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Neighborhood Social Capital and Social Learning for Experience Attributes of Products

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Social learning can occur when information is transferred from existing customers to potential customers. It is especially important when 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, on 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, a leading U.S. online fashion retailer, we find not only that local social learning facilitates customer trial but also that the effect is economically important because 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
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1. Introduction

Information about new products passed from existing to potential customers is an influential and widely studied driver of sales (e.g., Iyengar et al. 2011, Manchanda et al. 2008). Information regarding *experience* attributes, i.e., attributes that cannot be fully observable and verifiable prepurchase, 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, on 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, ecommerce in the United States will see growth from $231 billion in 2013 to $370 billion in 2017 (compound annual growth rate of 10%); projected rates are almost identical in Europe, where the total market should reach $247 billion by 2017 (Lomas 2013). This phenomenon is not confined to developed markets; in China, year-on-year growth through March 2012 exceeded 50%, and the *Economist* (2013) predicts that China will quickly become the largest ecommerce market by value. 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, which we define below, 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.

The institutional setting for our empirical work is best understood by example. Premier and rapid-growth U.S. Internet retailers such as 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

[1] Complementary terms have been introduced to the literature for use in particular contexts; e.g., Degeratu et al. (2000, p. 62) refer to "searchable sensory attributes" for goods sold online, whereas Lal and Sarvary (1999, p. 485) use the term "nondigital attributes" to describe product attributes that cannot be fully conveyed when items are sold over the Internet.

Figure 1 **A Screenshot of Bonobos.com**

Note. Used with permission.

consumer uncertainty about the experience attributes of the products they sell. In September 2012, leading industry observer GigaOm.com reported on a $40 million fundraising round by WarbyParker.com and noted that the company's home try-on program "has helped Warby Parker overcome one of the *biggest hurdles* for online fashion brands, getting people to feel comfortable about their online purchase" (Kim 2012, emphasis added).

Naturally, these firm-initiated methods can be costly. We document a complementary customer-initiated process for the resolution of pretrial uncertainty that occurs intrinsically off-line: 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, Duflo and Saez 2003, Sorensen 2006); we add to this body of literature by demonstrating why social learning is so important for the growing consumer Internet sector. Furthermore, we 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, a leading pure-play U.S. fashion retailer (Figure 1 is a screenshot of the website), and neighborhood social capital data from the Social Capital Community Benchmark Survey (SCCBS).[2] 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 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 et al. 2005). The Bayesian learning assumption behind social learning is justified conceptually in §4.1.2 and validated empirically in §5.2.1. Specifically, we develop a model of individual learning and from there derive a neighborhood (zip code)-level model of new trials arising in each time period.

Our model identifies a 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

[2] For an interesting introduction to social capital concepts and data by one of the foremost authorities on the SCCBS, see Putnam (2000). See also Putnam's initiative focusing on the study of social capital, The Saguaro Seminar: Civic Engagement in America (http://www.hks.harvard.edu/saguaro/communitysurvey/index.html). The project 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 §§2 and 3, respectively.

(Amaldoss and Jain 2005), and network externality (Manchanda et al. 2008). Moreover, we control for possible confounding effects from correlated unobservables (§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 50% of all trials in the first three and a half years of operations at Bonobos 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* stimulate trial and diffusion per se; rather, it operates only on the learning process itself. It reduces inefficiency in information transmission; in our empirical application, the moderating effect influences 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 et al. 2009, Choi and Bell 2011, Forman et al. 2009) and that insights from geographic variation in online buying are actionable. SCCBS data are not available commercially for managers, so we identify and justify a readily accessible measure: the *number of 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 §4. Section 5 reports the findings, and §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 et al. 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 prepurchase. 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 prepurchase. The consequences are well known. Uncertainty about experience attributes decreases purchase frequency (Cox and Rich 1964) and dollars spent (Jasper and Ouellette 1994) for catalog and home shopping purchases.[3]

In some instances, off-line distribution that allows customers physical access to products is imperative, at least for some segments: According to Andy Dunn, CEO of Bonobos, "There are still people who want to *touch and feel* clothing before they purchase" (emphasis added).[4] Moreover, when a product is available online *and* off-line, consumers might visit the off-line store to inspect it and then order it online, perhaps from a competing seller.[5] Thus, in general, the experience attribute issue is particularly acute for consumers when they consider buying from vertically integrated brands without off-line distribution. As a result, Bonobos.com touts "insanely easy returns," Zappos.com, an online shoe and apparel retailer, offers totally free returns, and eyewear retailer Warby-Parker.com 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.

[3] The first cataloger in the United States is thought to be Benjamin Franklin. His first catalog was produced in 1744 and sold scientific books (see http://en.wikipedia.org/wiki/Mail_order, accessed September 14, 2012). TV home shopping emerged in 1977, and Amazon.com first opened an online bookstore in 1994. About 7%–8% of all U.S. retail sales are now online.

[4] See Clay (2012) for details.

[5] This phenomenon of "show-rooming" (see Tuttle 2012) where consumers scout out and examine products at giant off-line retailers such as Best Buy or Target and then purchase (at a lower price) at online alternatives such as Amazon.com is problematic for off-line stores. Show-rooming is a major reason why Circuit City went bankrupt (see Gustin 2012).

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 trials at Bonobos (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 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*—the learning that operates through signals from *physically close* others who have made *a prior purchase*, all else held constant.

