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Abstract

Internet retail sales are impeded when consumers have difficulty acquiring information about non-digital product attributes. Firms therefore employ creative (and sometimes costly) methods such as two-way free shipping to help consumers resolve the problem of incomplete consumer knowledge on non-digital attributes. We argue that consumers and firms can benefit from social learning processes that occur "naturally" and emanate from neighborhood characteristics. We use trial data from Bonobos.com, a leading US online retailer for men's fashion apparel, to demonstrate that social learning occurs. We further show that geographic variation in "neighborhood social capital" moderates this process and explains geographic variation in online sales. We find that social learning reduces pre-trial consumer disutility by reducing bias in consumers' initial evaluation of non-digital attributes. The estimates imply that up to 50% of all trials in the first three and a half years of Bonobos' sales were influenced by social learning. In addition, social learning is more efficacious in neighborhoods with more social capital. Our estimates imply that a one-standard deviation reduction in the social capital stock of all zip codes would slow trials and reduce them by about 4%.

Key Words: Bayesian Learning; Non-digital Attributes; Poisson Model; Social Capital; Social Learning;

Online retailing is the fastest growing retail sector and in the first half of 2011 US Internet retailers recorded sales of over $90 billion (about 4.5% of total retail sales). The percentage increase (relative to the first half of 2010) is over 15%.[1] This pattern is evident in many other markets as well—*Forrester Research* forecasts a 10% compound annual growth rate for Asia-Pacific: "The fastest growth by far will occur in China, where online retail sales are expected to more than triple to $159.4 billion in 2015 from $48.8 billion this year (2010)." It is therefore important for researchers and managers alike to better understand the mechanisms underlying the sales evolution process for individual Internet retailers.

Many of the high growth areas for Internet retail in the US and elsewhere are in products that exhibit significant *non-digital* attributes as ecommerce evolves naturally from categories like books and music to those like fashion and apparel. The concepts of *digital* and *non-digital* attributes are discussed by Lal and Sarvary (1999) who define digital attributes as those that can be communicated through the Internet without any information loss; price, for example, is such an attribute as is the length of a book, or delivery time. Conversely, non-digital attributes are those that can be evaluated via physical inspection only and include things such as the look and fit of an apparel item. In offline retailing any incomplete consumer knowledge around digital or non-digital product attributes is resolved at the time of purchase. In Internet retailing pre-purchase evaluation of non-digital attributes is more difficult than it is in traditional retailing and potentially a key inhibitor of customer trial (Brynjolfsson, Hu, and Rahman 2009; Lal and Sarvary 1999). Degeratu, Rangaswamy, and Wu (2000) analyze grocery items and find that "sensory attributes", e.g., touch and feel

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[1] Estimated Quarterly U.S. Retail Sales: Total and E-commerce, U.S. Census Bureau News, Aug 2011. (http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf). Moreover, growth rates in other countries (e.g., China) are even higher.

elements of a product, have relatively less impact on online brand choices than on offline

brand choices whereas "non-sensory" attributes such as price have relatively more impact.[2]

In this paper we show not only that social learning helps resolve incomplete knowledge for

non-digital attributes, but also how the social capital infrastructure of a neighborhood, i.e., the

propensity of individuals to communicate with each other and to trust one another, moderates

the resolution of incomplete consumer knowledge on non-digital attributes and therefore

helps drive Internet retail sales.

In short, shopping online for products with non-digital attributes, e.g., apparel, adds a

layer of uncertainty compared to shopping offline for the same product (Akaah and

Korgaonkar 1988; Bhatnagar, Misra, and Rao 2000) as customers cannot fully assess the "fit

and feel" of the products they are buying.[3] Moreover, non-digital attributes are different from

experience attributes as the latter cannot be evaluated prior to purchase either offline or

online but only through purchase and repeated experience (Nelson 1974; Wright and Lynch

1995).[4] Table 1 illustrates examples of digital, non-digital, and experience attributes and

highlights the fact that *incomplete consumer knowledge for non-digital attributes* is a key

feature that distinguishes online shopping from offline shopping.

Internet retailers recognize that because consumers cannot be fully informed about non-

digital attributes prior to making a purchase, this may inhibit sales (this concern is paramount

for "pure play" online retailers with no offline stores—the fastest growing category of

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[2] Throughout the paper we use the term "non-digital attributes"; however the term "sensory attributes" as used by Degeratu, Rangaswamy, and Wu (2000) in the context of Internet retailing has the same meaning.
[3] Products with non-digital attributes, e.g., apparel, shoes, eyewear and so on comprise a significant total fraction of online retail sales.
[4] Uncertainty on experience attributes is product-inherent or category-inherent, so it *does not* vary between online and offline shopping environments. The efficacy of a drug, for example, is a product-inherent experience attribute, which can only be evaluated through purchase and repeated experience irrespective of whether the drug is purchased online or offline. Thus, incomplete knowledge for non-digital attributes is unique to online shopping and these attributes are distinct from experience attributes.

Internet retailers in 2011[5]). As such, these retailers employ a number of creative mechanisms to provide consumers with information. Bonobos.com (fashion clothing for men) and Zappos.com (shoes), for example, have "totally free" return policies and pay shipping in both directions. WarbyParker.com (fashion eyewear) has both an "online try-on" system where customers upload photos and try frames virtually and a "home try-on" option where customers receive five frames (without lens') to try at no cost. These tactics are firm-oriented and *firm-initiated*.

Our goal is to establish the theoretical and empirical basis for the importance of *customer-initiated* information transfer on non-digital attributes; specifically, social learning about non-digital attributes. If potential customers obtain information about non-digital attributes by interacting with (local) others who have purchased the product then social learning may play a role in the evolution of online retail sales. In addition, since recent studies establish that geographic variation in tax rates, access to local stores, shipping times and the like explain geographic variation in Internet sales (see, for example, Anderson et al 2010; Brynjolfsson, Hu, and Rahman 2009; Choi, Bell, and Lodish 2012; Forman, Ghose, and Goldfarb 2009; Goolsbee 2000), we are also interested in the moderating role of local social capital in local social learning. Social capital is defined as the ability of focal actors to secure benefits by virtue of social networks, trust, and norms in the community (Adler and Kwon 2002; Portes 2000; Putnam 1995; Woolcock 1998) and several studies find that social capital facilitates information transfer among community members (Allcott et al. 2007; Coleman 1990; Hansen 1998; Hansen, Podolny, and Pfeffer 1999; Kraatz 1998; Uzzi 1997). In sum, we hypothesize that: (1) social learning helps consumers resolve the problem of incomplete information on

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[5] http://www.internetretailer.com/2011/11/01/focused-success

non-digital attributes and increases their pre-trial expected utility for an Internet retailer, and (2) social capital moderates the social learning process by enhancing the efficiency of consumer learning for non-digital attributes such that geographic variation in neighborhood social capital stock explains geographic variation in Internet retail sales. Thus, we conjecture that community members and Internet retailers benefit from social learning and that the benefits are greatest in high social capital neighborhoods.

We test our hypotheses using data from Bonobos.com, a pure play fashion retailer that sells trendy men's apparel online and under its own brand (Figure 1 is a screenshot of the website)[6]. We build an individual-level Bayesian learning model and from there derive a neighborhood (zip-code)-level model of sales. Social learning occurs through information updates and is represented by a Bayesian learning process (Erdem and Keane 1996; Narayanan and Manchanda 2009; Narayanan, Manchanda, and Chintagunta 2005). We focus on *social learning for non-digital attributes* and not other social mechanisms such as awareness dispersion, normative pressure, status competition, and so on (see Van den Bulte and Lilien 2001). Our model offers three important benefits: (1) it studies social learning as a process separate from other mechanisms, (2) the efficiency of learning is summarized by signal variance only, and (3) casual impacts of social learning are established without recourse to "overfull" fixed effects on the spatio-temporal patterns (Narayanan and Nair 2012). Our dependent data are the number of new customer trials in each zip code in the United States in each month since the inception of Bonobos.com in October 2007, i.e., the data are not left-censored. Neighborhood social capital data are from the Social Capital Community Benchmark Survey (SCCBS) undertaken by the John F. Kennedy School of

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[6] Although Bonobos is a pure play Internet retailer, it does allow consumers to visit its Manhattan office for fittings. We do not use sales data from Manhattan in our analysis (see Research Setting, Data and Measures).

Government, Harvard University.

We make two new contributions to the literature on online retailing and the factors that underlie geographic variation in an Internet retailer's sales. First, we find evidence for social learning about non-digital attributes. This means that incomplete consumer knowledge regarding non-digital attributes can be partly resolved without the need for potentially costly firm-initiated efforts. For Bonobos.com, about 50% of all trials are partially attributable to social learning (especially, bias reduction) on non-digital attributes. Furthermore, a greater proportion of later trials (relative to earlier trials) are driven by better knowledge on non-digital attributes that is acquired through social learning. This is consistent with the idea that later trials are often stimulated by better product knowledge and this is acquired through interpersonal communication with earlier adopters (see Rogers 2003, p. 194; Ryan and Gross 1947). Second, we add to the body of evidence that social capital enhances information transfer and also show that beneficiaries from social capital are not simply community members, as the firm benefits as well. We find that social capital moderates the social learning process by improving efficiency. The moderating effect is roughly constant through time and a one standard deviation decrease in social capital would reduce trials by about 4%.

The remainder of the paper is organized as follows. The next section introduces key concepts and hypotheses. We then describe the research setting, data and measures. The empirical model and the corresponding findings are discussed next. We conclude the paper with a discussion of the implications of our findings for managers and for future research.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

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We begin by describing social learning, the necessary and sufficient conditions for it to occur, and then hypothesize that it will help explain variation in sales for a pure play Internet retailer (H_1). (The application context is consumer trials at Bonobos.com; we provide details in Research Setting, Data and Measures.) We next explain why neighborhood social capital moderates the extent of social learning that takes place in a location and why more social capital leads to a more efficient social learning process (H_2).

