the former one, assigning higher weights to actors with a high betweenness centrality leads to forecasts which are significantly better than assigning higher weights to actors with a high degree centrality. Betweenness and degree outperform

indicators that have been discussed in literature so far, e.g., the competence of the experts or the confidence of the experts in their forecasts.

3. How can social network data help to consider the role of influentials in preference-based market forecasts and thus improve them?

This chapter develops a method to improve new product success forecasts by considering the role of influentials in market forecasts based on conjoint analysis. This approach is especially useful for the evaluation of new product concepts in early stages of the new product development process, when product configuration can still be altered. Social network measures help to account for the role of influentials in preference-based new product success forecasts based on conjoint analysis with the help of an easy-to-use weighting procedure. They lead to a higher forecasting accuracy than psychographic constructs.

4. Does the brokerage position provide information about the actor's role in social interaction and about the underlying preferences?

Brokers are actors in boundary-spanning positions. The results of this study indicate that they are very independent consumers. They are less susceptible to interpersonal influence, less active in information seeking than other consumers and they also consider status goods to be less important than other consumers. Further, they attribute lower importance to the price. The latter result indicates that brokers are an interesting target group in terms of profitability. The former result indicates that they are less suited to be subject to viral marketing campaigns and other marketing approaches that rely on social interaction between consumers.

5. What factors influence the success of viral marketing campaigns – psychographic constructs or social networks?

This study develops a multi-stage model of the consumers' decision making process in viral marketing campaigns. The results show that in early stages of the process psychographic indicators are important to arouse consumers' interest, whereas in late stages of the process social network indicators determine to how many of their peers consumers forward the message. Thus, both indicators are helpful to determine the overall success of the campaign.

7.2 Implications and Outlook

This thesis showed in four empirical studies that social network analysis can provide relevant information which can help to improve forecasts and provide relevant information for the development of new marketing techniques and strategies. The results lead to a variety of implications for practitioners and researchers.

For practitioners, relevant aspects in which social network analysis can be helpful include the improvement of existing marketing approaches, e.g., combined judgmental forecasts (chapter 3) or preference-based market forecasts (chapter 4), or the development new ones, e.g., the development of seeding strategies in viral marketing campaigns (chapter 6). Generally, social network analysis potentially provides relevant information in situations, in which humans interact with each other. Two relevant questions marketing practitioners frequently ask are “How can I get good data?” and “Is social network data superior to alternative methods like psychographic constructs?”

The first question is not easy to answer. Sometimes, for example in organizations or in the internet, observable network data can be available, e.g., if it can be constructed based on information exchange, like phone calls or e-mail, or based on stated relations like friend lists. If the social network has to be measured, practitioners should try to get information on total networks. For large scale survey-based studies, egocentric networks can be helpful. Although they are widely discussed in sociology, marketing literature has not paid a lot of attention to them.

The second question is relevant, because the collection of social network data tends to be expensive (Van den Bulte & Wuyts, 2007). Although there are first studies who compare psychographic and sociometric indicators (Iyengar, Van den Bulte & Valente, 2011), the additional benefits of social network data on top of alternative approaches has not been demonstrated yet. Two chapters of this thesis provide relevant insights in this context. Chapter 4 shows that in forecasting sociometric indicators outperform psychographic constructs when it comes to account for future social interaction. Chapter 6 analyzes the role of psychographic and sociometric indicators on consumers’ decision making in viral marketing campaigns. It finds that both types of indicators contribute significantly to the potential success of viral marketing campaigns – but on different stages of the process. Thus, both chapters find that for practitioners it can potentially be fruitful to invest in social network data.

In the area of forecasting situations of high uncertainty, like new product success forecasting in chapter 3, are usually characterized by a lack of historic market data. Thus, survey-based methods have to be used. In those situations, social networks can provide relevant information. Chapter 3 showed that actors in boundary-spanning position provide better forecasts than other actors, most likely because they possess information benefits (Burt, 1992; Granovetter, 1973). Therefore it may potentially be fruitful for the quality of forecasts to rely on informants in boundary spanning positions. They can be identified via regular networks or via egocentric networks. This finding is especially relevant for forecasting situations in which it is hard to receive forecasts from experts. Companies, who need to identify additional experts who can provide reliable forecasts, are recommended to focus on actors in boundary-spanning positions of a relevant network. They should target these experts with more effort than other experts to obtain their individual estimates. Chapter 4 showed that in the case of forecasts based on conjoint analysis, the preferences of hubs and brokers provide valuable information because they seem to influence other consumers. Over time, their preferences become more dominant in the market. This finding is potentially relevant in the process of new product development, in which a longer time period passes between the conjoint analysis and the new product's introduction into the market. Practitioners should design the products more according to the preferences of the influentials than according to the needs of all consumers. Afterwards, until the product is introduced into the market, it is likely that the preferences of all consumers in the market will develop in the direction of the influential's preferences.