Social scientists have a long-standing interest in how physically proximate neighbors influence each other (i.e., the 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 et al. 2010), but the underlying mechanisms remain largely unexplored. Local social learning is interactive (information senders and recipients know each other) and visceral (McShane et al. 2012), so it is potentially more powerful than learning via other sources such as online reviews and Internet-mediated interaction (Choi et al. 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.[6] In this study, we operationalize the relational dimension as social trust and the structural dimension as frequency of interaction and provide illustrative examples in Table 1. In §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 §1, geographic variation in the propensity of consumers to buy online is explained by geographic variation in various neighborhood characteristics (e.g., off-line tax rates, presence of stores). 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 because it arises from the "multiplier" produced by previous purchases.

Second, previous studies relate social learning and individual characteristics such as opinion leadership (Iyengar et al. 2011, Nair et al. 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; and 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.

[6] 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 et al. 2002). Our study therefore focuses on the relational and structural dimensions of social capital (Nahapiet and Ghoshal 1998) because they are a good conceptual fit to the mechanism, have operational variables available in the SCCBS, and, as explained in §3, have precedent in the extant literature.

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.*

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. Second, consumers should have incomplete consumer knowledge about experience attributes ex ante. Our data from Bonobos, an iconic Internet-based fashion retailer, satisfy these conditions. (More details about the company's origins are provided shortly.)

In the apparel category, fit, feel, and style are very important to consumers (Kwon et al. 1991), and these attributes are by definition experience attributes and nonverifiable prepurchase when consumers buy online for the first time (Park and Stoel 2002). Since Bonobos targets trendy and fashion-forward males, the importance of these attributes is amplified. (Industry observer TechCrunch refers to the target customer as a "hip, semi-athletic, 25-to-40 year old guy"; see Lacy 2010.)

By way of additional background, Bonobos has manufactured and sold fashionable men's apparel under its own brand online since October 2007. Even though the product line has expanded, unique pants are still the signature item and fit the differentiating attribute (see http://www.bonobos.com/about#about-nav under "fit starts here"). As Bonobos grew, it established off-line "guideshop" stores in Boston; Chicago; Washington, DC; and San Francisco. Bonobos then partnered with Nordstrom in April 2012. Nordstrom contributed $16 million in capital and agreed to carry Bonobos products; this accomplished two things: Bonobos could not only reach new segments of consumers but also provide consumers with an opportunity to "touch and feel" its products before purchase.[7] (As noted below, our data precede these moves into off-line 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 the SCCBS, and (3) zip code-level demographic information and information on spending at off-line 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 the inception of the site. As such, the data do not suffer from left-censoring. We focus on trials because pretrial 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 predate the period where Bonobos products were made available at either guideshops or local Nordstrom stores, so there is no alternative channel where consumers can touch and feel the products prior to purchase; see also §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 shopped at 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 experience attributes in the local social learning process (see §4.1). Second, it controls the potential confounding effects of

[7] For popular press stories on the Bonobos guideshop store concept and the Nordstrom deal, see DeCanio (2012) and Clay (2012), respectively.

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*	0.28	0.83													
2 *Lagged transactions*	0.62	1.94	0.61												
3 *Social capital*	0.00	1.00	0.08	0.09											
4 *Target population*	5.30[a]	3.13[a]	0.18	0.18	0.22										
5 *Population density*	1.04[a]	1.56a	0.24	0.24	0.30	0.40									
6 *Local stores*	541.87	412.54	0.11	0.12	0.18	0.40	0.52								
7 *Total spending*	5.14[b]	2.86[b]	0.21	0.21	−0.11	0.65	0.26	0.28							
8 *Average income*	87.16[a]	37.50[a]	0.21	0.20	−0.38	−0.05	−0.02	0.01	0.57						
9 *Gini coefficient*	0.62	0.06	−0.15	−0.16	−0.35	−0.03	−0.34	−0.18	0.17	0.33					
10 *Age 25*	0.19	0.06	0.14	0.16	0.42	0.24	0.39	0.16	−0.09	−0.40	−0.44				
11 *Age 40*	0.30	0.07	−0.17	−0.18	−0.46	−0.41	−0.45	−0.23	0.03	0.45	0.39	−0.87			
12 *Education*	0.42	0.17	0.27	0.26	−0.24	−0.13	0.12	0.02	0.39	0.69	−0.01	0.07	0.08		
13 *Race diversity*	51.91	22.18	0.05	0.05	0.31	0.50	0.50	0.41	0.19	−0.11	−0.22	0.32	−0.44	−0.23	
14 *Internet score*	0.00	1.00	0.10	0.10	0.01	0.06	0.11	−0.01	0.23	0.19	0.00	0.12	−0.11	0.29	0.05

Note. In the analysis we standardize all non-dummy variables aside from *Lagged transactions*.
[a]In thousands.
[b]In millions.

temporal, spatial, and time-varying spatial influences on the social learning process as well as social influence through mechanisms other than social learning (see §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 et al. 2003), and public health (Harpham et al. 2002). Documentation for the SCCBS describes it as the "first attempt at widespread systematic measurement of social capital [in the United States], especially within [local] communities" (Saguaro Seminar 2000, p. 3).

