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Modeling Product Choices in a Peer Network

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Selected Paper prepared for presentation for the 2016 Agricultural Applied Economics Association, Boston, MA, July 31-August 2

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Introduction

Information is provided by advertising, physical media, online media, and, perhaps most importantly, from peers. Research in a range of fields has shown that peers are critical in shaping preferences and choices (Manski 2000; Sacerdote 2001; Zimmerman 2003; De Giorgi, Pellizzari, and Redadelli 2010; Kuhn et. al. 2010; Richards, Hamilton and Allender 2014). Indeed, peers have been shown to be important in the apparent clustering of obesity (Christakis and Fowler 2007; Cohen-Cole and Fletcher 2008; Trogdon, Nonnemaker, and Pais 2008), the popularity of otherwise-unheralded movies (Reinstein and Snyder 2005; Moretti 2011), retirement plan participation (Duflo and Saez 2002, 2003), health-plan choice (Sorensen 2006), investing in the stock market (Hong, Kubik and Stein 2004), performance in college (Sacerdote 2001; Zimmerman 2003), behavior in school (Evans, Oates and Schwab 1992; Soetevent and Kooreman 2006), or new product purchases (Mayzlin 2006; Godes and Mayzlin 2004, 2009). In each case, we examine the exact mechanism through which peers exert influence on others differs.

The context for our investigation concerns the effect of peer influences on marketing an innovative new technology product, fitness trackers. Peer effects in a marketing environment are commonly referred to as word-of-mouth (WOM), and operate through mechanisms that include source expertise (Bansal and Voyer, 2000 and Gilly et al., 1998), tie strength (Granovetter 1973, Brown and Reingen, 1987 and Frenzen and Nakamoto, 1993), demographic similarity (Brown and Reingen, 1987), and perceptual affinity (Gilly et al., 1998). We focus on the first two of these mechanisms: source expertise[1] and tie strength[2].

Logically, consumers are more likely to follow recommendations from people who they know and trust. However, Granovetter (1973) finds that weak ties between groups provide the greatest increment in information. Intuitively, 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. On the other hand, people with strong ties are likely to share a similar background, so are less likely to introduce new information.

Empirically and conceptually, the mechanisms through which WOM operates are difficult to disentangle because of the "reflection problem" (Manski, 1993). The reflection problem "…is similar to an inferential problem that occurs when one observes the almost simultaneous movements of a person and of his image in a mirror" (Manski 2005, p. 2). When observing only an individual's movements, you cannot tell whether the mirror image is causing the person's movements, if the mirror is reflecting the person's movements, or if they are happening together. By the same token, when observing similar behaviors in a group, the analyst cannot always tell whether phenomena are caused by individual heterogeneity in preference, true peer effect, demographic similarities (contextual effect), or other effects.

Our aim is to identify true peer (endogenous) effects that cause individuals to have similar preferences. Importantly, we disentangle endogenous effects from contextual and correlated effects (Manski 1993) that are often overlooked in studies of social influence. We do so by conducting a randomized two-stage experiment to elicit

[1] Source expertise refers to the credibility or believability of a particular source of information. For

[2] **Tie strength** refers to the closeness of the relationship between the individuals exchanging WOM.

subjects' willingness to pay (WTP) for activity trackers. We analyze preference changes between the first and second stages using a spatial econometric approach that helps identify the peer effects we seek. By controlling for correlated and contextual effects, our experimental approach is able to cleanly identify significant endogenous effects.

These results are consistent with the findings of Freeman (1957) and Pornpitakpan (2004) in that sources having more credibility dimensions are more influential than those having less credibility on readership scores[3]. Moreover, in contrast to the findings of Richards, Hamilton and Allender (2014), people who are close in social space are not likely to have a significant influence on each other. We contribute to the theoretical marketing literature in that we find social learning via source expertise to be a more effective form of peer recommendation than tie strength. We also contribute to the methodological literature on estimating social learning effects as we introduce a new method of estimating peer effects using spatial econometrics. In this regard, we highlight an essential point of the social learning literature, namely that how relationships are defined is essential to understanding the nature and power of social influence within a network.

Building on previous studies, we first describe the experiment, and provide some summary evidence of the power of peers to shape behavior. A following section presents the empirical results, and discusses some of the implications for marketing practice. A final section concludes and offers some suggestions for further research in this area.

Experimental Procedure

We conduct a social choice-based conjoint (CBC) experiment in order to examine the effect of peers on activity-tracker attribute valuation. Fitness trackers not only contain multiple attributes, but are inherently complex, new to the market, and relatively little is known about them. We use a CBC approach because choices are a more realistic representation of true preferences compared to the ratings data gathered through other experimental methods (Rao 2007). Models estimated with choice data allow researchers to predict choice shares, which are of more interest to marketers. More importantly, choice models estimated in random utility form allow the derivation of willingness to pay (WTP) for product attributes.

We follow Narayan, Rao, and Saunders (2011) and Richards, Hamilton, and Allender (2014) in adopting this two-stage framework. In the first stage, we elicit preferences for each attribute. Each subject is presented with 12 choice sets, each with 4 alternatives, and an additional "no buy" option. After the first stage, we allow subjects in the treatment groups to express their preferences to others in the group, while subjects in the control groups are not allowed to communicate. After the exchange of information, subjects are asked to make the same choices again (stage two).

Based on prior research, the salient attributes of activity trackers are price, style, brand, and function (Oh 2014). We chose four major brands of activity trackers on the

[3] A source high in expertise, as compared to one low in expertise, appears to lead to positive attitudes toward the endorser and the advertisement (Braunsberger, 1996). Degree of perceived credibility of the source influenced recipients' intention to use suggestions made by the source as to how to improve performance (Bannister, 1986) and the acceptance or rejection of the suggestions from the source (Suzuki, 1978).

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, so 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[4]. 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 activity trackers. Each of these attributes, and levels, are shown in Table 1.

Table 1 Attributes and levels.

Attributes	Levels
Brand	Fitbit
	Jawbone
	Nike
	Garmin
Design	Clip-on
	Wristband
	Watch
Function	*Recording basic calories*
	Recording calories and sleep patterns
	Recording calories and text/email messages
	Recording calories and GPS locations
Price	$49.99
	$99.99
	$129.99
	$199.99

A full factorial design is able to estimate both the main effects and interaction terms in the utility function, but 196 (4*4*4*3) combinations is too many to present to the participants. Therefore, we use a fractional factorial design in which subjects were presented a subset of 48 combinations. Our design is fully orthogonal in that it allows for the estimation of all main effects included in the study. The design is blocked in four blocks, so that each individual receives a balanced subset of profiles, namely 12 choice sets. WE used SAS OPTEX to generate an orthogonal factional factorial design of 48 with a D-efficiency score of 80.64%. An example of one of the cards is presented in Table 2.

