Di Fang[1] / Timothy J. Richards[2] / Carola Grebitus[3]

Modeling Product Choices in a Peer Network

[1] University of Arkansas, Department of Agricultural Economics and Agribusiness, Fayetteville, AR, USA, E-mail: difang@uark.edu. https://orcid.org/0000-0002-0717-7576.
[2] Marvin and June Morrison Chair of Agribusiness, Morrison School of Agribusiness, W. P. Carey School of Business, Arizona State University, 7231 E. Sonoran Arroyo Mall, Mesa, AZ 85212, USA
[3] Associate Professor of Food Industry Management, W. P. Carey School of Business, Arizona State University, 7231 E. Sonoran Arroyo Mall, Mesa, AZ 85212, USA

Abstract:
Consumers are uncertain about their preferences for innovative product attributes until the first trial. They search for information as a means of reducing uncertainty and improving the likelihood that they will be satisfied with their purchase. One way to receive information is through peer networks. As a peer network is often a priori unknown, we conduct an experiment to solicit self-reported peer nominations. We compare two mechanisms through which peer networks operate: Strength of social ties and perceived peer expertise, to draw inferences regarding consumers' preference reversal after exposure to peer recommendations. Our results indicate that perceived source expertise influences preferences while the closeness of social relationships has no statistically significant impact.

Keywords: experiment, fitness tracker, peer influence, spatial modeling

DOI: 10.1515/fhep-2018-0007

1 Introduction

Consumers make decisions in a world of uncertainty with imperfect information and only partially-formed preferences for attributes they know little about. Their primary sources of information include advertising, physical media, online media, and, perhaps most importantly, peers. Research in a range of fields shows that peers are critical in shaping preferences and choices regarding, e.g. the popularity of otherwise-unheralded movies (Moretti 2011; Reinstein and Snyder 2005), retirement plan participation (Duflo and Saez 2002, 2003a), health-plan (Sorensen 2006), investing in the stock market (Hong, Kubik, and Stein 2004), and new product purchases (Godes and Mayzlin 2004, 2009). However, the exact mechanism through which peers exert influence on others is still not well understood. In this article, we investigate two different types of peer recommendations on the revision of consumer preferences.

We restrict our attention to source expertise (Bansal and Voyer 2000; Gilly et al. 1998) and tie strength (Brown and Reingen 1987; Gee, Jones, and Burke 2017; Granovetter 1973). Source expertise refers to the credibility of a particular source of information. For example, recommendations provided by professionals and authorities are often perceived as more credible. Tie strength refers to the closeness of the relationship between the individuals exchanging word of mouth (WOM). Logically, consumers are more likely to follow recommendations from people whom they know and trust (Kremer and Levy 2008; Sacerdote 2001). However, others find that weak ties between groups, somewhat surprisingly, provide the greatest impact (Gee, Jones, and Burke 2017; Granovetter 1973). Weak ties can have a stronger effect because individuals tend to have weak ties with people from backgrounds that differ from their own and are, therefore, more likely to provide new information.

The context for our investigation is peer influences on marketing an innovative technology product, fitness trackers. Fitness trackers are small, wearable (worn attached by a clip or embedded into a wristband, necklace or other attachment) devices that are intended to monitor movement, and other physiological metrics. Trackers generally use accelerometers, that is, 3-axis inertial positioning sensors, to sense movement and, combined with other user information, calculate steps taken, distance walked, calories burned, and exercise intensity (Prince (2014)). Fitness trackers represent an ideal product for studying the influence of others on consumer choices because they are relatively new, innovative, and not well understood. Moreover, they are highly differentiated, and this differentiation rests on a small set of important attributes. Activity trackers combine modern technology with consumers' health awareness, so they are at the nexus of two trends (technology and healthy lifestyle) that improves the likelihood that our experiment-subjects have an inherent interest in the products themselves.

Di Fang is the corresponding author.

Sales of fitness trackers are very strong. Statista estimates sales of all wearable trackers to be 4 billion US dollars worldwide in 2015 (Statista.com 2018). Researchers foresee that this technology will have lasting effects on health and wellness, patient care, and medical research (Prince 2014).

In this paper, we conduct a randomized two-stage experiment to measure the effect of peer-relationships on preference changes. In the first stage, our experiment establishes a baseline preference for different fitness trackers through a simple choice experiment. We then expose all subjects to information from their peers and conduct a second-stage choice experiment to determine whether preferences change as a result of the new information. With this two-stage approach, we effectively control for unobserved individual factors and isolate the impact of peer influence (Narayan, Rao, and Saunders 2011). We use a spatial econometric approach to identify the effect of source expertise and closeness, which are two important mechanisms identified in the social-learning literature.

We find that credibility is associated with positive attitudes toward both the endorser and the advertisement, consistent with Freeman (1957), Pornpitakpan (2004), and Munnukka, Uusitalo, and Toivonen (2016). In contrast to the findings of Richards, Hamilton, and Allender (2014), we find people who are close in social space are not likely to have a significant influence on each other. We interpret this finding as a manifestation of the more general "weak ties" phenomenon.

Our study has a broader impact on understanding the influence of website reviews and in estimating the value of different marketing techniques. As marketers increasingly employ social media to grow their businesses (Stelzner 2014), our research provides evidence on how social-network relationships shape market growth for innovative products. For example, some brands create Facebook pages by filling out relevant information, posting updates, providing opportunities for customers to comment, and responding to comments from customers. We suggest this approach is most likely to succeed by involving recommendations from people who are experts in the relevant area, e.g. personal trainers for fitness tracker reviews. These activities will likely generate important peer effects while shaping the brand's social media identity and reputation as shown in Ferguson et al. (2015), Parsons (2013), and Pinto and Yagnik (2017).

2 Theoretical Background

Peer effects, and social networks more generally are likely to influence individual behavior regardless of the setting. In fact, the importance of peer effects has been examined empirically in the context of educational behavior (Hanushek 2003; Kremer and Levy 2008; Marmaros and Sacerdote 2002), crime (Billings, Deming, and Ross 2016; Gaviria and Raphael 2001), teenage pregnancy (Arai 2007; Fletcher and Yakusheva 2016), and purchase behaviors (Bollinger and Gillingham 2012; Narayan, Rao, and Saunders 2011; Richards, Hamilton, and Allender 2014). In practice, marketers often attempt to account for peer recommendations when determining the targeting and intensity of marketing activities. The idea is that the utility an individual receives from pursuing a given activity depends on the recommendations of the other people in the person's reference or peer group. Therefore, the microeconomic underpinnings of peer effects are clear and well-understood.