Information from social network analysis promises to be useful in targeting strategies. Chapter 5 showed that actors in boundary-spanning positions display a lower importance weight for the price; thus, they consider the price to be less relevant than other product characteristics for their purchase decision. For practitioners this finding is relevant in two ways. First, it indicates that brokers are potentially a very interesting target group. Producers of more expensive goods should directly target brokers, because they promise to be a wealthy target group. Second, this finding shows that social networks can provide relevant information about consumer characteristics. This finding forms the base for the development of new marketing tools, e.g., the development of network based segmentation and positioning strategies. Further, the finding that the network position does provide information about the importance weight of a product's price potentially allows to include observable sociometric indicators as proxies in the calculation of financial indicators, like the customer's lifetime value.

Sociometric indicators promise to be useful in seeding strategies. However, there are different approaches what network positions should be targeted exactly. There are three lines of argumentation (Van den Bulte, 2009). The first is that companies should use hubs, i.e., actors with a lot of contacts, as seeding points, because they have more contacts they can forward the message to. The second is that they should target isolates, i.e., actors without or with very few contacts, because they receive less attention and thus forward the message with a higher probability. The third is that actors in boundary-spanning positions, i.e., actors who connect otherwise unconnected parts of the network, are the ideal seeding points, because they forward the information in various groups. Chapter 6 shows that degree centrality has a significant influence on the number of referrals. This finding indicates that the first line of argumentation is correct, whereas the second one is not. Chapter 5 found out that brokers, who are actors in boundary spanning positions, rather tend to be consumers who are not susceptible to interpersonal influence. This result shows that they are independent consumers who are unlikely to influence other consumers substantially in their purchase decisions. Thus, practitioners should focus on hubs when they are planning to increase the effectiveness of viral marketing campaigns.

The results of this thesis provide relevant information for scientists' future research.

In the area of forecasting, the results of this thesis show that social network data can help to increase forecasting accuracy. In the case of combined judgmental forecast, the results of chapter 3 deliver input for relevant research questions. Two of them promise to determine the future practical applicability of this method and to lead to additional improvements in forecasting accuracy. First, future studies should try to gain additional insights in the evaluation, for which group of experts social network analysis is likely to increase the forecasting accuracy significantly. For example, do sociometric indicators only provide information about forecasting accuracy in professional networks, or does this approach also provide relevant forecasting accuracy in consumers' networks? If the latter one was true, the relevance of this approach could rise significantly, because the number of experts which can be asked to provide forecasts, e.g., consumers in selected online communities, would increase. Companies could approach a high number of consumers online, e.g., in social networks, and ask them to forecast the success of new products – and then benefit from the wisdom of crowds (Surowiecki, 2004). Second, there are several sources of forecasting errors in experts' forecasts. Important ones include (1) the information the expert has access to and (2) the ability of the informant to transform relevant information into reliable forecasts. Social networks mainly address the informants' access to information as source of the forecasting error and thus can help to reduce it. Indicators for the

informants' ability to generate good forecasts from a given level of information include the informants' confidence in the own forecast as well as a measurement of individual forecasting competence. Future research should develop approaches that consider both types of indicators jointly. This can help to reduce both sources of the forecasting error, the informant's level of information and her ability to generate reliable forecasts, and should thus increase forecasting accuracy.

For researchers, the finding in chapter 4, that the consideration of influentials in market forecasts based on conjoint analysis helps to increase forecasting accuracy, leads to several research opportunities. Future research should focus on gaining further insights in the role of influentials in the formation of preferences. In this context a number of research questions can provide further insights. First, researchers should evaluate how influentials' influence on other consumers changes over different time horizons. It is unclear, whether the effects that occur rather depend on the time period which passes between conjoint analysis and market introduction of the product – which would be an indicator for a slow, but constant change in preferences – or whether the effects occur after the market introduction – which would rather be an indicator for strong changes in preferences that occur suddenly. Second, although the results of chapter 4 show the relevance of the concept of influentials in social networks, it currently remains unclear, whether influentials themselves are subjects to stronger changes in preferences than other consumers or not. This research question is relevant, because it provides some insights whether targeting influentials is useful for companies or not. If influentials' preferences were fairly stable, it would make sense to develop new products according to their needs and then benefiting from their important role in the market. Contrary, if their preferences were subject to stronger changes, it could also make sense to develop the products according to the needs of the market and then try to alter influentials' preferences, e.g., with marketing activities like tailored communication campaigns for influentials. Third, the important role of influentials in the market place has been demonstrated in a number of studies (Godes & Mayzlin, 2009; Goldenberg, Lehmann, Shidlovski & Barak, 2006; Rogers, 1995). However, Watts and Dodds (2007) have demonstrated that that large cascades of influence are not driven by influentials, but by a critical mass of easily influenced individuals. Although their results were based on a simulation, this finding calls for further examination with empirical works, also in the context of preference formation. Fourth, researchers should search for indicators that complement information about influentials and that help to gain further insights. One example could be to observe the link building behavior of influentials. One benefit is that this behavior can be observable, e.g., in an

online context. For example, to date it remains completely unclear which hub is more likely to be influential, given the same number of contacts in the end: (1) someone who sends a lot of friend requests in a short period of time, (2) someone who constantly sends a small number of friend requests over a longer time period, (3) someone who mainly receives friend requests, or (4) someone who does both, receive and send friend requests. Answering this question can help to identify the most important actors in the network.