Our key zip code-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 A 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 code residents serve as controls in the empirical analysis (Brynjolfsson et al. 2009, Forman et al. 2009). Our control variables are constructed from data purchased from Esri in Redlands, California, and are available through the 2010 Esri Demographics and Business Database (see http://www.esri.com/data/esri_data/demographic-overview, accessed March 9, 2012, for details on the demographics data). Specific variables describing zip code characteristics are *Target population* (the total number of 25- to 45-year-old males residing in the zip code), *Population density* (target density per square mile), and *Local stores* (the number of off-line clothing stores in the three-digit zip code area). *Nonmetro area*, *Near-suburb area*, and *Far-suburb area* dummies control for the geographic proximity of the focal zip code to city centers.

Variables aggregated from individual demographics of residents residing in a zip code are *Total spending* (the total annual off-line 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), *Age 25* (proportion of males younger than age 25), *Age 40* (proportion of males over age 40, i.e., those somewhat outside the target demographic), *Education* (proportion of people who 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).[8]

3.2.4. Combined Data for Analysis and Descriptive Patterns. We study how a *previous* trial influences potential subsequent trials by local neighbors,

[8] See Esri (2012) for the information on *Race diversity*. *Internet score* is operationalized as the average of the zip code-level average frequency of Internet usage and the zip code-level average participation in online discussions as recorded in the SCCBS.

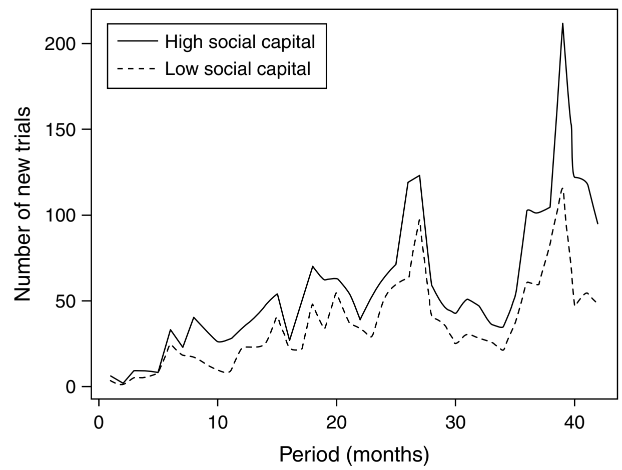
so we focus on 495 zip codes where the SCCBS is conducted and with *at least one* customer within 42-month period after the site was launched. Thus, the data consist of 20,790 zip-month observations on the number of new customers. The SCCBS covers 1,104 zip codes, so it is possible that the 609 (1,104 − 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 that has at least one trial, using data from all 1,104 zip codes (see Appendix B). There is no effect of neighborhood social capital in this model, confirming that there is no "selection" of zip codes with buyers versus no buyers on the basis of neighborhood social capital.

These data are not geographically condensed because 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 Bonobos.com has high sales. This strengthens our study because it means 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). Furthermore, removing Manhattan zip codes makes it extremely unlikely that potential customers in our sample are visiting the Bonobos headquarters on 25th Street in Manhattan and evaluating products in person.[9]

Figure 2 is a model-free view of trial evolution based on the final data set. It compares the number of new trials in each time period in zip codes that are in the top one-third based on their social capital scores (165 zip codes) with the number in the bottom one-third (165 zip codes). In both groups, the number of new trials increases over time ($p < 0.001$). Furthermore, in every period, the number of new trials in zip codes with higher social capital tends to be greater than the number of new trials in zip codes with lower social capital ($p < 0.001$). Absent a formal model (see §§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

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



Note. The peaks at months 27 and 39 are December 2009 and 2010, respectively.

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 neighbors, we mitigate potential bias arising from the Bayesian learning mechanism (see §§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

$$\tilde{U}_{ijt} = \tilde{U}^E_{ijt} + U^D_{ijt} + \varepsilon_{ijt}, \text{ where } \varepsilon_{ijt} \sim \text{IID standard Gumbel distribution.} \quad (1)$$

The random utility under incomplete knowledge about experience attributes is denoted by $\tilde{U}^E_{ijt}$. This utility component evolves through social learning and information acquisition on experience attributes. U^D_{ijt} denotes deterministic utility and is unrelated

[9] Potential customers have always had the option of visiting the Bonobos headquarters and examining products; there in a showroom that is part of the head office. (As noted in §3.1, in 2012, *after* the period of our data, Bonobos opened additional guideshops in Boston and Palo Alto and obtained distribution via Nordstrom.) It is approximately 200 miles from the Bonobos headquarters to the nearest zip code in our data, 02215, in Boston, Massachusetts. This makes it very unlikely that potential customers in our data were resolving their prepurchase uncertainty about experience attributes by physically inspecting products in Manhattan.

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 (IID stands for independent and identically distributed).

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 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 to the service Bonobos provides This is reasonable because in the 2007–2011 period in the United States there should be no uncertainly about the legitimacy of the site; e.g., Bonobos is not going to take orders and then not fill them. In addition, the promise of "fast and free shipping" and "insanely easy returns"[10] eliminates uncertainty about service-dependent experience attributes.