Social Learning for Non-Digital Attributes (H_1)

For some products online shopping involves incomplete consumer knowledge about non-digital attributes and this incomplete consumer knowledge is a natural barrier to (first) purchase. Not surprisingly, online retailers engage in a number of activities from free shipping to virtual try-on in an attempt to mitigate this factor—they understand sales will take off more quickly when consumers have an ability to learn about non-digital attributes prior to making a purchase. There are various ways that a consumer can learn about non-digital attributes and the approach depends on both the type of website deployed and also the product category. Some products sold online are also available offline so non-digital attributes can be fully evaluated through physical inspection in retail stores (e.g., many products sold on Amazon.com are also available at local stores so consumers can gather information on non-digital attributes through physical inspection).[7] Likewise, products at JCrew.com can be fully evaluated by visiting a JCrew store. Hence, these kinds of websites selling products that are also available in offline channels are not of interest here.

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[7] Unfortunately for many offline retailers they are essentially becoming "storefronts for Amazon". This factor is in part behind the bankruptcy of firms like Circuit City and the increasing pressure on once stellar performers like Best Buy. See, for example http://seekingalpha.com/article/310849-best-buy-s-eroding-competitive-advantages

Conversely, when consumers shop at "pure play" online retailers, it is impossible for them to physically inspect products before purchase. Although some of these retailers offer options such as "home try-on", direct product experience facilitated by firm-oriented sources is not always available. Furthermore, free "home try-on" may involve some psychological costs as potential customers may not want to be bothered by the process of home try-on (waiting for delivery, returning unsuitable products, etc.). Also, it goes without saying that firm-initiated attempts to help customers gather information on digital attributes are likely to be costly. Therefore, pure play Internet retailers can benefit where is a possibility that information on non-digital attributes will spread through buyer-oriented information sources.[8] We refer to this process of learning from the indirect experience of others as a *social learning process* (Bandura 1977).

Conceptually, this social learning process describes a context where a potential consumer with incomplete prior knowledge updates their beliefs with *signals* on non-digital attributes that are received from others. There are various types of signals on non-digital attributes (e.g. observing others' using the product, hearing about the purchase experience, reading reviews online, etc.), and all these signals may drive social learning by a focal customer. We confine our interest to signals that are most likely to significantly drive *local social learning* and therefore focus on signals satisfying three conditions. First, signals should be from sources that have complete information on non-digital attributes, i.e., the information should be based on actual prior purchases. Second, signals should emanate from visible real products. Since a signal provides information on non-digital attributes, any communication without the actual

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[8] Although this approach may not be as efficient as physical inspection by individual buyers (Marks and Kamins 1988; Smith and Swinyard 1988), it is nevertheless available to the firm "for free". In addition, since Internet retailers have enormous trading areas (e.g., the entire US), small sales improvements in individual locations resulting from information transmission among customers can, in aggregate, deliver significant economic benefits to the firm.

presence of the product does not significantly help potential consumers. In that sense, previous purchases made by customers who live a long distance from potential customers, i.e., those who live external to the local neighborhood, are not considered as sources of signals here. Third, signals should accompany feedback or communication (it is not enough for a potential customer to simply *observe* someone wearing Bonobos.com products). Without an interaction, a potential customer will be unable to recognize that the apparel comes from Bonobos.com. To summarize: even though one could consider other types of social learning in other contexts (e.g., online reviews), in our research only *previous purchases* made by *physically* and *relationally* close others constitute signals.[9]

As result, we conjecture that the sending of signals from physically and relationally close customers will help potential customers learn about non-digital attributes and update their beliefs accordingly.

H$_1$: Social learning helps resolve the problem of incomplete consumer knowledge on non-digital attributes and increases pre-trial expected utility. In the model, this is expressed through bias reduction (posterior mean) and uncertainty reduction (posterior variance).

Social Capital as a Moderator of Social Learning (H$_2$)

H$_1$ states that social learning improves the pre-trial expected utility of consumers and thereby spurs online retail purchases. If this is true, then it is interesting to also consider the

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[9] Thus, social learning as defined here is distinct from other social contagion mechanisms such as awareness dispersion, normative pressure, or status competition (Van den Bulte and Lilien 2001). Social learning is *contextual*—in the sense that operates for pure play retailers who do not make their products available offline. Note that we are not arguing that social learning is at work *only* when those three conditions are met. There could certainly be other ways for social learning to operate (e.g. reading online reviews, etc.); however, in this study, we are specifically interested in social learning from physically and relationally proximate others (controlling for other types of learning).

social means associated with information transition, i.e., the facilitators of the social process that allows information to flow from customers to potential customers. Here, we focus on *neighborhood social capital* as a moderator of social learning. As noted in the Introduction, social capital is created when focal actors secure benefits by virtue of social networks, trust, and other norms in the community (Adler and Kwon 2002; Putnam 1995). Numerous studies find that a higher level of social capital leads to more efficient information transfer (Allcott et al. 2007; Coleman 1990; Granovetter 1973; Hansen 1998, Hansen, Podolny, and Pfeffer 1999; Kraatz 1988; Reagans and McEvily 2003; Uzzi 1997).

Given prior findings, we hypothesize that social capital enhances social learning by affecting both the proportion of signals arising from previous purchases and their quality (e.g. richness, reliability, etc.). Nahapiet and Ghoshal (1998) discuss the three distinct dimensions of social capital—cognitive, relational, and structural—and we explain these in general terms and with respect to our study in Table 2. We cannot see the number of signals actually being sent in a local neighborhood; network structure, interaction occasion, and interaction content are of course unobserved. This is exactly the condition under which Internet retailers operate as well—they observe sales but they do not observe offline discussions about their products.[10] Proxy variables for social capital are described in Research Setting, Data and Measures and we anticipate that social capital moderates social learning as follows:

H$_2$: Social capital enhances social learning by positively influencing the proportion and quality of signals arising from previous purchases. Consequently, higher levels of social capital lead to a lower variance for the signal distribution and therefore a more efficient social learning process.

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[10] An important practical contribution of our work is to show how secondary data can be used to "proxy" for social capital in a neighborhood (see Research Setting, Data and Measures).

Summary

We test two hypotheses. First, that incomplete consumer knowledge on non-digital attributes prior to trying an online retailer is partially resolved through social learning from past local purchases made by others. Our model captures this phenomenon via a Bayesian learning process. The significance of social learning is assessed through a test of the significance of the entire Bayesian learning process (this involves the interplay of several model parameters). The process is deemed significant when there is significant utility gain from either bias reduction (favorable updates in the posterior mean) or uncertainty reduction (favorable updates in the posterior variance) through learning (H_1).

Second, that social capital enhances the likelihood that signals are both observed by potential customers and of high quality. In general, in a Bayesian learning framework the speed (efficiency) of learning is represented by signal variance. Thus, in our model, we expect that the signal variance decreases with social capital (H_2). In this sense, H_2 tests whether or not neighborhood social capital moderates the social learning process.

RESEARCH SETTING, DATA AND MEASURES

We first describe the research setting in generic terms. (While Bonobos.com data are used in the empirical application, our approach and findings are relevant to any pure play retailer meeting the five conditions outlined below.) Next, we describe the data from Bonobos.com and then conclude this section with a description of the measures used in the empirical model.

Research Setting

For us to investigate how information on non-digital attributes spreads through social learning and how local social capital moderates the social learning process, the data we use must satisfy the following five general conditions:

(1) *Appropriate Product Category.* First and foremost, the product category should have significant non-digital attributes (e.g., fit, feel, texture, etc.).

(2) *Incomplete Consumer Knowledge.* Second, potential consumers should have incomplete consumer knowledge about non-digital attributes *ex ante*. Post-trial, consumers have complete information on non-digital attributes; hence, we focus on trial behavior only.

(3) *No Offline Availability.* Third, products sold at the Internet retailer should not be available at offline stores (otherwise potential customers could obtain complete information on non-digital attributes by visiting stores).

(4) *Social Visibility*. Fourth, the product should be socially visible so that potential customers can assess non-digital attributes from others' purchases.

(5) *Experience Attributes*. Fifth, experience attributes should not be key attributes in the category. Experience attributes are those that, by definition, can only be evaluated through purchase and *repeated* experience (see Table 1). Unless this condition is met, it is hard to distinguish social learning on non-digital attributes from product-inherent uncertainty on the experience attributes.[11]

Bonobos.com manufactures and sells trendy men's apparel under their own brand online. The brand is relatively upscale in fit, style, and service, and targets 20-40 year-old working males. Bonobos has been quite successful since its launch in October 2007 as more than 40,000 people have tried Bonobos.com (sales reached about $15 million by March 2011).[12] Furthermore, data from Bonobos.com satisfy all five conditions. First, pants and apparel have significant non-digital attributes and since Bonobos.com targets trendy and stylish young males, non-digital attributes such as fit or texture are keys. Second, we have data on all first

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[11] For instance, for cosmetic products, "fit to one's skin", which can be evaluated only through repeated usage, is a key attribute. For these kinds of products it is hard to for a model to separate social learning on non-digital attributes from knowledge acquired through repeated experience.

[12] In December 2010 the firm secured an additional round of venture funding of $18 million for a post-money valuation of around $40 million (see www.techcrunch.com).

trials of Bonobos.com since the site was launched so we can focus on the trial decisions of consumers who have incomplete knowledge about non-digital attributes *ex ante*. Third, Bonobos.com is a pure play fashion retailer. Fourth, clothes are socially visible so information on non-digital attributes can spread when existing and potential customers communicate. Fifth, there is little uncertainty remaining about the clothes *after* customers try them on, i.e., when the first purchase arrives at the home.

For the purposes of exposition, Table 3 lists illustrative non-digital attributes for Bonobos.com products and describes how they could be incomplete knowledge about them could be resolved through social learning.

