Anonymous Social Networks versus Peer Networks in Restaurant Choice

by

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ABSTRACT

I compare the effect of anonymous social network ratings (Yelp.com) and peer group recommendations on restaurant demand. I conduct a two-stage choice experiment in which restaurant visits in the first stage are informed by online social network reviews from Yelp.com, and visits in the second stage by peer network reviews. I find that anonymous reviewers have a stronger effect on restaurant preference than peers. I also compare the power of negative reviews with that of positive reviews. I found that negative reviews are more powerful compared to the positive reviews on restaurant preference. More generally, I find that in an environment of high attribute uncertainty, information gained from anonymous experts through social media is likely to be more influential than information obtained from peers.

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Chapter 1

INTRODUCTION

Food Away From Home (FAFH) constitutes 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, I 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. Consumers face uncertainty regarding not only the food offered in the restaurant, but the overall dining experience as restaurant meals are archetypical multi-attribute experiences. 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-controlled 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, I compare the relative effect of each type of WOM in driving the demand for restaurants. More generally, I study the role of both anonymous social media and social peer networks in shaping trends in FAFH demand, which often portend more general changes in food consumption.

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 obtain 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.

Empirical social learning effects are well-documented in investment decisions (Hong, Kubic and Stein, 2004), new product purchase (Mayzlin 2006, Godes and

[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.

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. I 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.

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, I conduct an economic experiment to compare the effectiveness of anonymous versus peer networks as tools for marketing restaurant meals. I 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. Manski (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? When behavioral effects of a peer group on an individual, who is a peer member of that group herself are modeled, the results obtained are biased. Reflection is best mitigated through appropriate controlled experimental design, which generates rich data and hence mitigates the reflection problem. I conduct a two-stage group-subgroup experiment under strict uniform network size restrictions to tackle the identification problems associated with social learning. I 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 by design. 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. I then aggregate the data during econometric estimation to incorporate group level heterogeneity in a manner similar to Georgi et.al (2007) and Bramoullé et.al (2009). By dividing each peer group into two sub groups, I avoid the reflection problem.

Other than the reflection problem, peer networks are typical to have endogeneity problems. Manski (1993) formed three hypotheses for peers as why they behave in similar fashion: 1) endogenous effects, which explain existence of a herd behavior, in that peers behave as other members in the peer group, 2) contextual effects, which are similarities with respect to the exogenous factors such as similar demographics or psychographics within a peer group, and 3) correlated effects, which are similar environmental factors under which peers within a network reflect similar behavior. I address endogeneity of network membership through an instrumental-variables estimation approach. Specifically, I 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, I use an ordered probit model to estimate the importance of network effects in restaurant preference because demand is expressed in terms of a five-point rating scale measuring whether the consumer would visit the restaurant again. I 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, I am able to identify peer effects at individual level (Bramoullé, Djebbari and Fortin 2009).

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

I find that information obtained from anonymous social media experts anonymous has a stronger influence on restaurant choice than peers. Online rating websites especially restaurant review websites such as Yelp, contain numerous reviews from the past users with detailed user stories and experience. This large pool of specific information about particular restaurants likely helps decision makers and hence influences restaurant choice. Whereas peer reviews despite of being more trustworthy have limited amount of information about specific restaurants. In most cases peers networks are generally smaller as compared to anonymous networks and a small percentage of peers provide information on a single restaurant due to different tastes and preferences within the peer group. Online rating services have a higher variance in their impact due to the relative depth of the online rating service. I also find that individuals in the peer 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. Other than interconnectedness, level of influence also depends upon other factors such as strength of connections (Weimann, 1983) and communication frequency (Zenger and Lawrence, 1989).

My research has both managerial importance, and a more general contribution in providing a better understanding how social media effects demand. By understanding the relative role of peer and social networks, restaurant managers may be able to avoid the boom-or-bust dynamic typical of startups in the foodservice industry. The research may also help guide foodservice managers to develop effective online social media marketing strategy and helps optimize their marketing budget. More generally, I identify the relative importance of online rating sites to peer networking sites. To the extent that firms in other industries share the same type of uncertainty faced by restaurant owners, my findings are suggestive of how social media strategies may be designed for maximum effect. The next section describes a conceptual model that I use to formulate the hypotheses that follow from the theory of social learning through peer and anonymous networks. In the third section, I explain the social dining experiment design and execution, while fourth section presents the econometric model. I present the results from my econometric model in section five, and conduct a number of specification tests to establish the validity of my approach. Section six summarizes my findings, and suggests some limitations.

Chapter 2

ECONOMIC MODEL OF SOCIAL NETWORK EFFECTS

Restaurant offerings are fundamentally different than other service offerings as they have an aesthetic and emotional component to them (Johns, 1999). Restaurants face a challenge to offer variety on their menus and at the same time to standardize the experience for the same menu item over time. The restaurant market in the U.S is mature, having developed in response to diverse consumer preferences for multiple dining options (Mack et.al, 2000). While the fast food market offers more standardized products and services, fine-dining restaurant offerings are generally more complex, each offering a unique combination of various desired dining attributes. Other than the attributes of food served, factors such as customers' sense of style, ambiance and service play vital role in diners' decision making process (Muller and Woods, 1994). Fusion of all these observable and unobservable factors makes restaurant offering a complex combination. 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 service, it is commonly spread through WOM. 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 2009 and Domingos 2005). When a consumer dines at a restaurant and then shares her experience with other members in the social network, perceptions of, and preferences 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 the strength of his or her connection with other members (Dierkes, Bichler and Krishnan, 2011). The direction of WOM, however, depends on the nature of the message. It is intuitive that 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. If utility is concave (increases at a decreasing rate) in the amount of information received, then the response is likely to be asymmetric with negative information providing a larger negative impact than positive information provides in the opposite direction. According to this concave utility theory the incremental loss of utility by receiving negative reviews is much more than the gain in utility by receiving positive reviews. If the utility gain by positive reviews is defined by U_p and the utility loss is defined by U_n and these utility levels are functions of corresponding positive and negative information provided to the respondents in the form reviews, then according to the concave utility theory, for the same absolute value of positive reviews and negative reviews the magnitude of U_n and U_p will be different (see figure 1).

