AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Anonymous Social Networks versus Peer Networks in Restaurant Choice

Ashutosh Tiwari and Timothy J. Richards*

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013

May 31, 2013

Abstract

We compare the effect of anonymous social network ratings (Yelp.com) and peer group recommendations on restaurant demand. We conduct a two stage choice experiment and combine it with online social network reviews from Yelp.com and find that peers have a stronger impact on restaurant demand than anonymous reviewers.

Keywords: Peer Networks, Anonymous Networks, Economic Experiment, Social Dining

---

* Authors are graduate student and Morrison Professor of Agribusiness and Resource Management, Morrison School of Management and Agribusiness, Arizona State University, Mesa, AZ. Contact author: Richards: 7171 E Sonoran Arroyo Mall, Mesa, AZ. 85212. Ph. 480-727-1488, FAX 480-323-2294, email: trichards@asu.edu. Copyright 2013. All rights reserved. Do not copy or cite without permission.

1 Introduction

Food Away From Home or FAFH forms a major share of the household food budget, and yet we know very little about why some restaurants succeed, and others fail. Fully 26 % of the restaurants fail within the first year, and around 50 % within the first three years (Parsa et al. 2005). Restaurants seem to be either extremely successful or they struggle to survive, which suggests that there is some form of non-linearity or bandwagon effect driving restaurant demand (Becker 1991). Banerjee (1992), Cai, Chen, and Fang (2009), and Anderson and Magruder (2012) each find that diners rely on information derived from social networks to inform restaurant choices. Social learning, in turn, implies a "social multiplier" effect that would explain the observed bi-modal nature of restaurant success (Manski 1993, 2000). In this study, we use experimental methods to test for social learning effects in a restaurant environment.

Restaurant meals embody multiple attributes, many of which are either experience or credence attributes in the sense of Nelson (1974). As such, consumers face considerable *a priori* uncertainty in choosing where to go. It is not just the food offered in the restaurant but the overall dining experience that drives demand. Attributes such as food taste, food quality, ambiance, service quality, location of the restaurant, menu choices and price, all contribute to the overall dining experience. Diners face uncertainty when they have limited or no prior experience when choosing among available restaurants. To resolve this uncertainty, diners seek various sources of information, which include both marketer-controlled and marketer-uncontrolled sources.

Marketer-uncontrolled sources such as word-of-mouth (WOM) are generally more credible and influential than marketer-uncontrolled sources such as paid advertising (Buttle, 1998; Mangold et al., 1999; Buda and Zhang, 2000). It is well-understood that word of mouth

(WOM) has a strong effect on consumer decision making process (Herr, Kardes and Kim 1991; Maxham 2001; Bruyn and Lilien 2008), but traditional WOM takes place in small social groups and the conversations are ephemeral (Hu and Li 2011). In the last decade, increasing user-based online interaction has eliminated some of the limitations of traditional peer-to-peer communication, and yet has created a sharper distinction between WOM in peer and anonymous networks.

There are two categories of online social networks: peer networks and anonymous networks. In peer networks every member is connected to other members by a primary connection (friend), secondary connection (friend's friend) or tertiary connection (secondary friend's friend) and so on. Watts and Strogatz (1998) show that there is a maximum of six degrees of separation in any peer network -- a phenomenon known as the "small world" effect. Examples of online peer networks are Facebook, Linkedin, Twitter and Instagram. Anonymous networks consist of online communities, where members are past users of different products services, who share their experiences with other members. Yelp, Tripadvisor and Citiguide are examples of few popular anonymous networks. In this study, we compare the relative effect of each type of WOM in driving the demand for restaurants. More generally, we study the role of both anonymous social media and social peer networks in shaping the food trends and fads.