[4] For example, Fitbit Surge, priced from $200 to $249 on Google shopping, is built for multiple sports with a watch-type full OLED screen that will display calls, texts and notifications. Garmin Vivoactive, priced at $249.99, has GPS to accurately track running, cycling and swimming with live pace and distances.

Table 2 Example Choice Set

	A	B	C	D	E
Brand	Garmin	Jawbone	Nike	Fitbit	None of These
Design	Clip-on	Watch	Wristband	Clip-on	
Function	Cal+Sleep	Cal+GPS	Cal+Msg	Cal+Msg	
Price	$99.99	$199.99	$129.99	$49.99	
Choice					

One month before the experiment, a survey was sent out using Qualtrics to all students in the W.P. Carey School of Business and Ira A. Fulton School of Engineering at Arizona State University. The survey included a brief introduction to the experiment, detailed instructions, and an estimate of the time that would be required to complete the experiment. With the Qualtrics[5] online sign up system, we collected basic information from respondents who were willing to participate.

Respondents were required to be over the age of 18, ASU students, and able to communicate in English. The online sign-up procedure generated 80 eligible respondents. In order to keep the groups of a manageable size, WE selected 20 people for each group. Before assigning groups, we asked each subject if they would be coming with someone they knew, and assigned people who knew each other to the same group. The group assignments resulted in four groups in total. WE randomly selected two groups to be treatment groups and the other two served as control groups. Among the 80 responses we received, we then randomly selected 40 to be assigned to two control groups and another 40 to two treatment groups.

In the treatment groups, subjects were exposed to the attribute preferences of others between stages 1 and 2 of the experiment, whereas subjects in the control groups received no input before their stage two choices. Hence, the treatment effect measures the extent of peer influence, relative to the control in which no peer influence is allowed. In each treatment group, we asked the subjects to talk about their choices, and why they made them. In addition, we asked the subjects to discuss the factors that influenced their choice of attribute packages. For example: what is the first thing you look at when you buy a tracker, the style or a specific function? The discussion regarding attributes was purposefully robust, with more experienced subjects often sharing firmly-held beliefs regarding the superiority of trackers they preferred.

Following the discussion, subjects were asked in stage two to again make their preferred choices between alternatives from the same choice sets as in stage one. Subjects 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 subjects' mind off the choices from stage one. After reading the article subjects 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, WE collected socio-economic and demographic data that is used to control for unobserved heterogeneity in the econometric choice model described below.

In any social experiment, characterizing relationships among the subjects forms a critical component of the analysis. These relationships form elements of the social relationship matrix. In a spatial model, these measures form the social "weights" that are used to filter out contextual effects, and to identify peer effects. We gathered data measuring closeness and source-credibility. Variation in "closeness" identifies tie strength because people who are closer to each other are characterized by stronger ties. More specifically, we measure closeness by asking subjects to report how well they know each of the other subjects. we follow the relationship measure of Richards, Hamilton and Allender (2014) where tie strength is defined as how well the subjects know each other, rated on a 5-point scale ranging from "Do not Know" (tie strength = 1) to "Know Very Well" (tie strength = 5)[6]. By choosing subjects that have the same major, the experiment is likely to include a range of relationships, from emergent "best friends" to only casual relationships. Variation in "perceived credibility" identifies source credibility (perceived expertise and trust) because people who are perceived as credible information carriers serve as opinion leaders, whose opinions are thought as more important. We measure source credibility by asking subjects to report how reliable they think each of the other subjects is. Reliability is measured on a 5-point scale from "Not Reliable" (reliability =1), "Somewhat reliable" (reliability =2), "indifferent" (reliability =3), "Somewhat reliable" (reliability =4), and "Very reliable" (reliability=5) (Bannister 1986, Borgatti and Cross 2006). This provides me with an assessment of source credibility from "most credible" to "not credible".

Among the 80 invitations sent out, 63 subjects completed the experiment in a useable way, leading to a turnout rate of 78.75%. Each subject provided 120 observations, resulting in a total of 7,560 observations.

The sample we used for our study was a student sample. Student samples are often used for laboratory experiments (Narayan, Rao and Sanders 2011, Richards, Hamilton and Allender 2014). Although samples from the general population may be more representative of the relevant market in terms of demographic and socioeconomic characteristics, we focus on the behavioral patterns and not the actual WTP for activity trackers, *per se*. That is, even though students may not choose exactly the same trackers as subjects drawn from the general population, any differences in sample composition should not affect how the individuals respond to peers.

In order to provide a sense of what the sample looks like relative to the general population, we provide a set of summary statistics that compares the composition of our sample to the population in Table 3. The sample consists of mostly junior and senior business and engineering students. Subjects 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 our sample is female compared to the state mean of 50.6%, which again is to be expected given that our sample is drawn from colleges that tend to be overrepresented by male students. Regarding ethnicity, our sample contains 46% White, 21% Asian, 16% Hispanic, 2% of Native American, and 7% other races. Compared to the state mean of 57.8% White, 3.4% Asian, 30.3% Hispanic, and 0.3% Native American, White and Hispanic are under-represented while Asian and Native American are over-represented.

[6] A copy of the survey can be found in the appendix.

Table 3 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	7.0		
	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 (purchase frequency)	How often do you purchase sports goods?			
	At least once a week=5	4.8		
	Once a month=4	17.5		
	Once every three months=3	34.9		
	Once every six month=2	27.0		

	Once a year or less often=1	15.9		
Purchase_expPurchase expenditure	How much money do you spend sports goods?		187.30	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	0.250

In the next section we estimate attribute-preferences by calibrating two models: a random parameter model to derive subjects' willingness to pay, and a spatial model to identify peer effects. Attribute preferences can only be inferred in a CBC experiment by econometrically estimating their marginal value in a formal, utility-theoretic framework. Peer effects are derived then by studying the driving factors of willingness to pay.

Econometric Model of Preference Revision

For the purpose of studying activity tracker choices and deriving individual preferences, we calculate the individual WTP and utilize a set of spatial models to analyze preference revision and peer effects. In the following section, we present the discrete models that derive WTP first, followed by the spatial models that analyze the preference revisions.

Choice modeling

The objective of the experiment is to elicit changes in preferences due to social interaction. Because we are interested in preference changes from stage one to stage two as it relates to social interaction, our econometric model estimates preferences in stage one, and then testis for the significant preference revision between stages one and two. We do this in two ways. First, we test for changes in attribute valuation from stage one to stage two due to the treatment effect of interacting with others in a direct way. Second, we calculate WTP for activity trackers, and test whether changes in WTP depend upon the social influence from stage one to stage two, moderated by the degree of social relationship between each subject.

