Neighborhood Social Capital and Social Learning for Experience Attributes of Products

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Abstract

"Social learning" can occur when information is transferred from existing customers to potential customers. It is especially important in cases where the information that is conveyed pertains to *experience attributes*, i.e., attributes of products that cannot be fully verified prior to the first purchase. Experience attributes are prevalent and salient when consumers shop through catalogs, home shopping networks, and over the Internet. Firms therefore employ creative and sometimes costly methods to help consumers resolve uncertainty; we argue that uncertainty can be partially resolved through social learning processes that occur "naturally" and emanate from local neighborhood characteristics. Using data from Bonobos.com, a leading US online fashion retailer, we find that local social learning not only facilitates customer trial, but also that the effect is economically important as about half of all trials were partially attributable to it. Merging data from the Social Capital Community Benchmark Survey we find that "neighborhood social capital", i.e., the propensity for neighbors to trust each other and communicate with each other, enhances the social learning process, and makes it more efficient. Social capital *does not* operate on trials directly; rather, it improves the learning process and therefore indirectly drives sales when what is communicated is favorable.

KEY WORDS: Bayesian Learning; Experience Attributes; Poisson Model; Social Capital; Social Learning

1. Introduction

Information about new products passed from existing to potential customers is an influential and widely studied driver of sales (e.g., Iyengar, Van den Bulte, and Valente 2011; Manchanda, Xie, and Youn 2008). Information regarding *experience* attributes, i.e., attributes which cannot be fully observable and verifiable pre-purchase, plays a key role in reducing the uncertainty faced by potential customers in their first-time purchases. The "experience attribute problem" is a general one; it is, however, particularly acute for consumers who buy products through catalogs, home shopping networks, and over the Internet.[1] Firms selling through these channels face a ubiquitous issue: How to help consumers overcome initial apprehension about buying what they sell.

By any measure, online retailing is by far the fastest growing retail sector around the world. According to Forrester research, the United States will see growth from $231b in 2013 to $370b in 2017 (*CAGR* of 10%); projected rates are almost identical in Europe where the total market should reach $247b by 2017.[2] This phenomenon is not confined to developed markets; in China, year-on-year growth through March 2012 exceeded 50% and *The Economist* predicts that China will quickly become largest market by value.[3] Thus, the global consumer economy is one in which information about experience attributes plays an increasingly larger and more important role in buying decisions.

In this paper, we document how social learning reduces consumer uncertainty for experience attributes in this context; more specifically, we explain why and how neighborhood social capital (defined shortly) makes the social learning process more efficient. Critically, it is not simply the case that social capital stimulates trial and adoption of new products per se—it does not—rather, it works through a specific mechanism to improve the quality of information transmitted in the social learning process.

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[1] Complementary terms have been introduced to the literature for use in particular contexts, e.g., Degeratu, Rangaswamy, and Wu (2000) refer to "searchable sensory attributes" for goods sold online, whereas Lal and Sarvary (1999) use the term "non-digital attributes" to describe product attributes which cannot be fully conveyed when items are sold over the Internet.

[2] http://techcrunch.com/2013/03/13/forrester-2012-2017-ecommerce-forecast/.

[3] http://www.economist.com/news/briefing/21573980-alibaba-trailblazing-chinese-internet-giant-will-soon-go-public-worlds-greatest-bazaar.

The institutional setting for our empirical work is best understood by example. Premier and rapid-growth US Internet retailers like Bonobos.com, Trunkclub.com and WarbyParker.com employ methods that include "totally free" return policies, "home-try on", and "pop-up stores" in large part to combat consumer uncertainty about the experience attributes of the products they sell. In September 2012, leading industry observer GigaOm.com reported on a $40m fundraising round by WarbyParker.com and noted: "That (home try-on) has helped Warby Parker overcome one of the *biggest hurdles* (italics added) for online fashion brands, getting people to feel comfortable about their online purchase."[4]

Naturally, these firm-initiated methods can be costly. We document a complementary customer-initiated process for the resolution of pre-trial uncertainty that occurs naturally offline: Social learning and information transmission between existing and potential customers. Neighborhood social learning is observed in numerous settings including diffusion of information about agricultural, healthcare, and retirement practices (e.g., Conley and Udry 2010; Sorensen 2006; Duflo and Saez 2003); we add to this body of literature by demonstrating why social learning is so important for the growing consumer Internet sector. Furthermore, show why social capital, i.e., "the information, trust, and norms of reciprocity inhering in one's social networks" (Woolcock 1998, p. 153) moderates local social learning, and makes the learning process about experience attributes more efficient.

We model social learning and the proposed moderating effect of social capital using data from Bonobos.com, a leading pure play US fashion retailer (Figure 1 is a screenshot of the website), and neighborhood social capital data from the Social Capital Community Benchmark Survey (SCCBS).[5] Identification of social influence from secondary data is challenging (Manski 2000) and the identification of a specific mechanism of social influence requires additional model assumptions that are based on the

[4] See http://gigaom.com/2012/09/10/warby-parker-raises-36-8m-to-expand-fashion-eyewear-brand/ for details.

[5] For an interesting introduction to social capital concepts data by one of the foremost authorities on the SCCBS, see Robert D. Putnam (2000), *Bowling Alone: The Collapse and Revival of American Community*. These data are housed at the Kennedy School of Government at Harvard University and have been widely used in social science research; we are the first researchers, to our knowledge, to utilize them in marketing. We provide more details on applications and the data themselves in Sections 2 and 3, respectively. For information on access, visit http://www.hks.harvard.edu/saguaro/communitysurvey/index.html.

institutional setting.

In this study, we identify the social learning process under the widely-employed Bayesian Learning approach for modeling learning through direct experience (Erdem and Keane 1996) or from advertisements (Narayanan, Manchanda, and Chintagunta 2005). The Bayesian Learning assumption behind social learning is justified conceptually in Section 4.1.2 and validated empirically in Section 5.2.1. Specifically, we develop a model of individual learning model and from there derive a neighborhood (zip code) level model of new trials arising in each time period.

Our model identifies social learning process as a process that is distinct from alternative forms of social influence such as awareness dispersion (Van den Bulte and Lilien 2001), social conformity (Amaldoss and Jain 2005), and network externality (Manchanda, Xie, and Youn 2008). Moreover, we control for possible confounding effects from correlated unobservables (Section 4.2), and capture the efficiency of social learning in a single parameter.

We make three new substantive contributions. First, we show that social learning about experience attributes is a key phenomenon in the rapidly growing consumer Internet sector. In our empirical application, more than fifty percent of all trials in the first three and a half years of operations at Bonobos.com are partially attributable to social learning. Second, we explain and document a novel and critical role of local social capital in this process. Again, it is important to note that local social capital does *not* per se stimulate trial and diffusion; rather, it operates only on the learning process itself. It reduces inefficiency in information transmission; in our empirical application the moderating effect impacts about 8% of all trials. This effect is roughly constant throughout the data period, suggesting that a fixed increment in social capital results in a fixed improvement in information transmission, independent of the total number of customers at any time period, or when they arrive.

Third, we highlight an important theme from recent related work; namely, that "real world" factors influence consumer decisions to buy online (see, for example, Anderson et al 2010; Brynjolfsson, Raman

and Hu 2009; Choi and Bell 2011; Forman, Ghose and Goldfarb 2009) and that insights from geographic variation in online buying are actionable. SCCBS data are not available commercially so we identify and justify a readily accessible measure, the "number local bars and liquor stores per capita per zip code" as a proxy for neighborhood social capital in the target group. We show that this variable moderates learning (of course it is *not* significant in a model that also contains the "true" measure of social capital).

The remainder of the paper is organized as follows. Section 2 summarizes relevant prior research and develops the conjectures for social learning and social capital. Section 3 describes the research setting, data, and measures. The empirical model is developed in Section 4. Section 5 reports the findings and Section 6 concludes the paper.

2. Background and Prior Research

2.1 Consumer Uncertainty about Experience Attributes of Products Sold Online

Prior to their first purchase, consumers buying via catalogs, home shopping networks, and the Internet lack complete knowledge about experience attributes of products (e.g., "fit, feel, touch, and taste"); for example, " … fit is not fully observed by the customer prior to purchase … [in] retail settings where customers select from a catalog or Internet site without being able to fully inspect the product." (Anderson, Hansen, and Simester 2009, p. 408).

For a consumer who is considering buying a pair of pants in a store, the texture of the pants is a search attribute, i.e., an attribute that is directly verifiable pre-purchase. As implied by Anderson et al. (2009), when the consumer considers buying the same item online or through a catalog, this same attribute—the texture of the pants—becomes an experience attribute, i.e., not fully observable and verifiable pre-purchase. The consequences are well known. Uncertainty about experience attributes decreases purchase frequency (Cox and Rich 1964) and dollars spent (Jasper and Ouelette 1994) for

catalog and home shopping purchases.[6]

In some instances, offline distribution that allows customers physical access to products is imperative, at least for some segments, as: "There are still people who want to *touch and feel* (italics added) clothing before they purchase." (Andy Dunn, CEO of Bonobos.com).[7] Moreover, when a product is available online *and* offline, consumers might visit the offline store to inspect it and then order it online, perhaps from a competing.[8] Thus, in general, the experience attribute issue is particularly acute for consumers when they consider buying from vertically integrated brands without offline distribution. Consequently, Bonobos.com (fashion apparel) has "insanely easy returns", Zappos.com (shoes) offers "totally free" returns and WarbyParker.com (eyewear) has a "home try-on" option where potential customers are shipped five frames (without lenses) to try for free.

