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Online Social Interactions:

A Natural Experiment on Word of Mouth versus Observational Learning

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ABSTRACT

Consumers' purchase decisions can be influenced by others' opinions, i.e., word-of-mouth (WOM), and/or others' actions, i.e., observational learning. While information technologies are creating increasing opportunities for firms to facilitate/manage these two types of social interaction, researchers so far have encountered difficulty in disentangling their competing effects and have provided limited insights into how these two social influences may differ from and interact with each other.

Based on a unique natural experimental setting resulting from information policy shifts at the online seller Amazon.com, we design three longitudinal, quasi-experimental field studies to examine three issues regarding the two types of social interaction: (1) their differential impact on product sales, (2) their lifetime effects, and (3) their interaction effects. An intriguing finding is that, while negative WOM is more influential than positive WOM, positive observational learning information significantly increases sales but negative observational learning information has no effect. This suggests that reporting consumer purchase statistics can help mass-market products without hurting niche products. Our results also reveal that the sales impact of observational learning increases with WOM volume.

Keywords: Social Interactions, Social Influences, Observational Learning, Word of Mouth, Natural Experiment

Consumers tend to be influenced by their social interactions with others when they make purchase decisions (Godes et al. 2005). They can learn from and be affected by other consumers' opinions and/or others' actual purchase decisions. For instance, when choosing between two restaurants, an individual may be heavily influenced by the opinions and experiences of her friends, or by simply observing how many diners are already in each restaurant even without knowing their identities and reasons for choosing the restaurant (Becker 1991). The former type of opinion- or preference-based social interaction is defined as *word-of-mouth* (WOM) in the marketing literature (e.g., Arndt 1967). The latter type of action- or behavior-based social interaction is defined as *observational learning* in the psychology and economics literature (Bandura 1977, Bikhchandani, Hirshleifer, and Welch 1998, 2005).

While such social channels have influenced consumers since the advent of trade, recent advances in technology have significantly increased the importance of consumer social interactions as a market force. Not only are consumers now better able than ever to exchange information via online forums, chat rooms, and blogs, but firms are gaining increasing capacity to directly initiate and manage consumer social interactions (Godes et al. 2005), tasks either impossible or too costly in the past. For example, the Internet, e-commerce, and information technology have created opportunities for a firm to effectively facilitate WOM communication by allowing buyers to post consumer reviews based on their personal experiences on its website or by licensing consumer reviews from third-party sites, such as Epinions.com (Chen and Xie 2008). New technology has also created opportunities for a firm to directly facilitate consumer observational learning by reporting past buyers' purchase actions on its website. For example, on each product's homepage, Amazon.com provides observational learning information under the section "What do customers ultimately buy after viewing this item?" .[1] Thus, online consumer

[1] For example, on the page of the digital camera HP Photosmart R707 on September 21, 2005, the observational learning section lists how many consumers purchased this and two other cameras in decreasing order of the purchase

social interactions, which are often initiated or facilitated by firms, are playing increasingly significant roles in consumer purchase decisions. One recent survey reported by the *Wall Street Journal* finds that 71 percent of U.S. adults who purchase online use consumer product reviews for their purchases, and 42 percent of them trust such a source (Spors 2006).

While advances in technology are creating new opportunities for firms to directly facilitate and manage consumer social interactions, they also impose new challenges because separate strategic actions are often required to manage WOM and observational learning. For example, an online seller manages WOM by its policies on *consumer-generated product reviews*, but manages observational learning via its policies on *firm-reported consumer actions* based on the firm's sales data. The seller can choose to facilitate either WOM or observational learning exclusively or both simultaneously. Clearly, a good understanding of the *competing* impacts of *each* type of social interaction *over product lifetime* as well as their potential *joint* impact is essential for developing the firm's strategy for effectively managing consumer social interactions in today's market environment.

We study social interactions following the definition and framework proposed in Godes et al. (2005), and focus on two common types, WOM and observational learning.[2] We first develop theoretical propositions concerning three essential issues regarding the impacts of these two types of social interaction: (1) Whether and how WOM and observational learning create different effects, (2) how these effects vary over product lifetime, and (3) how WOM and observational learning interact with each other to influence sales.

statistics: "36% buy this item (HP Photosmart R707)," "13% buy HP Photosmart M407," and "9% buy HP Photosmart R607." Traditional sellers such as restaurants and booksellers can also provide previous purchase information (Cai, Chen and Fang 2008, Miller 2000). However, information technology makes this decision much easier and more cost-efficient for the seller.

[2] Social interactions are broadly defined as any actions by a non-selling party impacting other consumers' valuations for the product or service (Godes et al. 2005). This treatment of social interactions is more in line with the economics literature (Scheinkman 2007) than the sociology and psychology literature (e.g., Bagozzi, Dholakia and Pearo 2007, Cialdini and Trost 1998, DeLamater 2004). Some other names used in the literature include social contagion (e.g., Van den Bulte and Lilien 2001), social capital (e.g., Mouw 2006), social learning (e.g., Bandura 1977), social communication (Guo, Zhao and Zhao 2007), and peer recommendation (Zhao and Xie 2010).