Data

Data for estimation are compiled from three sources. First, we have monthly observations on the number of trial and repeat transactions and new triers for all the zip codes in the entire US from October 2007 to March 2011. Since we observe the aggregate level diffusion pattern from its inception the data are not "left-censored". Second, we collected zip-level demographic information and information on the presence of local offline retailers (obtained from the 2010 ESRI Demographics and Business Data 2010[13]). Third, and critically for this study, we have information on zip-level local social capital from the Social Capital Community Benchmark Survey (SCCBS). Researcher 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." It was undertaken by the John F. Kennedy School of Government, Harvard University between July 2000 and

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[13] Refer to http://www.esri.com/data/esri_data/demographic-overview.html.

February 2001 and the data are widely used by social science researchers. Published articles

report effects of social capital on local behaviors such as home ownership (Hilber 2010),

labor force participation (Aguliera 2002), social vulnerability (Cutter, Boruff, and Shirley

2003), and public health outcomes (Harpham, Grant, and Thomas 2002; Subramanian, Kim,

and Kawachi 2002). To our knowledge, we are the first to introduce these data to the

marketing community.

Our analysis focuses on 495 zip codes where the SCBBS is conducted and *at least one*

consumer tried Bonobos.com within the 42-month period after the site was launched. Thus,

the data consist of 20,790 zip-month observations on the number of new customers.

Furthermore, the 495 zip codes span 23 different states and 201 different cities, i.e., the zip

codes used are not geographically condensed.[14]

Measures for Key Variables

Management provided information on both the number of new customers and the number

of total transactions within the zip code at each period (month) since the site opened in

October 2007. (The number of total transactions is the sum of trial and repeat transactions.)

Our dependent variable of interest is the number of new customers in a zip code each period,

i.e., an aggregate count of individual customer trials. As explained below, the lagged number

of total transactions works both as a source of signals on non-digital attributes as well as a

control for other social contagion mechanisms (as described previously) and spatio-temporal

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[14] 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 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).

patterns (discussed shortly).

Local social capital variable is the key independent variable and for the empirical analysis we construct a measure based on the relational and structural dimensions of social capital, i.e., two of the three dimensions of social capital that are described in Table 2 and also available in the SCCBS. These are: (1) trust among local neighbors (relational dimension), and (2) the frequency of interaction (structural dimension) between neighbors. The local trust and interaction scores are defined as the average of related survey questions from the SCCBS (we use questions such as "How much do you trust neighbors?" to construct the local trust score, and questions such as "How often do you interact with co-workers?" to construct the local interaction frequency score; see Appendix I).[15] Following past research, social capital is then operationalized as the average between local trust and interaction frequency scores, i.e., we place equal importance on trustworthiness and cohesiveness in defining social capital (Burt 1992; Hansen, Podolny, and Pfeffer 1999; Marsden and Campbell 1984).

Figures 2 and 3 provide a model-free view of the data and provide a sense of how trial behavior, the dependent behavior of our interest, works over time and varies over location. Figure 2 shows total number of new trials over the 495 zip codes in each of the 42 periods. The number of new trials increases over time ($p < .001$). This may imply that social learning is at work in the diffusion process and helping new customers to resolve their incomplete knowledge of non-digital attributes and thereby increasing the expected utility of trial of an online retailer (H_1). Figure 3 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 general, the number of new trials in zips with higher social

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[15] The full list of questions is given in Appendix I.

capital tends to be greater than the number of new trials in zips with lower social capital (p < .001). This may imply that social capital moderates the diffusion process and makes it more efficient (H_2).

Control Variables

Following prior research (e.g., Brynjolfsson, Hu, and Rahman 2009; Choi and Bell 2011; Forman, Ghose, and Goldfarb 2009), we include characteristics of zip codes and the aggregated individual demographics of zip residents to serve as controls. Zip-code variables are: Target Population (total number 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.

The following variables are aggregated from individual demographics of zip residents. They are: Total Spending (total annual offline retail spending on the men's clothing category in the zip code as estimated by ESRI), Average Income (average annual income among target population), Gini Coefficient, 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), and Race (the diversity measure defined by ESRI)[16]. We also aggregated individual-level information from the SCCBS to define the measure Internet Score. This variable proxies for the extent to which individuals in the focal zip code use the Internet and rely on online information. It is operationalized as the average of the zip-level average frequency of Internet

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[16] Refer to http://www.esri.com/library/whitepapers/pdfs/diversity-index-methodology.pdf.

usage and the zip-level average participation in online discussions as recorded in the SCCBS[17]. Table 4 provides descriptive statistics for our variables.

<div align="center">MODEL</div>

We begin by describing the fundamental modeling assumptions and the individual-level random utility specification for learning about non-digital attributes. Next, we describe deterministic utility and then specify the aggregate (zip-level) model that is actually estimated.

Fundamental Model Assumptions

Our Bayesian learning model rests on three standard but fundamental assumptions:

A1: Expected Utility Maximization. Consumers who have not previously tried make a discrete choice between trial and non-trial at each period so as to maximize expected utility. The *expected* utility maximization assumption stems from the uncertainty on non-digital attributes (uncertain beliefs on non-digital attributes are represented in the form of a distribution). Potential customers reduce their bias and uncertainty in regard to non-digital attributes through social learning from previous purchases in the local community. Therefore, utility based on incomplete knowledge is represented in the form of distribution *before* trial, so an observed trial decision is assumed to be made so as to maximize expected utility.

A2: Bayesian Learning. Social learning cannot fully resolve uncertainty concerning non-digital attributes (uncertainty is resolved on when the product is tried on). Thus, the update in beliefs from social learning is represented by an update in the distribution (updates operate through Bayes' Theorem). An uncertain belief on non-digital attributes is updated with observed signals from previous purchases in the local community. The updates make beliefs less biased and less uncertain so expected utility on non-digital attributes evolves through social learning (discussed in more detail shortly).

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[17] All the other ZIP-level demographic variables are constructed from ESRI survey.

A3: Utility Components. Total consumer utility consists of random utility on non-digital attributes (described in *A2*), deterministic utility, and an individual and time-specific random component. Deterministic utility (specified shortly) is the component of utility unrelated to the learning process on non-digital attributes. Individual and time-specific random errors are not observed by modelers, yet fully observed consumers, i.e., for consumers they are deterministic and fully considered when trial decisions are made.

Random Utility on Non-Digital Attributes and the Social Learning Process

Let $\tilde{Q}_{ijt}$ denote the belief on non-digital attributes of consumer *j* in ZIP *i* at time *t* who has yet to try Bonobos.com. All consumers begin with an initial prior belief (represented by a distribution) about the non-digital attributes such that:

$$\tilde{Q}_{ijt=1} \circ \tilde{Q}_0 \sim N(Q_0, 1),$$

(1)

where Q_0 denotes the mean of initial belief distribution (the variance of the initial belief is fixed to one for identification) and the initial belief is independent of local signals.

Following *A2*, updates of prior beliefs (i.e., social learning), operate through signals. Earlier we justified why only previous purchases made by physically and relationally close others constitute signals. Signals are operationalized via *A4-A8*:

A4: Source of Signals. Prior purchases in the local community are the only source of observable signals; signals at *t-1* update the prior and form the posterior belief at *t*.

A5: Signal Uncertainty. An observed signal involves uncertainty from a signal-recipient's point of view (this is represented via a distribution).

A6: Unbiased Signal. A (random) local signal is unbiased on average (consistent with the notion that non-digital attributes are fully evaluated consumers try the product on), i.e., all previous triers have unbiased evaluations. To reflect *A5* and *A6* potential signals are normally distributed around the true quality of non-digital attributes (*Q*), and dispersed with a variance of τ_i^2.

A7: Independent and Identically Distributed Signals. All local signals are mutually independent, and identically distributed.

A8: "Proportional Observability" of Signals. The number of observed signals is *proportional* to the number of transactions in the previous period (Narayanan and Manchanda 2009; Narayanan, Manchanda, and Chintagunta 2005). Local transactions do not work as signals in social learning unless they are *actually observed* so the number of local transactions is not the number of observed signals, but the number of *potential* signals. The number of observed signals is latent and assumed proportional to the number of potential signals. Since the proportion of observable signals (out of potential signals) is not separately identifiable from signal quality we set the number of observed signals equal to the number of transactions for identification. The variance of a potential signal (τ_i^2) therefore captures: (1) the proportion of observed signals, and (2) the quality of an observed signal.

The variance of a potential signal (τ_i^2) varies by zip code and in accordance with H_2 is a function of social capital. Following signal assumptions *A4-A8*, the kth potential single signal to consumer j in zip i at the end of *t-1* is:

$$S_{ijkt-1} \sim N(Q, t_i^2), \text{ where } \log(t_i) = a_0 + a_1 SC_i.$$

(2)

where Q is the true quality of non-digital attributes. Consumers in different zips have different τ_i^2 values depending on the extent of local zip social capital (SC_i) that is present in zip code i. Since all zip code-level variables are mean-centered $\log(\tau_i) = \alpha_0$ when $SC_i = 0$, i.e., when zip i has an average amount of social capital. The impact of social capital on local signals is captured by α_1. We hypothesize that social capital increases the efficiency of social learning by reducing signal variance (H_2); hence, we expect that $\alpha_1 < 0$. (Recall that H_1 concerns the entire Bayesian learning process and several parameters. We provide the final expression for the process in Equation 9 and explain the test for H_1 in Empirical Findings.)