Peer and anonymous WOM differ in several important ways. While peer networks have a trust advantage over anonymous networks (Hilligoss and Rieh 2008), anonymous networks include a far deeper well of knowledge, and different perspectives that may be valuable for potential customers (Cheung and Lee 2012). Web-based interaction or electronic word of mouth (e-WOM) can take place among distant individuals and, more importantly, does not require individuals to send and receive messages at the same time. Moreover, in most cases the

messages are stored in the medium and available for a future reference (Bhatnagar and Ghose 2004; Godes and Mayzlin 2004; Duan, Gu and Whinston 2008). At the same time, consumers rely on peer networks for similar information on services they may have limited experience with. With the rise of web 2.0[1] technology in the last decade and its two way interactive power, online social networking, is a ubiquitous phenomenon. While peer social networking websites such as Facebook.com, Twitter.com, Myspace.com, and Instagram.com enable customers to get feedback and recommendations for products and services based on peer user experiences, anonymous networking websites such as Yelp.com, Traveladvisor.com and CitiGuide.com use customer reviews to disseminate e-WOM. Which category of social networks, anonymous or peer, is more effective in increasing demand, therefore, is an empirical question.

Social learning effects are well-documented in investment decisions (Hong, Kubic and Stein, 2004), new product purchase (Mayzlin 2006, Godes and Mayzlin 2004, 2009) and retirement plan participation (Duflo and Saez 2002, 2003). Reviews and recommendations from members of a consumer's peer network have a strong impact on choice (Narayan, Rao and Sanders 2011; Cai, Chen and Fang 2009; Trusov, Bodapati and Bucklin 2010). These studies, however, focus on peer networking and not anonymous social networks. Anderson and Magruder (2012), on the other hand, show that positive ratings from anonymous Yelp reviewers can raise the apparent demand for restaurants, but they do not compare the value of anonymous and peer networks to consumers and, thereby, to restaurant owners. We aim to compare the relative effect of each type of social network on demand, and quantify the importance of each in driving restaurant success or failure.

[1] Web 2.0 is the newer version of World Wide Web that enables two way interaction and user created content unlike its predecessor, Web 1.0 (Lia and Turban, 2008). These two features are of prime importance to induce the existence and proliferation of online social networks.

The lack of research comparing peer and anonymous social networks is primarily due to a lack of data. While this observation seems paradoxical, given the ubiquity of each, the fact that each represents a fundamentally different concept of social learning means that there is no source of revealed-demand data from both. Therefore, we conduct an economic experiment to compare the effectiveness of anonymous versus peer networks as tools for marketing restaurant meals. We directly compare the impact of publicly available user reviews from a customer review website (Yelp) to that of peer reviews on restaurant demand.

In any empirical model of social learning, identification is always an issue because the individual is also part of the group. Maskin (1993) describes this as the "reflection problem:" How can a researcher infer the effect of the group behavior on the behavior of an individual, when the individual contributes to some of the observed group behavior? Reflection is best mitigated through appropriate experimental design. We conduct a two-stage group-subgroup experiment to tackle the identification problems associated with social learning. We randomly assign members of each peer-group into sub-groups and do not allow peers to decide their subgroup. Such random assignment ensures that peers do not choose subgroups of similar preferences and thus correlation between observed peer attributes and the error term in the restaurant choice regression equation is limited. Recommendations based on restaurant visits in the first-stage by one sub-group are given to members of the other sub-group prior to visiting same restaurant. We then aggregate the data during econometric estimation to incorporate group level heterogeneity in our model similar to Georgi et.al (2007) and Bramoullé et.al (2009). By dividing each peer group into two sub groups, we avoid the reflection problem.

Endogeneity is addressed through an instrumental-variables estimation approach. Specifically, we estimate social learning effects with an ordered probit model, estimated using a

control function approach (Park and Gupta 2009; Petrin and Train 2010). Brock and Durlauf (2002, 2007) demonstrate that peer effects are identified in a discrete choice model, even in the presence of correlated effects with binary or multinomial choice models. In this paper we use an ordered probit model to estimate restaurant demand. We create full information adjacency matrices for each group that gives us complete information about how well a peer knows other members in the same network. Using this information along with individual demographic and behavioral attributes, we are able to identify peer effects at individual level (Bramoullé, Djebbari and Fortin 2009).

While our experimental design allows us to exclude the individual from the group for whom we want to test the peer effect, our control function modelling approach helps up handle endogeneity problem. Combining these two features mean that our experimental design and modelling approach is both unique and appropriate to study peer effects.