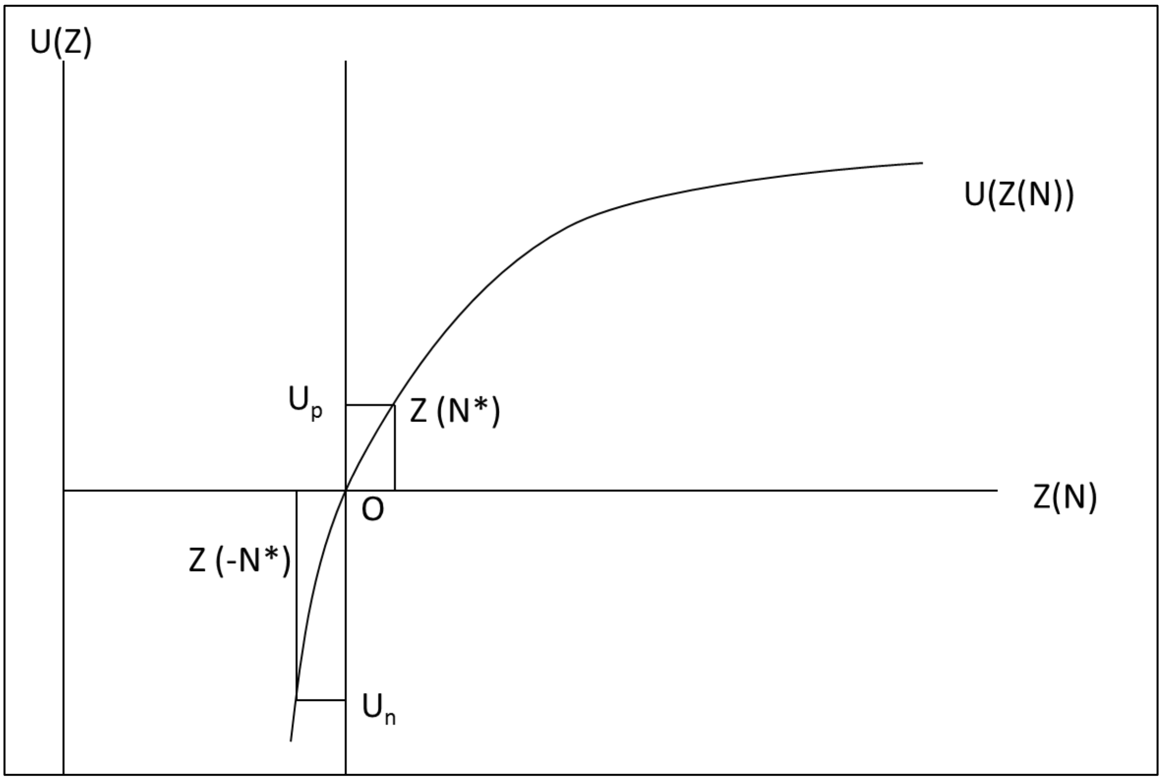

Figure-1, Marginal Utility of Positive and Negative Reviews

Magnitude of U_n will be larger than magnitude of U_p. I test this theory using my experimental review data. I incorporate both positive and negative online Yelp reviews in my experiment and compare the relative effect each on restaurant demand.

The power of WOM depends not only on the nature of the message, but the source as social network members who disseminate WOM can be either known peers or unknown experts. 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 (Weimann 1983; Zenger and Lawrence 1989; Ibarra and Andrews 1993). However, the most connected member is not necessarily the most influential as network members vary in their individual persuasiveness (Goldenberg et al, 2009). Similarly, experts with more experience and more followers are likely to be viewed as more credible, so may be more influential. Therefore, finding who is the most influential is an econometric problem.

This experiment is designed to test two 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.

Chapter 3

THE SOCIAL DINING EXPERIMENT

To compare the influential power of anonymous and peer networks and to compare the relative effect of positive and negative reviews in the case of restaurant choice, I designed a two stage experiment. A two stage model is required to understand the influence of information (Urberg et al, 2003). The experiment allows direct comparison between the influences of information from two different sources. In the first stage information provided to the respondents was from anonymous experts and in the second stage the information provided was from known peers. Narayan, Rao and Saunders (2011) also conducted a two stage experiment to but my experiment is different from theirs in three ways. First they only consider peer effects while I compare the peer and anonymous effects. Secondly they follow an attribute influence approach by providing no information in stage one and information from peers in stage two. While I use a control group and follow a panel approach in each of the stages. Lastly I add one more dimension to my experiment by classifying the information provided to respondents into positive and negative information.

As explained by (Manski 1993), social experiments with peer groups are susceptible to the reflection problem. The reflection problem raises the question that, how to infer the influence of a group on an individual, when the individual is herself part of the group? My experiment design helps avoid the problem of reflection as I divide each peer group into two equal subgroups. I provide peer reviews from one subgroup to the other subgroup and vice versa. This way the controlled nature of my experiment helps us avoiding the endogeneity problem persistent in the social networks (Jackson, 2008) and the reflection problem.

To test my hypotheses, I conduct a social network dining experiment. My experiment consists of two stages (figure 2). In the first stage, I recruit 10 individuals to serve as "hubs." Hubs are individuals who are selected as organizational nodes for each network, but are not necessarily the most influential people in each network. The purpose of choosing hubs is to recruit a "friend network" in which I can be assured that each individual knows the others to varying degrees. That is, some members of the network organized by the hub may be best friends, while others may be only rare acquaintances.