Consistent with the data generated by our CBC experiment, the core of the econometric model consists of a discrete-choice model, which is particularly adept at estimating marginal attribute valuations (Train 2003, Hensher, Rose and Greene 2005). This point is important because discrete choice models, particularly those of the logit form used here, provide closed-form choice probability expressions that are useful in calculating choice probabilities under a range of peer-influence assumptions.

When using discrete choice models, an individual's utility is considered a random variable either because the researcher has incomplete information, or there is unobserved

heterogeneity in individual preferences (Manski,1977). Formally, let the i th consumer's utility from choosing alternative j be given by:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1)$$

where V_{ij} is the deterministic component of the utility function determined by the interested activity tracker attributes and ε_{ij} is the random component. Assuming V_{ij} is linear in parameters, the form of the utility function for alternative j can be expressed as:

$$V_j = \sum_i \beta_i x_{ij} = \beta_1 x_{j1} + \beta_2 x_{j2} + \cdots + \beta_n x_{jn} \quad (2)$$

where x_{jn} 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, and β_i is a vector of parameter estimates associated with x_{jn} The estimated β values in this exercise are of particular importance because they measure the marginal utility of each tracker attribute. The explanatory x_{jn} variables are listed in Table 4. The variable "None" represents the "none of these" option in the consumer's choice set, and serves as the "outside option" in discrete-choice modeling terminology (None = 1 if "none of these" option is selected, None = 0 otherwise). Garmin, Jawbone, Nike, and Fitbit are dummy variables that represent the four different brands, while Clip-on, Wristband, and Watch are dummy variables that represent the different activity tracker designs. Different functions are represented as 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). The variable Price captures the price of the respective alternative. Besides the attributes, I also included 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. Three-way interactions of stage and treatment represent the attributes effect at stage 2 among treatment groups. These interactions will help reveal whether there exist treatment effect in the second stage.

Table 4 List of Variables

Variable Name	Meaning
Garmin	The brand is Garmin
Nike	The brand is Nike
Fitbit	The brand is Fitbit
Jawbone	The brand is Jawbone
Clipon	Design is clip on
Watch	Design is watch
Wristband	Design is wristband
Cal	Function is recording calories only
Sleep	Has additional function of recording sleeping patterns
GPS	Has additional function of recording workout route
MSG	Has additional function of receiving messages
Price	Price of the tracker

S_garmin	The brand is Garmin in the second stage: Garmin*stage 2
S_nike	The brand is Nike in the second stage: Jawbone*stage 2
S_jawbone	The brand is Jawbone in the second stage: Jawbone*stage 2
S_watch	The design is watch in the second stage: watch*stage 2
S_wristband	The design is wristband in the second stage: wristband*stage 2
S_sleep	Has additional sleeping function in the second stage: Sleep*stage 2
S_gps	Has additional GPS function in the second stage: GPS*stage2
S_msg	Has message function in the second stage: MSG*stage 2
ST_garmin	Three-way interaction: Garmin*Treat*Stage2
ST_nike	Three-way interaction: Nike*Treat*Stage2
ST_jawbone	Three-way interaction: Jawbone*Treat*Stage2
ST_watch	Three-way interaction: watch*Treat*Stage2
ST_wristband	Three-way interaction: Wristband*Treat*Stage2
ST_sleep	Three-way interaction: Sleep*Treat*Stage2
ST_gps	Three-way interaction: GPS*Treat*Stage2
ST_msg	Three-way interaction: msg*Treat*Stage2
None[b]	Choose the "none of these function"

Assuming the random error term in equation (1) is distributed Type I Extreme Value (EV), the probability of choosing option j over option *k* is:

$$Prob\{j\ is\ chosen\} = Prob\{V_{ij} + \varepsilon_{ij} \geq V_{ik} + \varepsilon_{ik}\} = \frac{e^{V_{ij}}}{\sum_{k \in C} e^{V_{ik}}} \qquad (3),$$

where choice *j* is chosen over choice *k* if the overall utility for choice *j* is greater than the utility of choice *k*.

One well-understood problem with the logit framework is that it implies that the ε_{ij} are independent and identically distributed (IID) across individuals and alternatives. The IID assumption is restrictive in that it does not allow for the error components of different alternatives to be correlated (Hensher, Rose and Greene 2005). Therefore, we relax the iid assumption by using a random-parameter logit (RPL), or mixed logit, model.

Importantly, a RPL model allows taste parameters to vary randomly in the population. Formally, each marginal attribute value is written as (Hensher, Rose and Greene 2005):

$$\beta_{ik} = \beta + \delta'_k z_q + \eta_{ik} \qquad (4),$$

where η_{ik} is a random term that is distributed randomly over individuals. The random term can assume a range of distributions, depending on the choice environment. In this model, z_q is observed data specific to the individual with q random variables and, η_{ik} denotes a vector of *k* random components in the set of utility functions in addition to the J random elements in ε_{ij}. The error term can assume different distributional forms such as normal, lognormal and triangular. For our study we choose triangular distribution for Price and normal for all other random parameters[7]. Triangular distribution guarantees a

[7] Hensher, Rose and Greene (2005) suggest specifying the parameters associated with each attribute (including price) as random (see Hensher, Rose and Greene 2005, pg.618) because inter-alternative error correlation could be confounded with unobserved preferences if the latter is not explicitly taken into account (Daniels and Hensher 2000, Bhat and Castelar2003).

positive price estimate therefore a positive WTP, while normal distribution is the most common practice for random variables. For a give value of η_q, the conditional probability L_{jq} of choosing option j is the following (given the remaining error term is IID):

$$L_{jq}(\beta_q|X_q,\eta_q) = \exp(\beta'_q x_{jq}) / \sum_j \exp(\beta'_q x_{jq}) \quad (5)$$

Equation (5) is the simple MNL model, but for each sampled individual, there is additional information defined by η_q. The unconditional choice probability is the expected value of the logit probability over all the possible values of β_q, that is, integrated over the values of β, weighted by the density of β_q. The probability is presented as:

$$P_{iq}(X_i,z_i) = \int L_{jq}(\beta_q|X_q,\eta_q) f(\eta_q|z_q) d\,\eta_q, \quad (6),$$

where $\beta_q = \beta + \Delta Z_q + \eta_q$. Thus, the unconditional probability that individual q will choose alternative j given the specific characteristics of their choice set and the underlying model parameters is equal to the expected value of the conditional probability as it ranges over the possible values of β_q. The random variation in β_q is induced by the random vector η_q.

The choice probabilities associated with the RPL will not exhibit the same IIA property as the fixed-coefficient logit, and may yield different substitution patterns by appropriate specification of $f(\eta_q|z_q)$. 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 subjects, we are able to determine how preferences are influenced by exposure to the choices of others.