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Following *A7*, we express the aggregate of all cumulative local signals to a consumer *j* in zip *i* until the end of period *t-1* (or at the beginning of *t*) as:

$$\bar{S}_{ijt-1} = \bar{S}_{it-1} = \frac{\sum_{k=1}^{N_{it-1}} S_{ijkt-1}}{N_{it-1}} \sim N\left(Q, \frac{t_i^2}{N_{it-1}}\right),$$

(3)

where $\bar{S}_{ijt-1}$ denotes an aggregate of all local signals to consumer *j* in zip *i* at the end of period *t-1*, and N_{it-1} denotes the lagged number of local transactions (or potential signals) in ZIP *i* at period *t-1*. The initial prior distribution and aggregate local signal distribution are normally distributed and given the self-conjugacy of the normal distribution, the posterior belief at any period *t* is also normally distributed:

$$\tilde{Q}_{ijt} \sim N(\bar{Q}_{ijt}, S_{ijt}^2).$$

(4)

The variance and mean of the posterior belief can be derived as follows:

$$\sigma_{ijt}^2 = \sigma_{it}^2 = \frac{1}{1 + \frac{\sum_{\ell=1}^{t-1} N_{i\ell}}{\tau_i^2}}, \text{ and } \bar{Q}_{ijt} = \bar{Q}_{it} = S_{it}^2 \times \left(\frac{\bar{Q}_{it-1}}{S_{it-1}^2} + \frac{N_{it-1} \times \bar{S}_{it-1}}{t_i^2}\right).$$

(5)

Let $\tilde{U}_{ijt}^N$ denote the random utility on non-digital attributes for consumer *j* in zip *i* at time *t*. $\tilde{U}_{ijt}^N$ is a quadratic function of the uncertain belief as this allows for a flexible specification with respect to risk (Erdem and Kean 1996; Narayanan, Manchanda, and Chintagunta 2005):

$$\tilde{U}_{it}^{n} = \tilde{Q}_{it} + r\tilde{Q}_{it}^{2},$$

(6)

where *r* denotes the risk aversion parameter.

Deterministic Utility and Means of Establishing Social Learning

Deterministic utility is unrelated to the social learning process on non-digital attributes. Given that we investigate the importance of social learning (H_1) and the moderating impact of social capital on social learning (H_2), the components of deterministic utility serve as controls. Since geographically proximate neighbors are the relevant reference group, i.e., the source of signals, failure to control for geographic heterogeneity could lead to spurious inferences about social learning (Narayanan and Nair 2012). For instance, perhaps consumers in cities with more opportunities for socializing prefer Bonobos.com. In such cases 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 past adoption on current behavior. Therefore, we include a rich set of observed heterogeneity controls for zip-level characteristics that may affect the likelihood of trial (see Table 4).

We control for unobservable zip-level heterogeneity with two-digit zip fixed effects and the lagged number of local transactions (N_{it-1}). In several previous studies (e.g., Choi, Hui, and Bell 2010; Manchanda, Xie, and Youn, 2008; McShane, Bradlow, and Berger, 2010; Nam, Manchanda, and Chintagunta, 2010), the lagged number of local transactions or a function thereof captures various forms of social influence. We are interested in a very specific form of social influence: Social learning as represented by a Bayesian learning

process. Hence, the lagged number of local transactions serves to control for the impact of unobserved heterogeneity or social influence through mechanisms other than social learning.

We also control for temporal effects unrelated to social learning. For instance, perhaps a global increase in the number of trials results from an increase in the general level of awareness. We use a flexible semi-parametric approach (41 period-specific dummies) to control for issues of this type (Iyengar, Van den Bulte, and Valente 2011; Narayanan and Nair 2012). Beyond this, we also allow the possibility that period effects unrelated to social learning are local. For example, a price promotion might stimulate trials more in zips with lower average incomes. We therefore include time since the first adoption in the zip and the lagged number of local transactions as spatio-temporal controls.

Let U_{ijt}^D denote the deterministic utility of consumer j in zip code i at period t:

$$U_{ijt}^D = U_{it}^D = bX_{it}$$

(7)

where X_{it} is a $(1 \times K)$ vector of all variables in Table 4, plus the spatial, temporal, and spatio-temporal controls just described.

Expected Utility Function

Following *A3* and collecting the three utility components together:

$$\tilde{U}_{ijt} = \tilde{U}_{ijt}^N + U_{ijt}^D + e_{ijt}, \text{ where } e_{ijt} \sim \text{i.i.d. Standard Gumbel Distribution.}$$

(8)

ε_{ijt} differs by consumer, zip, and period and although it is fully observed by a consumer,

$\tilde{U}_{ijt}$ is still random from a consumer's point of view because of the randomness of $\tilde{U}_{ijt}^{N}$.

Following *A1* consumers maximize expected utility μ_{ijt} when making trial decisions:

$$m_{ijt} = E\left(\tilde{U}_{ijt}\right) = E\left(\tilde{U}_{ijt}^{N}\right) + U_{ijt}^{D} + e_{ijt} = E\left(\tilde{Q}_{it}\right) + rE\left(\tilde{Q}_{it}^{2}\right) + U_{ijt}^{D} + e_{ijt} \qquad (9)$$

$$= \bar{Q}_{it} + r\bar{Q}_{it}^{2} + rS_{it}^{2} + U_{ijt}^{D} + e_{ijt}.$$

H$_1$ states that bias and uncertainty reduction with respect to incomplete knowledge on

non-digital attributes occurs through a social learning process and leads to a higher expected

pre-trial utility for an online retailer. The test of H$_1$ therefore involves $E\left(\tilde{U}_{ijt}^{N}\right)$ and details

are given in Empirical Findings.

Aggregate Model of Trial

From Equation (9) the probability that consumer *j* in zip *i* tries Bonobos.com at *t* is:

$$\text{Pr}_{ijt} = \frac{\exp(m_{ijt})}{1 + \exp(m_{ijt})}. \qquad (10)$$

Given Equation 10, Y_{it}, the number of trials in a zip code, i.e., the aggregate of individual

behavior, follows a binomial distribution. The likelihood of y_{it} new trials is:

$$\text{Pr}(Y_{it} = y_{it}) = \begin{pmatrix} M_{it} \\ y_{it} \end{pmatrix} \cdot \text{Pr}_{ijt}^{y_{it}}(1 - \text{Pr}_{ijt})^{y_{it}}, \qquad (11)$$

where M_{it} denotes the number of non-triers in zip code i at time t. The Poisson distribution is a special case of a Binomial distribution when the population size is large and the event probability is small (a Binomial distribution with parameters (n, p) can be expressed as a Poisson distribution with the parameter np). In our setting, the range of M_{it} is [1086, 13129] and the observed proportion of trials is low so we rewrite the likelihood of y_{it} new trials as (see also Choi, Hui and Bell 2010):

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it}) \times \lambda_{it}^{y_{it}}}{y_{it}!}, \text{ where } \lambda_{it} = M_{it} \times \frac{\exp(m_{ijt})}{1 + \exp(m_{ijt})}. \tag{12}$$

The Poisson model assumes that the variance is equal to the mean and if this is not the case estimates are consistent but the standard errors can be underestimated (Agresti 2002).[18] To estimate the model we simulate 50 draws for serially correlated non-digital attribute related signals as follows. First, we compute the entire belief vector on the quality of non-digital attributes for these for these draws. We then compute the individual likelihood for all 50 draws, perform Monte Carlo integration of the individual probabilities, and estimate the parameters by maximizing the integrated likelihood.

EMPIRICAL FINDINGS

We assess H_1 and H_2 with the empirical results in Table 5. We present evidence that social learning is at work (H_1) even in the presence of the rich set of controls described above and also find that social capital moderates the social learning process by making it more

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[18] We also fit the Negative Binomial Distribution (NBD) model as a robustness check and report the findings in Table 5. Although the NBD model is more flexible model than the Poisson model, the source of over-dispersion is not tightly linked to the model we developed in equations 1-11 so the Poisson serves as our main model. As shown in Table 5 the NBD and the Poisson give almost identical estimates.

efficient (H_2). We examine the statistical and economic significance of both hypotheses.

Statistical Significance of the Social Learning Process (H_1)

Statistical significance of the social learning process is established when consumers receive significantly better expected utility from trying the website as a result of social learning. In the Bayesian learning framework, social learning operates through updates on the mean and the variance. Updates on the mean adjust the prior expectation (Q_0) closer to the true value (Q), and updates on the variance (σ^2) reduce perceived uncertainty on the prior belief. Therefore, a necessary condition for statistical significance of social learning is either: (1) that the prior belief underestimates the true value, such that bias reduction increases the expected utility, i.e., $Q\text{-}Q_0 > 0$, or (2) that consumers are risk averse so uncertainty reduction increases the expected utility, i.e., $r < 0$. If neither condition is satisfied, it is not possible for social learning (through bias and uncertainty reduction) to significantly increase the expected utility.

Table 5 shows that the initial prior expectation significantly underestimates the true quality of non-digital attributes of an unfamiliar pure play online retailer ($Q\text{-}Q_0 = 1.49$, $p < .001$), so bias reduction leads to higher pre-trial expected utility. Consumers are not significantly better off with risk reduction as while the risk aversion parameter is negative, it is close to zero and not significant ($r = -.001$, $p = .217$). Risk neutrality has been observed in recent papers with Bayesian learning models (Narayanan, Manchanda, and Chintagunta 2005) and this finding is intuitive here. Men's clothing is not a risky category in the sense that a "bad" purchase decision could have a "fatal" consequence. Moreover, Bonobos.com offers free returns. In short, consumers benefit from an increase in pre-trial expected utility

for Bonobos.com as a result of social learning. The expected utility increase is derived especially from bias reduction and not *directly* from uncertainty reduction[19].

Given the importance of bias reduction, the overall significance of social learning is established when the either the "observability" and/or quality of signals (which drive social learning) is good enough to reduce bias. As shown in Equation 5, consumers will put little weight on information from (unbiased) local signals ($\bar{S}_{it-1}$) and will barely update when the quality of signal is not very good, i.e., τ_i^2 is very large. The estimated average signal variance τ_i^2 is around 11 times the initial prior variance so according to the expression for the posterior variance in Equation 5, $\tau_i^2 = \sum_{\ell=1}^{t-1} N_{i\ell}$, is required to reduce the initial uncertainty (variance) from the fixed value of one to one half.[20] In other words, an update with 11 signals will reduce uncertainty to one half of the initial uncertainty.