We then address these issues using a unique dataset collected from Amazon.com. During a period between 2005 and 2007, Amazon.com first removed and then reintroduced the section of observational learning information in the digital camera category. These observational learning policy shifts provide a unique natural experimental setting to test our theoretical propositions. Based on this unique setting, we design three longitudinal, quasi-experimental field studies that include the combination of both treatment-removal and treatment-reintroduction studies. This combination design allows us to separate the two types of social interaction, and examine how their sales impacts are different from and interact with each other. Furthermore, our design includes not only the same product sample over product lifetime (within-subjects) but also two independent samples with significantly different product ages (between subjects). This allows investigation of the lifetime effects of WOM and observational learning with a high validity.

Our longitudinal studies lead to several interesting results. First, our data reveal that WOM and observational learning differ in their impacts on sales. Specifically, negative WOM information has a bigger impact on product sales than positive WOM information. However, the opposite holds for observational learning. These findings underscore the importance of separating the effects of the two types of social interaction. The asymmetric effect of observational learning can be encouraging for online infomediaries between buyers and sellers. Notice that the popular (niche) products tend to attract more (fewer) purchases and thus have a positive (negative) observational learning signal. This result suggests that offering information about existing buyers' purchase actions can help consumers as well as sellers of popular products without necessarily harming the sellers of niche products. Second, although one may expect that the purchase decisions of less sophisticated consumers, who often arrive later in the product life cycle, would be more likely to be affected by existing buyers' opinions or actions, our data reveal that the impacts of both types of social interaction diminish over product lifetime. Third, our data show that interaction effects exist between the two types of social influences. We find a significant complementary effect between the sales impact of observational learning and WOM *volume* (i.e., the positive impact of the purchase action by the existing buyers becomes stronger when the number of WOM postings is higher). However, no significant interaction between observational learning and WOM *valence* is detected (i.e., we find no clear evidence that the impact of others' purchase actions will increase or decrease when consumer *ratings* increase).

The rest of this paper is organized as follows. We first present the theoretical background and conceptual development in the next section. Then we describe the design of the empirical study and the data, and present the analysis and results of our quasi-experimental studies. Finally, we discuss the managerial and theoretical implications of the key findings.

THEORETICAL BACKGROUND AND CONCEPTUAL DEVELOPMENT

We start by defining the concepts of WOM and observational learning studied in this paper. Then we discuss why WOM and observational learning might produce different effects, how they may influence sales over a product's lifetime, and how these two types of information might interact with each other.

WOM versus Observational Learning

The first form of social interaction, WOM, is a well established construct in the marketing literature (Arndt 1967). In general, WOM refers to the dissemination of information (e.g., opinions and recommendations) via communication among individuals. The two most important WOM attributes studied in the literature are *valence* (i.e., whether the opinions from WOM are positive or negative) (e.g., Herr, Kardes, and Kim 1991) and *volume* (i.e., the amount of WOM information) (e.g., Anderson 1998, Bowman and Narayandas 2001). WOM valence can influence product sales by changing consumer valuation of the products (e.g., Mizerski 1982, Chevalier and Mayzlin 2006), and WOM volume plays an informative role by increasing the degree of consumer awareness and the number of informed consumers in the market (Liu 2006).

The second form of social interaction examined in this paper, observational learning, however, is less explored in the marketing literature. The concept of observational learning can be traced back to social learning studies in psychology (Bandura 1977). How observational learning influences an individual purchase decision is largely centered on the information cascade theory in the economics literature (Bikhchandani, Hirshleifer, and Welch 1992). According to this theory, observational learning information contains the discrete signals expressed by the actions of other consumers, but not the reasons behind their actions. With limited information available, when people observe the purchase actions of all previous individuals, this publicly observed information outweighs their own private information in shaping their beliefs. Eventually, an information cascade can occur, such that all subsequent observers will hold similar beliefs. As a result, people follow their predecessors' actions and become engaged in a type of "herd behavior" (Banerjee 1992).