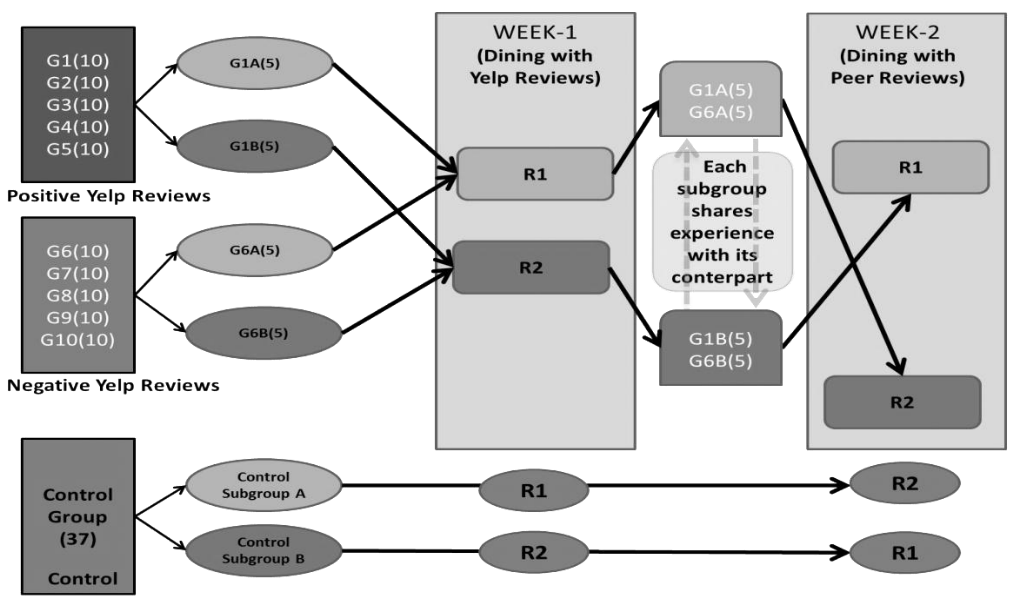

Figure 2, Two Stage Experiment Outline

Each hub was asked to recruit a group of 10 individuals. These 10 groups are independent peer networks (the groups are pre-selected to consist of 10 individuals who know each other and are connected through a primary, secondary or tertiary connection).[2] Then I randomly divide each peer group into sub-groups of five members each: The "A" subgroup and the "B" subgroup. In the first stage, "A" subgroup members visited a restaurant in Gilbert, AZ for lunch (rated 2.5 stars on Yelp).[3] Five A subgroups were provided with positive Yelp ratings information and 5 A groups with negative Yelp ratings. At the same time, B subgroup members visited a similar type of restaurant in Chandler, AZ for lunch (rated 4.0 stars on Yelp) following a similar procedure. I also recruited 37 individuals as control group members who visited both the restaurants separately in stage 1 and stage 2 without any prior reviews or information about the restaurants. These control group members were individually recruited following a random selection process in a popular shopping complex located near both restaurants.

The primary data generated from this social dining experiment includes responses from 136 respondents for each of two restaurants. I collected all reviews available on Yelp.com for both the restaurants and after evaluating these reviews by reading them all I only filtered those, which were clearly positive or clearly negative (table 1). Based on Yelp reviews restaurant two in Chandler is more famous than restaurant one in Gilbert. I randomly compiled sets of five reviews for each positive and negative review types for both the restaurants. This way I had two negative and two positive sets of reviews for the first restaurant in Chandler and six positive and three negative sets of reviews for the

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[2] 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. Also one of the 100 peer network members did not respond to the second stage survey but I was able to recover 99 peer responses for both stage 1 and stage 2.

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

second restaurant in Gilbert. Again I randomly sent these sets of reviews to the corresponding positive and negative groups of respondents in stage one.

Table-1 Yelp Reviews for Restaurants

		Filtered Review Type	
	Total Review Count	Count of Positive Reviews	Count of Negative Reviews
Restaurant-1 (Gilbert)	24	10	10
Restaurant-2 (Chandler)	100	60	30

After visiting the assigned restaurant in round one, each respondent was asked to provide a rating (on a scale of 1 – 5) on each of the following seven 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 my econometric model, I asked the respondents to rate (on a scale of 1-5) their likelihood to revisiting the restaurants and whether they would recommend a friend visit each restaurant. At the end of the first stage all the respondents were asked to write a Yelp style review about their dining experiences.[4] These reviews serve as peer reviews for the other subgroup in stage two.

I 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-

[4] I 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).

Genie (https://secure.networkgenie.com). While the stage one survey had five sections: demographic information, behavioral information, network information, eating out preferences and stage one restaurant experience; stage two has only one section, gathering data on the nature of each respondent's restaurant experience. In the behavioral information section, I 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, I asked respondents to rate all the peers in their network on a scale of 1-5 based on how well they do they know other members in their network. This way, I obtained a full 10×10 social adjacency matrix for each peer network (Appendix-1).

Members in a peer group are connected to each through 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, then the connection between A and B is deemed a secondary connection. Similarly, there can be various tiers of connections within a peer network. I allowed multiple connection tiers while recruiting the peer groups as network intransitivity may strongly affect the quality of the peer-effect estimates (Bramoullé, Djebbari and Fortin, 2009). Due to the presence of network intransitivity in peer networks, peer effects will likely include direct effects, generated from primary connections as well as indirect effects, generated from secondary, tertiary or higher degree connections. Transitivity is a sufficient condition but not a necessary condition for indirect effects. To fully understand the peer network dynamics it is important to understand direct as well as indirect network effects.

The resulting sample is broadly representative of the general population. The mean age of my sample is 37.27 years. Interestingly, 95 percent of the respondents have recommended a new restaurant to their peers and 80 percent of all respondents have used online reviews in the past. Respondents with some college degree/trade school (non-bachelor and non-master degree) and bachelor's degree were the two most prevalent groups in the sample (figure-3). In the sample 69 percent respondents had an annual income between $25,000 and $125,000 (figure-4).