Individuals are indeed strongly motivated to reduce the amount of effort they exert during the decision-making process in information-intensive environments. Therefore, their behavior may be directly influenced by effort-saving, easily available cues such as peer recommendations (Smith, Menon, and Sivakumar 2005). Prior research suggests that consumer choices arise from various information cues such as information via websites (Mandel and Johnson 2002) or attributes that just happened to be included in the recommendation of an electronic agent (Häubl and Murray 2003). If we find significant preference revisions in our experiment, the implication is that participants indeed look for easy cues using peer recommendations to form their preferences in an environment of uncertainty. Therefore, we propose that positive recommendations by members of a social network are likely to influence other members' behavior in the same direction.

Hypothesis 1

Peer recommendations will lead to preference revision for the recommended option if individuals regard the attribute in question to be salient to the decision.

The decision to seek information from someone when facing a new problem or opportunity is likely affected by the closeness between the seeker and her peers. Research on homophily suggests that people are more likely to have social ties (especially strong ones) with those similar to themselves (Marsden 1990; Reagans 2005). Social network researchers examine the role of weak vs. strong ties in the acquisition of novel information. Granovetter (1973) argues that, compared to strong ties, weak ties are more likely to bridge to socially distant regions of a network. Subsequent research on the importance of weak ties demonstrates that they can be instrumental in finding a job (Granovetter 1973; Gee, Jones, and Burke 2017), individual advancement (Morrison 2002), and diffusion of ideas (Rost 2011; Levin and Cross 2004). Hansen (1999), for example, demonstrates the importance of strong ties in transferring tacit, complex knowledge across departmental boundaries in an organization.

We hypothesize that tie strength has a substantial effect on the influence of WOM communications (Brown, Broderick, and Lee 2007; De Bruyn and Lilien 2008). Strong ties are more likely to transfer useful knowledge (Levin and Cross 2004) and thus have more influence on others than do weak ties (De Bruyn and Lilien 2008; Smith, Menon, and Sivakumar 2005). Therefore, it is reasonable to expect that a strong tie between an individual and his or her peers is more likely to lead to preference revision than is a weak tie. We follow the previous literature by defining tie strength regarding the social distance (relationship) between two participants (e.g. Richards, Hamilton, and Allender (2014)). The relationship may be very close, for example, between relatives, or very casual, such as with acquaintances or strangers. The second hypothesis that follows from this theory is that:

Hypothesis 2

Preference revisions will be greater for strong ties than weak ties.

The information seeker is also likely to be influenced by her perception of another's credibility when making a decision about novel products. Knowledge of another person's expertise is a standard variable in the transactive memory literature, which identifies knowing where information is stored as a basic requirement of performance in distributed-knowledge systems (Cross et al. 2006). A consumer's subjective feeling of being influenced by the recommender may depend on how she feels about the recommender, or the perceived source credibility (Smith, Menon, and Sivakumar 2005). Highly credible sources usually lead to more behavioral compliance than low-credibility sources (Pornpitakpan 2004). The dimensions of source credibility consist of expertise, which refers to the extent to which a speaker is perceived to be capable of making correct assertions (Hovland, Janis, and Kelley 1953). Besides expertise, trustworthiness, defined as the degree to which an audience perceives the assertions made by a communicator to be true, is another important antecedent of behavior that demonstrates credibility (McKnight, Choudhury, and Kacmar 2002).

We investigate how perceived recommender-credibility impacts consumer preferences. Those receiving information from opinion leaders associate the correctness of the information with their perceptions of the opinion leader's expertise in that particular domain (Feick and Higie 1992). Therefore, we expect that perceived credibility, will positively influence a participant's preference revision, so that:

Hypothesis 3

Perceived credibility is positively related to revisions in attribute preferences.

To test these hypotheses, we analyze peer effects using a two-stage randomized experiment. Through variation in the nature of the ties among participants, the level of credibility perceived to be associated with each participant, and the levels of credibility in the recommender, we analyze how social relationships influence preferences for product attributes. We describe the research design in the next section.

3 Research Design

3.1 Experimental Procedures

Lab experiments provide researchers with more control over the attributes of the sample and the environment in which decisions are made. In a context similar to the one that frames our analysis, Narayan, Rao, and Saunders (2011) use a two-stage conjoint choice experiment in which they measure participants' willingness to pay for electronic book reader attributes. They collected participants' initial preferences in the first stage, then asked them to identify their influencers. In the second stage, which took place two weeks later, participants were shown the choices of their self-reported influencers and asked to choose from the same choice sets again bearing in mind the choices of influencers. They found that peer influence caused subjects to significantly revise their valuation of several attributes and that this influence grew with the number of peers. One limitation to their experiment is that the waiting period between first and second stage was weeks, during which participants' preferences could have changed for other reasons than the peer effect, or they could have forgotten why their preferences were initially formed as they were.

We conduct a two-stage experiment following Narayan, Rao, and Saunders (2011). In general, a two-stage design addresses some of the most important challenges presented in the elicitation of peer effects. First, we choose student participants based on their dorm assignment, which is unrelated to their preferences for fitness trackers. Second, we collect information on participants' social background and social proximity to control for unobserved correlation effects. Third, measuring respondents' preferences in two stages provides an opportunity to identify endogenous peer effects, independent from any other influence that may have caused the observed preference revisions between the two stages.

We recruit subjects randomly from the population of students, as is necessary to identify pure peer effects. Random assignment ensures that the difference in responses between the treatment and the control groups is due to the treatment alone, and not some pre-existing conditions that could have caused behaviors among group members to be similar. Participants in the experiment are recruited from their dormitory, which is matched on major, preference, and personality, then randomly assigned into a control or treatment group. This way, we allow social ties among participants but the fact that they may be classmates is unrelated to their preference for fitness trackers (see a similar argument in Duflo and Saez (2003b)).