We find that peers have a stronger influence on restaurant choice than anonymous rating services, but have a higher variance in their impact due to the relative depth of the online rating service. We also find that all individuals in the known networks do not have equal influence on other members and, similar to Godes and Mayzlin (2009), the most interconnected is not necessarily the most influential individual.

The significance of our research goes beyond the obvious managerial importance of better understanding how social media effects demand. More generally, we identify the relative importance of online rating sites to the peer networking sites. The research guides food retailers to develop effective online social media marketing strategy and helps optimize their marketing budget.

The next section describes a conceptual model that we use to formulate the hypotheses that follow from the theory of social learning through peer and anonymous networks. In the third section, we explain the social dining experiment design and execution. The fourth presents the econometric model, while we summarize our data in the fifth section. We present the econometric model in section six, and conduct a number of specification tests to establish the validity of our approach. Section seven presents and discusses the results, and the eighth summarizes our findings, and suggests some limitations.

2 Economic Model of Social Network Effects

The restaurant market in the U.S is very mature, and provides diners multiple options to choose from (Mack et.al, 2000). While the fast food market offers standardized products and services, fine-dining restaurant offerings are generally more complex, each offering a unique combination of various desired dining attributes. This complexity implies a high degree of uncertainty with respect to quality, or the general level of satisfaction with the experience. Consumers resolve this uncertainty by obtaining information. Among the various sources of information available, word of mouth (WOM) is particularly important. Individuals do not live in isolation and are part of various social communities. Members of these communities interact during social gatherings, formal or informal meetings, social events or even day to day unplanned encounters. These interactions induce a two way flow of information exchange. When this information is particular to any product or services, it is commonly known as spread of "word of mouth." Consumers are more receptive to WOM from members of their social networks than other marketer controlled sources of information such as advertisements and promotions (Reingen and Brown1987, Goldenberg et.al 2001 and Domingos 2005). When a consumer dines at a restaurant and then

shares her experience with other members in the social network, demand for the restaurant within the social network will change (Chevalier and Mayzlin, 2003; Nam, Manchanda, and Chintagunta, 2010). There are two dimensions of WOM effects: magnitude and direction. The magnitude of WOM effect will depend upon influential power and information dissemination power of the source within the network and her communication frequency (Reingen and Kernan 1986; Brown and Reingen 1987) and connection strength with other members (Dierkes, Bichler and Krishnan, 2011).

It is intuitive hat positive WOM will have a positive effect and negative WOM will have a negative effect on demand, but whether the effect is asymmetric is an empirical question. Chevalier and Mayzlin (2006) found some evidence that negative reviews have more powerful impact than that of positive reviews in case of book reviews using secondary online data. Richards and Patterson (1999) found that negative media reports have a greater effect on prices than positive reports after a foodborne disease outbreak in strawberries. . We incorporate both positive and negative online yelp reviews in our experiment and compare the relative effect each on restaurant demand. .

Social network members who disseminate WOM can be either known peers or unknown experts. Both peers and experts influence consumer decision making processes, but finding the most influential is an econometric problem. Within each social network, not every member has an equal effect on consumer choice. In peer networks, those who have strong connections, who frequently communicate with the consumer and who are central to the consumer's network likely have more influence than their counterparts. Similarly, experts with more experience and more followers likely are more influential.

This experiment is designed to test three hypotheses. First, peer WOM is more influential than WOM from anonymous networks in restaurant choice. Second, whether positive reviews from anonymous social networks have greater marginal impact than negative reviews. Third whether few members who are more connected, more centrally located, and who communicate more frequently are more influential in the peer network than others

3 The Social Dining Experiment

To test our hypotheses we conduct a social network dining experiment. Our experiment consists of two stages (Figure-1). In the first stage, we recruit 10 individuals to serve as hubs and