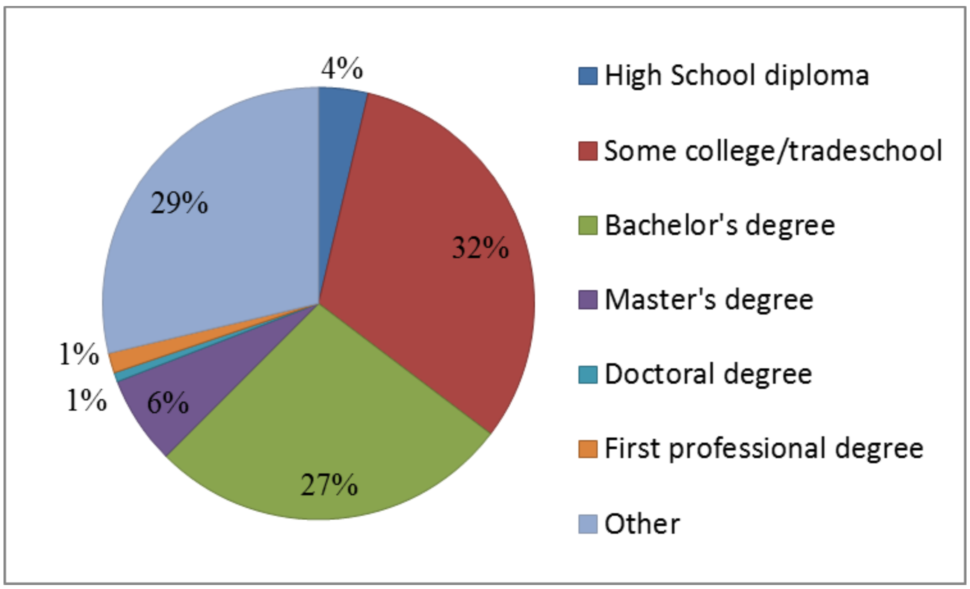
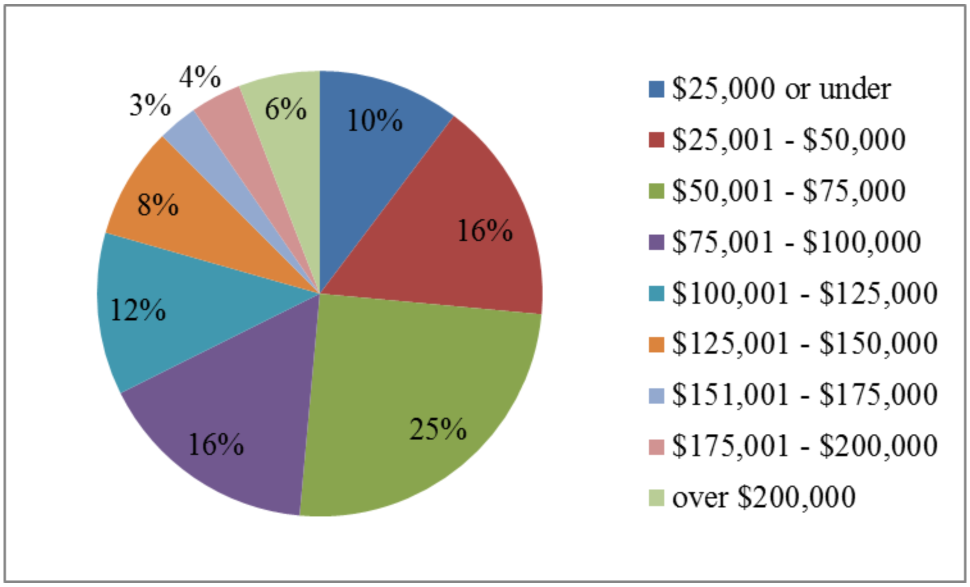


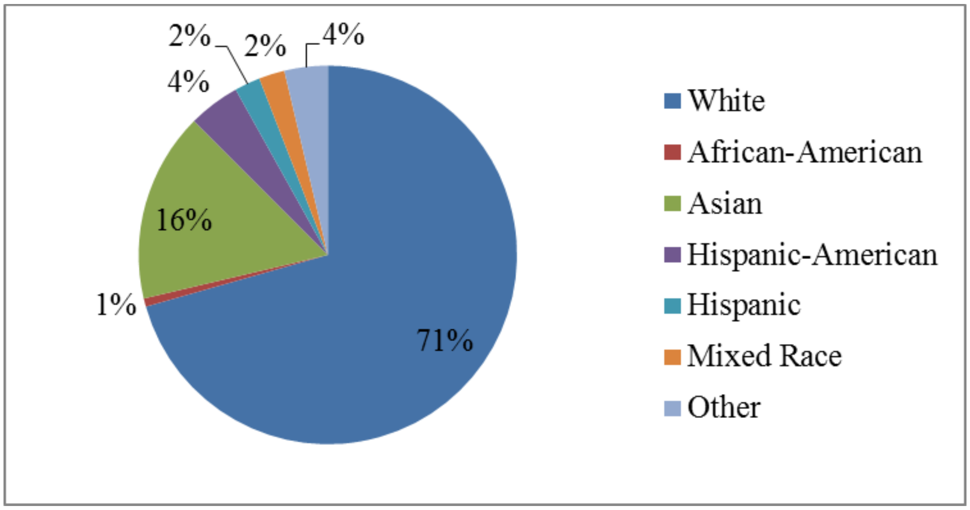
Figure-3, Educational Distribution

Figure-4, Annual Income Distribution



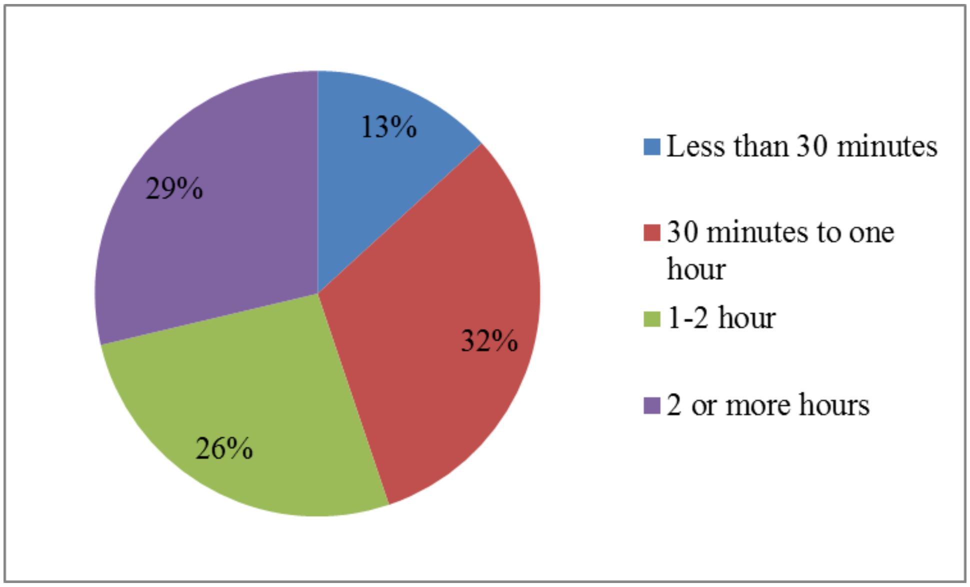
There is a representation of 7 ethnic groups in my sample, in which the 71 percent population is predominantly white. The second largest ethnic group is, Asian (figure 5). In the sample there is a proportionate share of four online leisure activity groups from