Random utility on experience attributes for consumer j in zip code i at time t is[11]

$$\tilde{U}^E_{ijt} = \tilde{Q}_{ijt}. \tag{2}$$

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

$$\tilde{Q}_{ij1} \equiv \tilde{Q}_0 \sim \mathrm{N}(Q_0, 1), \tag{3}$$

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 the 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 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 his or her assessments of the products to recipients. Given this, the kth local signal in zip code i at time t, S_{ikt}, is

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

Here, 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^2_{ui} and θ^2_{vi}, which vary over zip codes. Assuming independence between the two errors, we write Equation (4) as

$$S_{ikt} \sim \mathrm{N}(Q, \theta^2_{ui} + \theta^2_{vi}). \tag{5}$$

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.[12]

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

$$\tilde{Q}_{ijt} \sim \mathrm{N}(\bar{Q}_{ijt}, \sigma^2_{ijt}), \tag{6}$$

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

$$\sigma^2_{ijt} = \left(1 + \frac{1}{\tau^2_i}\sum_{l=1}^{t-1} N_{il}\right)^{-1},$$

$$\bar{Q}_{ijt} = \sigma^2_{ijt} \times \left(\frac{\bar{Q}_{ijt-1}}{\sigma^2_{ijt-1}} + \frac{1}{\tau^2_i}\sum_{k=1}^{N_{it-1}} S_{kit}\right), \quad \text{and} \quad \tau^2_i \equiv \frac{\theta^2_{ui} + \theta^2_{vi}}{\omega_i}.$$

[10] Please see http://www.bonobos.com/about#about-nav, top right.

[11] We can also define $\tilde{U}^E_{ijt}$ 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 Keane 1996, Narayanan et al. 2005). Here, the risk aversion parameter is theoretically estimable, but with 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 ($p = 0.45$) and that the substantive findings were unchanged. Details are available from the authors upon request.

[12] Narayanan et al. (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.

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 overparameterized model, although not directly estimable, is helpful for exposition.) Most straightforwardly, τ_i^2 represents the inefficiency of social learning 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 overparameterized model also helps in showing that the effect of local social capital on information transfer is unambiguous. Specifically, in §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 $\tau_i^2 \equiv (\theta_{ui}^2 + \theta_{vi}^2)/\omega_i$. We test this empirically by specifying

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

Zip code-level variables are mean centered, so $\log(\tau_i) = \alpha_0$ when zip code 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. Although 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. 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 factors such as awareness dispersion, social conformity, and network externality because they are competing mechanisms. Thus, we specify

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

The period-specific intercept β_{0t} controls global period effects unrelated to social learning, e.g., an increase in customer trials from (locally untargeted) marketing activities such as press coverage, using a flexible semiparametric approach. X_i is a vector of observed zip code-level characteristics (see Table 2) as well as two-digit zip code fixed effects,[13] and β_1 are the corresponding parameters. SC_i is zip code–level neighborhood social capital, and its direct impact on the utility is captured by β_2; 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), 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 autoregressive trends, so factors affecting μ_{it} will also be correlated with lagged local transactions. For instance, suppose a zip code area 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

$$\begin{aligned} U_{ijt}^D &= \beta_{0t} + X_i\beta_1 + SC_i\beta_2 + (\gamma_0 + \gamma_1 SC_i)N_{it-1} \\ &\quad + (\delta_0 + \delta_1 SC_i)N_{it-1} \\ &= \beta_{0t} + X_i\beta_1 + SC_i\beta_2 \\ &\quad + ((\gamma_0 + \delta_0) + (\gamma_1 + \delta_1)SC_i)N_{it-1} \\ &= \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} \\ &\quad + \beta_4 SC_i \times N_{it-1}. \end{aligned} \quad (9)$$

In Equation (9), γ_0 and δ_0 (γ_1 and δ_1) are not separately identified, but they are 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 the error term μ_{it}.[14]

[13] Ideally, we could include five-digit zip code period-specific fixed effects to control for potential correlated unobservables (Narayanan and Nair 2013); however, given the nonlinearity of our model, this will yield an inconsistent estimator with unconditional estimation methods (Arellano and Honore 2001).

[14] 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., using δ_1.

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, $E(\tilde{U}_{ijt})$, where

$$\begin{aligned} E(\tilde{U}_{ijt}) &= E(\tilde{U}^E_{ijt}) + U^D_{ijt} + \varepsilon_{ijt} \ = E(\tilde{Q}_{it}) + U^D_{ijt} + \varepsilon_{ijt} \\ &= \bar{Q}_{it} + \beta_{0t} + X_i\beta_1 + \beta_2 SC_i + \beta_3 N_{it-1} \\ &\quad + \beta_4 SC_i \times N_{it-1} + \varepsilon_{ijt}. \end{aligned} \tag{10}$$

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

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

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.[15] The likelihood of observing y_{it} is

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

M_{it} denotes the observed number of *nontriers* 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 code-level likelihood of observing $y_i = [y_{i1}\ y_{i2}, \ldots, y_{iT}]$ 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 code) 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.[16] The average inefficiency in information transferred, α_0 (Equation (7)), is identified from the pattern of increase in trials; α_1 (see 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

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 §§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 ($Q - Q_0 = 1.41$, $p < 0.001$). When the inefficiency (τ_i^2) of information transfer is small enough, local social learning reduces the underestimation and increases pretrial expected utility. The estimated average $\tau_i^2(\exp(\alpha_0)^2)$ is around nine 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 $\tau_i^2 = \sum_{l=1}^{i-1} N_{il}$ is required to reduce the initial uncertainty (variance) from the initial fixed value of 1 to 0.5.[17] In our data, this means that the uncertainty about experience attributes reduces to one half of the initial uncertainty when there are nine local transactions.

Statistical significance of the social learning process is established when the model indicates that consumers enjoy significantly better expected utility from a trial as a result of social learning, and it is based on

[15] 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, 19, 321] and the range of the empirical hazard rate is [0, 0.009].