These efforts are costly, and absent an understanding of how information about experience attributes spreads naturally and organically for free, e.g., through social learning, firms may be relying too much on efforts that undermine margins.

2.2 Local Social Learning in Local Neighborhoods and Internet Retailing

Consumers often learn from their peers before making purchase decisions, i.e., through social learning. When consumers shop online, we expect, *ex ante*, that social learning is a plausible source of information about experience attributes for new customers and thereby helps trial at Bonobos.com (our empirical application) and at other online retailers as well.

Conceptually, this social learning process operates as follows. A potential consumer updates her belief via signals on experience attributes that are received from previous purchasers. Signals relate to the

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[6] According to the National Mail Order Association, the first cataloger in the United States is believed to be Richard Sears in late 1880s (http://www.ehow.com/facts_4925839_history-mail-order-shopping.html). TV home shopping emerged in 1977 and Amazon.com first opened an online bookstore in 1994. About 7-8% of all US retail sales are now online.

[7] See http://www.forbes.com/sites/kellyclay/2012/04/12/nordstrom-invests-16-4-million-in-bonobos-now-available-in-stores/ for details.

[8] This phenomenon of "show-rooming" (see http://moneyland.time.com/2012/01/24/target-doesnt-want-to-be-a-showroom-for-the-stuff-you-buy-for-less-at-amazon/) where consumers scout out and examine products at giant offline retailers such as Best Buy or Target, and then purchase (at a lower price) at online alternatives like Amazon.com is problematic for offline stores. "Show-rooming" is a major reason why Circuit City went bankrupt (see http://business.time.com/2012/04/10/best-buy-ceo-brian-dunn-resigns-amid-shift-to-online-shopping/).

typical quality, "texture", and "style" of products sold on the website. There are various kinds of signals—including those from observations of use, direct conversations, and online reviews—all of which can drive social learning for a focal customer. We focus on *local social learning*; that is, learning that operates through signals from *physically close* others who have made *a prior purchase*, all else held constant.

Social scientists have a longstanding interest in how physically proximate neighbors influence each other, i.e., so-called "neighborhood effect" and how it drives consumption, investment and purchase decisions. In addition, recent studies pinpoint social learning as a key mechanism underlying the observed neighborhood effects in categories where agents face risk or uncertainty (Conley and Udry 2010; Duflo and Saez 2003; Sorensen 2006).

In the substantive domain of online retailing, contagion phenomena have been documented (e.g., Bell and Song 2007; Choi, Hui, and Bell 2010) but the underlying mechanisms largely unexplored. Local social learning is interactive (information senders and recipients know each other) and visceral (McShane, Bradlow, and Berger 2012), so it is potentially more powerful than learning via other sources such as online reviews and Internet-mediated interaction (Choi, Bell, and Lodish 2012). Thus, a more detailed elaboration of social learning as it relates to this important domain is needed.

2.3 Local Social Capital as a Moderator of Local Social Learning

In general terms, social capital is the ability of focal actors to secure collective, economic, or informational benefits by virtue of social networks, trust, and other norms in a community (Adler and Kwon 2002; Putnam 1995). In a review article, Nahapiet and Ghoshal (1998) provide a conceptual summary and describe relational and structural dimensions of social capital.[9] In this study, we operationalize the relational dimension as social trust and the structural dimension as frequency of

[9] In an influential paper Adler and Kwon (2002) note that, for substantive and ideological reasons, there is no "commonly agreed upon" definition of social capital that will suit all contexts. Thus, particular operational definitions may vary by discipline and level of investigation (Robison, Schmid, and Siles 2002). Our study therefore focuses on the relational and structural dimensions of social capital (Nahapiet and Ghoshal 1998) as they are a good conceptual fit to the mechanism, have operational variables available in the SCCBS, and as explained in Section 3, have precedent in the extant literature.

interaction and provide illustrative examples in Table 1. In Section 3, we develop our operational measure of local social capital from the SCCBS and note its consistency with extant approaches in the literature.

Prior work implies that a higher level of social capital leads to more efficient information transfer (Reagans and McEvily 2003; Uzzi 1997). In our context, we conjecture that local social capital enhances local social learning by affecting the *proportion* of signals arising from previous purchases and the *noise* associated with these signals. Specifically, we test whether higher levels of social capital reduce inefficiencies in the social learning process. The theoretical prediction is very specific—social capital operates on the information transformation process and there is no reason to expect that it will have a direct effect on the rate of diffusion. Our empirical specification mirrors this as we model the moderating effect on social learning while at the same time controlling for a potential direct effect on diffusion (and we find it to be insignificant).

There are three interesting aspects to this empirical test. First, as discussed in the Introduction, geographic variation in the propensity of consumers to buy online is explained by geographic variation in various neighborhood characteristics, e.g., offline tax rates, presence of stores, and so on. We examine whether variation in this propensity is related to the quality of interaction among members of a local community as well. Note too, that the effect of neighborhood social capital is qualitatively different from these other factors as it arises from the "multiplier" produced by previous purchases.

Second, previous studies relate social learning and individual characteristics such as opinion leadership (Iyengar, Van den Bulte, and Valente 2011; Nair, Manchanda, and Bhatia 2010). In contrast, we connect the efficiency of social learning to relational characteristics between individuals. Third, most studies focus on benefits from social capital accruing to community members; we show that Internet retailers (who are outside the local community) can benefit as well.

2.4 Summary and Testable Conjectures

We examine two new conjectures. First, that incomplete consumer knowledge about experience attributes prior to trial is partially resolved through local social learning from past local purchases made by others. Second, that local social capital reduces inefficiencies in the local social learning process by improving the likelihood that signals are: (1) observed by potential customers, and (2) less noisy. Finally, as noted previously, it is important to recall that social capital does not, per se, make purchases more likely. Rather, it improves the efficiency of the learning process itself. In instances where the social learning process results in favorable updating, i.e., potential customers come to learn that the product is better than they might have initially imagined, sales will be positively impacted.

3. Research Setting, Data, and Measures

3.1 General Condition and Research Setting

Our data for the empirical application need to satisfy two conditions. First, the products need to have experience attributes, and second, consumers should have incomplete consumer knowledge about experience attributes *ex ante*. Our data from Bonobos.com, an iconic Internet-based fashion retailer, satisfies these conditions. (More details about Bonobos' origins are provided shortly.)

In the apparel category fit, feel, and style are very important to consumers (Kwon, Paek, and Arzeni 1991) and these attributes are by definition experience attributes and non-verifiable pre-purchase when consumers buy online for the first time (Park and Stoel 2002). Since Bonobos.com targets trendy and fashion-forward males, the importance of these attributes is amplified. (Industry observer TechCrunch.com refers to the target customer as a "hip, semi-athletic, 25-to-40 year old guy."—See http://techcrunch.com/2010/12/16/bonobos-raises-18-5-million-metrosexuals-unite/ for details.)

By way of additional background, Bonobos.com has manufactured and sold fashionable men's apparel under their own brand online since October 2007. Unique pants are their signature product—even several years after launch—the site leads with "Pantsformation—Fit changes everything" (see http://www.bonobos.com/welcome/n and Figure 1). As Bonobos grew, they established offline "guide

shop" stores in Boston, Chicago, Georgetown and San Francisco and in April 2012 Bonobos also partnered with Nordstrom. Nordstrom contributed $16m in capital and agreed to carry Bonobos products; this accomplished two things—Bonobos could not only to reach new segments of consumers but also provide consumers with an opportunity to "touch and feel" the products before purchase.[10] (As noted below, our data precede these moves into offline retail.)

3.2 Data

The data come from three sources: (1) monthly observations on the number of purchases at Bonobos.com from October 2007 (when the site opened) to March 2011, (2) social capital data from SCCBS, and (3) zip-level demographic information and information on spending at offline retailers from the 2010 ESRI Business Database. Summary statistics for the key variables (all described subsequently) are given in Table 2.

3.2.1 Purchase Data at Bonobos.com. Our dependent variable is the number of new trials in a zip code for each period since the site opened, i.e., an aggregate count of individual customer trials from inception of the site. As such, the data do not suffer from "left-censoring". We focus on trials, because pre-trial customers have no direct experience, i.e., we deliberately model decisions of consumers who have incomplete knowledge about experience attributes *ex ante*. (The data we use pre-date the period where Bonobos products were made available at either "guide shops" or local Nordstrom stores, so there is no alternative channel where consumers can "touch and feel" the products prior to purchase; see also, Section 3.2.4). Specifically, we analyze data for 42 months from launch (October 2007 through March 2011), during which time more than 40,000 customers tried Bonobos.com.