Figure-5, Ethnic Group Representation



high online activity group, who spends more than two hours online per day to low online activity group who spend less than 30 minutes daily on the web (figure 6).

Figure-6, Non-work Online Time Spent (Hours per Day)



Crosstabulation on overall rating by restaurant shows that positive reviews have a positive impact and the negative reviews have a negative impact on overall rating for the both the restaurants with just one exception of negative review impact on second restaurant rating which is 3.79 with a standard deviation of 1.44 (table 2). By comparing different scenarios in the crosstabulation the effect of positive and negative reviews as

Table-2, Average Overall Rating (Standard Deviation) Cross Tabulation

	Positive		**Control**		**Negative**	
	Round-1	Round-2	Round-1	Round-2	Round-1	Round-2
Restaurant 1	3.72 (1.4)	3.4583 (1.31807)	3.6111 (1.24328)	3.6316 (1.16479)	3.5 (1.10454)	3.4583 (1.21509)
Restaurant 2	3.7917 (1.14129)	3.76 (1.05198)	3.4737 (1.21876)	3.7778 (1.11437)	3.7917 (1.444)	4.1538 (1.04661)

well as the effect of anonymous and peer reviews can be seen but a further econometric estimation is required to test the hypothesis.

I 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. Further I 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 may be the case 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 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%

Chapter 4
ECONOMETRIC MODEL

In this section, I describe two econometric models. The first model compares the marginal impact of information obtained via anonymous networks on restaurant preference with the marginal effect of similar information obtained through peer networks. The objective of this model is to find out which network has a greater impact on restaurant choice. In this model, I test three different measures corresponding to the degree of connectedness among members of the peer groups: a) proximity, b) centrality and c) betweenness. These network location measures are commonly used in the social network studies to identify the relative location of individuals in a social network (Freeman 1979; Hanneman and Riddle 2005; Opsahl, Agneessens and Skvoretz, 2010). The second model tests whether negative reviews have a greater marginal impact (in absolute value) than positive reviews in determining restaurant preference. Because my measure of preference is an ordinal ranking metric, an ordered probit framework is used throughout. I explain each model in turn.

4.1 Anonymous versus Peer Networks

I use a random coefficient ordered probit model to account for the ordinal nature of the rating data. In this model, I use consumers' assessment of the likelihood of revisiting each restaurant as a preference indicator. Each respondent was asked to rate the likelihood that they would revisit each restaurant on a 5 point Likert scale, each response reflecting their expected utility from re-visiting the restaurant in question.

An ordered probit model estimates the probability of moving from one scale level to another. I use a 5 point Likert scale throughout the experiment for the sake of simplicity as a 5 point Likert scale and a 7 point Likert scale provide comparable results (Dawes, 2012). A consumer can rate his or her likelihood of revisiting the restaurant by selecting an integer value from 1 to 5 on a Likert scale. Where 5 represents the maximum level of satisfaction and 1 represents the lowest level of satisfaction.

My two stage experiment generated 274 observations for 137 respondents. This sample size and number of observations is appropriate to use a 5 point Likert scale (Hinkin, 1995).

I start with a general utility model for a subject *i* who belongs to a peer network *j* and goes to a restaurant *k* in round *l*. The utility of individual *i* is represented by u_{ijkl}. Instead of assuming that utility of an individual *i*, (i=1…..n) depends upon the mean rating provided by the peers in network *j* as in a more typical social-learning model (Duflo and Saez 2002, 2003), I follow a more general spatial approach. In this approach utility (u_{ijkl}) depends on the combination of, information provided about the restaurant *k* by the peers in network *j* and the strength of the relationship of individual *i* with other peers in the network *j*.

Information about the restaurant provided by other members, in the network *j* is in the form of reviews and represented by y_{-i}. Review information y_{-i} is numerically coded on a 5 point Likert scale where 5 represents the highest level and 1 represents the lowest level rating. The relationship among peers in a network *j*, is defined by an adjacency matrix **G** (appendix-1). I ask all the members of the peer network to rate, how well they know their peers on a scale of 1-5. This way for a peer group with n members I construct a n×n full relationship information matrix. I call this matrix the adjacency matrix throughout. Adjacency matrix **G** is constructed using each individual's perception about his or her relationship strength with other peers in network *j*. If all the members in network *j*, know each other equally well and have equal strength connections among all the peers, this model becomes an average peer effect model as estimated by Sacerdote (2001), Duflo and Saez (2002, 2003). Utility (u_{ijkl}) also depends on the information provided by the anonymous reviewers on restaurant *k*, which is represented by X_{kl} and an iid random error term ε_{ij} .

$$u_{ijkl} = \beta_1 \mathbf{G}\mathbf{y}_{-\mathbf{ij}} + \beta_2 \mathbf{X}_{\mathbf{kl}} + \varepsilon_{ij} \qquad (1)$$

where each β_1 and β_2 are the parameters to be estimated. I assume both parameters, including the peer effect coefficient, β_1, and the anonymous effect coefficient, β_2 are normally distributed such that $\beta_q \sim N(\overline{\beta}_q, \sigma_\beta^2)$. These parameters account for unobserved heterogeneity or variations in tastes which are not accounted for observed differences among individuals. The results in my estimates do not suffer from the aggregation bias common in the past studies (Train, 2003). I write the indirect utility model derived from the original utility model in matrix notation as below:

$$\boldsymbol{Y} = \beta_1 \boldsymbol{G}\boldsymbol{y} + \beta_2 \boldsymbol{X} + \varepsilon \qquad (2)$$

Where **Y**, an n × 1 utility vector which represents indirect utility measured by the likelihood to revisit the restaurant. Matrix **G** is row normalized n × n, peer relationship matrix or the adjacency matrix (appendix 1). Vector **y** is an n×1 vector containing peer reviews for all the individuals. Term ε is the error term for the model.