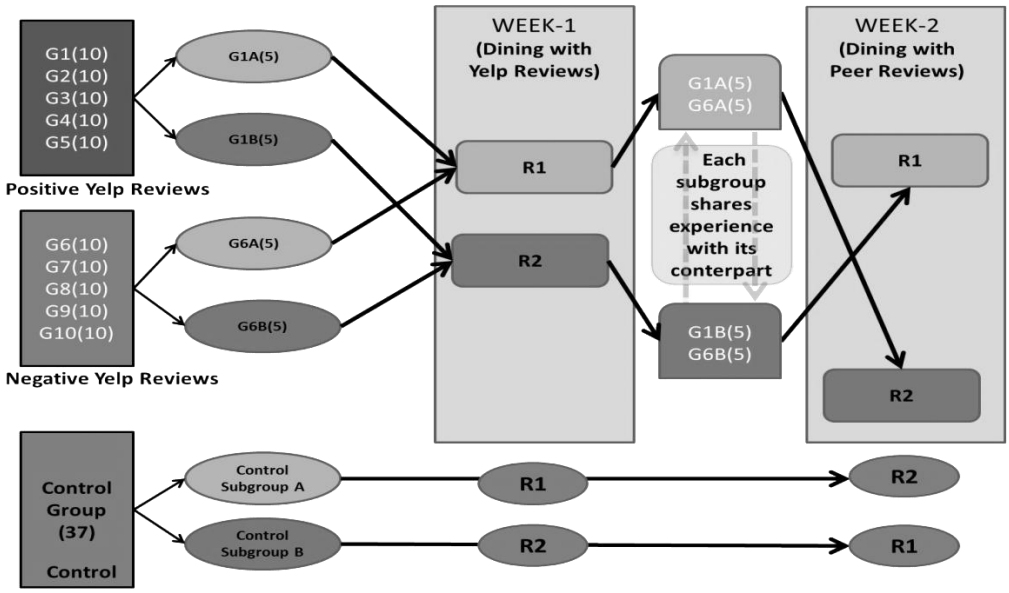

Figure-1, Two Stage Experiment Outline

each hub recruited a group of 10 individuals. These 10 groups are independent peer networks (the groups are pre-selected to consist of 10 individuals[2] who know each other and are connected

[2] One of the 100 peer network members did not respond to the second stage survey but we were able to recover 99 peer responses for both stage 1 and stage 2

through a primary, secondary or tertiary connection[3]). Then we randomly divide each peer group into sub-groups of 5 members each: The "A" subgroup and the "B" subgroup. In the first stage, "A" subgroup members visit a restaurant in Gilbert, AZ for lunch (rated 2.5 stars on Yelp[4]). 5 A subgroups are provided with positive Yelp ratings information and 5 A groups with negative Yelp ratings. We randomly selected and compiled 5 Yelp reviews per subgroup which could be clearly classified under positive or negative categories. At the same time, B subgroup members visit a similar type of restaurant in Chandler, AZ for lunch (rated 4.0 stars on Yelp) following a similar procedure. We also recruit 37 individuals as control group members who visit both the restaurants separately in stage 1 and stage 2 without any prior reviews or information about the restaurants. These control group members are individually recruited following a random selection process in a popular shopping complex located almost midway between the first and second restaurants. After visiting the restaurant, each subject will be asked to provide a rating (on a scale of 1 – 5) on each of the following 7 attributes of the restaurant experience: (1) taste of the food, (2) quality of the food, (3) availability of healthy menu choices, (4) ambience of the restaurant, (5) quality of the service, (6) price and (7) ease of locating the restaurant. To proxy demand, and measure the influence of yelp and peer reviews in our econometric model we ask the respondents to rate (on a scale of 1-5) their likelihood to revisiting the restaurants. At the end of each stage of survey all the respondents were asked to write a Yelp style review[5] about their dining experiences. These reviews serve as peer reviews for the counter subgroup in stage two.

---

[3] Primary connection is a direct connection between friends, secondary connection is a connection between an individual and her friend's friend and tertiary connection is a connection between an individual and secondary connection's friend.

[4] We carefully selected the restaurants and ensured that these two are open long enough to have sufficient Yelp reviews, yet still be unfamiliar to our respondents so that there is no past experience bias while rating or reviewing the restaurants

[5] We do not use Yelp star-rating system to compare peer and yelp reviews due to the problems associated with how the rating are defined as mentioned by Anderson and Magruder (2012).