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

[17] According to Equation (6), the posterior variance is $(1 + \sum_{l=1}^{t-1} N_{il}/\tau_i^2)^{-1}$. 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 the number of signals ($\sum_{l=1}^{t-1} N_{il}$).

Table 3 **Social Learning and Local Social Capital: Estimates from Bonobos**

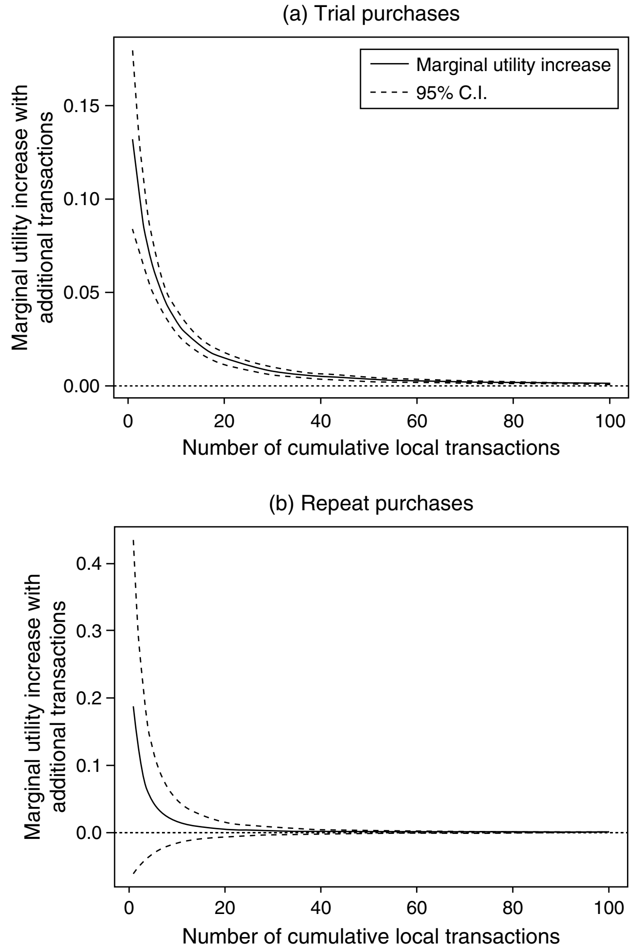
	Model estimates	SE
Parameters of the social learning process		
Q_0: Initial prior mean of the quality of experience attributes	-12.517^{**}	0.153
Q: True quality of experience attributes	-11.107^{**}	0.082
α_0: log(Signal SD | $SC = 0$)	1.092^{**}	0.089
α_1: ∂ log(Signal SD | SC)/∂SC	-0.204^{**}	0.065
Control variables		
Lagged local transactions (N_{it-1})	0.013^{**}	0.005
Social capital (SC_i)	-0.019	0.033
Lagged local transactions $\times$ *Social capital* ($N_{it-1} \times SC_i$)	-0.002	0.003
Race diversity	0.071	0.040
Gini coefficient	-0.318^{**}	0.029
Average income	0.329^{**}	0.062
Education	0.502^{**}	0.050
Population density (*target density per square mile*)	0.168^{**}	0.040
Local off-line stores in three-digit zip code	-0.232^{*}	0.092
Off-line spending in the men's clothing category	0.035	0.031
Observations and model fits		
Number of observations	20,790	
Log likelihood	$-9{,}846.2$	
BIC	20,607.04	

Notes. The models include 41 period fixed effects and 29 two-digit zip code fixed effects and all variables listed in Table 2. Estimates for the dummies and noncentral control variables are not reported for ease of exposition but are available from the authors upon request.
$^{*}p < 0.05$; $^{**}p < 0.01$.

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 pretrial expected utility; thus, we use a bootstrap method to quantify the marginal utility increase from an additional local transaction. In Figure 3(a), the solid line is the marginal utility increase 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 the common practitioner belief that incomplete knowledge about experience attributes in

Figure 3 **The Estimated Significance of Social Learning**



Notes. For Bonobos.com, the range of the cumulative number of transactions over all 20,790 observations (495 zip codes $\times$ 42 periods) is $[0, 525]$. The range of the 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 (a) and a diminishing and *insignificantly* positive marginal utility gain for (b). Given the underestimation of initial quality (see §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 he or she collects more information. C.I., confidence interval.

general, and underestimation of product quality in particular, is a major barrier to trial. We highlight an important remedy. Information transferred locally from existing customers to new customers helps 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 ($\alpha_1 = -0.20$; $p < 0.001$). 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 §5.1.1 we reported that for an average community, nine local transactions are required to accomplish this reduction; in neighborhoods that are one standard deviation above average in social capital, only six 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 zip codes 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 the 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 ($\beta_3 = 0.01, p < 0.05$), 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 ($\beta_2 = -0.19, p = 0.55$); social capital does not, per se, increase trial but operates only through the learning mechanism, which identifies the effect.[18] New trials are higher in more densely populated areas ($p < 0.001$), perhaps because of a greater use of the Internet in such locations (Katona et al. 2011), and in locations where residents are more educated and have higher average incomes ($p < 0.001$ in both cases). The presence of more off-line stores reduces new trials at the online retailer ($p < 0.05$), consistent with online/off-line demand substitution (Brynjolffson et al. 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) or by temporal, spatial, and spatiotemporal 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.