In the treatment groups, participants were exposed to peer discussion between stages 1 and 2. Hence, the treatment effect measures the extent of peer influence, relative to the control in which no peer influence is allowed. In a typical treatment group, participants were asked to talk about their choices as well as what attribute influenced their choice. Following the discussion, participants were asked in stage two to again make their preferred choices between alternatives from the same choice sets as in stage one. Participants in the control groups were not allowed to discuss their choices but were instead asked to read an article on an unrelated topic. Diverting their attention from the task at hand was intended to take participants' mind off the choices from stage one. After reading the article participants also made their stage two choices. Both the peer discussions for the treatment groups and the reading for the control groups took 10 minutes. The entire experiment took approximately 35–40 minutes. After the choice experiment in stage two, socio-economic and demographic data were collected.

We chose four major brands of fitness trackers on the basis of popularity: Nike, Fitbit, Jawbone, and Garmin. A Google shopping search revealed that reasonable price points include $49.99, $99.99, $129.99, and $199.99. Priced at $49.99, the Jawbone Up Clip on tracker attracts price-sensitive consumers. This type of tracker provides the basic function of tracking calories but is limited by its design because the clip-on is not particularly well suited to intense exercise such as running. With slim wristband designs, Fitbit, Jawbone, Nike, and Garmin all have trackers that are priced at $99.99 and $129.99. Newer versions are introduced every year. Thus, older trackers are priced below the new models. Also, trackers that add emerging functions, such as sleep pattern tracking, are usually priced slightly higher. Trackers that are priced at $199.99 and above are often equipped with superior functions. Trackers also vary in style, from watch-type to wristband, and clip-on. Functions vary as the market has not yet settled on the core purpose of fitness trackers. For a systematic review of fitness trackers as well as its attributes, please refer to Evenson, Goto, and Furberg (2015). An example of a choice set is presented in Table 1.

Table 1: Sample Choice Sets.

	A	**B**	**C**	**D**	**E**
Brand	Garmin	Jawbone	Nike	Fitbit	None of these
Design	Clip-on	Watch	Wristband	Clip-on	
Function	Calorie + Sleep Tracking	Calorie Tracking + GPS	Calorie Tracking + Messaging	Calorie Tracking + Messaging	
Price	$99.99	$199.99	$129.99	$49.99	
Choice					

Participants were required to be over the age of 18, students, and able to communicate in English. Among the 80 invitations sent out, 63 participants completed the experiment in a useable way, leading to a turnout rate of 78.75%. A total of 63 participants completed the experiment and assigned to two treatment groups and two control groups. Each participant provided 120 observations, resulting in a total of 7560 observations. We follow Hensher, Rose, and Greene (2005) in determining whether n = 63 is an acceptable sample size. The minimum threshold for an acceptable sample size is calculated as $n = \frac{1-p}{pa^2}[\Phi^{-1}(1-\alpha/2)]^2$, where p is the choice proportion of the relevant population, a is the level of allowable deviation as a percentage, α is the type I error, and Φ^{-1} is the inverse cumulative distribution of a standard normal distribution. Assuming they are equally likely to be chosen, the choice proportion $p = 1/4 = 0.25$. The choice of accuracy is somewhat subjective under the rule that the more accurate the estimates are the larger sample is required. If the desired level of accuracy is 30% from the mean (a = 0.3), then the required sample size is 65, approximately the sample we have. This is a reasonable sample size in social-networking experiments as samples are necessarily small due to the computational difficulty in estimating with large social weight matrices, and the practical necessity of ensuring that each participant can plausibly assign relational values to all others.

3.2 Gathering Relational Data

We gathered data measuring friendship and credibility. Variation in "friendship" identifies tie strength because stronger ties characterize people who are closer to each other. We follow the relationship measure of Richards, Hamilton, and Allender (2014) where tie strength is defined as how well the participants know each other, rated on a 5-point scale ranging from "Do not Know" (tie strength = 1) to "Know Very Well" (tie strength = 5). The second set of relationship data collected is "perceived credibility." Variation in "perceived credibility" identifies source credibility (perceived expertise and trust) because people who are viewed as credible information carriers serve as opinion leaders, whose opinions are thought as more important. We measure source credibility by asking participants to report how credible they think each of the other participants is. Credibility is measured on a 5-point scale from "Not credible" (credibility = 1) to "Very credible" (credibility = 5) (Bannister 1986; Pornpitakpan 2004).

We carefully evaluated the difference between friendship and credibility by performing a correlation test as well as a two-sample t test. A significant correlation of 0.53 ($p < 0.001$) indicates there is some overlap between the two measurements. This is to be expected as a friend is often deemed as a credible source. A t statistics of 6.28 ($p < 0.001$) between the mean of the two measurements indicates they captured inherently different information. To visualize the difference, we take a sample of 20 participants and illustrate their credibility network in Figure 1 and friendship network in Figure 2. Both graphs are displayed based on centrality and participants with similar centrality are grouped by the same color. An arrow indicates the direction of the relationship as the network is not necessarily symmetric. As illustrated, participant 9 is the hub of the credibility network, even though she is not connected with anyone by friendship. Participant 5, on the other hand, is considered as highly credible by her peers even though she deems everyone else to be not credible (as shown by the one-directional arrows).

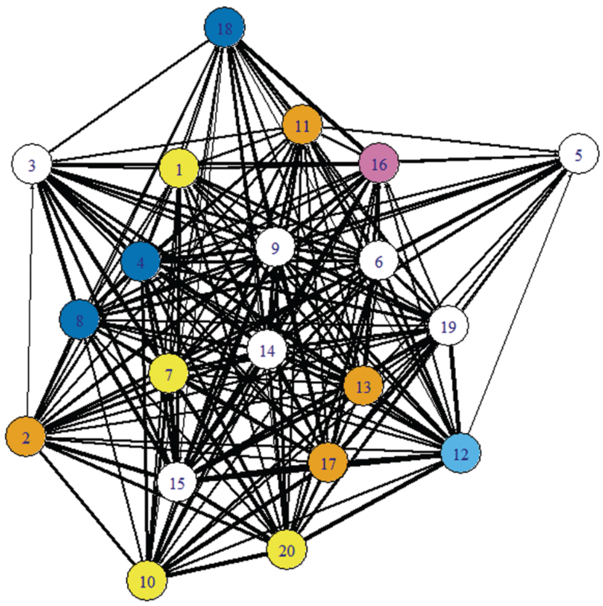

Figure 1: Sample Network for Credibility.
Note: Nodes are grouped by color based on betweenness centrality. The width of link indicates degree of credibility.