To provide further statistical evidence of signal efficiency, we quantify the marginal benefit from an additional signal given the number of signals already released under the average level of social capital, i.e., $\left(\dfrac{\partial E\left(\tilde{U}^n(N \mid SC = 0) \right)}{\partial N} \right)$. If $\dfrac{\P E\left(\tilde{U}^n(N \mid SC = 0) \right)}{\P N}$ is greater than zero for *N*, then consumers benefit from an additional local signal while there are already *N* local signals released. Given the randomness of released signals, there is no closed-

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[19] As shown in Equation 5, the posterior mean is a function of the posterior variance. So, even if the posterior variance does not *directly* affect expected utility due to risk neutrality, i.e., $r = 0$, the posterior variance affects the expected utility *indirectly* through the updates in posterior mean.

[20] According to Equation 5 the posterior variance is $\left(1 + \sum_{\ell=1}^{t-1} N_{i\ell} \Big/ \tau_i^2 \right)^{-1}$. 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 ($\sum_{\ell=1}^{t-1} N_{i\ell}$).

form expression for $E\left(\tilde{U}^n(N\mid SC=0)\right)$ so we use a simulation method to quantify the

marginal utility of an additional signal and test its significance (see Appendix II).

In Figure 4, the solid line denotes simulated $\dfrac{\P E\left(\tilde{U}^n(N\mid SC=0)\right)}{\P N}$, and dotted lines

denote the 95% bootstrap confidence interval of $\dfrac{\P E\left(\tilde{U}^n(N\mid SC=0)\right)}{\P N}$. The 95% bootstrap

confidence interval is always positive. This means that an additional signal increases

expected utility by, on average, reducing the bias in the evaluation of quality that is due to

incomplete knowledge of non-digital attributes..

Economic Significance of Social Learning

We quantify the economic value (EV) of social learning as the number of trials

attributable to social learning on non-digital attributes, i.e., the number of actual triers minus

the number who would have tried *without* the benefits of social learning. (In our model social

learning is the only source of signals on non-digital attributes so if there were no social

learning, the belief on non-digital attributes would remain constant from the initial period

onwards, i.e., there would be no updating).

To make this assessment, we fix all variables and parameters except for the belief

distribution on non-digital attributes (see Appendix II). In Figure 5 the solid line (left scale)

denotes estimated economic value of social learning and dotted line (right scale) denotes the

proportion of new trials driven by social learning. Time is on the *x*-axis. Figure 5 shows that a

number of trials are influenced by social learning on non-digital attributes; over 42 periods

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there are 5,745 new trials and in aggregate 2,781 (about 50% of them) are influenced by social learning on non-digital attributes. This finding highlights a common practitioner belief; namely, that incomplete knowledge on non-digital attributes, especially underestimation of product quality, is a major barrier for consumer trial. We demonstrate an important antidote: Local information transfer from customers to potential customers is effective in reducing the pre-trial bias of an underestimation of product quality due to incomplete knowledge.

Also notable is the fact that a greater proportion of later trials are affected by social learning[21]. Thus, a product with significant non-digital attributes can benefit from a "social multiplier" (e.g., Becker and Murphy 2000; Choi, Bell, and Lodish 2012) in the social learning process as each additional new customer becomes a potential source of signals for future customers. We find that just under 40% (60/160) of the trials in period 20 are influenced by social learning whereas more than 60% (163/258) in period 40 are influenced by social learning. Admittedly other factors such as marketing efforts or other types of social contagion (e.g. normative pressure, awareness dispersion, etc.) can also lead to temporal changes in the expected utility of trial, but this finding implies that the expected utility growth through social learning is faster than the utility growth through other mechanisms, at least for Bonobos.com. There is intuitive appeal to this finding: More of the later trials are driven by better knowledge of non-digital attributes and this knowledge is acquired through social learning. The finding is consistent with the notion that later trials are heavily affected by better product knowledge of later triers that is spread through interpersonal communication with earlier triers (see Rogers 2003, p. 194; Ryan and Gross 1947).

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[21] Our model has the desirable property that the component of utility driven by learning about non-digital attributes increases with signals, but at a diminishing rate. This means that the aggregate pattern of an overall increase in the total number of trials due to social learning is *not* driven by this property of the model. The overall pattern can be increasing, decreasing or constant, depending on temporal changes unrelated to the learning process.

Statistical Significance of Social Capital as a Moderator of Social Learning (H$_2$)

Table 5 shows that social capital significantly improves the quality of local signals

$(\dfrac{\P\ln(s_i)}{\P SC_i} = a_1 = -.198, p = .002)$. As the quality of signals improves, i.e., there is a reduction

in τ_i^2, consumers place more weight on unbiased local signals in the update process, so the

posterior expectation converges faster to the true quality of non-digital attributes. Thus, social

capital helps information transfer. The estimate of α_1 implies that the signal variance will be

brought down to about 60% of the original variance (for a 67% increase in precision) when

the level of social capital is increased by one standard deviation from the average. Previously

we noted that Equation 5 and the estimate of the signal variance τ_i^2 implied that about 11

signals were needed in the average community to reduce uncertainty to half of the initial

uncertainty. Again using Equation 5 and the estimated value of α_1, we see that in

communities that are one standard deviation above average in social capital only 7 signals are

required for a comparable reduction in uncertainty. Thus, we find support for H$_2$: Social

capital moderates the social learning process and makes it more efficient.

Economic Significance of Social Capital as a Moderator of Social Learning

To assess the economic value of social capital we investigate whether the impact of social

capital on utility is large enough to change consumer trial behavior. To do this, we define

economic value of social capital as the number of trials that *would not* have happened if the

level of social capital were lowered by one standard deviation in all zips. (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.)

The economic value of social capital is estimated via simulation (see Appendix II). In Figure 6 the solid line denotes the estimated economic value of social capital and the dotted line denotes the proportion of new trials that would not have happened under a lower level of social capital. Analysis of the quantitative effect reveals that a significant number of trials (250 out of 5,745 or about 4.3%) would not have occurred were the learning process less efficient due to a lower level of social capital. The proportion of trials affected by this change in the level of social capital is relatively consistent throughout the diffusion process: Just over 4.2% (7/160) of trials in period 20 would be affected and about 4.5% (12/258) of trials in period 40 would be affected. Recall the following two potentially offsetting effects discussed earlier: (1) more later trials than earlier trials are affected by social learning (which nests the effect of social capital) and (2) the marginal impact of a signal on the social learning decreases with number of signals (in intuitive terms, additional signals become less "valuable" even as more people spread them). So, even though a higher proportion of later trials are affected by social learning, the marginal impact of social capital on social learning decreases. It turns out that these two effects roughly offset each other, so the proportion of trials affected by the *level* of social capital remains flat throughout the sales evolution process.

Estimation Results of Control Variables

The model estimates for the effects of the control variables are not of interest per se, but they are nevertheless intuitive. For instance, demand for Bonobos.com is higher in areas with

greater population density. This could reflect greater use of the Internet (Katona, Zubcsek, and Sarvary 2011) or more offline word-of-mouth (Choi, Bell, and Lodish 2012). Demand at Bonobos.com and offline spending on men's apparel have a negative relationship. This is consistent with the finding that online and offline retailers compete against each other (Brynjolffson, Hu, and Rahman 2009). The estimated effect for the local Gini coefficient indicates that the demand for Bonobos.com is higher in areas with lower income inequality, consistent with idea that Bonobos.com customers are primarily "middle class".

DISCUSSION AND CONCLUSION

Internet retail is the fastest growing sector of the retail economy; however, the common problem of incomplete consumer knowledge for products that contain non-digital attributes remains a significant barrier to initial trial of pure play retailers. Not surprisingly, these firms actively search for creative ways to help consumers gather information on non-digital attributes. Most of the commonly used approaches (free shipping in both directions, home try-on, site enhancement, etc.) vary in their effectiveness and may involve significant costs. We suggest an option that is both an alternative and a complement—firms could benefit by relying on naturally occurring social processes to help consumers gather information about non-digital attributes. Specifically, we argue that information about non-digital attributes is transmitted through a social learning process (H_1) and that the efficacy of the social learning process is enhanced by local social capital (H_2).

Our focus on social learning and on neighborhood social capital is justified on theoretical, empirical, and practical grounds. First, a large body of theory in sociology and economics documents social learning and explains why social capital facilitates information transfer and

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learning. Second, numerous empirical studies (from diverse settings) find statistically and economically significant effects of social capital on economic decision-making. Third, Internet retailers, unlike their traditional counterparts, serve geographically disparate and diverse markets (e.g., potentially all residential zip codes in the US), that differ, *ex ante*, with regard to social capital.

Implications for Managers

Initially, potential consumers have a biased evaluation and lack complete knowledge about non-digital attributes of products sold at pure play Internet retailers and this translates into disutility of trying. Social learning acts as an antidote and helps potential customers mitigate this problem. The utility increase in the evaluation of non-digital attributes arising from social learning (especially, bias reduction) is large enough to change the trial behavior of potential customers (and the economic outcome for the firm). Our estimates imply that around one half of the trials occurring in the first three and a half years of operations at Bonobos.com are attributable to social learning (under the assumption that there is no other pre-purchase method available to customers acquire information on non-digital attributes). As time proceeds, the proportion of trials stimulated in part by social learning grows. Thus, it is clear that Internet retail managers should seek to leverage naturally occurring *customer-initiated* processes to reduce pre-trial quality bias. Managers can also expect that customers acquired can play an important role with those who come after them.