The lagged number of total transactions in a zip code (the sum of trial and repeat transactions) is a key independent variable that serves two control roles. First, it is the source of local signals on

[10] For popular press stories on the Bonobos.com "guide shop" store concept and the Nordstrom deal, see http://bostinno.com/2012/05/01/bonobos-launches-first-offline-store-on-newbury-st-bringing-color-fit-discounts-to-bostinno-readers/ and http://www.forbes.com/sites/kellyclay/2012/04/12/nordstrom-invests-16-4-million-in-bonobos-now-available-in-stores/, respectively.

experience attributes in the local social learning process (see Section 4.1). Second, it controls the potential confounding effects of temporal, spatial, and time-varying spatial influences on the social learning process as well as social influence through mechanisms other than social learning (see Section 4.2).

3.2.2 Social Capital Data from the SCCBS. The SCCBS was undertaken by the John F. Kennedy School of Government, Harvard University between July 2000 and February 2001 and the data are widely used by social science researchers. Published articles report effects of local social capital on local behaviors such as home ownership (Hilber 2010), labor force choices (Aguilera 2002), social vulnerability (Cutter, Boruff, and Shirley 2003), and public health (Harpham, Grant, and Thomas 2002). Documentation for the SCCBS describes it as the "first attempt at systematic and widespread measurement of social capital in the United States, particularly as it occurs within local communities."

Our key zip-level social capital measures for the main model and falsification tests were extracted from the SCCBS. Specifically, we utilized questions relating to the two dimensions of social capital described in Table 1: (1) trust among local neighbors (relational dimension), and (2) the frequency of interaction between neighbors (structural dimension). The local trust and interaction scores are simple averages of the relevant survey questions (e.g., "How much do you trust neighbors?") in the SCCBS. Appendix 1 provides the details. The neighborhood social capital measure is, in turn, a simple average of trust and interaction frequency, consistent with the standard concepts in the literature (Burt 1992; Marsden and Campbell 1984) and with empirical studies that utilize the SCCBS (e.g., Hilber 2010).

3.2.3 Data on Neighborhood Characteristics. Zip code characteristics and the aggregated individual demographics of zip residents serve as controls in the empirical analysis (Brynjolfsson, Hu, and Rahman 2009; Forman, Ghose, and Goldfarb 2009). Our control variables are constructed from data purchased from ESRI in Redlands, CA and are available through the 2010 ESRI Demographics and Business Database (see http://www.esri.com/data/esri_data/demographic-overview for details). Specific variables

describing zip code characteristics are: *Target Population* (total number of 25-45 year-old males in the zip code), *Population Density* (target density per square mile), *Local Stores* (number of offline clothing stores in the 3-digit zip code area). *Non-metro Area*, *Near-suburb Area*, and *Far-suburb Area* dummies control for the geographic proximity of the focal zip to city centers.

Variables aggregated from individual demographics of zip residents are: *Total Spending* (total annual offline retail spending on the men's clothing category in a zip code as estimated by ESRI), *Average Income* (average annual income among the target population), *Gini Coefficient* (income inequality), *Age25* (proportion of males aged less than 25), *Age40* (proportion of males over the age of 40, i.e., those somewhat outside the target demographic), *Education* (proportion of people who are "highly educated", i.e., have a graduate degree), *Race Diversity* (the diversity measure defined by ESRI), and *Internet Score* (a proxy for Internet use and reliance on online information).[11]

3.2.4 Combined Data for Analysis and Descriptive Patterns. We study how a *previous* trial influences potential subsequent trials by local neighbors, so we focus on 495 zip codes where the SCCBS is conducted and *at least one* customer within 42-month period after the site was launched. Thus, the data consist of 20,790 zip-month observations on the number of new customers. The SCCBS covers 1,104 zip codes so it is possible that the 609 (1,104 – 495) zip codes with no trials at all are somehow different from the 495 zip codes used in estimation, with respect to social capital status. To check that this is not the case we estimate a binary choice model of having at least one trial, using data from all 1,104 zips (see Appendix 2). There is no effect of neighborhood social capital in this model, confirming that there is no "selection" of zips with buyers versus no buyers, on the basis of neighborhood social capital.

These data are not geographically condensed as the 495 zip codes span 23 different states and 201 different cities. By virtue of where the SCCBS was conducted, the data exclude New York City and Los Angeles—two locations where Bonobo.com has high sales. This strengthens our study because it means

[11] See http://www.esri.com/library/whitepapers/pdfs/diversity-index-methodology.pdf for the information on *Race Diversity*. *Internet Score* is operationalized as the average of the zip-level average frequency of Internet usage and the zip-level average participation in online discussions as recorded in the SCCBS.

that the findings will not be skewed by particularly "high growth" locations where sales are potentially driven by other mechanisms (such as the fashion orientation of the community and so on). Furthermore, it removes Manhattan zip codes and makes it extremely unlikely that potential customers in our sample are visiting Bonobos.com headquarters on 25th Street and evaluating products in person.[12]

Figure 2 is a model-free view of trial evolution based on the final dataset. It compares the number of new trials in each time period in zips that are in the top one-third based on their social capital scores (165 zips) with the number in the bottom one-third (165 zips). In both groups, the number of new trials increases over time ($p < .001$). Furthermore, in every period, the number of new trials in zips with higher social capital tends to be greater than the number of new trials in zips with lower social capital ($p < .001$). Absent a formal model (see Sections 4 and 5) this is not conclusive evidence of our proposed effects, but it is nevertheless interesting to observe such a clear pattern in the raw data.

3.2.5 Steps Taken to Mitigate Threats to Validity. Our research setting and data provide us with an opportunity to identify social learning while at the same time offering protection from the four standard threats to validity in social contagion studies. First, we avoid truncation bias (see Van den Bulte and Iyengar 2011) by estimating the trial model on *all* potential consumers in the risk set of 495 zip codes, not just those who ultimately made a purchase in the 42-month data window.

Second, we avoid simultaneity bias by using the lagged rather than contemporaneous number of total transactions in a neighborhood. Third, endogenous group formation is not a credible threat to validity because individuals do not decide on where to live based on a neighbor's trial of a specific website. Of course, we also control for observed and unobserved factors that vary by location. Fourth, by using the lagged number of total transactions in a neighborhood as a control on correlated unobservables between

[12] Potential customers have always had the option of visiting Bonobos.com headquarters in Manhattan and examining products there in a showroom that is part of the head office. (As noted in Section 3.1, in 2012, *after* the period of our data, Bonobos.com opened additional "guide shops" in Boston and Palo Alto and obtained distribution via Nordstrom.) It is approximately 200 miles from Bonobos.com headquarters on 25th Street in Manhattan to the nearest zip code in our data, 02215 in Boston, MA. This makes it very unlikely that potential customers in our data were resolving their pre-purchase uncertainty about experience attributes by physically inspecting products in Manhattan.

neighbors, we mitigate potential bias arising from the Bayesian learning mechanism (see Sections 4 and 5 for details).

4. Model

Individual consumers make a binary decision every period—to try Bonobos.com or not—on the basis of the expected utility from trial. The overall utility that consumer *j* in zip code *i* obtains by trying Bonobos.com at period t is

$$\tilde{U}_{ijt} = \tilde{U}^{E}_{ijt} + U^{D}_{ijt} + \varepsilon_{ijt}, \text{ where } \varepsilon_{ijt} \sim \text{IID Standard Gumbel Distribution.} \quad (1)$$

$\tilde{U}^{E}_{ijt}$ denotes random utility under incomplete knowledge about experience attributes. This utility component evolves through social learning and information acquisition on experience attributes. U^{D}_{ijt} denotes deterministic utility and is unrelated to the social learning process. As explained shortly, deterministic utility serves as a control to help identify social learning and establish its significance. Finally, ε_{ijt} represents the individual- and time-specific random errors that are not observed

4.1 Experience Attributes and the Social Learning Process

4.1.1 Random Utility on Experience Attributes. We assume that there is general agreement about the objective quality of Bonobos.com products (in texture, style, color, etc.) among consumers who have tried them. We denote this by Q. For potential consumers, knowledge of Q (how good the texture is, how fashionable the color is, etc.) is a key input to the trial decision. However, when shopping online, potential consumers are not fully informed of Q because they cannot physically verify experience attributes. Thus, they form beliefs about Q.

Let $\tilde{Q}_{ijt}$ denote the belief about experience attributes for consumer *j* in zip code *i* at period *t* who has yet to try Bonobos.com. Beliefs relate to *products* only not Bonobos.com "service". This is reasonable because in the period 2007-2011 in the United States there should be no uncertainly about the legitimacy of the site, e.g., Bonobos.com is not going to take orders and then not fill them. In addition, the "Fast and

free shipping. Insanely easy returns"[13] promise eliminates uncertainty about service-dependent experience attributes.