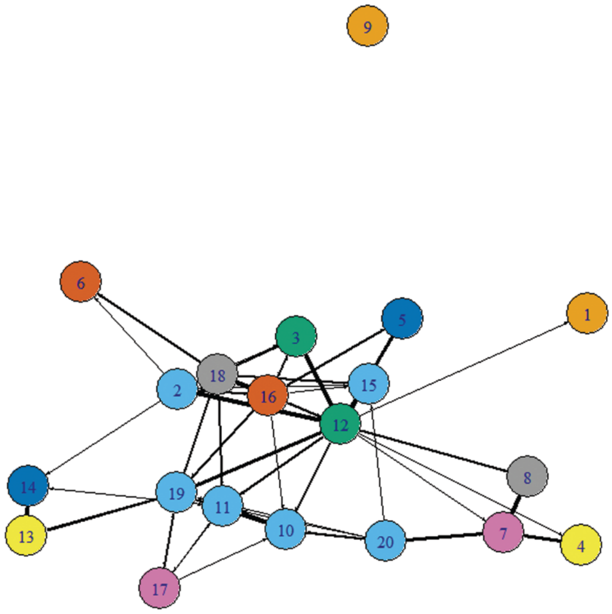

Figure 2: Sample of Friends Network.
Note: Nodes are grouped by color based on betweenness centrality. The width of link indicates degree of friendship.

Besides relationship data, we also collected socio-demographic information as controls. A description of the sample characteristics is presented in Table 2. The sample consists of mostly junior and senior business and engineering students. participants average 20.59 years of age, relative to the state mean of 37.2. A younger sample is to be expected because it consists entirely of students. Further, 28.6% of the sample is female compared to the state mean of 50.6%, but representative of the majors on the surveyed campus. The sample contains 46% White, 21% Asian, 16% Hispanic, 2% of Native American, and 7% other races. Only 17.5% of the sample own an activity tracker. Our sample is relatively active with 25.4% working out every day; while the majority (52.4%) work out at least once a week. On average, participants spend $187 annually on sports-related purchases with a standard deviation of $146. The frequency of purchases lies mostly in the category of "once every 3 months." The average BMI is 24.39, which is within the normal range of weight/height ratio. Our sample shows that the majority (54.3%) has an income of less than $39,000/year, while the rest has an income of more than $40,000/year. Comparing to the average income of Arizona at $48,510 and the average income of the nation at $52,250 (U.S. Census Bureau 2015), the sample income is below average but representative of a student sample.

Table 2: Descriptive Statistics for the Sample.

Variable	Definition	Frequency %	Mean	Std. dev
Gender	Gender of participant Female = 1; Male = 0		0.29	0.455
Age	Age in years		20.59	2.519
Annual household income	Total household income			
	Less than $10,000	33.3		
	10,000 *to* 19,999	10.5		
	20,000 *to* 29,999	10.5		
	30,000 *to* 39,999	0		
	40,000 *to* 49,999	3.5		
	50,000 *to* 59,999	8.8		
	60,000 *to* 69,999	12.3		
	70,000 *to* 79,999	5.3		
	80,000 *to* 89,999	0		
	90,000 *to* 99,999	3.5		
	100,000 *to* 149,999	7		
	More than $150,000	5.3		
Workout frequency	How often do you work out?			
	Every day = 5	25.4		
	At least once a week = 4	52.4		
	Once every other week = 3	11.1		
	Once a month = 2	6.3		

	Once a few months or less often = 1	4.8		
Purchase_freq	How often do you purchase sports goods?			
(purchase frequency)	At least once a week = 5	4.8		
	Once a month = 4	17.5		
	Once every 3 months = 3	34.9		
	Once every 6 month = 2	27		
	Once a year or less often = 1	15.9		
Purchase_expPurchase expenditure	How much money do you spend sports goods?		187.3	146.179
Tracker ownership	Yes = 1; No = 0		0.17	0.383
BMI			24.396	6.79
Ethnicity	White		0.46	0.502
	Hispanic		0.16	0.373
	Native American		0.02	0.128
	Asian		0.21	0.413
	Other		0.07	0.25

4 Models

4.1 Random Parameter Logit Model

The objective of the experiment is to elicit changes in preferences due to peer interaction. Because we are interested in preference changes from stage one to stage two, our first econometric model estimates the change in preference, as manifested in willingness-to-pay (WTP) between stage one and two. Our second econometric model then analyzes the change in WTP with respect to two different types of peer interactions with a spatial econometrics model. In the following, we discuss the random parameter logit model (RPL) employed to derive willingness-to-pay, as well as the Spatial Durbin Model (SDM) employed to study the peer effects induced by tie strength and perceived expertise. We start with the utility function where

$$U_{iq} = \beta_q^{'} X_{iq} + \eta_{iq} + \epsilon_{iq} \tag{1}$$

where X_{iq} is the full vector of explanatory variables that are observed by the analyst, including attributes of the alternatives, and variables that describe treatment and stage effects. Vector $\beta_q^{'}$ is parameter estimates associated with X_{iq}. Parameter η_{iq} is a random term with zero mean whose distribution over individuals and alternatives depends in general on underlying parameters and observed data relating to alternative q and individual i. Finally, ϵ_{iq} is a random term.

The explanatory X_{iq} variables include Garmin, Jawbone, Nike, and Fitbit that represent the four different brands; Clip-on, Wristband, and Watch that represent the different fitness tracker designs; dummy variables that capture the ability to record calories only (Cal), sleep patterns (Sleep), text and email messages (Msg), and recording workout routes with the aid of a Global Positioning Satellite (GPS); and the Price variable. Besides the attributes, we also include interaction variables to capture the difference between stages as well as treatment effects. Stage interactions variables are the product of a stage binary variable and all attributes, indicating whether there exist significant differences between stages. These interactions will help reveal whether there exist treatment effect in the second stage.