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 is limited to those who have tried the website previously, the aggregate number of repeat transactions follows a binomial rather than a Poisson distribution.

The graphs in Figures 3(a) (depicting trial purchases) and 3(b) (depicting repeat purchases) are very different even though they represent an identical test for social learning about experience attributes. For trial purchases, the 95% confidence interval never contains zero, whereas for repeat purchases, it always does. This is because, as shown in Figure 3(a), the estimated difference between the initial belief (*pretrial* 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. By contrast, in Figure 3(b), the estimated difference between the initial belief (*trial* Q_0) and the updated belief (*repeat purchase* Q) is not significant ($p = 0.41$), as expected. This 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 have 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.[19] The SCCBS asks respondents not only about trust and communication with neighbors but also about trust and communication with workplace colleagues (see Appendix A). Our proposed measure of social capital is defined using the questions about *neighbors* (see §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.[20]

Hence, we define a new variable, *workplace social capital*, and reestimate 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

[18] Moreover, as noted earlier and reported in Table B.1, there is no evidence that the 1,014 zip codes "select" into those with buyers (495 zip codes) and those without (609 zip codes) 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.

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

[20] According to a 2011 Organisation for Economic Co-operation and Development survey, the average commuting time per day in the United States is around 50 minutes (*Economist* 2011). It is therefore very unlikely that many U.S. residents live and work in the same zip code.

effect of workplace social capital. As with its 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 embeddedness of relationships with colleagues among those who reside in a specific zip code, not work in a specific zip code. Details are in Appendix A.

We fit two models to demonstrate the test. First, we replace neighborhood social capital with workplace social capital and reestimate the main model. When workplace social capital enters the model alone, it does not enhance the efficiency of the local neighborhood social learning process ($p = 0.06$). The corresponding effect for neighborhood social capital reported in Table 3 is, on the other hand, highly significant ($\alpha_1 = -0.20, p < 0.001$). Second, we include *both* variables in Equation (7) and find that neighborhood social capital moderates the local social learning process ($\alpha_1 = -0.26, p < 0.001$), whereas workplace social capital does not ($p = 0.38$).

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}). Although 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

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

Under this assumption, we estimate a model with a zip code-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 ($p = 0.06$). 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 carryover effects are captured by lagged local transaction. To relax this assumption, we specify η_{it} as

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

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 carryover effects if ρ is significantly different from 0. In this more general specification, neither the concurrent effects ($p = 0.21$) nor carryover effects ($p = 0.72$) of random shocks were significant. Again, the substantive conclusion is the same as the 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 products. If, however, there is any systematic difference in evaluation of Q, the assumption that signals are IID breaks down.[21] We relaxed this assumption and fit two models where Q (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 ($\alpha_1 = -0.21, p < 0.001$) but does not affect Q_i ($p = 0.14$).

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 off-line spending in the category. Again, we found that social capital still significantly reduces signal variance ($\alpha_1 = -0.21$,

[21] Unbiasedness of signals is a 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 hold. Conceptually, our findings are valid as far as (2) holds where Q becomes a "perceived agreement" rather than an "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 canceling out systematic deviation.

$p < 0.01$) *even when* Q_i varies over density, average income, and spending on the category ($p < 0.001$ in all three cases).

Our earlier findings in Table 3 are robust under spatially varying Q_i. In addition, the Bayesian information criterion (BIC) of the 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 $\text{BIC}_1 = 20{,}614$ and $\text{BIC}_2 = 20{,}632$.)

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 "embeddedness" (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 ($\alpha_1 = -0.20$, $p < 0.01$) but that diversity ($p = 0.41$) and income ($p = 0.12$) have no effect.

6. Summary

6.1. Key Findings

We began with the observations that information passed from existing to potential customers is a key driver of sales and that information about *experience* attributes (which cannot be fully observable and verifiable prepurchase) 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 although 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, a leading and iconic U.S. 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 influence trial of new products, per se. 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), a more efficient information transfer will therefore help trials indirectly.

6.2. 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 do not 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, that neighborhood social capital reduces inefficiency is potentially actionable as well. Although the SCCBS is extensive (more than 30,000 respondents), it covers only slightly more than 1,000 zip codes (there are more than 30,000 residential zip codes in the United States; 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 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 on the Internet, or, as we did, obtained 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 the 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 ($\rho = 0.32$, $p < 0.001$). 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 includes 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. Similar to neighborhood social capital, this variable does enhance the efficiency of social learning process ($p < 0.05$). Next, we included *both* the neighborhood social capital variable *and* the local bars and liquor shops variable into the model. In this case, the local bars and liquor shops variable loses its significance ($p = 0.80$), whereas neighborhood social capital remains significant ($\alpha_1 = -0.20$, $p < 0.05$) as before. These findings imply that the local bars and liquor shops variable, which is conceptually related to embeddedness 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) and use it as a proxy for the extent of off-line 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 also important, especially for experiential goods. Second, we controlled time-varying spatial effects using both the trend captured by past purchases and the 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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Appendix A. Measures from the SCCBS

A.1 Neighborhood Social Capital

The following survey question was 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 were used to construct the local interaction frequency score.

—How often did you interact with your neighbor within the last 12 months?

—How often did you have friends over to your home within the last 12 months?

—How often did you hang out with friends in a public place within the last 12 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 on 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 used the local average of standardized scores to construct social trust and interaction frequency scores. We operationalized neighborhood social capital as the average between neighborhood trust and interaction frequency scores.