Sub-group members who visited the Gilbert restaurant in the first stage visit the Chandler restaurant in the second-stage and vice-versa. For example stage 1 reviews from group1-subgroup A from for restaurant in Chandler are compiled together. These reviews are provided to group 1-subgroup B as peer reviews before they visit their stage two restaurant, which will be the same restaurant in Chandler for them. Similarly subgroup 1-B will visit the restaurant in Gilbert in stage one and that restaurant will serve as stage two restaurant in second stage. Each subject is then asked to rate the restaurant they visited in the second stage. The same procedure is replicated for all 10 peer groups. Both restaurants have sufficiently large Yelp reviews to peer group size ratio, so the mean rating is expected to be highly accurate. The control group members simply visit the other restaurant, and report their assessment with no Yelp nor peer evaluation information.

The primary data generated from this social dining experiment includes responses from 136 respondents for each of two restaurants. We compiled both Yelp and peer reviews for all the subgroups and individually emailed them to all the respondents. We allowed approximately 10 days for each round to be completed and then a week to fill out the surveys. The data was collected using an online survey service, Network-Genie (https://secure.networkgenie.com). While stage-1 survey had five sections: demographic information, behavioral information, network information, eating out preferences and stage one restaurant experience; stage 2 has only one section, stage 2 restaurant experience section. In the behavioral information section we asked respondents about their online activity level, involvement with online social media (both anonymous and peers networking websites) and use of online social media as a product/service information tool.

In the network information section, we asked respondents to rate all the peer network members in a scale of 1-5 in two criteria; connection strength and frequency of communication. These two attributes are very important in determining influence of a peer over other. In this way, we obtained a full 10×10 social adjacency matrix for each peer network by asking, how well a member knows other members in the network. Further we use this adjacency matric to calculate network location values such as betweenness, farness, core membership, and proximity by utilizing UCINET (http://faculty.ucr.edu/~hanneman/nettext/C10_Centrality.html) centrality algorithms for each member. Individuals used a 1-5 point scale to indicate their connection with other peers.

Communication frequency has strong effect on performance (Kacmar, Witt, Zivnuska and Gully 2003). A member can have a strong relationship with some other member but if they don't communicate frequently they will share their views and experiences fewer times and may have less influence on each other's choices or decisions than members with high communication frequency. Members in a peer group are connected to each other having a primary, secondary or a tertiary connection with other members in their group. In a peer network, if a member is familiar with another member in the same group that is considered as a primary connection. If two members A and B in a peer network don't know each other directly but have a common friend C, who knows both A and B, then the connection between A and B will be a secondary connection. Similarly there can be various tiers of connections within a peer network. We allowed multiple connection tiers while recruiting the peer groups as network intransitivity may strongly effects the quality of the estimates of the peer effects (Bramoullé, Djebbari and Fortin, 2009), which is the main focus of this study.

The resulting sample is broadly representative of the general population. The mean age of our sample is 37.27 years. Interestingly 95 percent of all respondents have recommended a new restaurant to their peers and 80 percent of all respondents have used online reviews in the past.

4 Results

In this section, we summarize the data obtained from the social networking experiment. We use cross tabulations for both stage 1 and stage 2. Our first null hypothesis is that there is no Yelp effect in stage 1, and the second is that there is no peer effect in stage 2. We test our hypothesis by comparing the effect of Yelp reviews (stage-1) with the effect of peer reviews (stage-2) on the respondents (Table-1) using chi-square tests for differences in mean. We cross tabulate the overall

Table-1 (Hypothesis Testing: Yelp and Peer effects)

Cross-Tabulation (Overall Rating-Yelp/Peer Rating)	**Stage-1 (Yelp Effect)**		**Stage-2(Peer Effect)**	
	Chi-Square Value	p-value	Chi-Square Value	p-value
Pearson Chi-Square	15.647	.048*	76.359	.006*
Likelihood Ratio	17.793	.023*	76.317	.006*

*significant at 95 percent confidence

experience rating provided by the diners with the Yelp and peer reviews they received in stage-1 and stage-2 respectively (Table-2). We found that both Yelp reviews and peer reviews have significant effects on the overall rating by the diners (Table-1).