Bikhchandani, Hirshleifer, and Welch (1992) illustrate the basic concept of observational learning with a model of consumer product adoption decision making, in which a consumer adopts (rejects) a product if she believes that the quality of the product is high (low). For simplicity, consider a case with three consumers. This model shows that the third consumer will adopt (reject) the product if she observes that both previous consumers adopt (reject) the product, regardless of her private information. She will rely on her own information only when one consumer adopts and another rejects. Whether an individual will follow previous choices largely depends on the percentage share of previous choices (Bikhchandani, Hirshleifer, and Welch 1998, p.156). This simple case helps to understand the concept of observational learning valence. The valence of observational learning is determined by the percentages of adoptions or the share of choices among all previous actions. Conceptually, the observational learning signal is more positive (negative) if the percentage of cumulative purchases among the choices made by all previous informed consumers is larger (smaller). The information cascade theory generally conjectures that the positive and negative observational learning signals both affect adoption behavior but in opposite directions, i.e., the former motivates but the latter discourages adoption. While observational learning *volume* is not a formally defined concept in the literature, we consider it intuitively as the total number of actions by existing consumers, which is essentially the number of all previous informed consumers. However, this information is usually unobservable to the public and, therefore, is not the focus of our study.

The Sales Effect of WOM versus Observational Learning

The first issue we explore concerns the possible differences between the impact of WOM and observational learning on consumer purchase decisions. The extant literature has consistently shown an asymmetric effect of WOM valence (e.g., Chevalier and Mayzlin 2006, Weinberger and Dillon 1980). Specifically, negative WOM information is more diagnostic and has been found to have a stronger impact on consumers' adoption decisions than positive WOM information (e.g., Mizerski 1982). However, much less is known about the impact of observational learning valence. While the information cascade theory generally suggests that positive (negative) observational learning can potentially increase (decrease) adoption (Bikhchandani, Hirshleifer, and Welch 1992, Bikhchandani and Sharma 2001, Welch 1992), the literature has provided few insights into whether or not the valence of observational learning has an asymmetric effect.

Observational learning differs from WOM in two important aspects—the amount and the credibility of the information. Compared with WOM, observational learning contains less information. Unlike WOM information, which often contains both opinions/recommendations of other consumers and the reasons for them, observational learning information reveals only the actions of other consumers, but not the reasons behind them (Bikhchandani, Hirshleifer, and Welch 1998). Since "actions speak louder than words," however, the action-based observational learning information might be perceived to be more credible than WOM.

According to the accessibility-diagnosticity model (Feldman and Lynch 1988), whether or not any accessible information will be used by consumers for their decision-making depends on the diagnosticity of the information. A piece of product information is diagnostic if it helps consumers assign the product to a unique category, and nondiagnostic if it has multiple interpretations or causes (Hoch and Deighton 1989). Although both positive and negative observational learning carry a limited amount of information on the reasons behind others' actions, negative observational learning can be relatively less diagnostic compared with positive observational learning information in product markets. This is because products often differ in both vertical (i.e., quality) and horizontal (i.e., taste) dimensions and, in general, given a price level, a small market share and purchase percentage can be caused by either low product quality or by narrow positioning of the product (i.e., offering unique features that are appreciated only by a small market segment). Hence, a product with a negative observational learning signal (i.e., a relatively small percentage of purchase actions) might not be perceived unfavorably for a consumer because it might be a high-quality niche product. However, given a price level, a product will achieve a very high market share only if it has high quality and matches most consumers' preference. Hence, a product with positive observational learning information (a relatively large percentage of purchase actions) is usually perceived favorably because consumers are more confident about the product quality and its generality in matching most consumers' tastes (or a higher probability to fit with an individual's taste). For instance, a mono classical music CD may have a small purchase percentage (negative observational learning information to a potential buyer) because most consumers prefer stereo sound, even though its music might be a top-quality performance. In contrast, the chance that a best-selling music CD (positive observational learning information) is of poor quality is very low. Therefore, a positive observational learning signal (a product with a relatively large purchase percentage) is more diagnostic for consumers than a negative observational learning signal (relatively small percentage of purchase actions), since it makes it easier for consumers to decide whether the underlying product is “desirable” or “undesirable.” Thus, according to the accessibility-diagnosticity model, the lower diagnostics of negative observational learning can reduce its use in consumers’ purchase decision making. Furthermore, while both positive and negative observational learning information are generally perceived to be credible signals, such high credibility is more likely to strengthen the impact of positive observational learning, but offers little help to the negative observational learning because of its low diagnosticity.

Overall, the accessibility-diagnosticity model and product differentiation in both quality and taste dimensions suggest that the sales impact of the two types of social interaction may differ. Specifically, we expect that the stronger impact of negative than positive signals found in WOM may not apply to observational learning. Rather, the opposite pattern, i.e., the stronger impact of positive than negative signals might hold.

The Lifetime Effects of WOM and Observational Learning

Our second issue concerns the dynamics of the two types of social interaction. We identify two factors that affect the sales impact of WOM and observational learning over time in opposite directions. First, the impacts of both types of social interaction may *increase* with time due to the change of the composition of consumer segments across different stages of a product life cycle. Mahajan, Muller and Srivastava (1990) find that experts tend to enter a market and adopt a new product earlier in the product life cycle than novice consumers. This suggests that the proportion of novice consumers in a market increases over time. Because of differences in causal inference capabilities, novices are less capable of processing a product’s attribute information (Alba and

Hutchinson 1987), and thus are more likely to rely on WOM and observational learning information than experts. As a result of this consumer segment dynamics, both WOM and observational learning can play more important roles in the later stages of the product life cycle than in the early stages.