Random utility on experience attributes for consumer *j* in zip *i* at time *t* is[14]:

$$\tilde{U}_{ijt}^{E} = \tilde{Q}_{ijt} . \quad (2)$$

4.1.2 Social Learning as Bayesian Learning. Uncertain beliefs about experience attributes ($\tilde{Q}_{ijt}$) are represented by a distribution:

$$\tilde{Q}_{ij1} \equiv \tilde{Q}_{0} \sim N(Q_{0},1) , \quad (3)$$

where Q_0 is the mean of initial belief distribution before trial. Initial uncertainty is set to 1 for identification. The prior belief comes from local signals emanating from previous purchases by local neighbors. Of course social learning alone cannot fully resolve uncertainty, which is resolved only when the product is tried on.

Because they are based on actual purchases, local signals convey information about average objective quality of experience attributes, but these observed signals do not perfectly represent Q. This is because: (1) previous buyers who are sources of signals might differ in their assessments of the average quality of Bonobos.com products depending on their experience, and (2) some information could be "lost in translation" in the sense that a prior buyer may not be able to fully express their assessments of the products to recipients. Given this, the k^{th} local signal in zip code *i* at time *t*, S_{ikt}, is:

$$S_{ikt} = Q + u_{ikt} + v_{ikt}, \text{ where } u_{ikt} \sim N(0,\theta_{ui}^{2}) \text{ and } v_{ikt} \sim N(0,\theta_{vi}^{2}). \quad (4)$$

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[13] See http://www.bonobos.com/welcome/n (top left) and especially http://www.bonobos.com/about/ where it states: "Free both ways. Always." under "Free Shipping" and "Return anything, any time, any reason." under "Painless Returns".

[14] We can also define $\tilde{U}_{ijt}^{E}$ as a quadratic function of the uncertain belief rather than a linear function to allow for a flexible specification with respect to risk (Erdem and Kean 1996; Narayanan, Manchanda, and Chintagunta 2005). Here, the risk aversion parameter is theoretically estimable, but with a single category data it is hard to know how meaningful this is. We estimated the quadratic model and found that the risk aversion parameter was not significant (p = .45), and that the substantive findings were unchanged. Details are available from the authors upon request.

u_{ikt} allows assessments of quality in zip code *i* at time *t* to vary by different purchases (*k*); similarly, v_{ikt} allows for individual-level variability in signal transmission. Spatial variation in the random components of signals is captured by θ_{ui}^2 and θ_{vi}^2 which vary over zip codes. Assuming independence between the two errors, we write Equation (4) as:

$$S_{ikt} \sim N(Q, \theta_{ui}^2 + \theta_{vi}^2). \quad (5)$$

As analysts, we cannot observe signals directly, so we assume that the number of signals sent in a location is *proportional* to the number of transactions there in the previous period.[15]

Now, let N_{it-1} denote the lagged number of local transactions in zip code *i* at period *t-1*. Our assumption implies that the number of observed signals is $\omega_i N_{it-1}$ where ω_i denotes the proportion of signals arising from the lagged local purchases (N_{it-1}). Spatial variation in the observability of signals, (perhaps stemming from spatial variation in local relationships), is captured by ω_i which varies over zip codes. Potential consumers update their prior beliefs in a Bayesian fashion so that the uncertain belief about Q in zip code *i* at time *t* ($\tilde{Q}_{ijt}$) is:

$$\tilde{Q}_{ijt} \sim N(\bar{Q}_{ijt}, \sigma_{ijt}^2), \quad (6)$$

where the variance (σ_{ijt}^2) and the mean ($\bar{Q}_{ijt}$) of the posterior belief are as follows:

$$\sigma_{ijt}^2 = \left(1 + \frac{1}{\tau_i^2}\sum_{1=1}^{t-1} N_{i1}\right)^{-1}, \quad \bar{Q}_{ijt} = \sigma_{ijt}^2 \times \left(\frac{\bar{Q}_{ijt-1}}{\sigma_{ijt-1}^2} + \frac{1}{\tau_i^2}\sum_{k=1}^{N_{it-1}} S_{kit}\right), \text{ and } \tau_i^2 \equiv \frac{\theta_{ui}^2 + \theta_{vi}^2}{\omega_i}.$$

We write the posterior mean and variance in terms of τ_i^2 because θ_{ui}^2, θ_{vi}^2, and ω_i are not separately identified, but identified only up to τ_i^2. (The over-parameterized model, while not directly estimable, is helpful for exposition.) Most straightforwardly, τ_i^2 represents the "inefficiency of social learning"

[15] Narayanan, Manchanda, and Chintagunta (2005) assume that the number of signals that a physician observes on the quality of a prescription drug is proportional to the dollars spent on marketing efforts.

because as it increases, potential consumers place *less* weight on local information. Thus, the smaller the value of τ_i^2 the more quickly $\tilde{Q}_{ijt}$ converges to the true Q, or, alternatively, the more efficient the social learning process.

The over-parameterized model also helps in showing that the effect of local social capital on information transfer is unambiguous. Specifically, in Section 2 we conjectured that social capital boosts the "observability" of signals and reduces noise in information transmission, i.e., that it increases ω_i and decreases θ_{vi}^2, respectively. (The nature of social relationships has no effect on variation in the assessment of Q, i.e., no effect on θ_{ui}^2). Thus, by increasing ω_i and decreasing θ_{ui}^2, an increase in social capital must lead to a smaller value of τ_i as $\tau_i^2 \equiv \frac{\theta_{ui}^2 + \theta_{vi}^2}{\omega_i}$. We test this empirically by specifying:

$\log(\tau_i) = \alpha_0 + \alpha_1 SC_i$, where SC_i is social capital in zip code *i*. (7)

Zip-level variables are mean-centered so $\log(\tau_i) = \alpha_0$ when zip *i* has an average amount of social capital, i.e., $SC_i = 0$. Since social capital reduces inefficiency in social learning, we expect that $\alpha_1 < 0$.

4.2 Deterministic Utility and Means of Identifying Social Learning

Deterministic utility (Equation 1) is unrelated to social learning. While not of central interest it nevertheless serves to control for confounds that might affect our ability to measure the social learning process, and the moderating role of social capital as well.

To control for correlated unobservables, we specify temporal, spatial and time-varying spatial effects that are separate from the effects of social learning, and the moderating role of social capital on social learning. It could be the case, for example, that consumers in cities with more opportunities for socializing prefer Bonobos.com. If this were true, an observed correlation between the propensity to try and the number of previous trials in the local community could simply reflect local preferences and not a causal effect of prior trials on current behavior. Since we focus on social learning as a *specific*

mechanism of social influence we need to control for awareness dispersion, social conformity, network externality, and so on, as they are competing mechanisms. Thus, we specify:

$$U_{ijt}^{E} = \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \left(\gamma_0 + \gamma_1 SC_i\right)N_{it-1} + \mu_{it}. \quad (8)$$

β_{0t} is the period-specific intercept and controls global period effects unrelated to social learning, e.g., an increase in customer trials from (locally untargeted) marketing activities such as press coverage, via a flexible semi-parametric approach. X_i is a vector of observed zip-level characteristics (see Table 2) as well as two-digit zip fixed effects[16] and β_1 are the corresponding parameters. SC_i is zip-level neighborhood social capital, and its direct impact on the utility is captured by β_2 and our theory of the mechanism predicts $\beta_2 = 0$.

Lagged local transactions (N_{it-1}) control for types of social influence other than social influence through social learning (e.g. awareness diffusion, social conformity, network externality, etc.), and their effects are captured by $\gamma_0 + \gamma_1 SC_i$. We allow them to vary with social capital to prevent the effect of social capital on social learning (α_1) from being confounded by its potential moderating effect on the other social contagion mechanisms (γ_1).