We compare the average change (taking average movement caused by negative reviews and positive reviews) with the change in rating distribution caused by peer reviews. We compare

the control groups with the groups which dined with yelp or peer reviews and found that, on an average peer reviews are 1.84 times more effective than yelp reviews.

Table-2 (Stage 1 and Stage 2 Data Summary for Overall Rating)

Rating		**Stage-1 Yelp Reviews**				**Stage-2 Peer Reviews**		
(1-5 scale)		Negative	No Review	Positive	Total	No Reviews	Peer Reviews	Total
		(50)	(37)	(49)	(136)	(37)	(99)	(136)
Overall	1.0	8.0%	5.4%	0.0%	4.4%	0.0%	0.0%	0.0%
	2.0	6.0%	13.5%	22.4%	14.0%	16.2%	17.2%	16.9%
	3.0	38.0%	32.4%	26.5%	32.4%	32.4%	35.4%	34.6%
	4.0	10.0%	18.9%	4.1%	10.3%	16.2%	6.1%	8.8%
	5.0	38.0%	29.7%	46.9%	39.0%	35.1%	41.4%	39.7%

We find that, in general negative Yelp reviews have more adverse effect in restaurant demand than the favorable effect of positive reviews. We cross tabulate the likeliness to revisit the restaurants (Table-3) for diners and find indication (unevenly distributed effect of peer reviews while comparing stage 2 peer and control reviews) that suggest, all peers might not have equal effect on others in the peer network and observe. We observe that few peers possess more influence in the network than others. Further we suspect there exist various combinations of properties such influential positions in the network, stronger connections with other members, more central locations to the network, frequent communication with other members for these influential members. It is clearly evident that control groups in both the stages rate the restaurants differently than Yelp review groups or peer review groups.

Table-3 (Stage 1 and Stage 2 Data Summary for Likeliness to Revisit)

Rating (1-5 scale)		**Stage-1 Yelp Reviews**				**Stage-2 Peer Reviews**		
		Negative (50)	No Review (37)	Positive (49)	Total (136)	No Reviews (37)	Peer Reviews (99)	Total (136)
Likely to Revisit	1.0	12.0%	13.5%	12.2%	12.5%	16.2%	12.1%	13.2%
	2.0	20.0%	18.9%	20.4%	19.9%	13.5%	18.2%	16.9%
	3.0	28.0%	21.6%	34.7%	28.7%	13.5%	25.3%	22.1%
	4.0	22.0%	29.7%	22.4%	24.3%	37.8%	29.3%	31.6%
	5.0	18.0%	16.2%	10.2%	14.7%	18.9%	15.2%	16.2%

These findings are important on a number of levels. First, we find that peers have stronger effect than anonymous reviewers in restaurant choice. Restauranteurs, therefore, would be well-advised to cultivate social networks that operate on a peer-to-peer level such as Facebook or Instagram, and less on anonymous networks such as Yelp. Successful restaurants are those that are able to generate significant peer-to-peer buzz and capitalized on a strong social multiplier effect. Second, negative WOM can do more damage than positive reviews can induce restaurant demand. Asymmetry in social network effects means that WOM can do more damage than it can provide help. Restaurants that fail are likely doomed by a negative bandwagon effect – whether through peer or anonymous WOM, negative information serves as a catalyst to move demand for a restaurant below some “tipping point” that ends in an unsustainably low level of demand.. More broadly, restaurant performance is most positively affected by WOM disseminated within peer networks of family, friends and coworkers.

5 Conclusion

In this study, we compare the effect of anonymous networks and peer networks in restaurant choice. We conducted a two stage experiment with the data collected in two different restaurants using both publically available online yelp reviews and peer reviews provided by peer subgroups. We carefully designed our experiment to avoid reflection problem and also identify endogenous and exogenous effects separately.