Among the variables included in the indirect utility function, we allowed the marginal utility of income (price parameter) to vary randomly with a triangular distribution. A triangular distribution is highly desirable because it binds the parameter on (-1,1). Allowing the marginal utility of income to vary randomly is a common practice, and reasonable as this parameter governs price-response and price-response is driven by behavioral attributes of the household, many of which are unobserved (Hensher, Rose and Greene 2005, Banerjee, Martin and Hudson 2006, Lusk and Norwood 2009, Tonsor, Olynk, and Wolf 2009).

Recall that the objective of this study is to reveal individual preferences, and how they are revised through peer influences. We measure preference revision through the WTP, which is the amount of money a subject is willing to pay for a unit change for a particular attribute. In the current model, we define the mean price parameter as β_1, and an attribute whose parameter is normally distributed with mean β_2 and standard deviation σ_2. Willingness to pay is calculated as:

$$\text{WTP} = -\frac{\beta_2}{\beta_1} \quad (7),$$

where the WTP for the attribute is distributed normally with mean $\frac{\beta_2}{\beta_1}$ and standard deviation $\frac{\sigma_2}{\beta_1}$ (Hensher, Rose and Greene 2005). Because WTP measures are calculated as the ratios of two parameters, they are sensitive to the range of each attribute level used in the estimation of both parameters. We then use the individual- and attribute-specific WTP calculated above and take difference between the second stage and the first stage WTP values to calculate a measure of preference revision:
$\Delta WTP_J = WTP_{J,Stage2} - WTP_{J,Stage1}$.

Differences between first- and second-stage valuations may be positive or negative, depending on the nature of the information received between the two sessions. For current purposes, however, we are more interested in how preferences are moderated by social interaction than the direction of change. For this purpose, we estimate using a spatial econometric approach that we describe in the next section.

Spatial Models

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 the social weight matrix (Anselin 2002, Yang and Allenby 2005, Richards, Hamilton and Allender 2014). Spatial models differ from traditional linear-in-mean models in that they address the need for a multidimensional relationship between consumers through the weight matrix (Lee 2004). Moreover, the natural exclusion restrictions implied by the social network structure ensure the separate identification of endogenous and contextual peer effects (Lin 2014). 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 in the same group. The consequence is that these two terms are linearly dependent, and the endogenous effects cannot be separated from the contextual effects.

There are a multitude of different forms of spatial model, but we focus on two types: a Spatial Autoregressive Model (SAR, or "spatial lag model" as it is referred to by Anselin (2002)) and a Spatial Error Model (SEM). The classic SAR model departs from the Manski (1993) model by measuring 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 SEM model instead captures spatial patterns in the error term; therefore, it accounts for the unobserved heterogeneity in consumer tastes. SEMs treat spatial correlation primarily as a nuisance, similar to how statistical approaches treat temporal serial correlation. This approach generally focuses on estimating the parameters for the independent variables of interest in the systematic part of the model, and essentially disregards the possibility that the observed correlation may reflect something meaningful about the data generation process (Ward and Gleditsch 2007). When peer outcomes are caused by an unobserved correlated effect, the SEM will capture it by regressing a spatial weight matrix on the residuals.

A SAR-SEM model is a spatial model that incorporates both SAR and SEM features. The SAR-SEM model used here similar to the one used by Lin (2014) in that I

use a spatial weight matrix that represents the actual relationship among members, but differs in that we relax the group-specific effect and instead use a binary variable to indicate differences between treatment and control groups. This is critical to our approach, because peer recommendations are only introduced in the treatment groups. If there indeed is a pure peer effect then the group fixed specific effect will capture it. With this assumption, the model is written as:

$$y_{ik} = \alpha + \rho \sum_{j=1}^{n} w1_{ij} y_{jh} + x_{ik}\beta + \sum_{j=1}^{n} w_{ij}\, h_{ik}\gamma + G\delta + u_{ik} \quad (9),$$

and:

$$u_{ik} = \lambda \sum w2_{ik}\, u_{ik} + \varepsilon_{ik}, \quad (10),$$

where y_{ik} is individual WTP revision for attribute k, ΔWTP_J. Variables x_{ik} are individual characteristics related to the purchase of activity trackers; h_{ik} are individual characteristics about *i*'s background 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 subjects, and *G* is a fixed-group effect with a binary indicator for treatment-group membership. The error terms (eq. 10) in the model, u_{ik}, follow an SEM process, which captures the unobserved effects that vary within the group and thus cannot be captured by the group fixed effects; and ε_{ik} is an idiosyncratic error term. This specification is the most general form of spatial model, termed the SAR-SEM model by LeSage (1998), because it captures both direct spatial effects through the SAR term and indirect effects, through unobservable elements, in the SEM term.

In the SAR-SEM social model, outcomes for individuals from the same group are correlated in multiple ways. First, the parameter ρ measures the endogenous effect of others' behavior on each agent's WTP, second, γ captures the contextual effect, and, third, the group fixed effect is represented by δ, capturing the common factors that affect all group members. Finally, the possibility that subjects' choices are correlated through spatially dependent unobservable is captured by λ in the error term. Intuitively, the parameter ρ estimates the presence of a spatial lag effect, or that consumer's preferences are influenced by her peers. The value of ρ is bounded by 0 and 1. A parameter close to 1 indicates greater influence, and a parameter of 0 means there is no influence at all. 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. Estimates of γ indicate contextual effects, which are the factors related to the common environment such as education, race, income, age, and gender. Group effects are estimated with the δ parameter, which is interpreted as the influence of peer recommendations introduced only in the treatment groups. In this regard it measures the difference in preferences between the control and treatment groups. Finally, after accounting for the peer, contextual, and group fixed effects, λ captures any "left-over" unobserved effects that exist in the data. In the rest of this section, we discuss how the peer effects are identified in the SAR-SEM model in econometric terms – an identification strategy that relies critically on the nature of the spatial weight matrix.

At the core of any spatial model is a social weight matrix. The structure of the social weight matrix, $\boldsymbol{W}$, is essential to estimating peer effects with this model. A social weight matrix is a $n \times n$ positive matrix where *n* is the number of members, $\boldsymbol{W}$, through

which the ‘‘neighborhood set’’ is specified for each observation. An observation appears both as a row and column, with non-zero matrix elements w_{ij} indicating the strength of the peer relationship between participants (row) i and (column) j. By convention, self-neighbors are excluded, such that the diagonal elements $w_{ii} = 0$. Also, the weight matrix is typically row-standardized, with weights $w_{ij}^{s} = w_{ij} / \sum_j w_{ij}$. Row-standardization means that pre-multiplying another vector creates an average of the neighboring values in the spatial lag operator (Anselin, 1988b). For this study, we use two set of spatial weight matrix: $\boldsymbol{W}_{CLOSENESS}$ that describes the tie strength, and $\boldsymbol{W}_{RELIABILITY}$ 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. The $\boldsymbol{W}$ (closeness) matrix captures tie strength in which preferences are revised through established social distance between individuals. On the other hand, $\boldsymbol{W}$ (reliability) 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.