The four research questions named in the paragraph above are related to preferences that change over time. They have in common that they can best be analyzed with longitudinal network data. Although in sociology and other disciplines longitudinal network data is common (Lazega, Mounier, Snijders & Tubaro, 2011; Snijders & Doreian, 2010; Steglich, Snijders & Pearson, 2010), marketing researchers are just beginning to make use of the potential to analyze large networks with longitudinal data sets (Ansari, Koenigsberg & Stahl, 2011). Further, future research should focus on the methodological development of approaches that directly incorporate information about influentials into the conjoint analysis and to estimate them in a one-step approach.

Another promising area for the development of marketing applications based on social network data is the targeting of consumers. The key assumption behind this idea is that the social network provides information about the consumer and her preferences without having to survey them. Chapter 5 showed that brokers' preferences differ from the preferences of other users with respect to the importance they attribute to the price. Although this is a first relevant finding, there is still need for additional research. One research design is especially promising in this context. In order to determine generalizable regularities in the relationship between actors' network positions and their preferences, researchers could use an experimental design, in which the relationships in the experimental network are constructed in a way that they are weaker than relationships in real-world networks. This could be done by randomly distributing actors, who only communicate with each other by chat, to positions in the social network. Further, actors receive financial incentives to maintain that network position. After having played for a couple of rounds, the network members can be asked to bid for status goods that are visible to the other participants of the experiment (normative influence) or for features that facilitate the communication with other participants (informational influence). It is best to use a second price sealed bid auction (Barrot, Albers, Skiera & Schäfers, 2010), which provides strong incentives to consumers to display their willingness to pay for the goods. The willingness to pay provides information about the underlying preferences. If the results yield significant differences in

preferences between network positions for these relatively weak networks, it is likely that the stronger real world networks also provide relevant information about actors' preferences.

In the area of seeding in mobile viral marketing campaigns the results of chapter 6 show that approaching hubs as seeding points increases the probability that the seeding point forwards the message to a high number of contacts. Currently, viral marketing campaigns are not very common in Germany. However, it is likely that their importance increases. This can lead to the consequence that consumers receive more messages than they receive today – and also that they receive messages from similar products that are competing in the market. Thus, van den Bulte (2009) raises the question how influentials can be convinced to serve as advocates for one product rather than another. This research question will become more important with an increasing number of viral marketing campaigns. Since companies become more interested in viral marketing campaigns, there are also more companies that offer the service to conduct these campaigns and to generate firm created word of mouth for other companies. Examples include BzzAgent, Matchstick, SheSpeaks, Tremor or Vocalpoint (Van den Bulte, 2009). So far, the author of this thesis is only aware of one such study in a major marketing journal (Godes & Mayzlin, 2009). This study yields interesting insights, but analyzes the research question focusing on actor related variables, like the initial awareness level, rather than on sociometric indicators. Thus, there still exist substantial research opportunities. Another research opportunity includes the question how firm created word of mouth is different from traditional or online word of mouth. Can companies really undertake systematic marketing actions which are as strong as the effects of traditional word of mouth? If yes, how do they have to be designed?

The technological development not only paves the road for more mobile viral marketing campaigns, but also for other interesting research questions in the area of mobile marketing. One key feature of mobile marketing is the fact, that consumers take their mobile or smartphone wherever they go, also when they make purchases. Each purchase takes place via a specific channel (store, online), at a specific point of time and a specific location. Researchers have analyzed the advantages of different channels (Anderson, Day & Rangan, 1998; Gensler, Dekimpe & Skiera, 2007), and found out that consumers possess present-biased preferences (Gilpatric, 2009; O'Donoghue & Rabin, 1999). Mobile marketing promises rich data sets which give researchers the opportunity to analyze the impact of the location's influence on purchase decisions. With respect to social networks, data sets from mobile marketing also promise further insights. Take for example Facebook's "Like-it" button. Consumers can use it to evaluate the shops, restaurants and even the products they find especially appealing. This data allows

researchers to gain further insights in the process of interpersonal influence, because it offers the ability to track both, communication patterns and consumption decisions. When consumers take a purchase decision, e.g., a new pair of shoes, will they purchase the pair which was recommended by the local hub or decide to buy the pair a good friend likes? The first decision would support the concept of the influentials, whereas the latter one would stress the relevance of tie strength.

One of the reasons why social network analysis gained renewed importance among marketing scholars is the availability of social network data due to the rise of social networks, like Facebook or Xing, and virtual worlds or online role games, like Second Life or World of Warcraft. By using these data sets researchers assume that online networks approximate consumer's real world social networks. However, this assumption has never been tested scientifically. There are reasonable doubts whether consumers can have more than 1000 friends in the real world as they can have on Facebook. Further, it is questionable whether two people who have never met, but whose avatars spend time with each other in a virtual world, are going to influence each other's purchase decision in the real world. The analysis whether the underlying assumption stated above is correct or not will determine the relevance of online network data in future marketing studies. If online networks and real world networks were found to be different, researchers should try to clarify how they relate to each other and which type of network can help to explain social influence in what type of consumption decisions.

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