Estimating the model above assumes that each type of network effect is exogenous. However, it is well understood that unobservables in each subject's utility function are likely to be correlated with their location in the network. Therefore, the ordered probit model above suffers from endogeneity bias *a priori*. In order to correct the model for endogeneity, I use a two-stage control function estimation method (Park and Gupta 2009; Petrin and Train 2010). Define $\mathbf{Gy}_{-\mathbf{ij}}$ in equation 1 as below:

$$\mathbf{Gy}_{-\mathbf{ij}} = \lambda \mathbf{Z}_p + \boldsymbol{e} \qquad (2)$$

In equation 2 above $\mathbf{Z_p}$ is an n × m matrix of instrumental variables where m is the number of instruments. The instruments include respondents' demographic and behavioral information such as age of the respondent, whether they consider peer reviews in decision making, whether they wrote any online reviews before, whether they check nutrient content before buying a food product, how important they think of taste as an attribute, interaction between age and gender and interaction between age and nutrient content consciousness. The parameter vector λ represents the marginal effect of each instrument on the endogenous peer effect. I assess the validity of each instrument using the Wu test (1973) and Hausman test (1978). I carefully test the instrumental variables that are likely to be correlated with the endogenous peer-effect, and yet mean independent of the error term in the estimating equation. I gathered more than 25 variables for this purpose and use the best after formally testing them in the next section. As I only estimate two parameters in the model, including these instruments are sufficient to identify all peer effects.

In the first model, u_{ijkl} is unobserved utility but my model allows the respondents to choose from five possible responses, *y*, on the bases of their utility level. The five different preference levels, represented by four cutoff points for the possible responses given by k_n (where p=1, 2…4). Using equation 1, with the ordered probit framework the ordinal data representing consumer demand, y and the five levels of consumer utility, Un are given by:

$y = 5: U > k_1$

$y = 4: k_1 > U > k_2$

$y = 3: k_2 > U > k_3$

$y = 2: k_3 > U > k_4$

$y = 1: k_4 > U$

The probability of consumer response y is given by P_q as below, where q =1, 2…5 representing utility from the lowest to the highest level and ϕ is the standard cumulative normal function.

$$P_1 = P(\varepsilon_{ij} < k_4 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$
$$= \phi(k_4 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$

$$P_2 = P(\varepsilon_{ij} < k_3 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - P(\varepsilon_{ij} < -\beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$
$$= \phi(k_3 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - \phi(k_4 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$

$$P_3 = P(\varepsilon_{ij} < k_2 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - P(\varepsilon_{ij} < k_3 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$
$$= \phi(k_2 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - \phi(k_3 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$

$$P_4 = P(\varepsilon_{ij} < k_1 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - P(\varepsilon_{ij} < k_2 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$
$$= \phi(k_1 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}}) - \phi(k_2 - \beta_1 \boldsymbol{e} - \beta_2 \mathbf{X_{kl}})$$

$$P_5 = 1 - (P_1 + P_2 + P_3 + P_4)$$

Using this model, I compare the absolute values of the two parameters: the parameter for the peer effects after the two stage endogeneity treatment and the anonymous effects parameter, β_2. If the peer effects parameter is significantly smaller than the anonymous effects parameter, I reject my original hypothesis that peer recommendations have stronger effect than anonymous expert reviews and vice versa.

4.2 Positive versus Negative Reviews

In the second model I compare the effect of positive and negative reviews for anonymous Yelp reviews. This model is also an ordered probit model because the dependent variable is the same as that used in the first model.

My underlying hypothesis is that the utility index describing each respondent's restaurant preferences is differentially affected by positive and negative reviews. Specifically, if the respondent's utility function is concave with respect to the nature of information (see figure 2), then I expect the utility function to be "steeper" in a negative compared to a positive direction. I test this hypothesis using a variant on the ordered probit model described above.

I construct the following model using an ordered probit framework that compares positive and negative anonymous review effects. Namely, utility is written as:

$$u'_{ijk} = \beta_3 \mathbf{P} + \beta_4 \mathbf{N} + \varepsilon_i \qquad (3)$$

Where vector **P** represents positive reviews and vector **N** represents negative reviews. Consumers are assumed to follow the same ordered-choice probit as that described above, so their choice reflects the ordinal choice that reflects the highest level of utility. In terms of the estimated probability model, I write the estimating equation as:

$$y' = \beta_3\mathbf{P} + \beta_4\mathbf{N} + \varepsilon_i \qquad (4)$$

Where y' is the likelihood of revisiting the restaurant by respondent i. The elements of each vector are constructed from the star ratings on each Yelp review where a star rating below average is deemed a "negative" review and an above average rating is defined as a "positive" review. The vector ε_i is the unobserved error term.

Using this model, I test my second hypothesis of whether negative or positive reviews have stronger effect on restaurant choice. Again in the second model I account for individuals' heterogeneity by adding demographic and behavioral variables. I compare the magnitude of coefficients β_3, which represents the effect of positive reviews and β_4, which represents the effect of negative reviews. If the positive review coefficient is greater than the negative review coefficient, I reject my original hypothesis, that negative reviews can decrease the restaurant demand than positive reviews can increase it.