Finally, μ_{it} represents *unobserved* spatial and time-varying spatial effects. Here too we use N_{it-1} to control μ_{it} because time-varying spatial effects are typically auto-regressive trends so factors affecting μ_{it} will also be correlated with lagged local transactions. For instance, suppose a zip code is revitalizing and over time residents have come to desire more fashionable apparel. This would increase μ_{it} over time, so N_{it-1} is a reasonable control for μ_{it}; hence, Equation 8 becomes:

$$U_{ijt}^{D} = \beta_{0t} + X_i\beta_1 + SC_i\beta_2 + (\gamma_0 + \gamma_1 SC_i)N_{it-1} + (\delta_0 + \delta_1 SC_i)N_{it-1}, \quad (9)$$

[16] Ideally, we could include five digit zip code-period specific fixed effects to control for potential correlated unobservables (Narayanan and Nair 2012); however, given the non-linearity of our model this will yield an inconsistent estimator with unconditional estimation methods (Arellano and Honore 2001).

$$= \beta_{0t} + X_i\beta_1 + SC_i\beta_2 + \left((\gamma_0 + \delta_0) + (\gamma_1 + \delta_1)SC_i\right)N_{it-1},$$

$$= \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} + \beta_4 SC_i \times N_{it-1}.$$

In Equation 9, γ_0 and δ_0 (γ_1 and δ_1) are not separately identified, but identified only up to β_3 and β_4. The equation clearly shows how lagged local transactions help with correlated unobservables and time-varying spatial trends in error term, μ_{it}.[17]

4.3 Expected Utility Function and Aggregate Model of Trial

Since $\tilde{U}_{ijt}$ is a random variable from a consumer's prospective, the consumer makes trial decisions so as to maximize expected utility, $E\left(\tilde{U}_{ijt}\right)$, where:

$$E\left(\tilde{U}_{ijt}\right) = E\left(\tilde{U}_{ijt}^{E}\right) + U_{ijt}^{D} + \varepsilon_{ijt} = E\left(\tilde{Q}_{it}\right) + U_{ijt}^{D} + \varepsilon_{ijt} \qquad (10)$$

$$= \bar{Q}_{it} + \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} + \beta_4 SC_i \times N_{it-1} + \varepsilon_{ijt}.$$

From Equation 1, the probability that consumer *j* in zip *i* tries Bonobos.com at period *t* is:

$$\Pr_{ijt} = \frac{\exp(\bar{Q}_{it} + \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} + \beta_4 SC_i \times N_{it-1})}{1 + \exp(\bar{Q}_{it} + \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} + \beta_4 SC_i \times N_{it-1})}. \qquad (11)$$

Our dependent variable is Y_{it}, the number of trials in a neighborhood (zip code) and is the aggregate of individual trial behavior. It follows a Poisson distribution as an approximation of a Binomial distribution. This is because given a large population size and a small event probability a Binomial distribution with parameters (n, p) can be expressed as a Poisson distribution with the parameter np.[18] The likelihood of observing y_{it} is:

[17] As with Equation 8, the interaction effect of social capital on the time-varying spatial pattern is included to prevent the effect of social capital on social learning (α_1) from being confounded by any potential interaction effect between N_{it-1} and social capital on μ_{it} i.e., via δ_1.

[18] These two conditions are met in our data: The range of the observed number of subjects at risk, i.e., target customers, in a zip code is [451, 19321] and the range of the empirical hazard rate is [0,0.009].

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it}) \times \lambda_{it}^{y_{it}}}{y_{it}!}, \text{ where } \lambda_{it} = M_{it} \times \Pr_{ijt}. \quad (12)$$

where M_{it} denotes the observed number of *non-triers* in zip code *i* at time *t.*

To estimate the model we simulate 50 draws for signals, and compute the entire belief vector on the quality of experience attributes for these draws. Next, we compute the conditional likelihood of observing y_{it} for all observations under different combinations between 50 different strings of $\tilde{Q}_{it}$. The unconditional zip-level likelihood of observing $y_i = [y_{i1} \quad y_{i2} \quad ... \quad y_{iT}]$ is obtained by sequentially integrating conditional y_{it} over conditional y_i over signal samples through Monte Carlo simulation. We estimate the parameters by maximizing the integrated likelihood.

4.4 Identification of Parameters

Observations with no local signals (i.e., before the first trial in the zip), identify Q_0. Similarly, Q is identified with the observations under steady state, i.e., when there are sufficiently large numbers of signals such that there is little updating; in our data the cumulative number of signals reaches 525 so we can assume that steady state is achieved.[19] α_0 (Equation 7), the average inefficiency in information transferred is identified from the pattern of increase in trials. α_1 (Equation 7), the effect of social capital on the inefficiency of information transferred, is identified from the differences in the cross-sectional variability of the pattern of increase in trials under different levels of social capital.

In the deterministic utility component, the average effect of lagged local transactions (β_3), is separately identified from the social learning process from the observations in the steady state. The interaction effect between social capital and lagged local transactions (β_4) is identified from the differences in sales evolution patterns by social capital under steady state.

5. Empirical Findings

[19] Figure 3a is additional evidence that the steady state is achieved in our data set. It shows that there is little change in utility when cumulative number of signals reaches around 100.

Table 3 shows the parameter estimates. They suggest that: (1) local social learning is at work, and (2) neighborhood social capital moderates the social learning process by reducing inefficiency in information transfer. The effects are statistically and economically significant and in Sections 5.2 and 5.3, we report falsification tests and robustness checks, respectively.

5.1 Main Model Findings

5.1.1 Local Social Learning. The initial prior expectation significantly *underestimates* the true quality of experience attributes ($Q - Q_0 = 1.41$, $p < .001$). When the inefficiency (τ_i^2) of information transfer is small enough, local social learning reduces the underestimation and increases pre-trial expected utility. The estimated average τ_i^2 $\left(exp(\alpha_0)^2\right)$ is around 9 times the initial prior variance (set equal to 1 for identification). According to the expression for the posterior variance in Equation 6, a totality of local transactions equivalent to $\tau_i^2 = \sum_{l=1}^{t-1} N_{il}$ is required to reduce the initial uncertainty (variance) from the initial fixed value of one to one half.[20] In our data, this means that the uncertainty about experience attributes reduces to one half of the initial uncertainty when there are 9 local transactions.

Statistical significance of the social learning process is established when the model indicates that consumers enjoy significantly better expected utility from trial as a result of social learning, and it is based on the interplay of several parameters (Q_0, Q, α_0, and α_1). This is identical to saying that the local social learning process is statistically significant when an additional local transaction significantly increases pre-trial expected utility; thus, we use a Bootstrap method to quantify the marginal utility increase from an additional local transaction. In Figure 3a the solid line is the marginal utility increase

[20] According to Equation 6 the posterior variance is $\left(1+\sum_{l=1}^{t-1} N_{il} \Big/ \tau_i^2\right)^{-1}$. Since the variance of initial prior distribution is 1, the posterior variance becomes a half of prior variance (0.5), when signal variance (τ_i^2) equals to the number of signals ($\sum_{l=1}^{t-1} N_{il}$).

from an additional local transaction under the average level of social capital (mean-centered $SC_i = 0$). The 95% bootstrap confidence interval (indicated by dotted lines) is always positive; hence, there is significant evidence of local social learning.

We quantify the economic value of social learning as the number of trials partly attributable to social learning on experience attributes, i.e., the number of actual triers minus the number who would have tried *without* the benefits of local social learning. This benchmark is computed as the number of new trials when the quality belief distribution does not update from the initial belief, all other parameters and variables held constant. We find that about 50% of trials (2,987 out of 5,745) are affected. This is consistent with a common practitioner belief; namely, that incomplete knowledge about experience attributes in general, and underestimation of product quality in particular, is a major barrier to trial. We demonstrate an important antidote: Information transferred locally from existing customers to potential customers helps to mitigate this problem.

5.1.2 Social Capital as a Moderator of Social Learning. The estimate of α_1 in Table 3 shows that social capital reduces the inefficiency in social learning ($\alpha_1 = -.20$; $p < .001$). In terms of magnitude, this implies that when social capital is *increased* by one standard deviation from the average, the inefficiency inherent in social learning (τ_i^2) will be brought down to about two-thirds of its original value (an approximately 50% increase in $1/\tau_i^2$). In Section 5.1.1 we reported that for an "average community" 9 local transactions are required to accomplish this reduction; in neighborhoods that are one standard deviation above average in social capital, only 6 local transactions are required.

We quantify the economic value of social capital as the number of trials partly attributable to the efficiency of social learning, i.e., the number of actual triers minus the number who would have tried if the level of social capital were lowered by one standard deviation in all zip codes. (Alternatively, we can interpret economic value as the difference in new trials between two zips that are exactly the same in all regards except one—they differ in the extent of social capital by one standard deviation.) Our simulations

show that about 8% (438 out of 5,745) of the new trials were affected by the efficiency of social learning process.

5.1.3 Control Variables. Effects of the control variables are not of interest per se; we document them to illustrate consistency with prior findings and provide additional face validity for our main findings. The number of lagged local transactions (N_{it-1}) is positively related to local demand ($\beta_3 = .01$, $p < .05$), perhaps a result of other contagion mechanisms, time-varying spatial effects, or both. As expected, there is no main effect of local social capital on local demand ($\beta_2 = -.19$, $p = .55$); social capital does not, per se, increase trial, but operates only through the learning mechanism, which identifies the effect.[21] New trials are higher in more densely populated areas ($p < .001$) perhaps due to greater use of the Internet in such locations (Katona, Zubcsek, and Sarvary 2011), and in locations where residents have more education and higher average incomes ($p < .001$ in both cases). More offline stores reduces new trials at the online retailer ($p < .05$), consistent with online-offline demand substitution (Brynjolffson, Hu, and Rahman 2009).

5.2. Falsification Tests

5.2.1 Falsification Tests for the Local Social Learning Finding. The controls in Equation 9 notwithstanding, additional evidence that the learning process for experience attributes is not contaminated by other contagion mechanisms (e.g., awareness dispersion, normative pressure, etc.), or by temporal, spatial, and spatio-temporal effects, is helpful.