Second, the impacts of both types of social interaction may *decrease* with time due to an increase of the amount of publicly available product information from various sources (e.g., consumer magazines, media reports, advertising, trade shows) as the product ages. This can shatter the information cascade and reduce the impact of observational learning (Bikhchandani, Hirshleifer, and Welch 1992). Similar effects also apply to the impact of WOM, since, in the later stages of the product life cycle, consumers are more informed and may have formed their attitudes towards a product based on information from other channels. As a result of this information substitution dynamic, the impact of both WOM and observational learning on consumer purchases can decrease along the product life cycle.

In summary, the dynamics of consumer segment composition increases, but the dynamics of information substitution decreases the impact of the two types of social interaction on consumers across a product's life cycle. The direction of the overall effect is thus an empirical issue that needs to be tested using real market data.

The Interaction Effects of WOM and Observational Learning

The third issue we explore is the possible interaction effect between WOM and observational learning information. Specifically, we are interested in whether the two types of information strengthen or weaken each other's impact and how they might jointly influence product sales.

First, one might expect a complementary effect between WOM volume and observational learning information. The information cascade theory argues that the likelihood of an information cascade and the impact of observational learning increase with the observed total number of previous consumers who have evaluated the product (Bikhchandani, Hirshleifer, and Welch 1992). Although a consumer may be unable to directly observe the number of total consumers who have evaluated the product, she can be indirectly informed by the volume of WOM because the more people who have evaluated the product, the more WOM information will be generated. As a result, an individual is more likely to act according to the information conveyed by previous actions if she perceives a higher volume of WOM information. In other words, a positive complementary effect might exist—the volume of WOM can strengthen the impact of observational learning signals. Second, one might also expect a substitution effect between WOM valence and observational learning information because both types of information reveal the desirability of the product. Hence, they may weaken each other's effect.

The above discussion suggests that the interaction between WOM and observational learning can be dimension-specific (i.e., volume or valence). Specifically, we expect that the sales impact of observational learning increases with WOM volume; however, this effect can decrease with WOM valence.

METHODOLOGY: A NATURAL EXPERIMENT

Because of limited data availability, researchers so far have encountered great difficulty in disentangling the competing effects of WOM and observational learning and have provided limited insights as to how these two types of social influence may differ from and interact with each other. Some studies have indirectly inferred the impacts of social interactions via the "neighborhood effect" (e.g., Bell and Song 2007, Choi, Hui and Bell 2007, Grinblatt, Keloharju, and Ikäheimo 2005). Other recent field studies have collected data to directly measure the effect of WOM or observational learning, but not both (e.g., Chevalier and Mayzlin 2006, Dholakia and Soltysinkski 2001, Godes and Mayzlin 2004a 2004b, Hanson and Putler 1996, Liu 2006, Salganik, Dodds and Watts 2006, Tucker and Zhang 2009, Zhang 2009). In reality, however, consumers are usually subject to the influences of both WOM and observational learning simultaneously. To examine how WOM and observational learning jointly influence product sales, the listed criteria are required for our empirical research design. The design must be able to

- Separate the two types of social interaction, and decompose the impacts of observational learning from WOM.
- Investigate the impacts of WOM and observational learning over product lifetime.
- Exam how WOM and observational learning influence product sales jointly and how they interact with each other.
- Demonstrate that the observed effects are the result of social interactions rather than unobserved individual preferences.

Research Design: A Natural Experiment

Natural experiments investigate the effects of treatments that are not manipulable by the researchers (e.g., government interventions, policy changes) (Shadish, Cook, and Campbell 2002). Over the last decade, the natural experimental approach has gained considerable attention in economics, although it is still relatively rare in marketing (Meyer 1995, Moorman 1996). One major advantage of a natural experiment is that it can provide higher validity on causal inferences than can purely statistical adjustments (Shadish, Cook, and Campbell 2002). This is particularly important when studying social interactions, where it is difficult for researchers to conclude by using econometric models that their observations result from social interactions instead of from unobserved individual preferences (Manski 2000).

The online seller Amazon.com provides an ideal setting for our empirical study since it was the pioneer in allowing consumers to post product reviews and facilitate WOM interactions on its website. In recent years, in addition to offering consumer review information, Amazon.com has provided observational learning information for each product on that product's homepage under the section "What do customers ultimately buy after viewing this item?". From this public information, a potential buyer can observe what percentage of customers, among all those who considered a product, actually bought the product. This summary statistic on previous purchases among consumers who considered the same product closely matches the observational learning construct suggested by the theoretical literature and defined in the theoretical section in this paper. In early November 2005, however, Amazon.com removed the purchase percentage section and stopped providing this information for all digital cameras. Meanwhile, it kept its platform for consumers to post their product reviews for each camera. Then, in late 2006, Amazon.com resumed its purchase percentage section and once again provided observational learning information for the digital camera category. Throughout this time period, Amazon.com retained the same standard product attribute information policy. In addition, before and after the policy shifts, Amazon.com did not provide the purchase percentage information for some cameras, while it still maintained the standard product attribute and consumer review information for them. Thus, the only difference between the information available for the cameras without the purchase percentage information and those with such information is the availability of observational learning information. As a result, these models provide an untreated control group for our study.