For estimation purposes we define $\boldsymbol{W}$ in terms of a general weight matrix and rewrite Eq. (9) in matrix notation:

$$\boldsymbol{Y} = \rho \boldsymbol{W} y + \boldsymbol{X}\beta + \boldsymbol{W}\boldsymbol{H}\gamma + \boldsymbol{G}\delta + u \qquad (11),$$

where $\boldsymbol{Y}$ is a vector of individual differences in WTP regarding a specific attribute, $\boldsymbol{X}$ is a vector of individual characteristics that will influence the purchase of activity trackers, which includes purchase frequency, workout frequency, purchase amount in dollars, and whether the subject owns a tracker (Own). We expect that purchase frequency, workout frequency and purchase amount in dollars are positively related to WTP because these variables measure the extent of physical activity and expenditure on sporting goods that should be positively related to the WTP for an activity tracker.

The vector $\boldsymbol{H}$ measures characteristics of the reference group, including age, income, gender, and whether the subject is white (White) in this vector. To find the contextual effect, we pre-multiply the vector $\boldsymbol{H}$ that contains information about each subject’s background and environment with the row standardized weight matrix $\boldsymbol{W}$. The vector $\boldsymbol{G}$ represents membership in the treatment group and is noted as “1” for treatment groups and “0” for control groups. Table 5 shows a list of variables used in this model.

Table 5 Variables included in the SAR

Variables	Meaning
Individual characteristics	
Purchase_freq	Purchase frequency of sporting good
Purchase	$ spent on purchasing sporting goods annually
Workout	Workout frequency
Tracker	Whether the subject owns a tracker
Contextual effects	
Age	Age of the subject
Gender	Gender of the subject
Income	Household income
White	If the subject is white

Spatial models are rarely estimated in the form given in (11), however, due to the obvious endogeneity of the lagged peer-effect variable. Instead, reduced-form expressions are derived, and estimated. Specifically, the dependent variable $\boldsymbol{Y}$ appears on both sides of (11). Clearly, this variable is not exogenous, so we re-write the structural form of (11) in a reduced form in order to solve for Y:

$$\boldsymbol{Y} = (1-\rho\boldsymbol{W})^{-1}\boldsymbol{X}\beta + (1-\rho\boldsymbol{W})^{-1}\boldsymbol{W}\boldsymbol{Z}\gamma + (1-\rho\boldsymbol{W})^{-1}\boldsymbol{G}\delta \quad (12),$$
$$+ (1-\rho\boldsymbol{W})^{-1}\lambda\boldsymbol{W}u \quad + (1-\rho\boldsymbol{W})^{-1}\epsilon$$

where $(1-\rho\boldsymbol{W})^{-1}$ is defined as the "inverse Leontief matrix." Writing the model in reduced form highlights the value of using a spatial approach to estimating models of social influence as the inverse Leontief matrix is often described as a "spatial filter". Spatial filtering essentially means that the econometric procedure extracts that part of the variation in the endogenous variable that is due solely to relationships with other spatial observations. What is left, therefore, has the spatial effects removed, or "filtered" out. More formally, this matrix is a full inverse, which yields an infinite series that involves all neighbors: $1 + \rho\boldsymbol{W} + \rho^2\boldsymbol{W}^2 + \cdots \rho^n\boldsymbol{W}^n$. This means that each neighbor is correlated with every other neighbor, but the correlation decays with the order of contiguity (the powers of $\boldsymbol{W}$ in the series expansion). Higher powers of the weight matrix ($\boldsymbol{W}^n$) reflect neighbor sets in more remote contiguity (nth neighbor). This illustrates the global nature of the spatial multiplier effect in the spatial lag model (Anselin 2002). Specifically, if a unit change were introduced in a given explanatory variable X_k, the effect on y would amount to $[1/(1-\rho)\beta_k]$. More generally, for any vector of changes in a given explanatory variable, $\Delta\mathrm{x}_k$, the resulting spatial pattern of changes in the dependent variable is a function of the spatial filter and the change of given explanatory variables:

$$\Delta y = (1-\rho\boldsymbol{W})^{-1}\Delta\mathrm{x}_k\beta_k \quad (13).$$

This expression conveys the intuition that changes in preferences in a social environment derive from two sources: a spatial component and an explanatory variable component.

Indeed, the global nature of social interactions is apparent through the reduced form. For instance, the spatial lag term $\rho\boldsymbol{W}$ for observation *j* is correlated with its own error u_j, and with all other errors in the system, which accounts for spatial correlation among the explanatory variables and peer effects. Thus, the estimate of β (obtained after spatially filtering the dependent variable *y*) is a consistent estimate of the marginal value of product attributes ($\boldsymbol{X}$ on $\boldsymbol{Y}$). This means that after spatially filtering out the network effect by multiplying the βs with $(1-\rho\boldsymbol{W})^{-1}$, the estimated βs are truly the individual impact of product attributes without confounding social effects, or perpetual affinity because it shows how a subject's personal preference towards activity trackers influence her WTP. Further, the estimate of ρ is a consistent estimate of the peer effect because the SAR process accounts for the global nature of peer influence, that is, to which degree a subject is influenced by all her peers at once.

Estimation of the SAR-SEM model is difficult, yet the consequences of ignoring spatial dependence in models can be substantial. If a causal relationship of the dependent variables among peers does exist, but the model is estimated without the spatial autoregressive term, then a significant explanatory variable has been omitted, and the estimated coefficients will be biased and inconsistent (Kalnins 2003). On the other hand, if there is unobserved correlation among the error terms due to spatial dependence, then a SEM is required to obtain unbiased and consistent estimates. In the next section, we

address how the model is estimated with a two-stage instrumental variable (IV) method. Moreover we present the specification tests that evaluate spatial lag dependence, spatial error dependence and both.