The choice probabilities associated with the RPL is:

$$P_{iq}(X_i, z_i) = \int L_{jq}(\beta_q | X_q, \eta_q) f(\eta_q | z_q) d\eta_q \tag{2}$$

where L_{jq} is the conditional probability of choosing option j. Flexible substitution is introduced through the random parameters, specifying each element of β_q associated with an attribute of an alternative as having a mean, a standard deviation, and possibly a measure of correlation with another random parameter. By allowing marginal attribute valuations to vary across sample participants, we are able to determine how preferences are influenced by exposure to the choices of others.

Following Hensher, Rose, and Greene (2005), we allow the marginal utility of the income (price parameter) to vary randomly with a triangular distribution. The randomness in the RPL allows for estimation of individual tastes. Specifically, individual-specific willingness to pay estimates are calculated by dividing the attribute estimate of interest by the marginal utility of income estimate. For example, the willingness to pay for Garmin trackers is found as:

$$\Delta WTP_i = -\frac{\beta_{s_{Garmin}}}{\beta_{price,i}} \tag{3}$$

Differences between first and second-stage valuations may be positive or negative, depending on the nature of the information received between the two sessions. However, we are more interested in how preferences are moderated by social interaction than the direction of change. Comparing the first and second stage RPL estimates and WTP revisions does not address the issue of how the definition of peers affects preference revision. Therefore, we estimate the extent of preference revision as moderated by each participant's location in the social-spatial network in our second econometric model.

4.2 The Spatial Model

Spatial models are used to estimate preferences in a social environment because they are non-linear in structure and account for simultaneous interactions among individuals through weight matrices (Anselin 2002; Richards, Hamilton, and Allender 2014). Moreover, the natural exclusion restrictions implied by the social network structure ensure the separate identification of endogenous and contextual peer effects (Lin 2014).[1] In our case, the spatial weight matrices are the credibility network and friendship network.

We apply a spatial lag model with lagged error specification[2] to measure peer variables as the weighted averages of observed peer outcomes and characteristics instead of group expectations. Both peer outcomes and peer characteristics are specific to the individual and vary across group members. The spatial error term captures unobserved spatial patterns therefore accounting for the unobserved heterogeneity in consumer tastes. The model is written as:

$$\Delta WTP_{iq} = \alpha + \rho \sum_{j=1}^{n} w_{ij} \Delta WTP_{jh} + y_{iq}\beta + \sum_{j=1}^{n} w_{ij} h_{iq}\gamma + u_{iq} \tag{4}$$

where

$$u_{iq} = \lambda \sum w_{ij} u_{iq} + \varepsilon_{iq} \tag{5}$$

ΔWTP_{iq} is the difference in preference between stage one and two for each individual; y_{iq} are individual characteristics related to the purchase of fitness trackers; h_{iq} are individual characteristics averaged over the group; w_{ij} is the ij element of a row-standardized, zero diagonal weight matrix that captures the network structure where i and j are different individuals. The error term in the model u_{iq} captures the unobserved effects that vary according to a social network w_{ij}. ε_{iq} is an idiosyncratic error term.

We interpret the parameter ρ as the endogenous peer effect. As shown in the equation, ρ is the average effect of one's social network (excluding oneself) on the decision of the focal person.[3] The absolute value of ρ is bounded by 0 and 1: a negative value of ρ indicates a consumer is negatively influenced by her peers, whereas a positive value of ρ indicates the consumer follows her peers' decisions. To control for the other effects that could have contributed to peers making a similar decision, as suggested by Manski (1993), we use γ to capture the contextual effect and λ to capture the unobserved, correlated effect.

The structure of the weight matrix, $\sum w_{ij}$, is essential to estimating peer effects with this model. A weight matrix is a n by n matrix where an observation appears both as a row and column, with non-zero matrix elements w_{ij} indicating the peer relationship between participants (row) i and (column) j. We use two set of spatial weight matrices: $W_{friends}$ that describes the tie strength, and W_{cred} that describes the source expertise of network members. These two weight matrices essentially represent two different mechanisms through which preferences may be revised through social interaction. $W_{friends}$ captures tie strength in which preferences are revised through established social distance between individuals; W_{cred} captures "source credibility" in that revisions are moderated by the extent of credence individual i lends to individual's j's comments regarding the product. We follow Anselin (2002) and apply the Maximum Likelihood method to analyze our data with the *splm* package in R (Millo and Piras 2012).

5 Results

Participant-specific WTP for all attributes is also calculated and presented in Table 3. Prior to any peer influence, participants have the highest WTP for GPS capacities, followed by watch design and sleep capacities. After learning about peers' experiences with fitness trackers, and being informed about their preferences, the participants' WTP significantly decreased for GPS and wristbands and, at the same time, increased for all brand attributes. Among the other revisions, one notable result is that, prior to peer influence, the average WTP for wristband design is positive ($129), whereas the WTP for the same design drops (by $152) below zero after peer influence. This shows that peer influence negatively affects choice on wristband design. For example, participants may have discussed the disadvantages of a design that prevent people from wanting to include this attribute. Table 3 shows that peer recommendations positively enhanced brand knowledge. All brand attribute preferences (Garmin, Nike, and Jawbone) are revised higher after peer influence compared to the baseline (Fitbit), with Garmin being revised higher by $95, Nike revised by $36, and Jawbone revised by $63.

Table 3: Participant-Specific Marginal WTP by Attribute.