For that purpose, we perform a falsification test for social learning. The test relies on the premise that the Bayesian updating process on learning about experience attributes should *not* be significant when estimated on *repeat* transaction data where Bonobos.com consumers have been able to resolve their uncertainty about product quality in general via their first purchase.

[21] Moreover, as noted earlier and reported in Table A2.1 there is no evidence that the 1,014 zip codes "select" into those with buyers (495 zips) and those without (609 zips) on the basis of social capital stock. The absence of a main effect in Table 3 further affirms that social capital works not directly on sales, but indirectly through the specific mechanism of reducing inefficiency of information transfer among local residents.

To analyze repeat purchases we use the same model as before (Equation 11), but this time the dependent variable is the count of repeat customers. Since the number of consumers who can make repeat purchases are limited to those who have tried the website previously, the aggregate number of repeat transactions follows a Binomial rather than a Poisson distribution.

The pictures in Figures 3a (trial) and Figure 3b (repeat) are very different even though they represent an identical test for social learning about experience attributes. For trial (Figure 3a), the 95% confidence interval never contains zero, whereas for repeat (Figure 3b) it always does. In Figure 3a this is because the estimated difference between the initial belief (*pre-trial* Q_0) and the updated belief (*trial Q*) is highly significant as noted previously (see Table 3). Consumers have a positive update after trying the product. In Figure 3b, as expected, the estimated difference between the initial belief (*trial* Q_0) and the updated belief (*repeat purchase Q*) is not significant ($p = .41$). The finding is additional evidence that our model of social learning for experience attributes performs as it should—it does not find evidence of social learning when individual customers already direct experience with the product.

5.2.2 Falsification Test for the Moderating Role of Social Capital. This falsification test is a subtle test of social capital measure itself.[22] The SCCBS asks respondents not only about trust and communication with neighbors but also about trust and communication with workplace colleagues (see Appendix 1). Our proposed measure of social capital is defined using the questions about *neighbors* (see Section 3.2). Neighbors, by definition, live in the same zip code, whereas work colleagues need not. In fact, commute times and related data strongly suggest that they often do not.[23]

Hence, we define a new variable "workplace social capital" and re-estimate the model with this variable as a replacement for "neighborhood social capital". If the moderating effect of social capital really is about local information transfer, there should be no moderating effect of workplace social capital.

[22] We are extremely grateful to an anonymous reviewer for suggesting this analysis.

[23] According to a 2011 OECD survey, the average commuting time per day in the U.S. is around 50 minutes. (http://www.economist.com/blogs/freeexchange/2011/10/surveys). It is therefore very unlikely that many US residents live and work in the same zip code.

As with the counterpart, neighborhood social capital, workplace social capital is a simple average of local scores on: (1) workplace trust (the average among related SCCBS survey questions such as "How much do you trust colleagues?"), and (2) workplace interaction frequency (the average among related SCCBS survey questions such as "How much do you socialize with your colleagues outside work?"). This measure captures the embedded-ness of relationships with colleagues among those who "live" in a specific zip code, not "work" in a specific zip code. Details are in Appendix 1.

We fit two models to demonstrate the test. First, we replace neighborhood social capital with workplace social capital and re-estimate the main model. When workplace social capital enters the model alone it does not enhance the efficiency of the local neighborhood social learning process (p = .06). The corresponding effect for neighborhood social capital reported in Table 3 is, on the other hand, highly significant (α_1 = -.20, p < .001). Second, we include *both* variables in equation 7 and find that neighborhood social capital moderates the local social learning process (α_1 = -.26, p < .001) whereas workplace social capital does not (p = .38).

5.3 Robustness Checks

5.3.1. Unobserved Time-Varying Spatial Effects. In Equation 9, we used lagged local transactions (N_{it-1}) to control unobserved time-varying spatial effect (μ_{it}). While this is in some respects a reasonable control, it is potentially incomplete in that we cannot be fully assured that there is no *concurrent* demand shock in a specific zip code that is not explained by past local transactions. To alleviate this, we would ideally find a proxy to control concurrent demand shocks, but it is challenging to find such a variable for each zip code every period. As an alternative we introduce a random component for the *unobserved* time-varying spatial effect unexplained by lagged local transaction (η_{it}) and specify Equation 9 as:

$$U_{ijt}^{D} = \beta_{0t} + X_i\beta_1 + SC_i\beta_2 + (\gamma_0 + \gamma_1 SC_i)N_{it-1} + (\delta_0 + \delta_1 SC_i)N_{it-1} + \eta_{it}. \quad (13)$$

Note that Equation 9 is a special case of Equation 13 where there is no unobserved time-varying spatial effect that is unexplained by past local transaction (i.e., $\eta_{it} = 0$).

We fit models with two different distributional assumptions for η_{it}. First, we assume that:

$$\eta_{it} \sim IID \;\; N(0, \phi_\eta^2). \tag{14}$$

Under this assumption, we estimate a model with zip-period specific random effect. To estimate ϕ_η, we simulated 50 draws of η_{it} for each observation and integrated numerically when computing the likelihood. Under this relatively straightforward model of *IID* shocks, we found no significant effect of time-varying spatial elements that are unexplained by lagged local transactions (p = .06). Moreover, the substantive findings from our focal model are preserved.

In Equation 14, the *IID* assumption implies that a random shock has no influence on demand in a subsequent period, and all those carry-over effects are captured by lagged local transaction. To relax this assumption, we specify η_{it} as:

$$\eta_{it} = \rho \eta_{it-1} + \xi_{it}, \text{ where } \xi_{it} \sim IID \;\; N(0, \phi_\xi^2). \tag{15}$$

To estimate ρ and ϕ_ξ, we simulated 50 draws of ξ_{it} for each observation, computed entire vectors of η_{it}, and numerically integrated as before. There is evidence of significant concurrent effects of ξ_{it} if ϕ_ξ is significantly greater than 0, and carry over effects if ρ is significantly different from 0. In this more general specification, neither the concurrent (p = .21) nor carry-over effects (p = .72) of random shocks were significant. Again, the substantive findings while our key findings remain robust.

5.3.2 Spatially Varying *Q*. In the main specification, we assume that previous triers agree on the quality of Bonobos.com products. If, however, there is any systematic difference in evaluation of Q, the assumption that signals are *IID* breaks down.[24] We relaxed this assumption and fit two models where Q

[24] Unbiasedness of signals is standard assumption. We assume that: (1) signals represent agreement about quality with no systematic deviation, and (2) potential consumers believe that signals are unbiased. It is hard to test whether both assumptions

(now Q_i) is a function of observed demographics. In the first model, *both* Q_i and τ_i are defined as functions of neighborhood social capital, SC_i. The purpose of the specification is to show that the estimate of α_1 in Table 3 is not confounded by spatially-varying Q_i over SC_i. We found that social capital still significantly reduces signal variance (α_1 = -.21, p < .001), but does not affect Q_i (p = .14).

Next, we define Q_i as a function of three variables most likely to be related to the evaluation of fashion items—population density, average income among target customers, and offline spending in the category. Again, we found that social capital still significantly reduces signal variance (α_1 = -.21, p < .01) *even when* Q_i varies over density, average income, and spending on the category (p < .001 in all three cases).

Our earlier findings in Table 3 are robust under spatially varying Q_i. In addition, the BIC of main model reported earlier (20,607) is better than either of the alternative models that allow Q_i to vary by location. (The respective values are BIC_1 = 20,614 and BIC_2 = 20,632.)

5.3.3 Alternative Specification of Moderation. Equation 7 specifies inefficiency of information transfer as a function of social capital only. The falsification tests in 5.2.2 notwithstanding, it is helpful to examine alternative specifications. From a conceptual perspective, previous purchases by local neighbors with demographics similar to those of potential customers, but with whom potential customers do not interact, should boost *neither* the observability of signals (ω_i) nor the richness of signals (θ_{vi}). What matters is the "embedded-ness" (Granovetter 1985) of relationships. When we allow signal variance to depend on racial diversity, income inequality, and social capital we find that social capital reduces inefficiency as before, (α_1 = -.20, p < .01), but that diversity (p = .41) and income (p = .12) have no effect.

6. Summary

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hold or not. Conceptually, our findings are valid as far as (2) holds where Q becomes "perceived agreement" rather than "objective agreement" about quality. When (2) breaks down, our finding will be valid only when consumers know the direction and extent of systematic deviation, and Q becomes objective agreement after cancelling out systematic deviation.

6.1 Key Findings

We began with the observations that information passed from existing to potential customers a is key driver of sales, and that information about *experience* attributes (which cannot be fully observable and verifiable pre-purchase) is important in reducing the uncertainty faced by potential customers. Moreover, the global consumer economy is driven increasingly by online commerce, such that information about experience attributes plays a critical and ever larger role in buying decisions. The top-line message from our research is that while firms can expend considerable resources to reduce consumer uncertainty about experience attributes, naturally occurring *customer-driven* processes, specifically interactions between existing and potential customers, could perform a similar role.