In the next chapter, I first formally test the null hypothesis that both peer networks and anonymous networks have no influence on restaurant choices. Second, I test the validity of the instruments used in the first model. Then I test which network category: peer networks or anonymous networks, is more influential in restaurant choice. I test the first model using proximity, as a peer network location measure using the relationship adjacency matrix in appendix 1.[5] Lastly I test, whether the positive or the negative reviews from anonymous sources can influence the demand of restaurants.

[5] Adjacency matrix is constructed according to the response of peers in a peer network by asking them how they perceive their relationship with other peers in the network (I asked: How well do you know 'peer p'?). I measure this on a scale of 1 to 5, where 1 is the weakest relationship (do not know the individual) and 5 is the strongest relation (best friend)

Chapter 5

RESULTS

In this section, I present the results obtained from estimating the models described in the previous chapter. Before presenting detailed results from testing each hypothesis, however, I conduct a battery of tests to establish the validity of my model. I use cross tabulations for both stage 1 and stage 2. My 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. I test the null hypothesis by comparing the effect of Yelp reviews (stage-1) with the effect of peer reviews (stage-2) on the respondents (table 4) using chi-square tests for differences in mean. I cross tabulate the overall experience rating provided by the diners with the

Table-4 (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

Yelp and peer reviews they received in stage-1 and stage-2 respectively. I found that both Yelp reviews and peer reviews have significant effects on the overall rating by the diners as p values for both Pearson Chi-squares and Likelihood ratios are less than 0.05 (table 4). Also I test the above mentioned hypothesis using the Wald test and found that both peer networks and anonymous networks have a significant effect on restaurant choice (-0.001 and -0.153 respectively) at 90 percent confidence (table 5).

Table-5, Hypothesis Test using Wald Statistics

	Coefficient	t-value
Peer Network Effects	-0.001**	-2.06
Anonymous Network Effects	-0.153*	-1.78

*Significant at 10%, ** Significant at 5%,

My first model compares the influence of peer reviews weighted by the connection strength among peers with anonymous Yelp reviews. In this model I took respondents likelihood to revisit the restaurant as a measure of restaurant preference. As discussed in the previous section to avoid the endogeneity bias and the reflection problem in peer network I run an OLS regression with the dependent variable, network proximity weighted peer reviews, $\mathbf{Gy}_{-\mathbf{ij}}$. The results obtained by this OLS are presented in table 6.

Table-6, Stage-1 OLS Regression with Instrument Variables

Dependent Variable: Likeliness to Revisit	Coefficient	t-value	p-value
Age	0.0230**	2.08	0.039
Consider Peer Review	-1.245**	-4.42	0.000
Written Online Review	0.312**	2.64	0.009
$(\text{Age} \times \text{Gender})^2$	-0.051**	-10.09	0.000
Nutrient Consciousness	-1.183**	-3.77	0.000
Taste as an Attribute	0.267**	3.24	0.001
Age $\times$ Nutrient Consciousness	0.027**	3.16	0.002
F value		30.5	
Hausman Test		47.87*	
Wu Test t-value		13.60*	

*Significant at 5%

I selected age of the respondent, whether they consider peer reviews in decision making, whether they wrote any online reviews before, whether they check nutrient content before buying a food product, how important they think of taste as an attribute, square of interaction between age and gender and interaction between age and nutrient content consciousness.[6] To insure the validity of the instruments I perform Wu test (statistic = 13.60) and Hausman test (statistic = 47.87) and found my instruments to be valid. Also the first stage instrument OLS model is significant with an F-value of 30.5. Also all seven variables are significant at 95 percent and have t-statistics larger than 1.96.

In my first model, I compare the anonymous network effects and the peer network effects on restaurant choice. Instead of using network proximity weighted peer reviews, $\mathbf{Gy}_{-\mathbf{ij}}$, I use the residuals form the above estimated OLS to correct for endogeneity (Park and Gupta 2009; Petrin and Train 2010). I estimate two models to compare the network effects; first model uses fixed coefficients for both peer and anonymous network effects, while the second model uses random parameters for both the networks. In both these models, I use likelihood of individuals to revisit the restaurants as the dependent variable, which is taken as a proxy to the restaurant choice.

The table 7 below presents the results obtained from the fixed parameter network effects comparison model. The model converges at a log likelihood value, -422.87. This model suggests that information from anonymous networks has a significant (t-statistic, -1.78) impact at 90 percent confidence but the peer network effect is significant at 95

[6] I tested over 26 demographic and behavioral variables and selected the these three variables which quality as best instrument variables

percent confidence (t-statistic, |-2.06|>1.96). To account for individual heterogeneity, I included individuals' preference for service, taste and healthy menu choices. To validate the results from this model I test a random parameter model for both peer effects and anonymous effects.

Table-7, Ordered Probit: Network Effects

Dependent variable: Likelihood to Revisit	**Fixed Parameter Ordered Probit**		**Random Parameter Ordered Probit**		**Random Parameter O.P (Cholesky)**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
Treated Peer Effect	-0.001**	-2.06	8.371**	2.94	0.568**	7.12
Anonymous Yelp Effect	-0.153*	-1.78	-3.815	-0.80	0.272**	3.02
Preference for Service	0.235**	2.92	1.300**	4.84	1.300**	4.84
Preference for Taste	-0.013	-0.16	3.414**	-4.18	3.414**	-4.18
Pref. for Healthy Choices	0.049	0.84	0.796**	4.65	0.796**	4.65
Threshold 1	0.641**	9.67	0.421**	6.37	0.421**	6.37
Threshold 2	1.309**	18.03	1.000**	17.55	1.000**	17.55
Threshold 3	2.177**	22.73	1.872**	17.42	1.872**	17.42
Log-likelihood	-422.87			-444.80		

** Significant at 10% level, * Significant at 5% level

In the second network influence model, I allow both the peer network and anonymous network coefficients to be random following a normal distribution. Probit models are well suited for incorporating random coefficients, provided the coefficients are randomly distributed (Hausman and Wise, 1978). The results using a random coefficient model for both the networks are reported in table 7. This model converges at a log likelihood value of 444.80. The log likelihood value suggests that the random parameter model is better than the previous fixed parameter model. The random parameter model indicates that only peer reviews influence consumer demand for restaurants as weighted peer reviews term (t statistic = 2.94) is statistically significant at a 5% level, whereas anonymous review variable is insignificant (t statistic = -0.80).[7] Thresholds in both the models represent cut off points, which divide the utility distribution into five different parts in each model. The coefficients in this model reflect the marginal effect imposed by information received from each peer networks and anonymous networks in restaurant choice. These two models present conflicting results but in the fixed parameter model the signs of the coefficients are negative. The random parameter model suggests that peer effect is significant and hence stronger (coefficient of peer network effect, is larger 8.371) than that of anonymous effect, which is insignificant.