In addition, because the efficiency of the social learning process is determined by the observability and quality of signals, the process works better in neighborhoods with more social capital. Social capital turns out to have a significant impact: In our data a one standard

deviation reduction in the social capital stock of all zip codes reduces trial by about 4%. Of course Internet retail managers cannot do much to actively influence the stock of social capital in a neighborhood; nevertheless, they can seek to identify and then target neighborhoods with higher than typical levels of social capital. Our research implies that doing this could yield significant economic benefits—given that the (potential) trading area of an Internet retailer in the US is more than 30,000 residential zip codes.

Implications for Researchers

A number of recent papers demonstrate that for shoppers the "benefit of buying online" differs by location (e.g., Forman, Ghose, and Goldfarb 2009). The disparity between online and offline tax rates (Anderson et al 2010; Goolsbee 2000), access to local offline stores (Brynjolffson, Hu, and Rahman 2009) and "preference isolation" of target customers (Choi and Bell 2011) are among several important factors that explain geographic variation in the success of Internet retailers. To this list of important explanatory factors we add the stock of neighborhood social capital; hence, further research could establish the theoretical and empirical basis for additional geographic factors. Second, other articles examine mechanisms whereby actors become influential in the information dissemination process (e.g., Iyengar, Van den Bulte and Valente 2011). Since we document evidence for the social learning process, additional insights into the location of influential customers and the methods by which they convey information to others has enormous significance for Internet retailers. Third, it would be useful to compare the economic gain from creative but costly firm-driven efforts to provide information on non-digital attributes (e.g., home try-on, free shipping, pop-up stores, etc.), to that from consumer-driven information transfer (which occurs "free of charge").

Finally, all non-experimental analyses of "social contagion" are potentially subject to an identification problem that arises due to the challenge of separating correlations in observed behavior from true causal effects of one agent on another (Hartman et al. 2008). Past studies employing panel data typically use subject (or location) and time-specific fixed effects to control correlations in observed behaviors (Nair, Manchanda, and Bhatia 2010; Narayanan and Nair 2012). However, any such approach typically makes estimation more complex (especially for non-linear models). Since we are not interested in the significance of social influence in *general*, but in a specific mechanism of social influence—social learning—we can model it using a Bayesian learning approach. This allows us to rule out spurious social contagion and establish the significance of a specific phenomenon, the social learning mechanism, without including "overfull" fixed effects. Future studies might also seek to avoid overfull fixed effect controls in the same way and focus on other specific mechanisms of social contagion using accepted models (such as Bayesian learning).

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Table 1. Digital, Non-Digital, and Experience Attributes

	Digital Attributes	Non-Digital Attributes	Experience Attributes
Definition	Can be communicated through the Internet without any information loss	Can only be evaluated through physical inspection	Can only be evaluated through purchase and repeated experience
Examples	- Price of a product - Length of a book	- Fit of clothes - Taste of foods	- Efficacy of drugs - Performance of cosmetic products
Offline Shopping	Can evaluate pre-purchase	Can evaluate pre-purchase	Evaluate post-consumption
Online Shopping	Can evaluate pre-purchase	*Cannot* evaluate pre-purchase	Evaluate post-consumption

Table 2. Cognitive, Relational, and Structural Dimensions of Social Capital

Dimensions	Definition	Effect on Social Learning
Cognitive Dimension	Resources such as language and representation as they allow communication around shared experiences (e.g., Cicourel 1973).	Uzzi (1997) shows that shared experiences and representations help transfer subtle information on non-digital attributes of fashion products. *Hence, a stronger cognitive dimension will lead to higher quality signals.*
Relational Dimension	Social assets in a relationship such as trust and intimacy (Coleman 1988; Granovetter 1985; Putnam 1995).	Social cohesion arising from the relational dimension of social capital motivates actors to devote time and effort to communicating and should enable potential customers to get a better sense of non-digital attributes (Van Alstyne and Aral 2011). *Hence, a higher relational dimension will lead to higher quality signals.*
Structural Dimension	The pattern of connections and interactions between actors; this is represented by strength of ties, e.g., interaction frequency (Granovetter 1974) and network closure, e.g., network density (Coleman 1990).	Actors connected by stronger and denser networks are more likely to interact. *Hence, a higher structural dimension with make it more likely that signals are observed.*

Table 3. Illustrative Non-digital Attributes and Social Learning at Bonobos.com

Non-digital Attribute	Potential Customer Inability to Fully Assess Non-Digital Attributes	Social Learning as a Facilitator of Information Transfer
Fit	"Yes. It looks great on your website, but I am not a model. How will I look on me when I try it on?"	My neighbor's body proportions are similar to mine and he looks very cool. It will look nice to me too.
Size	"The size of 'waist 30' pants differs by brand. What's the exact size of waist 30 pants of Bonobos?"	My neighbor also wears waist 30, and it looks a bit small. I should try 31.
Color	"I want red pants, but not too gaudy. I cannot tell from the website …"	I can tell seeing these products and colors on my neighbors that the colors are stylish and not gaudy.
Style	"I want trendy 'boot-cut' pants but I can't tell how much they will flare out?"	After talking to my neighbor I can see that the style is just right.
Texture	"Every brand says "luxurious 100% wool" on the	After seeing the pants on some local friends I can tell

	website. I want to actually see and feel it."	that the texture is very high quality.

Table 4. Correlation Among Variables

	Mean	SD	New	Lag Trans	Period	SC	Pop	Dens	Local	Total Spend	Ave Income	Genie	Age25	Age40	Educ	Race
New Adopters	.28	.83														
Lagged Transactions	.62	1.94	.61													
Period	21.5	12.12	.17	.25												
Social Capital	0	1	.04	.05	0											
Target Population	5.30K	3.13K	.18	.18	0	.18										
Density	1.04K	1.56K	.24	.24	0	.28	.4									
Local Stores	541.87	412.54	.11	.12	0	.11	.4	.52								
Total Spending	5.14M	2.86M	.21	.21	0	-.18	.65	.26	.28							
Average Income	87.16K	37.50K	.21	.2	0	-.44	-.05	-.02	.01	.57						
Genie Coefficient	.62	.06	-.15	-.16	0	-.4	-.03	-.34	-.18	.17	.33					
Age25	.19	.06	.14	.16	0	.39	.24	.39	.16	-.09	-.4	-.44				
Age40	.3	.07	-.17	-.18	0	-.41	-.41	-.45	-.23	.03	.45	.39	-.87			
Education	.42	.17	.27	.26	0	-.28	-.13	.12	.02	.39	.69	-.01	.07	.08		
Race	51.91	22.18	.05	.05	0	.26	.5	.5	.41	.19	-.11	-.22	.32	-.44	-.23	
Internet	0	1	.1	.1	0	.07	.06	.11	-.01	.23	.19	0	.12	-.11	.29	.05

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

Table 5. Model Estimates

	Poisson Estimates	(SE)	NBD Estimates	(SE)
Parameters of the Social Learning Process				
Q_0, Initial Prior Mean of the Quality of Non-Digital Attributes	-12.454	(.149)**	-12.748	(.153)**
Q, True Quality of Non-Digital Attributes	-11.021	(.180)**	-11.210	(.182)**
r, Risk aversion	-.001	(.001)	.001	(.001)
α_0, log (Signal SD|SC=0)	1.207	(.090)**	1.174	(.097)**
α_1, $\P$ log (Signal SD|SC)/$\P$ SC	-.198	(.063)**	-.201	(.064)**
Control Variables				
Lagged Transactions (N_{it-1})	.052	(.030)	.059	(.032)
Social Capital (SC_i)	.040	(.110)	.035	(.112)
Target Population Density	.158	(.040)**	.158	(.041)**
Local Offline Stores in Three-Digits Zip	.051	(.031)	.050	(.031)
Offline Spending on the Men's Clothing Category	-.433	(.051)**	-.442	(.053)**
Average Income	.373	(.058)**	.386	(.058)**
Gini Coefficient	-.331	(.028)**	-.330	(.028)**
Education	.535	(.051)**	.526	(.051)**
Shape Parameter (NBD)			12.570	(3.393)**
LL	9,870.5		9,861.4	
BIC	20,665.6		20,657.5	

Notes: * indicates that $p \le .05$ and ** indicates that $p \le .01$. The models include 41 period fixed effects and 29 two-digit zip fixed effects and all variables listed in Table 4. Estimates for the dummies and non-central control variables are not reported for ease of exposition but are available upon request.