	Pre-influence		Difference in WTP	
	Mean WTP	**Std. err**	**Mean WTP**	**Std. err**
Garmin	39.2900*	25.7862	94.6470*	23.4557
Nike	63.0608*	53.1249	36.2421	23.5743
Jawbone	−5.9432	46.0103	62.8538*	40.8843
Watch	155.6978*	134.9679	−79.4125*	51.6551
Wristband	129.1619*	80.9048	−151.9357*	98.829
Sleep	149.5709*	94.4735	−137.622*	89.5187
GPS	159.9482*	123.1506	−175.8147*	114.3615
MSG	105.2684*	75.6572	−87.2695*	56.7658

***, **, * indicate statistically significance at 0.1, 1 and 5 per cent level respectively.

Participants also exhibited a willingness to change preferences for design. For example, the WTP for the watch-style attribute after peer interaction is revised to be lower by $79. In the same way, the WTP for the wristband style after peer recommendations is negative. WTP for all functions is revised lower after peer recommendations. WTP for the function of tracking sleeping patterns is reduced by $138, the WTP for the GPS function is reduced by $176, and the WTP for the messaging is reduced by $87. Clearly, peer communications discouraged participants from paying for additional functions. In general, peer discussions lead participants to be more brand-conscious and discouraged participants from paying for specific additional function.

Results from the spatial model are presented in Table 4.[4] We use the Lagrange-Multiplier statistic (Anselin 2002) to test whether the variation in preference revision can be explained by our two types of social peer matrices: tie strength or perceived expertise. In the case of tie strength, the LM value is 0.6919, smaller than the critical value, meaning that consumer preferences do not depend on peers that are defined through friendship. On the other hand, the LM statistics for spatial lag (3.0414) and spatial error (3.2679) using peers defined by "source credibility" are both significant, rejecting the null hypothesis of an OLS in favor of both spatial lag and error specification. This means that source credibility is able to explain the causal relationship between consumer preferences and peers' preferences as well as the unobserved correlations. Based on these tests we conclude that consumers indeed depend on their peers (who they perceive as credible) for recommendation and that there exist unobserved correlations that cause consumers to arrive at the same choices. Based on these results, we reject the notion that preference revisions will be greater for friends and support that perceived credibility is positively related to revisions in attribute preferences. The distinction is important, as it suggests that when facing innovative products, consumers do not turn to their friends for recommendations but rather people who they perceive as having expertise on the product. This extends the literature on proximity by identifying relational mechanisms through which social propinquity leads to information exchange.

Table 4: Results of Spatial Models.

Explanatory variables	OLS	t	Tie strength	z-value	Source expertise	z-value
Purchase	−0.0699	−1.93703	−0.056	−1.4432	0.0308**	1.9893
Workout	8.7206	1.6808	5.75	0.9729	7.606	0.1301

Tracker	0.0611	0.0444	5.5335	0.3884	9.2621	0.483
BMI	−1.1913	−1.3878	−1.375	−1.518	0.7832*	1.6384
Contextual effects						
Age	0.1628**	2.5931	0.0039	0.0495	−0.0496*	−2.323
Gender	−2.0359*	−1.3344	2.875	1.1848	0.7100*	1.9359
Income	−0.0001	−1.6211	0	−0.712	0	0.6147
Endogenous effect						
	NA	NA	0.8125	1.032	0.8505*	3.5559
Unobserved effect						
	NA	NA	0.605	0.4367	0.3977	0.5035
Fixed Group effect						
Treatment	−35.9161	−1.4364	−5	0.1779	23.8401*	2.7842
Model Fit						
Log likelihood	−314.668					
				p-value		p-value
LM(lag)			0.6919	0.2549	3.0474*	0.0808
LM(error)			1.2959	0.5041	3.2679*	0.0706

***, **, * indicate statistically significance at 0.1, 1 and 5 per cent level respectively.

Our finding is consistent with Granovetter (1973) in that "weak ties" rather than "friends." Take participant 9 as an example – a stranger in a social network can be more influential as long as she is considered credible. People who have close social proximity are likely to share similar information, so they are not the best candidates for new product promotion. From a marketing perspective, this finding explains why online practices such as Yelp and TripAdvisor are successful because they rely on expertise and experiences from strangers to promote their products and services. Since influential individuals are not necessarily close friends, this finding highlights a notable difference between traditional marketing procedures, where WOM plays an important role, and the more current, viral marketing where online recommendations are given by anyone who is perceived as credible. Our finding is similar to Godes and Mayzlin (2004), who demonstrate that it is the less loyal customers instead of the most loyal customers who provide influential WOM. In a similar manner, our results suggest that marketers should get out of the traditional word-of-mouth marketing where friends recommend friends, and instead should target those who are credible representatives of the product.

Two contextual effects were found to be significant: age and gender. Age is negatively related to the WTP, as participants who are younger are likely to be more fitness aware. Gender is positively related, meaning that males are less likely to pay a higher price. Income, on the other hand, does not show a significant relationship with consumers' preferences for fitness trackers. This notion can be explained that for each brand it has a range of trackers that satisfy consumers of different income levels, therefore indicators such age and gender that identify with certain traits of a fitness tracker turn out to be determining factors. Identifying the relationship between contextual factors and preference revisions is important because contextual factors help marketers target a group of people with a similar background.

6 Conclusion and Discussion

Relationships are important ways for consumers to acquire information given that the creation of knowledge is a social process. When consumers are considering the purchase of innovative, new products, little is known prior to the release of truly new products. Despite the importance of social interaction as a vehicle for knowledge acquisition and extensive literature on peer effects, limited research has made an effort to investigate how peers influence the adoption of innovative products. This article offers evidence as to how consumer preferences are revised through peer recommendations in the context of fitness trackers.

We use a two-stage experiment to examine preference revision via peer recommendations. We detect factors that are important in consumers' choices of fitness trackers. Among which, the brand is a general representation of specific attributes and consumer recognition embodied in fitness trackers. We find that brand-related information such as design, function, and price are significant when consumers choose to buy fitness trackers. However, brand serves as a representation of all traits when consumers revise their preference according to peer recommendations. That is, when consumers seek information from their peers, they tend to generalize certain attributes or make the connection between the brand and other people (peers)' the discussion of attributes. This finding sheds light on how marketers can best use peer networks to promote innovative new products. That is, instead of promoting specific attributes of a fitness tracker, marketers should link the innovative feature to the brand in general. For example, Garmin is the top brand in GPS. When promoting Garmin fitness trackers, instead of emphasizing on the perks of the GPS function itself, the marketer could link Garmin fitness trackers with excellent GPS performance compared to other brands.