The observational learning policy shifts at Amazon.com provide a unique natural experimental setting with both treatment and control groups. It allows us to disentangle two types of social influence, and to examine the causal inferences concerning the sales effects of WOM and observational learning information. The control group allows us to control for the time trend and to rule out the history threat to internal validity. More importantly, it can help determine whether the possible correlation between the observational learning signals and sales is the result of the impact of observational learning signals or of unobserved consumer preferences.

An important characteristic of natural experiments is that researchers have no control over the treatments (Meyer 1995, Shadish, Cook, and Campbell 2002). To examine the effects of WOM and observational learning in this natural setting, we adopt a longitudinal, quasi-experimental approach where the treatment assignment might be nonrandomized (Shadish, Cook, and Campbell 2002). Since researchers have no control over information policy changes at Amazon.com, the quasi-experimental approach allows us to control the data collection schedule without having control over the scheduling of experimental stimuli (Shadish, Cook, and Campbell 2002, Moorman, Du and Mela 2005). The experimental stimuli here are the information policy changes at Amazon.com (i.e., the removal and later reintroduction of observational learning information). The policy changes at Amazon.com imply three periods in which different information policies were adopted:

- Period 1: Before the removal of observational learning information;
- Period 2: After the removal of observational learning information;
- Period 3: After the reintroduction of observational learning information.

Data

Data were collected accordingly three times over one-and-a-half years. The first collection was on September 21, 2005 (in Period 1), the second on March 15, 2006 (in Period 2), and the third on March 18, 2007 (in Period 3).

Digital cameras provide an ideal product category for the empirical study. First, the Internet has become the most important channel for consumers interested in buying digital cameras (Photo Marketing Association International 2001). Second, digital cameras are a technology-intensive product. A high level of buyer involvement and extensive information searching are often required in the decision-making process. Thus, product information from social interactions could be important in consumers' purchase decisions. Third, as a high-value product category, the digital camera market provides a more general setting to study the sales impact of observational learning than the non-paid product adoption cases used in previous studies (e.g., free software downloads in Hanson and Putler 1996). Fourth, digital cameras were an emerging major product category for consumers at the time of data collection. According to the Consumer

Electronic Association's annual ownership study (Raymond 2006), digital cameras have become one of the top five most-wanted consumer electronic products. Specifically, the following data were collected for the empirical study:

WOM data. For each digital camera model sold on Amazon.com, consumers are asked to give a star rating (from one to five) when posting their reviews. Amazon.com then provides an average customer rating for each model based on all consumer reviews. We collected the following WOM information: 1) The number of consumer reviews (#CR) for each camera; and 2) in line with the work of Chevalier and Mayzlin (2006), data on two different measures: a) The average customer rating (ACR) for each camera, and b) the percentages of five-star reviews (PER5) and one-star reviews (PER1) for each camera. The second measure is used to examine the potential difference in sales impact between positive and negative WOM.

Observational learning data. For each camera at Amazon.com, the observational learning section is presented under the section: "What do customers ultimately buy after viewing this item?" .This section reports the aggregate sales statistics based on previous buyers actions. Specifically, it lists the purchase percentages of those cameras that have sufficient shares based on the purchase actions of all consumers who have viewed a certain camera. The cameras are listed in decreasing order of their purchase percentages. For example, when a consumer views a specific camera *i*, she will find the purchase percentage of camera *i* in the observational learning section unless camera *i*'s purchase percentage is too small to be listed compared with all other models. For each camera in our sample, we collected the purchase percentage data for all listed cameras in this section in both Period 1 (before this information was removed) and Period 3 (after this information was reintroduced). If camera *i* is not listed under its own observational learning section, it means that camera *i*'s purchase percentage is too small to be listed compared with all other models, i.e., most of the consumers who viewed camera *i* have rejected this camera and chosen other models.[3] Hence, we consider the observational learning signal of a product as negative if its purchase percentage is too small to be listed in its observational learning section. In contrast, the observational learning signal can be viewed as positive if the purchase percentage of camera *i* is sufficiently high to be listed under this section (i.e., camera *i* is a popular model based on the choices of previous buyers who have viewed *i*). We have also used several alternative observational learning measures and shown that our findings are robust (See the Appendix A1 for detailed analyses and discussion).