Drawing on existing conceptual frameworks and empirical studies, we proposed that: (1) local social learning is a specific mechanism for reducing uncertainty about experience attributes, and (2) the local social learning process is enhanced by neighborhood social capital such that higher levels of social capital reduce inefficiency in the learning process. Both conjectures are supported from models estimated on data from Bonobos.com, a leading and iconic US online apparel retailer.

To our knowledge, our paper is the first in marketing to identify the proposed mechanism of social learning in this important context, and in addition, to demonstrate the novel moderating role of social capital. It is crucial to note that social capital does not, per se, influence trial of new products. It operates directly on the learning process itself, by reducing inefficiency in information transfer. In instances where consumers update favorably, e.g., in the case of Bonobos.com where initial beliefs underestimated true quality, more efficient information transfer will naturally help trials indirectly.

6.2 Actionable Insights, Limitations, and Future Research

Managers are of course well aware that existing customers are important sources of information and uncertainty resolution for potential customers, i.e., that "social learning" is a mechanism for information transmission about experience attributes in particular, even if they don't phrase it in exactly those terms.

Nevertheless, the magnitude of this effect might be cause for surprise—we estimate that up to half of all Bonobos.com trials were affected by it.

Furthermore, the fact that neighborhood social capital reduces inefficiency is potentially actionable as well. While the SCCBS is extensive (over 30,000 respondents), it covers only just over 1,000 zip codes (there are more than 30,000 residential zip codes in the US; moreover, it may not be possible for managers to obtain the SCCBS from the Kennedy School.) To demonstrate the practical value of the social capital finding, we first conceived and obtained data on a proxy variable that is widely available.

As noted earlier, the Bonobos.com target customer is a "hip, semi-athletic, 25-to-40 year old guy". We sought a neighborhood-level proxy for the "potential for interaction" among such individuals and this led us to collect data on the number of bars and liquor shops per capita per zip code, for all 495 zip codes in our data (these data can be obtained manually via the Internet, or, as we did, from a professional supplier such as ESRI). This proxy is suitable because individuals are not usually alone (or, at least, not exclusively!) when they drink liquor. Most likely, they are with friends or neighbors watching sports, celebrating birthdays, having parties, and so on. Likewise, local bars are places where people, especially males, socialize with neighborhood residents.

Therefore, we expect that the number of bars and liquor shops is a reasonable proxy for embeddedness of local relationships and interaction frequency among local neighbors. Consistent with this expectation, the correlation between the neighborhood social capital measure from the SCCBS and the number of bars and liquor shops per capita is significantly positive ($\rho = .32$, $p < .001$). Of course, as we found with our falsification test using workplace social capital, we would not expect the bars and liquor store variable to be significant in a model that also included the true neighborhood social capital measure.

First, we fit a model where neighborhood social capital is replaced with the "local bars and liquor shops" variable. Like neighborhood social capital, this variable does enhance the efficiency of social learning process ($p < .05$). Next, we included *both* the neighborhood social capital variable *and* the local

bars and liquor shop variable into the model. In this case, the local bars and liquor shop variable loses its significance (p = .80) while neighborhood social capital remains significant (α_1 = -.20, p < .05) as before. These findings imply that the local bars and liquor shop variable, which is conceptually related to embedded-ness of relationships—especially among males in the target segment—is a proxy for neighborhood social capital in our context. More generally, managers could act on the "social capital finding" by looking for observed local characteristics that suit their own product context (e.g., number of churches, gyms, or cooking clubs, etc.), and use it as a proxy for the extent of offline social relationships that are product-relevant. In locations with better and more frequent interaction among constituents, information transfer will be more efficient, which is of course desirable when firms have valued products.

The limitations of our study suggest future research directions. First, we focus on social learning on vertical quality only, but social learning on horizontal fit is important too—especially for experiential goods. Second, we controlled time-varying spatial effects using both the trend captured by past purchases and alternative error structures for concurrent demand shocks. Alternative methods (perhaps natural experiments) with other exogenous controls on time-varying spatial effects would be helpful in further establishing the implied casual relationships in our work. Third, we focus exclusively on the identification of social learning only; one could of course explicitly separate other social contagion mechanisms such as awareness dispersion, and attempt to determine the relative importance of each.

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Table 1. Dimensions of Social Capital and Illustrative Effects on Local Social Learning

Dimensions	Definition	Effect on Local Social Learning
Relational Dimension	Social assets in a relationship. This involves factors such as trust and intimacy (e.g., Coleman 1988; Granovetter 1985; Putnam 1995).	Social cohesion arises from the *relational dimension* of social capital because it motivates actors to devote time and effort to communicating and should enable potential customers to get a better sense of experience attributes (e.g., Aral and Van Alstyne 2011). *Hence, a higher relational dimension will lead to higher quality signals.*
Structural Dimension	The pattern of connections and interactions between actors. This involves strength of ties, interaction frequency (e.g., Granovetter 1985), and network closure and density (e.g., Coleman 1988).	Social cohesion arises from the *structural dimension* of social capital because actors connected by stronger and denser networks are more likely to interact. *Hence, a higher structural dimension will make it more likely that signals are observed*.

Table 2. Descriptive Statistics for Model Variables

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	New Trials	.28	.83													
2	Lagged Transactions	.62	1.94	.61												
3	Social Capital	.00	1.00	.08	.09											
4	Target Population	5.30K	3.13K	.18	.18	.22										
5	Density	1.04K	1.56K	.24	.24	.30	.40									
6	Local Stores	541.87	412.54	.11	.12	.18	.40	.52								
7	Total Spending	5.14M	2.86M	.21	.21	-.11	.65	.26	.28							
8	Average Income	87.16K	37.50K	.21	.20	-.38	-.05	-.02	.01	.57						
9	Gini Coefficient	.62	.06	-.15	-.16	-.35	-.03	-.34	-.18	.17	.33					
10	Age25	.19	.06	.14	.16	.42	.24	.39	.16	-.09	-.40	-.44				
11	Age40	.30	.07	-.17	-.18	-.46	-.41	-.45	-.23	.03	.45	.39	-.87			
12	Education	.42	.17	.27	.26	-.24	-.13	.12	.02	.39	.69	-.01	.07	.08		
13	Race Diversity	51.91	22.18	.05	.05	.31	.50	.50	.41	.19	-.11	-.22	.32	-.44	-.23	
14	Internet Score	.00	1.00	.10	.10	.01	.06	.11	-.01	.23	.19	.00	.12	-.11	.29	.05

Note: In the analysis we standardize all non-dummy variables aside from Lagged Transactions.

Table 3. Social Learning and Local Social Capital: Estimates from Bonobos.com

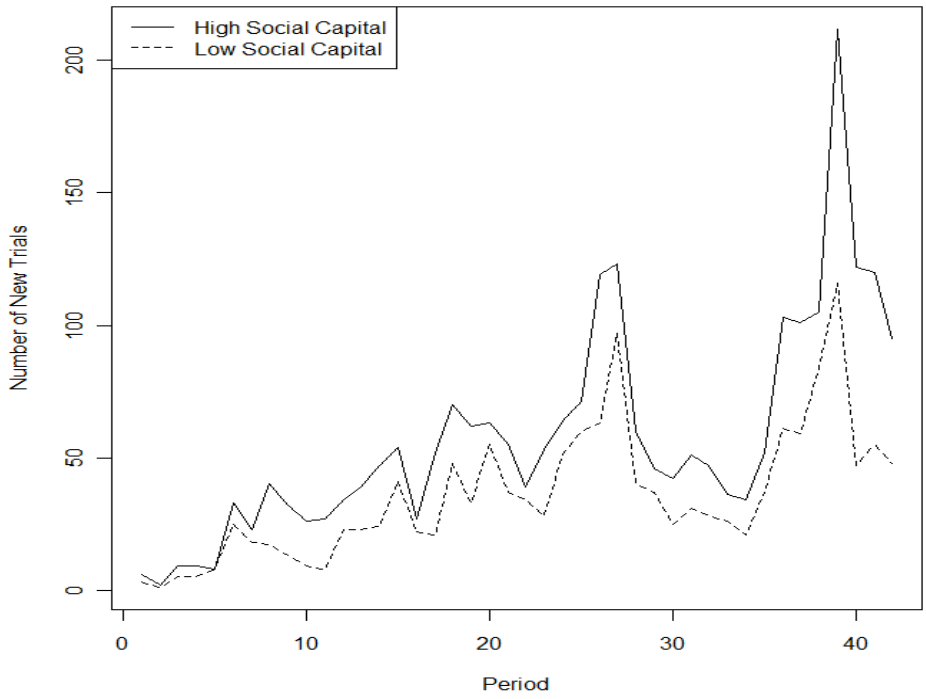
	Model Estimates	Standard Errors
Parameters of the Social Learning Process		
Q_0, Initial Prior Mean of the Quality of Experience Attributes	-12.517	(.153)**
Q, True Quality of Experience Attributes	-11.107	(.082)**
α_0, log (Signal SD|SC=0)	1.092	(.089)**
α_1, ∂ log (Signal SD|SC)/ ∂ SC	-.204	(.065)**
Control Variables		
Lagged Local Transactions (N_{it-1})	.013	(.005)**
Social Capital (SC_i)	-.019	(.033)
Lagged Local Transactions×Social Capital ($N_{it-1}\times SC_i$)	-.002	(.003)
Race Diversity	.071	(.040)
Gini Coefficient	-.318	(.029)**
Average Income	.329	(.062)**
Education	.502	(.050)**
Target Population Density	.168	(.040)**
Local Offline Stores in Three-Digits Zip	-.232	(.092)*
Offline Spending on the Men's Clothing Category	.035	(.031)
Observations and Model Fits		
Number of Observations	20,790	
Log Likelihood	-9,846.2	
BIC	20,607.04	

Notes: * indicates that $p < .05$ and ** indicates that $p < .01$. The models include 41 period fixed effects and 29 two-digit zip fixed effects and all variables listed in Table 2. Estimates for the dummies and non-central control variables are not reported for ease of exposition but are available from the authors upon request.