A.2 Workplace Social Capital

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

—How much can you trust coworkers?

1. Trust not at all.
2. Trust only a little.
3. Trust some.
4. Trust a lot.

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

—How often did you socialize with coworkers outside of work within the last 12 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 on average
18. More than once a week

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

Table B.1 Parameter Estimates from a Binary Probit of the Probability of at Least One Customer in a Zip Code

	Model estimates	SE
Estimated parameters		
Intercept	−0.219	0.468
Social capital (SC_i)	0.063	0.060
Race diversity	0.609	0.372
Gini coefficient	−7.216	1.382**
Average income	−0.355	0.297
Education	0.794	0.180**
Population density (*target density per square mile*)	0.102	0.112
Local off-line stores in three-digit zip code	0.033	0.109
Off-line spending in the men's clothing category	1.388	0.554*
Observations and model fits		
Number of observations	1,055	
Log likelihood	−428.5	
BIC	1,198.1	

*$p < 0.05$; **$p < 0.01$.

Appendix B. 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 zip codes 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 is possible that the 609 (1,104 − 495) zip codes with *no* trials at all could be different from the 495 zip codes 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 zip codes. The results are in Table B.1.

Significant effects for some control variables are to be expected; indeed, there is higher probability of least one Bonobos customer in zip code areas with a more educated population and in those areas 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 ($p = 0.29$).[22]

References

Adler P, Kwon S (2002) Social capital: Prospect for a new concept. *Acad. Management Rev.* 27(1):17–40.

Aguilera M (2002) The impact of social capital on labor force participation: Evidence from the 2000 Social Capital Community Benchmark Survey. *Soc. Sci. Quart.* 83(3):853–74.

Amaldoss W, Jain S (2005) Pricing of conspicuous goods: A competitive analysis of social effects. *J. Marketing Res.* 42(1):30–42.

Anderson ET, Hansen K, Simester D (2009) The option value of returns: Theory and empirical evidence. *Marketing Sci.* 28(3):405–423.

[22] We thank an anonymous reviewer for suggesting this analysis.

Anderson E, Fong N, Simester D, Tucker C (2010) How sales taxes affect customer and firm behavior: The role of search on the Internet. *J. Marketing Res.* 47(2):229–239.

Aral S, Van Alstyne M (2011) The diversity-bandwidth trade-off. *Amer. J. Sociol.* 117(1):90–171.

Arellano M, Honore B (2001) Panel data models: Some recent developments. Heckman J, Leamer E, eds. *Handbook of Econometrics*, Vol. 5 (North-Holland, Amsterdam), 3229–3296.

Bell D, Song S (2007) Neighborhood effects and trial on the Internet: Evidence from online grocery retailing. *Quant. Marketing Econom.* 5(4):361–400.

Brynjolfsson E, Hu Y, Rahman MS (2009) Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Sci.* 55(11):1755–1765.

Burt R (1992) *Structural Holes: The Social Structure of Competition* (Harvard University Press, Cambridge, MA).

Choi J, Bell D (2011) Preference minorities and the Internet. *J. Marketing Res.* 48(4):670–682.

Choi J, Bell DR, Lodish LM (2012) Traditional and IS-enabled customer acquisition on the Internet. *Management Sci.* 58(4):754–769.

Choi J, Hui K, Bell D (2010) Spatiotemporal analysis of imitation behavior across new buyers at an online grocery retailer. *J. Marketing Res.* 47(2):65–79.

Clay K (2012) Nordstrom leads $16.4 million investment in Bonobos, now available in stores. *Forbes* (April 12) http://www.forbes.com/sites/kellyclay/2012/04/12/nordstrom-invests-16-4-million-in-bonobos-now-available-in-stores/.

Coleman J (1988) Social capital in the creation of human capital. *Amer. J. Sociol.* 94(Supplement):S95–S120.

Conley T, Udry C (2010) Learning about a new technology: Pineapple in Ghana. *Amer. Econom. Rev.* 100(1):35–69.

Cox D, Rich S (1964) Perceived risk and consumer decision-making—The case of telephone shopping. *J. Marketing Res.* 1(4):32–49.

Cutter S, Boruff B, Shirley W (2003) Social vulnerability to environmental hazards. *Soc. Sci. Quart.* 84(2):242–261.

DeCanio L (2012) Bonobos launches first offline store on Newbury St., bringing color, fit, and discount to BostInno readers. *BostInno* (May 1) http://bostinno.com/2012/05/01/bonobos-launches-first-offline-store-on-newbury-st-bringing-color-fit-discounts-to-bostinno-readers/.

Degeratu A, Rangaswamy A, Wu J (2000) Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes. *Internat. J. Res. Marketing* 17(1):55–78.

Duflo E, Saez E (2003) The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quart. J. Econom.* 118(3):815–842.

Economist, The (2011) Surveys: How long are American commutes? *Free Exchange* (blog), October 16, http://www.economist.com/node/21533155.

Economist, The (2013) Alibaba: The world's greatest bazaar. (March 23) http://www.economist.com/news/briefing/21573980-alibaba-trailblazing-chinese-internet-giant-will-soon-go-public-worlds-greatest-bazaar.

Erdem T, Keane MP (1996) Decision making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Sci.* 15(1):1–20.