Sales data. Several recent studies based on data from Amazon.com have used sales rank data as a measure of product sales (e.g., Chevalier and Goolsbee 2003, Chevalier and Mayzlin 2006). This measure is used because the real sales data for each product from Amazon.com are not available, but sales rank data for each product are made public and are updated frequently. In line with the literature, we collected the data on the sales rank for each model *i* in Period *t* ($Rank_{i,\,t}$) as a measure of product sales. Chevalier and Goolsbee (2003) demonstrate a linear relationship between ln(sales) and ln(sales rank), given the Pareto distribution of the rank data, and offer a detailed discussion on the properties of sales rank data. Thus, according to their methodology, the sales rank can be transformed into sales to allow for the study of the effects of social interactions on sales.

Note the sales ranks at Amazon.com might reflect some recent sales up to a month (see detailed discussion in Chevalier and Goolsbee 2003 and Chevalier and Mayzlin 2006). To eliminate the possible simultaneity between the review/observational learning information and sales rank in that month, following the practice in Mayzlin and Chevalier (2006), we examine the log sales-rank change by time *t* relatively to the review/observational learning changes up to one month before time *t* in each study.

[3] The smallest purchase percentage listed in the observational learning section in our data is 2%.

Control variable. One common feature of a quasi-experimental design is that the sample and the treatment are nonrandomized (Shadish, Cook, and Campbell 2002). To rule out the selection bias threat to the internal validity of the study, we collected data on a set of control variables. To control for any product-fixed effects, data were collected on two product-specific variables, product quality (QUALITY) and age (AGE), from the leading consumer technology product website, CNET.com. Chen and Xie (2005, 2008) argue that third-party product reviews, such as the CNET editor's rating, mainly focus on product quality. Hence, we collected the CNET editor's rating for each camera as a measure of product quality. We also collected the product launch date for the reviewed cameras from CNET.com, which allows us to calculate the product age of each camera. Since Amazon.com provides consumers with the option to buy products from other merchants, the sales rank also reflects sales from these sellers. To control for this, for each camera, we also collected the lowest price and the number of sellers as control variables.

Given that we have to collect required data from two different sources, i.e., CNET.com and Amazon.com, our sample contains all digital cameras for which data from both sources are available. [4]

EMPIRICAL ANALYSIS AND RESULTS

The Sales Effects of WOM versus Observational Learning

The first research issue, i.e., whether and how WOM and observational learning differentially affect consumer purchase decisions is examined first by a quasi-experimental Study 1. Using Shadish, Cook, and Campbell's (2002) notation, the quasi-experimental design is depicted in Figure 1. O_t denotes the measurement observation in period t, and $\cancel{X}$ and X denote the removal and reintroduction of the observational learning treatment, respectively. The dashed line

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[4]Amazon.com lists hundreds of different cameras. For instance, it listed 2556 cameras in March 2006. However, many of them were no longer available for sale. We confined our sample to those newly reviewed by CNET.com. Given the relatively short life cycle of digital cameras, these new cameras allow us to study lifetime effects with control data on product characteristics. The quality level of these cameras varies across different levels and provides a general sample for our study.

distinguishes between the treatment and the control groups. Study 1 includes Periods 1 and 2 (i.e., before and after the removal of observational learning information). Note that, in contrast to many quasi-experiments in the literature that study the effects of treatment by comparing the outcomes before and after its implementation (e.g., Godes and Mayzlin 2004b, Moorman 1996, Moorman, Du and Mela 2005, Simester et al. 2000), Study 1 is a removed-treatment design in which the effects of the treatment are demonstrated by the opposite pattern in the change of observed outcomes before and after the treatment removal (Shadish, Cook, and Campbell 2002). The impact of observational learning is detected through the sales change resulting from the *removal* of this information. Specifically, we test how the sales difference for a camera over the two periods (both WOM and observational learning available to consumers in Period 1, but only WOM in Period 2) is affected by the removal of its observational learning signal and the changes in its WOM information.

[INSERT FIGURE 1 ABOUT HERE]

The initial sample of Study 1 includes all 120 digital cameras that were both available for sale on Amazon.com, and also reviewed by CNET.com from June 2004 to September 2005. These cameras are newly reviewed models at CNET.com and tend to be in their early stage of product lifetime (i.e., Period 1 of our study). Among these 120 cameras, 90 were available for sale at Amazon.com in both Periods 1 and 2. To rule out the mortality threat to the internal validity of the study (i.e., observed effect is due to sample attrition), the final sample for Study 1 is confined to the 90 digital camera models available in both periods. In addition, a *t*-test shows the sales ranks are not significantly different between the attrition products and the retained products (see details on sample attrition in Appendix A2). Table 1 presents the descriptive statistics of the overall data in our paper.