Figure 1. A Screenshot of Bonobos.com



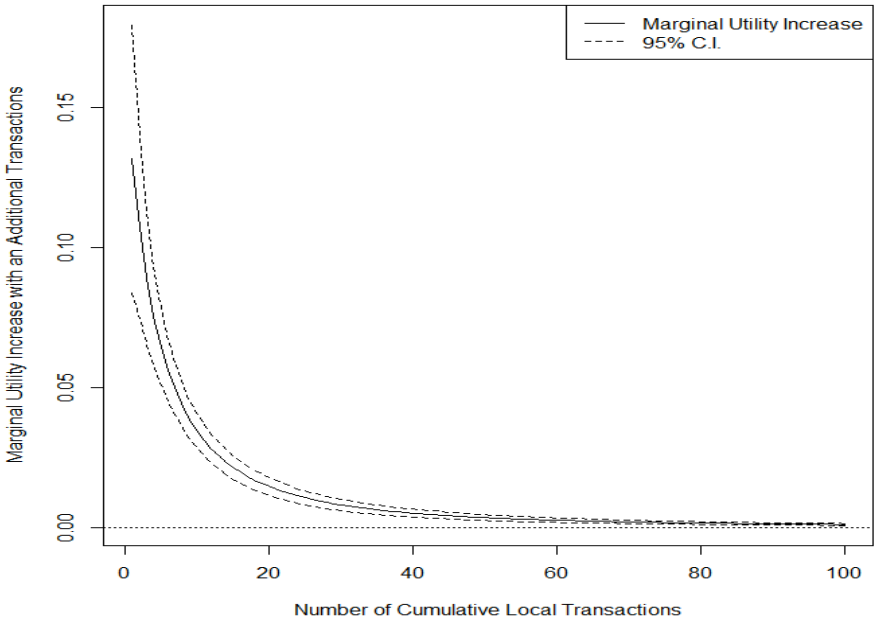
Figure 2. The Number of New Trials in High Versus Low Social Capital Zip Codes



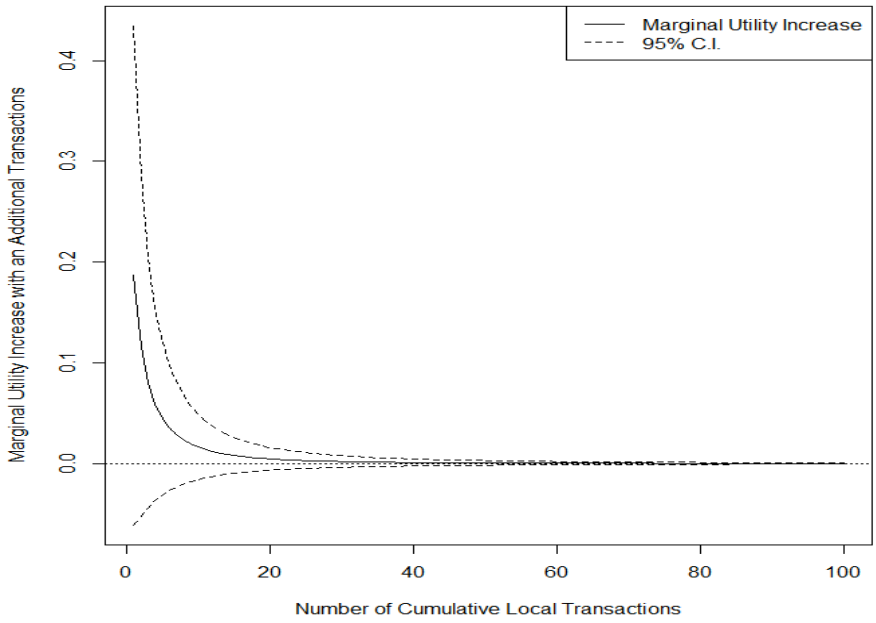
Note: The peaks at month 27 and 39 are December of 2009 and 2010, respectively.

Figure 3. The Estimated Significance of Social Learning

(a) Trial—Marginal Utility Increase



(b) Repeat—Marginal Utility Increase



Notes: For Bonobos.com, the range of the cumulative number of transactions over all 20,790 observations (495 zips * 42 periods) is [0,525]. For Diapers.com, the range of the cumulative number of transactions over all 19,305 observations (495 zips * 39 periods) is [0,763]. In Figure3, the range of *x*-axis is [0,100] for better visualization. The result in the rest of range is also consistent with what is shown here—a diminishing but *significantly* positive marginal utility gain for Figure 3A and a diminishing and *insignificantly* positive marginal utility gain for Figure 3B. Given the underestimation of initial quality (see Section 5.1.1), the observed diminishing marginal return to local transactions (*N*) is an assumption of the Bayesian learning model. It is consistent with the notion that a consumer observes "overlap" in each new piece of information, as s/he collects more information.

Appendix 1: Measures from the SCCBS

A1.1 Neighborhood Social Capital

The following survey question is used to construct the neighborhood social trust score.

- How much can you trust neighbors?
  1. Trust not at all.
  2. Trust only a little.
  3. Trust some.
  4. Trust a lot.

The following survey questions are used to construct the local interaction frequency score.

- How often did you interact with your neighbor within last twelve months?
- How often did you have friends over to your home within last twelve months?
- How often did you hang out with friends in a public place within last twelve months?
  1. Never did this
  2. Once
  3. A few times
  4. 2-4 times
  5. 5-9 times
  6. About once a month on average
  7. Twice a month
  8. About once a week average
  9. More than once a week.

SCCBS data include two versions of variables for each question, the raw score and standardized score in the local community (zip code). For each question, we use the local average of standardized scores to construct social trust and interaction frequency scores. We operationalize neighborhood social capital as the average between neighborhood trust and interaction frequency scores.

A1.2 Workplace Social Capital

The following survey question is used to construct the workplace social trust score.

- How much can you trust co-workers?
  1. Trust not at all.
  2. Trust only a little.
  3. Trust some.
  4. Trust a lot.

The following are survey questions to construct local interaction frequency score.

- How often did you socialize with co-workers outside of work within last twelve months?
  10. Never did this
  11. Once
  12. A few times
  13. 2-4 times
  14. 5-9 times
  15. About once a month on average
  16. Twice a month
  17. About once a week average
  18. More than once a week.

For each question, we operationalize workplace social capital as the average between workplace trust and interaction frequency scores.

Appendix 2. Zip Codes With and Without Customers

The SCCBS data cover 1,104 zip codes and since the purpose of our research is to understand how information from a *previous* trial influences potential subsequent *first* trials by local neighbors, we focus on 495 zips with at least one customer within the 42 month period after the site launched. Since the observation period is quite long—three and a half years—it's possible that the 609 (1,104 – 495) zips with *no* trials at all could be different from the 495 zips used in estimation. To check and document these differences, we estimate a binary probit of the probability of at least one trial, using data from all 1,104 zips. The results are in Table A2.1.

Significant effects for some control variables are to be expected; indeed, there is higher probability of least one Bonobos.com customer in zip codes with a more educated population and in those where residents spend more on men's clothing. Most important however, is that zip codes *do not* sort on our key independent variable, neighborhood social capital. The estimate is not significantly different from zero ($p = .29$). We thank an anonymous reviewer for suggesting this analysis.

Table A2.1: Parameter estimates from a binary probit of the probability of at least one customer in a zip code

	Model Estimates	Standard Error
Estimated Parameters		
Intercept	-.219	(.468)
Social Capital (SC_i)	.063	(.060)
Race Diversity	.609	(.372)
Gini Coefficient	-7.216	(1.382)**
Average Income	-.355	(.297)
Education	.794	(.180)**
Target Population Density	.102	(.112)
Local Offline Stores in Three-Digits Zip	.033	(.109)
Offline Spending on the Men's Clothing Category	1.388	(.554)*
Observations and Model Fits		
Number of Observations	1,055	
Log Likelihood	-428.5	
BIC	1,198.1	