Estimation

The estimation problems associated with spatial regression models are distinct for the spatial lag and spatial error case (Anselin 2006). Spatial error models are special cases in which the error is non-spherical, or violate the fundamental assumptions of OLS estimation. In other words, if there exists unobserved correlation effect that causes consumers to make similar decision then a spatial error test should detect significant spatial dependence in the error term. On the other hand, the inclusion of a spatially lagged dependent variable results in a form of endogeneity. A classic solution to the endogeneity problem is to use instrumental variables. Kelejian and Robinson (1993) suggest the use of a subset of columns from {X, WX, W^2X^2,W^3X^3, . . . } as instruments. Specifically, the optimal instruments are:

$$= I - \lambda \boldsymbol{W_2} [\ , \boldsymbol{W_1} (I - \rho \boldsymbol{W_1}) - \boldsymbol{W_1} x\beta\ ] \quad (14),$$

where $\boldsymbol{Q}$ *(N × q)* is a vector of instrumental variables. In the case of peer outcomes, we use the lag of all explanatory variables as our instruments. This is a common practice for such models (Anselin 2009) and essentially adds to the explanatory power of peers. For the simplicity of notation, we write Equation (11) as:

$$\boldsymbol{Y} = \boldsymbol{Z}\xi + u \quad (15),$$

where $\mathbf{Z} = [\boldsymbol{W_1}\mathrm{y}, \mathbf{X}, \mathbf{WH}, \mathbf{G}]$ and $\xi = [\rho, \beta, \gamma, \delta]$. The generalized spatial two-stage least squares estimator developed in Kelejian and Prucha (1998) consists of three steps. The first step is a spatial two-stage least squares estimation. The predicted value of $\boldsymbol{Z}$ in a regression on the instruments is obtained as:

$$\widehat{Z} = \boldsymbol{Q}(\boldsymbol{Q}'\boldsymbol{Q})^{-1}\boldsymbol{Q}'\,\boldsymbol{WZ}, \quad (16),$$

The instrument $\widehat{Z}$ replaces $\boldsymbol{Z}$ in the second stage, resulting in the spatial two-stage least squares estimator:

$$\widehat{\xi_{S2SLS}} = [\widehat{Z}'\widehat{Z}]^{-1}\,\widehat{Z}'\xi, \quad (17),$$

or in full,

$$\widehat{\xi_{S2SLS}} = [\boldsymbol{Z}'\boldsymbol{Q}(\boldsymbol{Q}'\boldsymbol{Q})^{-1}\boldsymbol{Q}'\boldsymbol{Z}]^{-1}\,\boldsymbol{Z}'\boldsymbol{Q}(\boldsymbol{Q}'\boldsymbol{Q})^{-1}\boldsymbol{Q}'\boldsymbol{Z}\xi \quad (18).$$

With asymptotic covariance matrix given by:

$$AsyVar\left[\widehat{\xi_{S2SLS}}\right] = \hat{\sigma}^2[\boldsymbol{Z}'\boldsymbol{Q}(\boldsymbol{Q}'\boldsymbol{Q})^{-1}\boldsymbol{Q}'\boldsymbol{Z}]^{-1} \quad (19).$$

The solution of the system by nonlinear least squares yields a consistent estimate $\hat{\lambda}$ for the autoregressive error parameter (Anselin 2006).

The purpose of spatial econometrics is to determine whether any spatial relationship of the variables is merely random or responds to a pattern of spatial dependence. Specification testing is necessary to find the spatial patterns in any given data set. Each specification test is constructed with a specific alternative in mind, so that

the test consists of a test of restrictions on the parameters of a model that includes spatial dependence, such as a spatial error model or a spatial lag model. The literature on specification tests against spatial correlation in cross-sectional regression is by now quite extensive (Anselin and Bera, 1998; Anselin, 2001a; Florax and de Graaff, 2004). The most commonly used approach under maximum likelihood estimation is Lagrange Multiplier (or Rao Score) tests, which are based on the slope of likelihood function, or the "score" function. In particular, tests against the presence of spatial correlation are very important, as ignoring spatial correlation when it is present may lead to biased and inconsistent estimates of the model parameters, or inefficient estimates and biased t-test statistics. In the following section, we present the commonly used specification tests to detect spatial lag dependence and error dependence, organized as tests against spatial autocorrelation, tests based on the Maximum Likelihood principle, and tests against multiple sources of misspecification.

The $n \times n$ spatial weight matrices $\boldsymbol{W}$ consist of exogenously specified elements (that capture the neighbor relations of observations *i* and *j*) in order to identify peer effects. A Lagrange Multiplier tests the residuals of an ML estimate of the null model that includes a single $\boldsymbol{W}$ matrix. For our purposes, the specification is to estimate ρs for $\boldsymbol{W}$s, which is the matrix of peer relationships. The residuals can then be used for a test of whether the coefficient $\boldsymbol{X}$s of $\boldsymbol{W}$s is significant. The null is defined as the classic linear regression model. Mathematically, the LM test statistic is Chi-square distributed and is written:

$$LM_{\rho} = \{\frac{e'Wy}{\frac{e'e}{n}}\}^2/D, \tag{20},$$

where the first term is the residual sum of squares on $\boldsymbol{X}$, and the denominator is a scaling factor that is based on the weight matrix and estimates of the OLS. While e is the OLS residuals and the denominator D is:

$$D = \left[\frac{\left(\boldsymbol{WX}\hat{\beta}\right)'[I - \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}']\left(\boldsymbol{WX}\hat{\beta}\right)}{\hat{\sigma}^2}\right] + tr(\boldsymbol{W}'\boldsymbol{W} + \boldsymbol{WW}) \tag{21},$$

where the estimates for $\hat{\beta}$ and $\hat{\sigma}^2$ are from OLS. The test statistic is asymptotically distributed as $\chi^2(1)$. For this test, the null hypothesis is H_0: $\rho = 0$, so the alternative is an OLS model. Failing to reject the null hypothesis indicates consumers do not depend on their peers for opinions, while rejecting the null hypothesis indicates the existence of peer effects. Basically, the LM is testing the slope of the log-likelihood function when there exists spatial lag against the log-likelihood when there is no spatial lag. If the slope is significant, then we reject the null hypothesis of OLS in favor of a spatial lag specification.

The point of departure for a LM test for spatial error autocorrelation is that it tests the unobserved correlation in residuals that might cause consumers to show similar preferences. Therefore, instead of regressing consumer outcomes ($\boldsymbol{Y}$) on peer relations, the LM error test investigates whether the unexplained residual displays any sort of spatial correlation. Again, the null hypothesis is an OLS with H_0: $\lambda = 0$. Mathematically, the test is written as:

$$LM_\lambda = \frac{[\frac{e'\boldsymbol{W}e}{e'e/n}]^2}{tr[\boldsymbol{W}'\boldsymbol{W} + \boldsymbol{W}\boldsymbol{W}]}, \quad (22),$$

where e is a $n\times1$ vector of OLS residuals and is asymptotically distributed as $\chi^2(1)$. Failing to reject the null hypothesis indicates peer relationships and the explanatory variables explain all social effects, while rejecting the null hypothesis means there are unexplained effects that correlate with peer relationships.