[INSERT TABLE 1 ABOUT HERE]

Before presenting the formal analysis, we first examine some descriptive statistics. Table 2 presents the sales change comparison between the treatment group and the control group in Study 1. Among the 90 cameras in Study 1, 26 (28.9%) were presented with positive observational learning information, and 48 (53.3%) with negative observational learning information in Period 1. The other 16 (17.8%) cameras were not supplied with observational learning information and constitute the control group. The sales change measure, D_LNRANK, is the subtraction of the sales ranks (in natural log) in Period 1 from those in Period 2 (i.e., $\text{D\_LNRANK}=\ln(\text{Rank}_{i,2})-\ln(\text{Rank}_{i,1})$). It is linearly correlated with the real sales change over time, since $\ln(\text{Rank}_{i,t})$ is linearly correlated with $-\ln(\text{Sales}_{i,t})$ (Chevalier and Goolsbee 2003, Chevalier and Mayzlin 2006).[5] As shown in Table 1, the sales ranks slide (i.e., the rank numbers are increasing) over time for products in our dataset. Thus, D_LNRANK can be interpreted as the degree of the sales decline between the two periods. As shown in Table 2, after removing the observational learning information, the degree of sales decline is significantly larger for the cameras with positive observational learning information in Period 1 than for the control group (t = 2.252, p < .05) . However, the difference in sales rank is not significant between the cameras with negative observational learning information in Period 1 and the control group (t = -.751, p > .45). These statistics provide us some preliminary empirical evidence of an asymmetric sales effect of observation learning, where positive observational learning information is more influential on sales than the negative observational learning signal. This finding is opposite to the asymmetric pattern of WOM effect shown in the literature (e.g., Chevalier and Mayzlin 2006).

[INSERT TABLE 2 ABOUT HERE]

Model specification. To thoroughly examine the sales effects of WOM versus observational learning, two "first-difference" econometric models are estimated to control for a potential

[5] This holds even if there is an overall sales growth at Amazon.com. A simple algebra transformation can show that the category sales growth between the two periods can be incorporated in the constant intercept term in the model.

endogeneity issue and alterative explanations (Wooldgidge 2002). Specifically, we estimate the following two separate models, which differ in the measures of WOM valence used (see Table 3 for the variable definition):

$$\text{(1)}\quad \begin{aligned} \text{D\_LNRANK}_i &= \eta_0 + \eta_1\text{D\_LNPRICE}_i + \eta_2\text{D\_\#SELLER}_i + \eta_3\text{QUALITY}_i + \eta_4\text{LNAGE}_i \\ &+ \alpha_1\text{OL\_POS}_i + \alpha_2\text{OL\_NEG}_i + \beta_1\text{D\_LN\#CR}_i + \beta_2\text{D\_ACR}_i + \varepsilon_i \end{aligned}$$

$$\text{(2)}\quad \begin{aligned} \text{D\_LNRANK}_i &= \eta_0 + \eta_1\text{D\_LNPRICE}_i + \eta_2\text{D\_\#SELLER}_i + \eta_3\text{QUALITY}_i + \eta_4\text{LNAGE}_i \\ &+ \alpha_1\text{OL\_POS}_i + \alpha_2\text{OL\_NEG}_i + \beta_1\text{D\_LN\#CR}_i + \beta_3\text{D\_PER5}_i + \beta_4\text{D\_PER1}_i + \varepsilon_i \end{aligned}$$

[INSERT TABLE 3 ABOUT HERE]

In both models, D_LNRANK_i is the difference of sales ranks (in natural log) between the two periods for a camera *i*, D_LNPRICE_i and $\text{D\_\#SELLER}_i$ are the changes in the lowest prices (in natural log) and number of sellers, QUALITY_i is the CNET editor's rating (from one to ten) for camera *i*, and AGE_i is the number of dates (in natural log) from the product launch to Period 2 in Study 1. Since unobserved product characteristics can influence both product sales and social interactions, given the nature of the current data, a "first difference" model is adopted to circumvent this endogeneity problem (Mouw 2006, Wooldridge 2002). Specifically, the sales differences over time eliminate all unobserved time-invariant fixed effects. In addition, the control variables are used to control for possible time-variant effects related to the constant variables over two periods (Wooldridge 2002). [6]

Two variables are included to measure the impacts of positive and negative observational learning information. The variable, OL_NEG_i, measures the impact of removing *negative* observational learning signals in Study 1. This is a dummy variable, such that $\text{OL\_NEG}_i = 1$ if in period 1, camera *i's* observational learning section on Amazon.com is provided (i.e., it does not

[6] A Hausman test has been conducted to ensure that D_LNPRICE_i and $\text{D\_\#SELLER}_i$ are exogenous in the model (Hausman 1978, Wooldridge 2002). QUALTIY_i and AGE_i in our first-difference model are in fact the difference of the interaction variables between time period *t* and QUALTIY_i and AGE_i, which control for the time-varying effects related to quality and age (the time-invariant effect of quality and age is cancelled out by taking the first difference).