We find that peer networks are more influential than the anonymous networks in determining restaurant choice. Peers reflect a trust advantage over anonymous reviewers and hence are more influential source as compared to their anonymous counterparts. This has a very important managerial implication for online marketers to make their social marketing efforts more streamlined and produce cost effective results. This study focuses on restaurants but the results can be extended to similar industries such as hotels, local contractors, bars and amusement parks. As the user activity and the online user base increase in the future, social media marketing will become even more important and snatch an even larger proportion of marketing budget from the traditional advertising media. The results of this research can help local small businesses who have a limited marketing budget and WOM plays even a more important in driving demand for their services.

There are also few limitations of this research. Firstly small size of peer groups can be a limiting factor for this paper. On a practical level, it is challenging to conduct a multi stage experiment with larger groups but future research with the involvement of lager peer groups will be a significant contribution to the literature. Also the results are vulnerable to data collection and experimental errors.

Future research should expand the idea of comparing anonymous network effects with peer network effects in other high involvement categories such as durable home appliances, automobile, medical care, holiday packages, house purchases and education investments. Anonymous network effect studies which include attributes of reviewers, review characteristics and dynamic changes in reviews in terms of importance over time will enrich the existing social network literature.

References

Anderson, M., & Magruder, J. (2012). “Learning from the crowd: Regression discontinuity estimates of the effects of an online review database”. The Economic Journal, 122(563), 957-989.

Banerjee, A. V. (1992). “A simple model of herd behavior.” The Quarterly Journal of Economics, 107(3), 797-817.

Becker, G. S. (1991). “A note on restaurant pricing and other examples of social influences on price.” Journal of Political Economy, 1109-1116.

Bhatnagar, A., & Ghose, S. (2004). “Online information search termination patterns across product categories and consumer demographics”. Journal of Retailing, 80(3), 221-228.

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). “Identification of peer effects through social networks.” Journal of econometrics, 150(1), 41-55.

Brock, W. A., & Durlauf, S. N. (2002). “A multinomial-choice model of neighborhood effects.” The American Economic Review, 92(2), 298-303.

Brock, W. A., & Durlauf, S. N. (2007). “Identification of binary choice models with social interactions.” Journal of Econometrics, 140(1), 52-75.

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

De Bruyn, A., & Lilien, G. L. (2008). “A multi-stage model of word-of-mouth influence through viral marketing.” International Journal of Research in Marketing, 25(3), 151-163.

Buda, R., & Zhang, Y. (2000). “Consumer product evaluation: the interactive effect of message framing, presentation order, and source credibility.” Journal of Product & Brand Management, 9(4), 229-242.

Buttle, F. A. (1998). “Word of mouth: understanding and managing referral marketing.” Journal of strategic marketing, 6(3), 241-254.

Cai, H., Chen, Y., & Fang, H. (2007). “Observational learning: Evidence from a randomized natural field experiment” (No. w13516). National Bureau of Economic Research.

Cheung, C. M., & Lee, M. K. (2012). “What drives consumers to spread electronic word of mouth in online consumer-opinion platforms.” Decision Support Systems, 53(1), 218-225.

Chevalier, J. A., & Mayzlin, D. (2003). “The effect of word of mouth on sales: Online book reviews” (No. w10148). National Bureau of Economic Research.

Dierkes, T., Bichler, M., & Krishnan, R. (2011). “Estimating the effect of word of mouth on churn and cross-buying in the mobile phone market with Markov logic networks.” Decision Support Systems, 51(3), 361-371.

Domingos, P. (2005). “Mining social networks for viral marketing”. IEEE Intelligent Systems, 20(1), 80-82.

Duan, W., Gu, B., & Whinston, A. B. (2008). “Do online reviews matter?—An empirical investigation of panel data.” Decision Support Systems, 45(4), 1007-1016.

Duflo, E., & Saez, E. (2002). “Participation and investment decisions in a retirement plan: The influence of colleagues’ choices.” Journal of public Economics, 85(1), 121-148.

Duflo, E., & Saez, E. (2003). “The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment.” The Quarterly Journal of Economics, 118(3), 815-842.