Besides testing for peer effects and unobserved effects separately, Anselin (1998b) provides a joint test where the null hypothesis is H_0: $\rho = \lambda = 0$. This LM test is not simply a summation of the two statistics above, but takes on a more complicated form given by:

$$LM_{\rho\lambda} = \frac{d_\lambda^2 D + d_\rho^2 T_{22} - 2d_\lambda d_\rho T_{12}}{DT_{22} - T_{12}^2} \quad (23),$$

where $d_\lambda = \frac{e'We}{e'e/n}$, $d_\rho = \frac{e'Wy}{\frac{e'e}{n}}$ and $T_{ij} = tr[W_iW_j + W_j'W_j]$. Intuitively, if both spatial lag dependence and spatial error dependence are significant, then the joint test statistic should be significant too. We apply each of these tests before choosing the preferred specification in interpreting the experimental data below.

Results

In order to get attribute and individual specific WTP, a Random Parameter Model (RPL) is needed to account for the randomness in tastes. As discussed above, the RPL model is able to capture unobserved heterogeneity, so should provide a better representation of not only the mean parameter estimates, but peer effects as well. Heterogeneity of consumer taste is introduced by allowing variables to be randomly distributed according to a triangular distribution. Technically, any and all of the parameters estimated in the utility model can be regarded as random parameter estimates. Following Hensher, Rose and Greene (2005, pg. 618), we first allow all variables to be random according to a triangular distribution, and then remove the variables that are not statistically significant according to the Wald statistics and the LR test. We define the marginal utility of income with respect to price in terms of a triangular distribution because it binds the parameter dispersion on (-1, 1). Because of this, a triangular distribution on price guarantees positive price thus positive WTP estimates. After selecting the variables for which unobserved heterogeneity appeared to be the most important, we chose Price, Nike, Watch, Wristband, Sleep, GPS and Msg. Among these variables, the scale parameters (standard deviation) are statistically significant for Price, Nike, Watch, GPS and MSG. These results suggest that the random parameter specification is indeed appropriate in these data.

We estimated the extent of preference revision, and test for the effect of peer influence, by comparing marginal attribute valuations between the first and second stages of the experiment. We pooled the data from stage 1 and stage 2 together, and estimate the stage 2 effects by multiplying each variable by a stage 2 indicator variable. If the stage 2 variables are statistically significant, then we can conclude that subjects revise their preferences based on interactions with others in their group. If there is significant revision, then, the parameter estimate for stage 2 is obtained by adding the parameter

estimate from stage 1 with the interaction variable. For example, the estimate for Garmin in the second stage is:

$$\beta_{\text{Garmin}} + \beta_{\text{S_Garmin}} = 0.3739 + 0.9020 = 1.2817$$

These estimates are shown in Table 6. Consumers had a higher parameter estimate for all brands after exposure to input from others. However, the parameter values for design (Wristband, Watch) and functions (Sleep, GPS, MSG) were reduced from the first to the second stage. The fact that all the estimated marginal values for the tracker attributes were statistically significant means that subjects clearly revised their preferences between the first and second stages. More specifically, a positive estimate for the Garmin variable (S_garmin) means that, on average, respondents tended to prefer the Garmin brand, while a negative estimate of the GPS variable (S_gps) means that, during the second stage, respondents were less likely to choose a tracker with the GPS function.

Besides the two-way interactions with stage, we also include a set of three-way interactions with both stage and treatment. These interactions indicate the marginal effects of attributes specific to the treatment group in the second stage. The RPL results show no significant estimates among these interactions, meaning that the RPL does not show significant treatment effect on preferences. The fact that Jawbone was not significant in the first stage, but was significant in the second stage, means that subjects revised their preferences to choose the Jawbone brand between the first and second stages. Whether this preference revision was due to information from specific members of the group, however, requires an econometric model that is able to separate out specific group-member influences. For this reason, we employ a set of spatial models to study the matter.

The randomness in the RPL allows for estimation of individual tastes. Individual-specific (conditional) estimates are obtained from the RPL estimates, assuming a triangular distribution for the random parameters. 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:

$$WTP_i = -\frac{\beta_{S_Garmin}}{\beta_{price,i}}$$

Subject-specific WTP for all attributes are then calculated in the same fashion and presented in Table 7.

In general, significant revisions in WTP are found in every attribute but Nike, with varying magnitudes. Prior to allowing for any peer influence, subjects have the highest WTP for GPS capacities, followed by watch design and sleep capacities. After learning about peer's experiences with activity trackers, and seeing their preferences, the sample subjects are significantly less willing to pay for the GPS and wristbands, while more willing to pay for all brand attributes. Among the other revisions, one notable result is that, before 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 discussion plays a negative role with respect to wristband design. For example, subjects may have discussed the disadvantages of a design that prevent people from wanting to include this attribute.

We also expected asymmetric responses to peer recommendations: Peers may provide either positive or negative feedback, each with a different effect on changes in

WTP. Brand proved to be a topic of much discussion among subjects. This discussion clearly had an impact on subjects' tendency to revise their valuations as prior to peer recommendations consumers' preferences depend on both brands and specific attributes such as design, function and price. After peer recommendations, however, subjects revise their preferences more positively on brands instead of specific attributes. Table 7 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 6 Subject-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*	98.8290
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

Note: a single asterisk indicates significance at a 5% level.

Subjects 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, meaning that subjects' WTP for the wristband attribute drop to a point that they are not willing to pay for a tracker with this style. In terms of functions, the WTP for all functions are revised lower after peer recommendations. WTP for the function of tracking sleeping patterns is revised by $138, the WTP for the GPS function is revised by $176 via peer recommendation, and the WTP for the messaging function is revised by $87. Clearly, peer communications discouraged subjects from paying for additional functions. In general, peer discussions lead subjects to be more brand-conscious, and discouraged subjects from paying for every additional function. Comparing the first and second stage RPL estimates and WTP revisions, however, does not address the issue of how the definition of space affects preference revision. That is, we do not include the spatial weight matrix directly in the RPL comparisons. For this purpose, we estimate the extent of preference revision as moderated by each subject's location in the social-spatial network in the next section.

Results of Spatial Models

Spatial models suffer from an embarrassment of riches in terms of the ways in which relationships among network members can be defined[8]. In this study, we focus on

[8] Prior research shows many possible ways to define social relationships, including frequency of communication (Goldenberg et al. 2009), degree of acquaintance (Godes and Mayzlin 2009), respect or leadership (Mullen, Johnson, and Salas 1991 ; Grippa and Gloor 2009), and trust (Buskens 1998 ; Berrera

two different ways: tie strength and source expertise. In this section, we examine the nature of preference revisions under each definition. To test the second and third hypotheses developed above, namely which definition generates larger preference revisions, and how credibility is related to attribute preference revisions, we compare the estimate of ρ obtained from a model that uses tie strength as a measure of social proximity and the estimate of ρ from using source expertise as the measure of social proximity. In this way, we can examine which mechanism is more likely to have influenced subjects' preferences between the first and second rounds. In Table 10, we present two SAR-SEM models in which Model 1 uses the tie strength as spatial weight ($W_1 = W_2 = social\ closeness$); and Model 2 uses the source expertise as spatial weight ($W_1 = W_2 = perceived\ Credbility$).