Esri (2012) Methodology statement: 2011 diversity index. White paper, Esri, Redlands, CA. http://www.esri.com/library/whitepapers/pdfs/diversity-index-methodology.pdf.

Forman C, Ghose A, Goldfarb A (2009) Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Sci.* 55(1):47–57.

Granovetter M (1985) Economic action, social structure, and embeddedness. *Amer. J. Sociol.* 91(3):481–510.

Gustin S (2012) Best Buy CEO Brian Dunn resigns amid shift to online shoppinig. *Time* (April 10) http://business.time.com/2012/04/10/best-buy-ceo-brian-dunn-resigns-amid-shift-to-online-shopping/.

Harpham T, Grant E, Thomas E (2002) Measuring social capital within health surveys: Key issues. *Health Policy Plan.* 17(1):106–111.

Hilber C (2010) New housing supply and the dilution of social capital. *J. Urban Econom.* 67(3):419–437.

Iyengar R, Van den Bulte C, Valente TW (2011) Opinion leadership and social contagion in new product diffusion. *Marketing Sci.* 30(2):195–212.

Jasper C, Ouellette S (1994) Consumers' perception of risk and the purchase of apparel from catalogs. *J. Direct Marketing* 8(2):23–36.

Katona Z, Zubcsek P, Sarvary M (2011) Network effects and personal influences: The diffusion on an online social network. *J. Marketing Res.* 48(3):425–443.

Kim R (2012) Warby Parker raises $36.8M to expand fashion eyewear brand. *Gigaom* (September 10) http://gigaom.com/2012/09/10/warby-parker-raises-36-8m-to-expand-fashion-eyewear-brand/.

Kwon Y, Paek S, Arzeni M (1991) Catalog vs. non-catalog shoppers of apparel: Perceived risks, shopping orientations, demographics, and motivations. *Clothing Textiles Res. J.* 10(1):13–19.

Lacy S (2010) Bonobos raises $18.5 million. Metrosexuals unite! *TechCrunch* (December 16) http://techcrunch.com/2010/12/16/bonobos-raises-18-5-million-metrosexuals-unite/.

Lal R, Sarvary M (1999) When and how is the Internet likely to decrease price competition? *Marketing Sci.* 18(4):485–503.

Lomas N (2013) Forrester: U.S. online retail sales to rise to $370BN by 2017 (10% CAGR) as ecommerce motors on with help from tablets and phones. *TechCrunch* (March 13) http://techcrunch.com/2013/03/13/forrester-2012-2017-ecommerce-forecast/.

Manchanda P, Xie Y, Youn N (2008) The role of targeted communication and contagion in product adoption. *Marketing Sci.* 27(6):961–976.

Manski C (2000) Economic analysis of social interactions. *J. Econom. Perspect.* 14(3):115–136.

Marsden P, Campbell K (1984) Measuring tie strength. *Soc. Forces* 63(2):482–501.

McShane B, Bradlow E, Berger J (2012) Visual influence and social groups. *J. Marketing Res.* 49(6):854–871.

Nahapiet J, Ghoshal S (1998) Social capital, intellectual capital, and the organizational advantage. *Acad. Management Rev.* 23(2):242–266.

Nair H, Manchanda P, Bhatia T (2010) Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *J. Marketing Res.* 47(5):883–895.

Narayanan S, Nair HS (2013) Estimating causal installed-base effects: A bias-correction approach. *J. Marketing Res.* 50(1):70–94.

Narayanan S, Manchanda P, Chintagunta P (2005) Temporal differences in the role of marketing communication for new products. *J. Marketing Res.* 42(3):278–291.

Park J, Stoel L (2002) Apparel shopping on the Internet: Information availability on U.S. apparel merchant web sites. *J. Fashion Marketing Management* 6(2):158–176.

Putnam R (1995) Bowling alone: America's declining social capital. *J. Democracy* 6(1):65–78.

Putnam R (2000) *Bowling Alone: The Collapse and Revival of American Community* (Simon & Schuster, New York).

Reagans R, McEvily B (2003) Network structure and knowledge transfer: The effects of cohesion and range. *Admin. Sci. Quart.* 48(2):240–267.

Robison L, Schmid A, Siles M (2002) Is social capital really capital? *Rev. Soc. Econom.* 60(1):1–21.

Saguaro Seminar (2000) Social Capital Banchmark Survey, 2000. Report prepared by The Roper Center for Public Opinion Research, University of Connecticut, Storrs. http://www.ropercenter.uconn.edu/misc/usmisc2000-soccap/usmisc2000-soccap.PDF.

Sorensen AT (2006) Social learning and health plan choice. *RAND J. Econom.* 37(4):939–945.

Tuttle B (2012) Target doesn't want to be a showroom for the stuff you buy for less at Amazon. *Time* (January 24) http://moneyland.time.com/2012/01/24/target-doesnt-want-to-be-a-showroom-for-the-stuff-you-buy-for-less-at-amazon/.

Uzzi B (1997) Social structure and competition in inter-firm networks: The paradox of embeddedness. *Admin. Sci. Quart.* 42(1):35–67.

Van den Bulte C, Iyengar R (2011) Tricked by truncation: Spurious duration dependence and social contagion in hazard models. *Marketing Sci.* 30(2):233–248.

Van den Bulte C, Lilien G (2001) Medical innovation revisited. Social contagion versus marketing effort. *Amer. J. Sociol.* 106(5):1409–35.

Woolcock M (1998) Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory Soc.* 27(2):151–208.