In this random parameter model, the standard deviation of anonymous effect random parameter is 0.40, whereas standard deviation of peer effect parameter is 0.58. I also found that the correlation between these two random parameters is very high (-0.99). High correlation between these two parameters is undesirable, and may cause inconsistency in the model. Hence I again estimate the model using Cholesky decomposition approach to correct for the correlation between the two random parameters similar to Natarajan, Nassar, and Chandrasekhar (2000). Cholesky decomposition procedure is a valuable tool as it produces the most accurate results (McCullough, 1998). Results from this model are presented in table 7. Cholesky

[7] I used 1000 points while conducting the simulation as suggested by Bhat (2001) and Train (2009) to ensure an appropriate value.

decomposition model corrects for the random coefficient correlation problem. The Cholesky random parameter model indicates that both peer effects (t value = 7.12) and anonymous effects (t value = 3.02) are significant. This model also corrects the signs of coefficients as both coefficients have same positive signs. This model also suggests that peer networks have stronger marginal effects than that of anonymous networks on restaurant choice as the coefficient of peer effects, 0.57 is greater than coefficient of anonymous effects (0.27).

Interestingly, above models show that, on average, peer reviews have significant and strong effects on restaurant choice, while anonymous reviews have significant but weaker effect on restaurant choice. Thus results support my original hypothesis that peer reviews are more influential than anonymous reviews. Depth and variety in anonymous reviews and presence of a large pool of information are dominated by the trust and familiarity in the peer networks. At least this is true in the case of restaurant choice. Peer networks are in general more trusted and hence likely overpower anonymous networks with unbiased information.

My second model compares the power of negative reviews and positive reviews and answers the question: Are positive reviews as beneficial as negative reviews are detrimental? This model converges at a log likelihood value -234.93. The results in table 8, show that both positive and negative reviews have significant impact on restaurant demand (measured by the likelihood to recommend a restaurant) but negative reviews can damage the restaurant demand more than the positive reviews can improve (positive review coefficient 0.62 and negative review coefficient -0.79). This result clearly supports the findings of Richards and Patterson (1999) and Chevalier and Mayzlin

(2006). To validate the results from this model I also estimate a random parameter model and found the exact coefficients for both negative and positive reviews which are both significant (t statistic for negative reviews, |-5.46|>1.96 and t statistic for positive reviews 3.18 >1.96) with improved log likelihood ratio (-238.05).

Table-8, Ordered Probit Model Comparing Negative and Positive Reviews

Dependent variable: Likelihood to Recommend	**Fixed Parameter Ordered Probit**		**Random Parameter Ordered Probit**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Positive Reviews	0.624***	4.74	0.624***	3.18
Negative reviews	-0.790***	-6.76	-0.790***	-5.46
Threshold 1	0.641**	9.67	0.430***	5.78
Threshold 2	1.309**	18.03	0.886***	9.48
Threshold 3	2.177**	22.73	1.865***	14.19
Log-likelihood	-234.934		-238.049	

* Significant at 5% level

To sum, I found that peer networks are more influential than anonymous networks in the case of restaurant choice and negative reviews have more powerful impact than that of positive reviews in the case of anonymous networks. The next chapter concludes the study by discussing, contribution and implications of my thesis, possible weaknesses of the research and my thoughts on possible future research.

Chapter 6

CONCLUSION

In this study, I compare two categories of social networks (anonymous and peer networks) in terms of their effect on restaurant preference. I consider the proximity among individuals in their peer network, while comparing the effect of recommendations from one's peers to those obtained from anonymous "experts" through Yelp.com. I also compare negative and positive reviews and determine the relative effect of each on restaurant preference. I use a controlled, experimental approach in order to address the reflection problem (Manski 1993) that typically bedevils inference in empirical problems of social learning.

My experiment consists of two stages using real online anonymous restaurant reviews from Yelp.com and peer reviews from multiple peer groups to compare anonymous and peer networks. In the first stage I provide anonymous Yelp reviews, and in the second stage peer reviews and measure subjects' preferences after each stage.

Peer reviews are weighted by each subject's location in the peer network. These weights are constructed from adjacency matrices that reflect the proximity of each member to all others, where proximity is defined as how well each member knows the others. I include an equal proportion of positive Yelp and negative Yelp review groups along with a proportionate number of control respondents to accurately measure the negative and positive effects of anonymous reviews.

I find that, though both peer as well as anonymous reviews are have a significant impact, anonymous reviews are more influential than peer reviews in determining consumer preferences. I also find both negative and positive reviews can affect preferences, but negative reviews can more adversely affect the demand than positive review can boost the demand for restaurants.

This research has many important implications for both future researchers as well as industry practitioners. My research provides a framework to setup multistage social network experiments to perform economic research. My research is the first of its kind to compare the most prevalent form of social networks in real as well as in the virtual world. A significant portion of advertising budget is lost because of poorly targeted advertising (Greenyer, 2004 and Iyer, Soberman, Villas-Boas 2005). By more accurately targeting these expenditures to influential network members, much of this loss can be avoided. My study focuses on restaurants, but the results likely extend to similar industries such as hotels, local contractors, bars and amusement parks. In each case, consumers face a high degree of prior uncertainty in consuming a multi-attribute good and are likely to turn to social media – whether populated by peers or anonymous experts – to resolve this uncertainty. As the user activity and the online user base increase in the future, social media marketing will become even more important and collect 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 the small size of peer groups can be a limiting factor for any controlled social-networking experiment. On a practical level, however, 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.

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.

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