The Lagrange-multiplier statistic tests the appropriateness of a model with a $\boldsymbol{W}$ matrix. In the case of tie strength, the LM value is 0.6919, which is smaller than the critical value of $\chi^2{}_1$ (with 1 degree of freedom), meaning that consumer preferences do not depend on peers that are defined through "social closeness". Moreover, unobserved correlation that cannot be explained with the social closeness matrix, as evident by the failure to reject the hull hypothesis of a spatial error specification (LM=1.2959<$\chi^2{}_1$). 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, the SAR-SEM model using tie strength does not reject the null hypothesis, our results show that preference revisions will be greater for strong ties relative to weak ties. On the other hand, the SAR-SEM model with the "credibility" definition of social relationship rejects the null hypothesis of simple OLS in favor of the maintained SAR-SEM structure. This means that there is significant spatial dependence using reliability as weight matrix, indicating 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.

Moreover, regarding weak ties those who are not social acquaintances, but possess perceived expertise on the subject of matter, are significant influencers. This finding is consistent with Granovetter (1993) in that "weak ties" rather than "friends" in a social network can be more influential. That is, 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

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2007). In this article I follow Richards, Hamilton and Allender (2014) in defining social closeness.

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 (2009), 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.

The preferred model contained a number of other explanatory variables, but few showed a significant influence, independent of peer effects. The individual characteristics that were found to be significant in the preferred Model 2 were purchase frequency and BMI. This is intuitive as activity trackers are associated with fitness (within the healthy range of BMI) and the WTP is determined by how often an individual is likely to shop for sports goods. The sign for Purchase is positive, meaning that people who shop for sports goods more frequently are more willing to pay higher price for Jawbone. The sign for the BMI is also positive in Model 2, meaning that the higher a subject's BMI, the more likely he/she will choose Jawbone. This finding is intuitive as Jawbone is positioned as a lower-end product, with lower prices and fewer innovations. In other words, Jawbone is an introductory tracker, which is preferred by people who are new users, and perhaps not dedicated to physical fitness. Less fit subjects tend to have higher BMIs, hence the positive relation between Jawbone and BMI. The finding that BMI is an important factor in consumers' choices of activity tracker is not surprising as the main function of an activity tracker is to record physical activities. Besides individual-specific characteristics such as BMI, other factors that refer to more general characteristics of the sample are also apparent.

Two contextual effects were found to be significant: age and gender. Age is negatively related to the WTP for Jawbone, as subjects 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 for a Jawbone. Note that this does not necessarily mean that males are more into fitness, and hence more willing to pay for activity trackers than females, but that males are more likely to pay for Jawbone. Income, on the other hand, does not show a significant relationship with consumers' preferences for activity 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 an activity 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 similar background. For example, in this case, older female college students that are willing to pay more for Jawbone trackers.

In the previous section, we showed that consumer preferences are significantly altered in the second stage, which provides support in that peer recommendations will lead to preference revision for the recommended option if individuals regard the attribute in question to be salient to the choice decision. To tie such revisions more clearly to peer effects, we also estimate a group fixed effect. The group fixed effect examines whether there exists a significant difference in WTP between control groups and treatment groups,

and is measured by the estimate of δ. Group fixed-effect was found in Model 2: subjects that were assigned to treatment groups revised their WTP for Jawbone by $23.84 after peer influence. This is evidence that WTP can be influenced by peer recommendations. Combined with the fact that those influencers are not necessarily friends, this finding suggests that intense promotion from people who have perceived expertise is effective. Moreover, the group fixed is not significant trough revision by source expertise but not by strong ties, showing that the strong ties have no influence on peer preferences. For innovative products, people who are considered to have expertise on the products serve as more influential agents to promote the products.

Table 7 Results of Spatial Models.

Explanatory variables	OLS	t ratio	Model 1 using Tie strength	z-value	Model 2 using Source expertise	z-value
Purchase	-0.0699	-1.93703	-0.0560	-1.4432	0.0308**	1.9893
Workout	8.7206	1.6808	5.7500	0.9729	7.6060	0.1301
Tracker	0.0611	0.0444	5.5335	0.3884	9.2621	0.4830
BMI	-1.1913	-1.3878	-1.3750	-1.5180	0.7832*	1.6384
Contextual effects						
Age	0.1628**	2.5931	0.0039	0.0495	-0.0496*	-2.323
Gender	-2.0359*	-1.3344	2.8750	1.1848	0.7100*	1.9359
Income	-0.0001	-1.6211	-0.0000	-0.712	-0.0000	0.6147
Endogenous effect						
ρ	N.A.	NA	0.8125	1.032	0.8505*	3.5559
Unobserved effect						
λ	NA	NA	0.6050	0.4367	0.3977	0.5035
Fixed Group effect						
Treatment	-35.9161	-1.4364	-5.00	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

* Significant at 90%
** Significant at 95

Conclusion

Relationships are important ways for consumers to acquire information, because the creation of knowledge is a social process. This is especially true when consumers are considering the purchase of innovative, new products, as little is known prior to the release of truly new products. Despite the importance of social interaction as a vehicle for knowledge acquisition and the 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 activity trackers.

In this article, we use a two-stage experiment to examine preference revision via peer recommendations. We detect factors that are important in consumers' choices of activity trackers. Among which, brand is a general representation of specific attributes and consumer recognition embodied in activity trackers. We find that brand-related information such as design, function, and price are significant when consumers choose to buy activity 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 brand and other people (peers)' the discussion of attributes. This finding shed lights on how marketers can best use peer networks to promote innovative new products. That is, instead of promoting specific attributes of an activity tracker, marketers should link the innovative feature to the brand in general. For example, Garmin is the top brand in GPS. When promoting Garmin activity trackers, instead of emphasizing on the perks of the GPS function itself, the marketer could link Garmin activity 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 activity trackers. Our econometric model is non-linear while addressing for 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 allows for peer recommendations to enter through a weight matrix that address interrelationships, and yield true peer effect as a result.

We find that source 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's (1973) 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 reliable they perceive their peers to be. Because our research products are activity trackers, people who are perceived to be reliable are those who dress in gym gear, are physically fit, and have previous experiences with activity trackers. These people serve as "hubs" in the network as they are the influencers of consumers' preference revision. In the broader sense of marketing, individuals who are perceived to have professional and reliable 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 activity 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.

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