Identifying the effect of peer relationships on consumer choice is a matter of both experimental design, and econometric estimation. In this study, our experiment is random in the sense students who are sampled are based on their preferences for academic majors, which should not correlate with their preferences for fitness trackers. Our econometric model is non-linear while addressing two different mechanisms of peer recommendations. Peer recommendations work through the social proximity among members of the network. Such interaction is spatial and simultaneous in nature, which calls for spatial models. Spatial models allow for peer recommendations to enter through a weight matrix that addresses interrelationships, and yield true peer effect as a result.

We find that credibility is more important in moderating social learning than social proximity. This provides evidence that individuals who are perceived to have expertise on the product rather than those they are friends with. Consistent with Granovetter (1973)'s expectation that weak ties exhibit stronger interpersonal effects than do strong ties, we find that consumers do not revise their preferences according to how well they know each other, but rather how credible they perceive their peers to be. Because our research products are fitness trackers, people who are perceived to be credible are those who dressed in gym gear, are physically fit, and have previous experiences with fitness trackers. These people serve as "hubs" in the network as they are the influencers. In the broader sense of marketing, individuals who are perceived to have professional and credible opinions of the subject of matter should introduce new products, rather than close friends and family.

Although this study is conducted in the context of fitness trackers, our approach is applicable when studying other products that are innovative in nature and can be recommended via source credibility. Future research can extend this study in a number of ways: first, we did not consider information externalities, which could be another application of the data. Also, we used a choice-based conjoint experiment, which provided many observations from the same individual but suffers from the fact that attribute values do not vary over time. Replication with different items that vary in terms of their attribute content would help identify the model from this perspective.

Acknowledgement

The authors thank the Morrison School of Agribusiness at Arizona State University for providing funding for the experiment.

Notes

1 In particular, for the linear-in-means model, peers' outcomes are measured by group mean outcomes, and peers'characteristics are captured by group mean characteristics. Both measurements are group-specific and constant for all members of the same group. The consequence is that these two terms are linearly dependent, and the endogenous effects cannot be separated from the contextual effects. In the non-linear model we use, however, there is enough variation across individuals in the group, therefore enable us to identify both endogenous and exogenous effects.
2 Please refer to Chapter 2 of Elhorst (2014) for details of different spatial model specifications.
3 The interpretation of ρ as peer effect is discussed extensively in Elhorst (2014), Anselin (2002), and Lin (2014)
4 Given limited space, the full set of results of OLS, RPL, and spatial models for each attribute with alternative weight matrices can be provided upon request.

References

Anselin, L. 2002. "Under the Hood Issues in the Specification and Interpretation of Spatial Regression Models." *Agricultural Economics* 27 (3): 247–267.
Arai, L. 2007. "Peer and Neighbourhood Influences on Teenage Pregnancy and Fertility: Qualitative Findings from Research in English Communities." *Health & Place* 13 (1): 87–98.
Bannister, B. D. 1986. "Performance Outcome Feedback and Attributional Feedback: Interactive Effects on Recipient Responses." *Journal of Applied Psychology* 71 (2): 203–210.
Bansal, H. S., and P. A. Voyer. 2000. "Word-of-Mouth Processes within a Services Purchase Decision Context." *Journal of Service Research* 3 (2): 166–177.
Billings, S. B., D. J. Deming, and S. L. Ross. 2016. "Partners in Crime: Schools, Neighborhoods and the Formation of Criminal Networks." Technical report, National Bureau of Economic Research.
Bollinger, B., and K. Gillingham. 2012. "Peer Effects in the Diffusion of Solar Photovoltaic Panels." *Marketing Science* 31 (6): 900–912.