Figure 1. A Screenshot of Bonobos.com

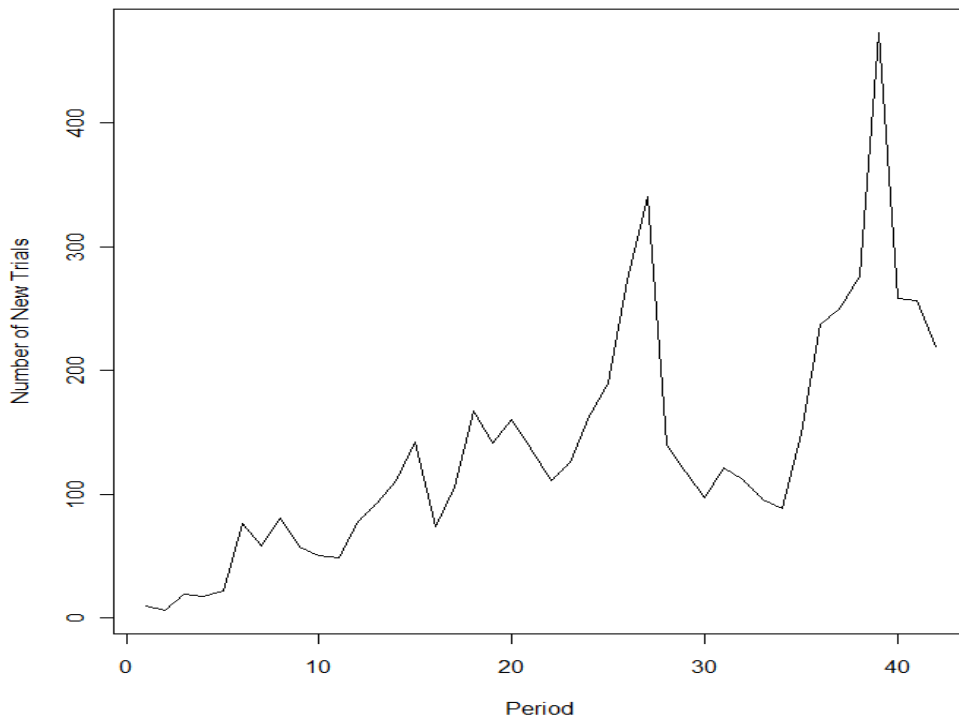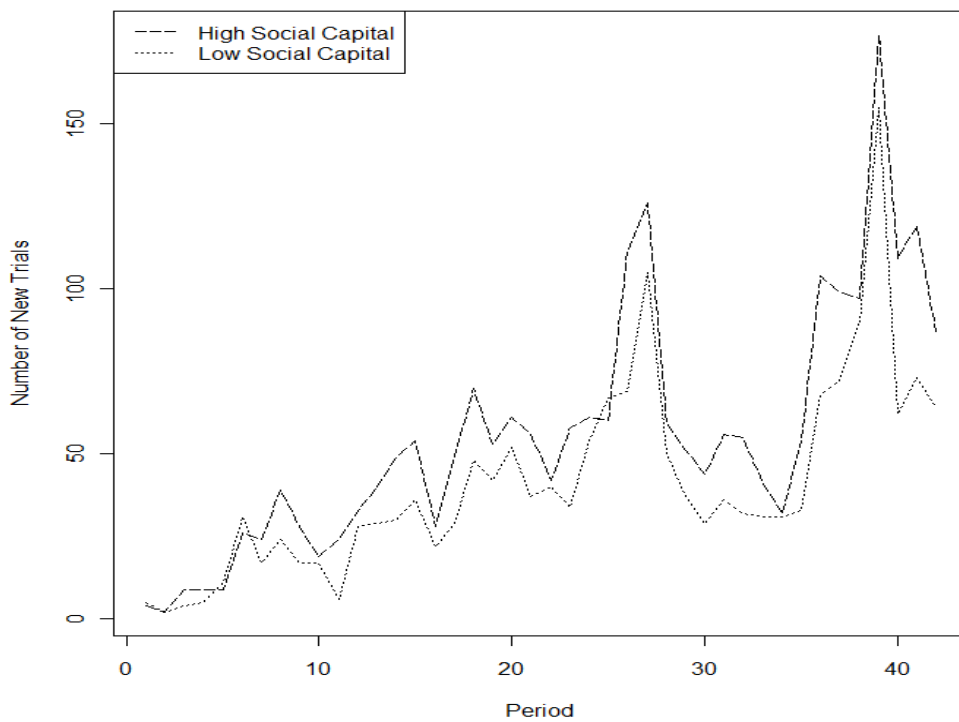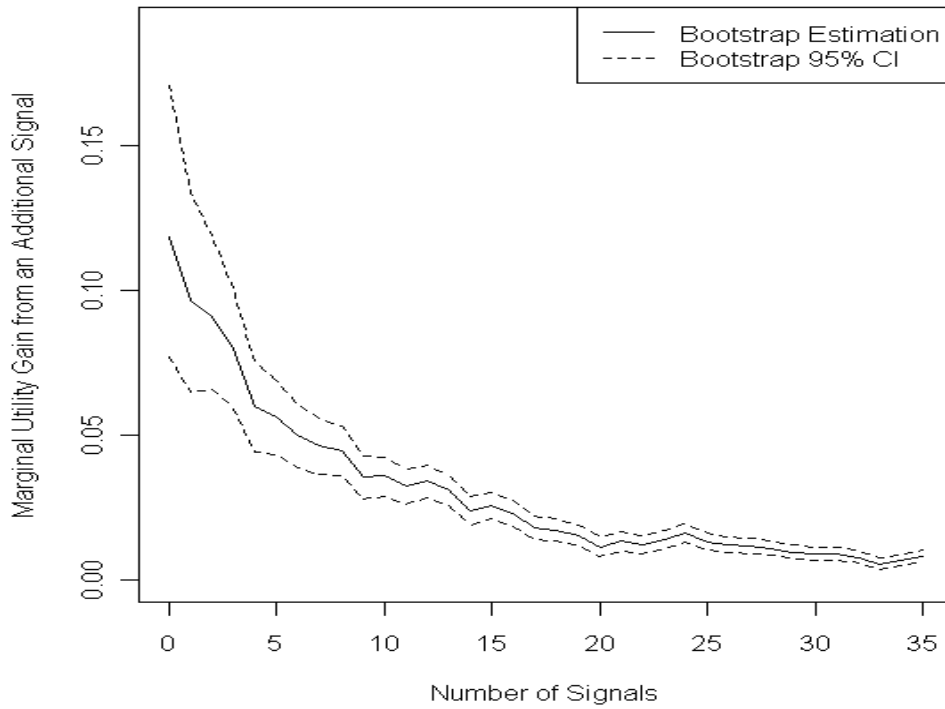Figure 2. Number of New Trials Each Month at Bonobos.com

Figure 3. Number of New Trials in Low and High Social Capital Zip Codes

Note: The peaks at month 27 and 39 are the number of new triers in December of 2009 and 2010, respectively.

Figure 4. Marginal Utility Increase with an Additional Signal

Notes: We are interested in whether an additional signal increases consumer utility given the cumulative number of local signals released ($\sum_{\ell=1}^{t-1} N_{i\ell}$). Our model has the desirable property that the component of utility driven by learning about non-digital attributes increases with signals, but at a diminishing rate. It is natural to assume that as a potential customer encounters more existing customers there will be some degree of "overlap" in each new piece of information about Bonobos' products. Therefore, the observed pattern of a diminishing marginal return to signals (*N*) is a part of the modeling assumption in a Bayesian learning model. The range of the cumulative number of signals over all 21,588 observations (514 zips * 42 periods) is [0,525]. In this plot, the range of *x*-axis is [0,35] for better visualization. The result in the [36,525] range is also consistent with what is shown here—a diminishing but significantly positive marginal gain.

Figure 5. Economic Value of Social Learning Expressed as Number of New Trials Affected and Proportion of Total Trials Affected
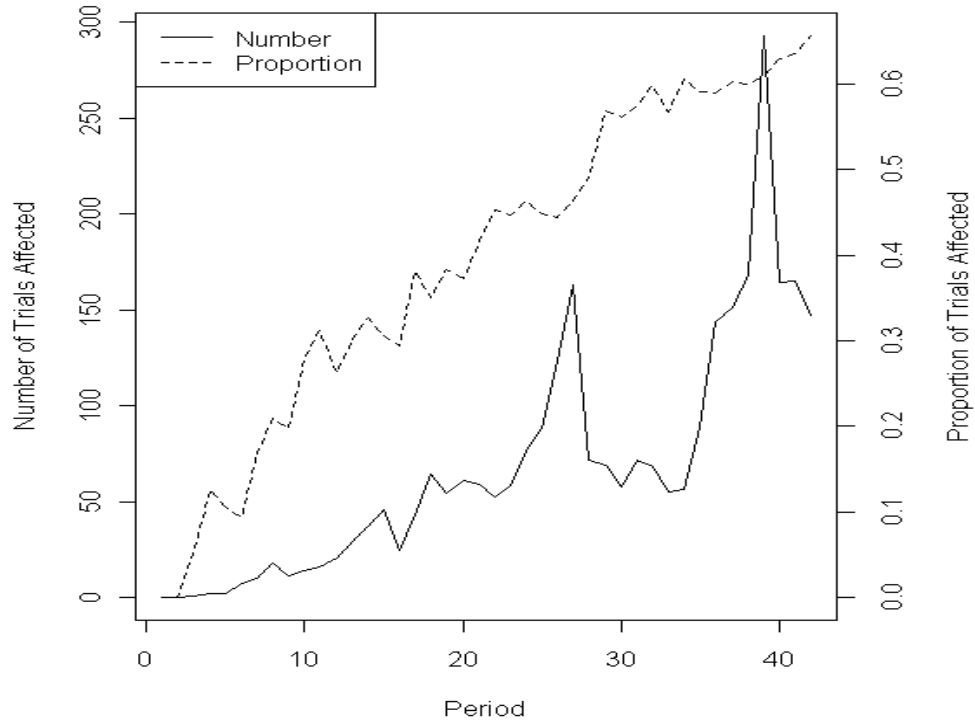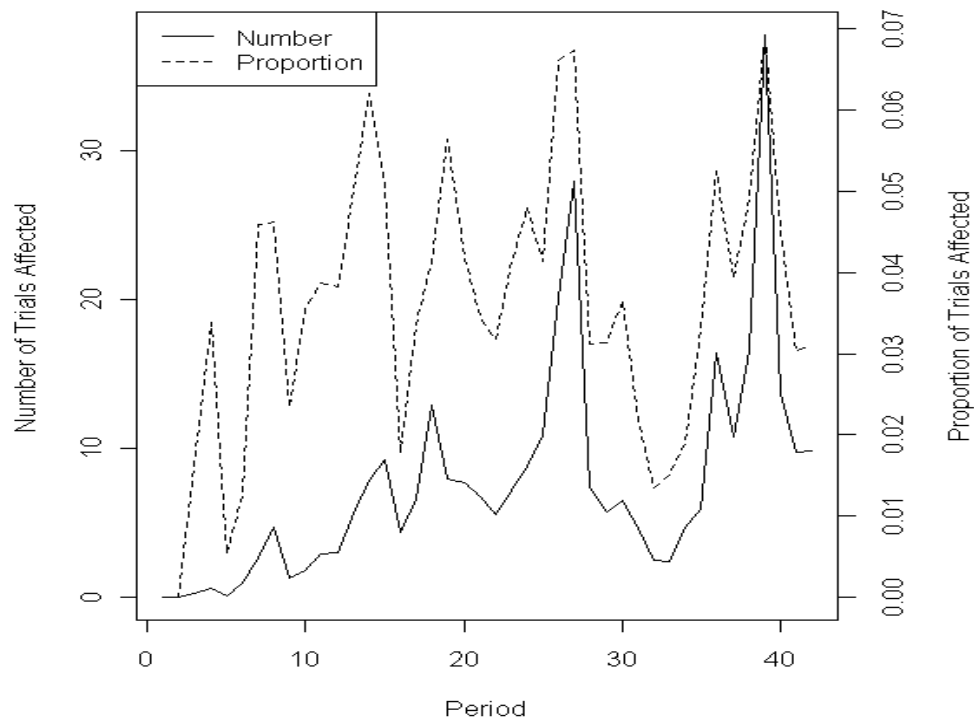
Figure 6. Economic Value of Social Capital Expressed as Number of New Trials Affected and Proportion of Total Trials Affected

APPENDICES

Appendix I: SCCBS Survey Questions

The following survey questions are used to construct the local social trust score.
- How much can you trust neighbors?
- How much can you trust co-workers?
    0. Trust not at all.
    1. Trust only a little.
    2. Trust some.
    3. Trust a lot.