Giorgi, G. D., Pellizzari, M., & Redaelli, S. (2007). “Be as careful of the books you read as of the company you keep: Evidence on peer effects in educational choices,” IZA Discussion Papers 2833. Institute for the Study of Labor (IZA).

Godes, D., & Mayzlin, D. (2009). “Firm-created word-of-mouth communication: Evidence from a field test.” Marketing Science, 28(4), 721-739. doi: 10.1287/mksc.1080.0444

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

Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). “The role of hubs in the adoption process.” Journal of Marketing, 73(2), 1-13. doi: 10.1509/jmkg.73.2.1

Herr, P. M., Kardes, F. R., & Kim, J. (1991). “Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective.” Journal of Consumer Research, 454-462.

Hilligoss, B., & Rieh, S. Y. (2008). “Developing a unifying framework of credibility assessment: Construct, heuristics, and interaction in context.” Information Processing & Management, 44(4), 1467-1484.

Hong, H., J. D. Kubik and J. C. Stein. 2004. “Social Interaction and Stock-Market Participation.” Journal of Finance 59: 137-163.

Hu, Y., & Li, X. (2011). “Context-dependent product evaluations: an empirical analysis of internet book reviews”. Journal of Interactive Marketing, 25(3), 123-133.

Kacmar, K. M., Witt, L. A., Zivnuska, S., & Gully, S. M. (2003). “The interactive effect of leader-member exchange and communication frequency on performance ratings.” Journal of Applied Psychology, 88(4), 764-772.

Mack R, R Mueller, J Crotts and A. Broderick. 2000. “Perceptions, corrections and defections: implications for service recovery in the restaurant industry”. Managing Service Quality 10 (6): 339-346.

Mangold, W. G., Miller, F., & Brockway, G. R. (1999). “Word-of-mouth communication in the service marketplace.” Journal of Services Marketing,13(1), 73-89.

Manski, C. F. (1993). “Identification of endogenous social effects: The reflection problem.” The review of economic studies, 60(3), 531-542.

Manski, C. F. (2000). “Economic analysis of social interactions”. (No. w7580) National Bureau of Economic Research.

Maxham III, J. G. (2001). “Service recovery's influence on consumer satisfaction, positive word-of-mouth, and purchase intentions.” Journal of Business Research,54(1), 11-24.

Mayzlin, D. (2006). “Promotional chat on the Internet.” Marketing Science, 25(2), 155-163.

Nam, S., Manchanda, P., & Chintagunta, P. K. (2010). “The effect of signal quality and contiguous word of mouth on customer acquisition for a video-on-demand service.” Marketing Science, 29(4), 690-700.

Narayan, V., Rao, V. R., & Saunders, C. (2011). “How peer influence affects attribute preferences: A Bayesian updating mechanism.” Marketing Science, 30(2), 368-384.

Nelson, K. (1974). “Concept, word, and sentence: Interrelations in acquisition and development.” Psychological review, 81(4), 267.

Park, S., & Gupta, S. (2009) “A simulated maximum likelihood estimator for the random coefficient logit model using aggregate data”. Journal of Marketing Research, Vol. 46(August), pp. 531-542.

Parsa, H. G., J. T. Self, D. Njite, and T. King. 2005. “Why Restaurants Fail.” Cornell Hotel and Restaurant Administration Quarterly 46: 304-322.

Petrin, A., & Train, K. (2010). “A control function approach to endogeneity in consumer choice models.” Journal of Marketing Research, 47(1), 3-13.

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

Reingen, P. H., & Kernan, J. B. (1986). “Analysis of referral networks in marketing: Methods and illustration.” Journal of Marketing Research, 370-378.

Richards, T. J., & Patterson, P. M. (1999). “The economic value of public relations expenditures: Food safety and the strawberry case.” Journal of agricultural and resource economics, 440-462.

Watts, D. J., & Strogatz, S. H. (1998). “Collective dynamics of ‘small-world’networks.” Nature, 393(6684), 440-442.

Trusov, M., Bodapati, A., & Bucklin, R. E. (2010). “Determining influential users in internet social networks.” Journal of Marketing Research Vol. XLVII (August 2010), 643–658