Brown, J. J., and P. H. Reingen. 1987. "Social Ties and Word-of-Mouth Referral Behavior." *Journal of Consumer Research* 14 (3): 350–362.
Brown, J., A. J. Broderick, and N. Lee. 2007. "Word of Mouth Communication within Online Communities: Conceptualizing the Online Social Network." *Journal of Interactive Marketing* 21 (3): 2–20.
Cross, R., T. Laseter, A. Parker, and G. Velasquez. 2006. "Using Social Network Analysis to Improve Communities of Practice." *California Management Review* 49 (1): 32–60.
De Bruyn, A., and G. L. Lilien. 2008. "A Multi-Stage Model of Word-of-Mouth Influence Through Viral Marketing." *International Journal of Research in Marketing* 25 (3): 151–163.
Duflo, E., and E. Saez. 2002. "Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues' Choices." *Journal of Public Economics* 85 (1): 121–148.
Duflo, E., and E. Saez. 2003a. "Implications of Information and Social Interactions for Retirement Saving Decisions." *Pension Research Council* 13: 1–28.
Duflo, E., and E. Saez. 2003b. "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.
Elhorst, J. P. 2014. "Spatial Panel Data Models." In *Spatial Econometrics*, 37– 93. Berlin, Heidelberg: Springer.
Evenson, K. R., M. M. Goto, and R. D. Furberg. 2015. "Systematic Review of the Validity and Reliability of Consumer-Wearable Activity Trackers." *International Journal of Behavioral Nutrition and Physical Activity* 12 (1): 159.
Feick, L., and R. A. Higie. 1992. "The Effects of Preference Heterogeneity and Source Characteristics on ad Processing and Judgements about Endorsers." *Journal of Advertising* 21 (2): 9–24.
Ferguson, T., A. V. Rowlands, T. Olds, and C. Maher. 2015. "The Validity of Consumer-Level, Activity Monitors in Healthy Adults Worn in Free-Living Conditions: A Cross-Sectional Study." *International Journal of Behavioral Nutrition and Physical Activity* 12 (1): 42.
Fletcher, J. M., and O. Yakusheva. 2016. "Peer Effects on Teenage Fertility: Social Transmission Mechanisms and Policy Recommendations." *American Journal of Health Economics* 2 (3): 300–317.
Freeman, W. M. 1957. *The Big Name.* New York, NY: Ink Books.
Gaviria, A., and S. Raphael. 2001. "School-Based Peer Effects and Juvenile Behavior." *Review of Economics and Statistics* 83 (2): 257–268.
Gee, L. K., J. Jones, and M. Burke. 2017. "Social Networks and Labor Markets: How Strong Ties Relate to Job Finding on Facebook's Social Network." *Journal of Labor Economics* 35 (2): 485–518.
Gilly, M. C., J. L. Graham, M. F. Wolfinbarger, and L. J. Yale. 1998. "A Dyadic Study of Interpersonal Information Search." *Journal of the Academy of Marketing Science* 26 (2): 83–100.
Godes, D., and D. Mayzlin. 2004. "Using Online Conversations to Study Word-of-mouth Communication." *Marketing Science* 23 (4): 545–560.
Godes, D., and D. Mayzlin. 2009. "Firm-Created Word-of-Mouth Communication: Evidence from a Field Test." *Marketing Science* 28 (4): 721–739.
Granovetter, M. 1973 . "The Strength of Weak Ties." *American Journal of Sociology* 78: 1360– 1380.
Hansen, M. T. 1999. "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits." *Administrative Science Quarterly* 44 (1): 82–111.
Hanushek, E. A. 2003. "The Failure of Input-Based Schooling Policies." *The Economic Journal* 113 (485): F64–F98.
Häubl, G., and K. B. Murray. 2003. "Preference Construction and Persistence in Digital Marketplaces: The Role of Electronic Recommendation Agents." *Journal of Consumer Psychology* 13 (1–2): 75–91.
Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. *Applied Choice Analysis: A Primer.* Cambridge: Cambridge University Press.
Hong, H., J. D. Kubik, and J. C. Stein. 2004. "Social Interaction and Stock-Market Participation." *The Journal of Finance* 59 (1): 137–163.
Hovland, C. I., I. L. Janis, and H. H. Kelley. 1953. *Communication and Persuasion.* New Haven, CT, US: Yale University Press.
Kremer, M., & Levy, D. 2008. "Peer effects and alcohol use among college students." *Journal of Economic perspectives* 22 (3): 189–206.
Levin, D. Z., and R. Cross. 2004. "The Strength of Weak Ties you can Trust: The Mediating Role of Trust in Effective Knowledge Transfer." *Management Science* 50 (11): 1477–1490.
Lin, X. 2014. "Peer Effects in Adolescents' Delinquent Behaviors: Evidence from a Binary Choice Network Model." *Regional Science and Urban Economics* 46: 73–92.
Mandel, N., and E. J. Johnson. 2002. "When Web Pages Influence Choice: Effects of Visual Primes on Experts and Novices." *Journal of Consumer Research* 29 (2): 235–245.
Manski, C. F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60 (3): 531–542.
Marmaros, D., and B. Sacerdote. 2002. "Peer and Social Networks in Job Search." *European Economic Review* 46 (4–5): 870–879.
Marsden, P. V. 1990. "Network Data and Measurement." *Annual Review of Sociology* 16 (1): 435–463.
McKnight, D. H., V. Choudhury, and C. Kacmar. 2002. "Developing and Validating Trust Measures for e-Commerce: An Integrative Typology." *Information Systems Research* 13 (3): 334–359.
Millo, G., and G. Piras. 2012. "splm: Spatial Panel Data Models in r." *Journal of Statistical Software* 47 (1): 1–38.
Moretti, E. 2011. "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales." *The Review of Economic Studies* 78 (1): 356–393.
Morrison, E. W. 2002. "Newcomers' Relationships: The Role of Social Network Ties during Socialization." *Academy of Management Journal* 45 (6): 1149–1160.
Munnukka, J., O. Uusitalo, and H. Toivonen. 2016. "Credibility of a Peer Endorser and Advertising Effectiveness." *Journal of Consumer Marketing* 33 (3): 182–192.
Narayan, V., V. R. Rao, and C. Saunders. 2011. "How Peer Influence Affects Attribute Preferences: A Bayesian Updating Mechanism." *Marketing Science* 30 (2): 368–384.
Parsons, A. 2013. "Using Social Media to Reach Consumers: A Content Analysis of Official Facebook Pages." *Academy of Marketing Studies Journal* 17 (2).
Pinto, M. B., and A. Yagnik. 2017. "Fit for Life: A Content Analysis of Fitness Tracker Brands use of Facebook in Social Media Marketing." *Journal of Brand Management* 24 (1): 49–67.

Pornpitakpan, C. 2004. "The Persuasiveness of Source Credibility: A Critical Review of Five Decades' Evidence." *Journal of Applied Social Psychology* 34 (2): 243–281.
Prince, J. D. 2014. "The Quantified Self: Operationalizing the Quotidien." *Journal of Electronic Resources in Medical Libraries* 11 (2): 91–99.
Reagans, R. 2005. "Preferences, Identity, and Competition: Predicting Tie Strength from Demographic Data." *Management Science* 51 (9): 1374–1383.
Reinstein, D. A., and C. M. Snyder. 2005. "The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics." *The Journal of Industrial Economics* 53 (1): 27–51.
Richards, T. J., S. F. Hamilton, and W. J. Allender. 2014. "Social Networks and New Product Choice." *American Journal of Agricultural Economics* 96 (2): 489–516.
Rost, K. 2011. "The Strength of Strong Ties in the Creation of Innovation." *Research Policy* 40 (4): 588–604.
Sacerdote, B. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *The Quarterly Journal of Economics* 116 (2): 681–704.
Smith, D., S. Menon, and K. Sivakumar. 2005. "Online Peer and Editorial Recommendations, Trust, and Choice in Virtual Markets." *Journal of Interactive Marketing* 19 (3): 15–37.
Sorensen, A. T. 2006. "Social Learning and Health Plan Choice." *The Rand Journal of Economics* 37 (4): 929–945.
Statista.com. 2018. *Wearable Device Sales Revenue Worldwide from 2016 to 2022*. Available at: https://www.statista.com/statistics/610447/wearable-device-revenue-worldwide/. Accessed June 3, 2019.
Stelzner, M. A. 2014. *How Marketers are using Social Media to Grow their Businesses*, Social Media Marketing Industry Report. Available at: https://www.socialmediaexaminer.com/social-media-marketing-industry-report-2014/. Accessed June 3, 2019.
U.S. Census Bureau. 2015. *2015 Census.* U.S. Department of Commerce Available at: https://www.census.gov/quickfacts/fact/table/AZ/LFE041217. Acccessed June 3, 2019.