The following are survey questions to construct local interaction frequency score.
- How often do you interact with your neighbor within last twelve months?
- How often do you have friends over to your home within last twelve months?
- How often do you hang out with friends in a public place within last twelve months?
- How often do you socialize with co-workers outside of work within last twelve months?
- How often play cards or board games with others 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

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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.

Appendix II: Simulation Algorithms

Simulation Algorithm for Figure 4

(1) Bootstrap iteration
   - Sample 36×100 random seeds of signals from i.i.d standard normal distribution (denote the matrix by S_0). Random seeds will be fixed throughout the iteration to rule out any randomness from signal sampling.
   - In every b^{th} iteration (where $b = 1 \ldots 2000$), repeat Step 2 to 4.

(2) Randomly sample parameters associated with learning $q^b(0) = \begin{bmatrix} Q_0^b & Q^b & r^b & t^b(0) \end{bmatrix}$ from the estimated multivariate normal sampling distribution.

   - In this simulation, $t^b(0)$ denotes signal variance when social capital is 0.

   - Construct random signal matrix as $S_0^b = Q^b + t^b(0)S_0$.

(3) Compute $E(\tilde{U}^n(N \mid q^b(0)))$, where $N = 0 \ldots 36$.

   - Compute $E(\tilde{U}^n(N \mid q^b(0), S_0^b(s)))$, where s denotes each column of S_0^b ($s = 1 \ldots 100$).

   - $E(\tilde{U}^n(N \mid q^b(0)))$ is the integration of $E(\tilde{U}^n(N \mid q^b(0), S_0^b(s)))$ over 100 columns of s. In other words, $E(\tilde{U}^n(N \mid q^b(0)))$ is a (1+N) vector of expected utility.

(4) Compute $\dfrac{\P E(\tilde{U}^n(N \mid q^b(0)))}{\P N}$, where N = 0 … 35.

   - $\dfrac{\P E(\tilde{U}^n(N \mid q^b(0)))}{\P N} = E(\tilde{U}^n(N + 1 \mid q^b(0))) - E(\tilde{U}^n(N \mid q^b(0)))$

(5) Bootstrap Estimation of $\dfrac{\P E(\tilde{U}^n(N \mid SC = 0))}{\P N}$.

   - Sample median of $\dfrac{\P E(\tilde{U}^n(N \mid q^b(0)))}{\P N}$ is a bootstrap estimate of $\dfrac{\P E(\tilde{U}^n(N \mid SC = 0))}{\P N}$.

   - 95% CI of $\dfrac{\P E(\tilde{U}^n(N \mid SC = 0))}{\P N}$ corresponds to $(2.5\%, 97.5\%)$ quantiles of $\dfrac{\P E(\tilde{U}^n(N \mid q^b(0)))}{\P N}$ samples.

Simulation Algorithm for Figure 5

(1) Bootstrap iteration
   - Sample 100 sets of random seeds of signal for each zip-period (*it*). In other words, sample $20,790 \times 100$ random seeds of signals from i.i.d standard normal distribution (we denote the matrix by S_0). Random seeds will be fixed throughout the iteration to rule out any randomness from signal sampling.

- In every b^{th} iteration (where $b = 1 \ldots 2000$), repeat Step 2 to 4.

(2) Randomly sample model parameters q^b from the estimated multivariate normal sampling distribution.

    - In this simulation, t^b denotes signal variance when social capital is as observed.

    - Construct random signal matrix as $S^b = Q^b + t^b S_0$.

(3) Compute m^b_{0it}. Also, compute $m^{b(s)}_{it}$ for each draw of sample signal, s ($s = 1 \ldots 100$).

    - We fix all the variables as observed. Suppose there are ten potential consumers and three of them adopted at the first period. Thus, there are three sources of signals and seven in the risk set at the second period. In the simulation, even if we sample only one trial at the first period, the number of sources remains three, and there remain seven consumers in the risk set. That is, we do not explicitly consider the dynamic impact of trials.

    - $m^b_{0it} = (Q_0 + r(Q_0^2 + 1) + U^d_{it} \,|\, q^b)$. Notice that the utility is independent of signals when there is *no learning*.

    - $m^{b(s)}_{it} = (\bar{Q}_{it} + r\bar{Q}_{it}^2 + rS_{it}^2 + U^d_{it} \,|\, q^b, S^b(s))$

(4) Compute y^b_{0it}.

    - We rule out the randomness from Poisson sampling by using CDF (F) and inverse CDF (F^{-1}).

    - Given the discreteness of Poisson distribution, $F^{-1}(F(y_{it}|m^{b(s)}_{it})|m^{b(s)}_{it}) \neq y_{it}$. Instead we use the property that $F^{-1}\left(\dfrac{F(y_{it}-1|m^{b(s)}_{it}) + F(y_{it}|m^{b(s)}_{it})}{2} \,\Big|\, m^{b(s)}_{it} \right) = y_{it}$.

    - Similarly, the number of purchases that would have happened ($w^{b(s)}_{it}$) under m^b_{0it} can be expressed as $F^{-1}\left(\dfrac{F(y_{it}-1|m^{b(s)}_{it}) + F(y_{it}|m^{b(s)}_{it})}{2} \,\Big|\, m^b_{0it} \right) = w^{b(s)}_{it}$.

    - By integrating $w^{b(s)}_{it}$ over all 100 samples, we get w^b_{it}.

 (5) Bootstrap Estimation of w_{it} (The number of trials that would have happened even when there is no social learning).

    - Sample median of w^b_{it} over b is a bootstrap estimate of w_{it}.

Simulation Algorithm for Figure 6

(1) Bootstrap iteration

    - Sample 100 sets of random seeds of signal for each zip-period (*it*). In other words, sample $20{,}790 \times 100$ random seeds of signals from i.i.d standard normal distribution (We denote the matrix by S_0). Random seeds will be fixed throughout the iteration to rule out any randomness from signal sampling.

    - In every b^{th} iteration (where $b = 1 \ldots 2000$), repeat Step 2 to 4.

(2) Randomly sample model parameters q^b from the estimated multivariate normal sampling distribution.

    - In this simulation, t^b denotes signal variance when social capital is as observed. In contrast, t^{b1} denotes signal variance when social capital is lowered by one standard deviation.

    - Construct random signal matrix for original SC as $S^b = Q^b + t^b S_0$.

    - Construct random signal matrix for SC-1 as $S^{b1} = Q^{b1} + t^{b1} S_0$

(3) Compute $m_{1it}^{b(s)}$. Also, compute $m_{it}^{b(s)}$ for each draw of sample signal, s (s = 1 … 100).

  - We fix all the variables as observed. Suppose there are ten potential consumers and three of them adopted at the first period. Thus, there are three sources of signals and seven in the risk set at the second period. In the simulation, even if we sample only one trial at the first period, the number of sources remains three, and there remain seven consumers in the risk set. That is, we do not explicitly consider the dynamic impact of trials.

  - $m_{it}^{b(s)} = (\bar{Q}_{it} + r\bar{Q}_{it}^2 + rS_{it}^2 + U_{it}^d \mid q^b, S^b(s))$

  - $m_{it}^{b1(s)} = (\bar{Q}_{it} + r\bar{Q}_{it}^2 + rS_{it}^2 + U_{it}^d \mid q^{b1}, S^{b1}(s))$.

(4) Compute y_{0it}^b.

  - We rule out the randomness from Poisson sampling by using CDF (F) and inverse CDF (F^{-1}).

  - Given the discreteness of Poisson distribution, $F^{-1}(F(y_{it} \mid m_{it}^{b(s)}) \mid m_{it}^{b(s)}) \ne y_{it}$. Instead we use the

property that $F^{-1}\left(\dfrac{F(y_{it}-1 \mid m_{it}^{b(s)}) + F(y_{it} \mid m_{it}^{b(s)})}{2} \mid m_{it}^{b(s)} \right) = y_{it}$.

  - Similarly, the number of purchases that would have happened ($z_{it}^{b(s)}$) under $m_{it}^{b1(s)}$ can be

expressed as $F^{-1}\left(\dfrac{F(y_{it}-1 \mid m_{it}^{b(s)}) + F(y_{it} \mid m_{it}^{b(s)})}{2} \mid m_{it}^{b1(s)} \right) = z_{it}^{b(s)}$.

  - By integrating $z_{it}^{b(s)}$ over all 100 samples, we get z_{it}^b.

(5) Bootstrap Estimation of z_{it} (The number of trials that would have happened even when social capital is lowered by one standard deviation).

- Sample median of z_{it}^b over b is a bootstrap estimate of z_{it}.