belong to the control group) but its purchase percentage is too low to be listed, and OL_NEG$_i$ =0, otherwise. The variable, OL_POS$_i$, measures the impact of removing the *positive* observational learning signals in Study 1. There are a number of ways to code this variable. The simplest way to categorize the positive observational learning signal is to treat the signal as positive (i.e., OL_POS$_i$=1) only if a camera *i*'s purchase percentage is the highest in display. The disadvantage of this simple measure is that it uses limited information in the analysis (i.e., only the strongest positive observational learning signal), and excludes all observations where the purchase percentage of a camera is high enough to be listed as a popular model (but not the most popular) under the observational learning section. An alternative way to code this variable is to include all positive observational learning observations, and use the ratio of camera *i*'s purchase percentage to the highest percentage in its observational learning section to capture the different degrees of positivity. Specifically, OL_POS$_i$ =1 if camera *i* has the highest purchase percentage in Period 1(i.e., camera *i* has the strongest positive observational learning information), OL_POS$_i \in (0, 1)$ depending on camera *i*'s purchase percentage relative to other cameras' purchase percentages in the section if the purchase percentage of camera *i* is listed but is not the highest in Period 1, and OL_POS$_i$ = 0, otherwise. This more general measure has the advantage of including all cameras with different degrees of positive observational learning signals and examining their impacts. We performed our empirical analysis using both the simplest and the general measures of OL_POS$_i$ discussed above (as well as some additional alternative measures of the observational learning signal) and reach the same conclusions. We report our results using the general ratio measure of the positive observational learning signal in the paper, and our results using other alternative measures in the Appendix (see Table A1 and A2).

In summary, in Models 1 and 2, the coefficient of OL_POS, α_1, captures the effects of the removal of various degrees of positive observational learning information, and the coefficient of

OL_NEG$_i$, α_2, reflects the potential effects of the removal of negative observational learning information. The estimates of α_1 and α_2 are the difference-in-differences (DID) estimators (Wooldgidge 2002), which capture the sales effects of positive and negative observational learning information relative to no observational learning signals (i.e., the control group).

To show that the effects of observational learning are robust to different measures of WOM, consistent with the extant literature (e.g., Chevalier and Mayzlin 2006), we use two different measures of WOM valence: The changes between the two periods in the average customer rating (D_ACR$_i$) in Model (1); and the changes between the two periods in the percentages of 5-star reviews (D_PER5$_i$) and 1-star reviews (D_PER1$_i$), which helps to detect the potential asymmetric effects of WOM, in Model (2). The term $D\_LN\#CR_i$ denotes the change in the number of consumer reviews (in natural log) or in WOM volume over the two periods. Multicollinearity is tested by calculating the variance inflation factor (VIF). The VIFs for all independent variables are well below the harmful level (Mason and Perrault 1991).

Empirical results. Table 4 presents the results of the estimation for Study 1, where Model (0) presents results for a regression in which no social interaction variables are included, and Models (1) and (2) present results of the two models specified above. Consistent with the results in Table 2, for both Models (1) and (2) the coefficient for negative observational variable α_2 is insignificant, but the coefficient for the positive observational learning variable α_1 is highly significant and positive. The insignificant result for the negative observational learning implies that the sales change is not significantly different between the control group and the cameras from which negative observational learning information is removed. In other words, compared with the cameras without observational learning signals, the presence of negative observational learning information did not significantly influence product sales before the removal of such information. The significantly positive coefficient α_1 implies that the removal of positive observational learning signals intensifies product sales decline over Periods 1 and 2, suggesting the converse, i.e., that the presence of positive observational learning signals led to higher product sales before the removal of observational learning information. However, the results in Table 4 reveal an opposite asymmetric effect of WOM: Model (2) has a significantly positive coefficient β_4 but an insignificant coefficient β_3, implying that an increase in the percentage of 1-star reviews worsens the sales decline over Periods 1 and 2, but an increase in the percentage of 5-star reviews has no impact on the sales change over the two periods. These results suggest that negative WOM information has a more significant sales impact than that of positive WOM information, which is consistent with the extant literature (e.g., Chevalier and Mayzlin 2006).

[INSERT TABLE 4 ABOUT HERE]

Robustness of the results. Study 1 shows that both WOM and observational learning have an asymmetric effect on product sales, but in opposing directions: While negative WOM information is more influential than positive WOM, the opposite holds for observational learning information. It is important to note that, for natural experiments, a possible threat to internal validity is that some events parallel to the treatment might also cause the observed outcome. For example, in our study, if an event occurred at the same time that observational learning information was removed, and if this event also affected sales, then the results based on Study 1 may be contaminated. [7]An effective way to address this threat to internal validity is to use a combination treatment design (i.e., "introduction" and "removal") because it is unlikely that this parallel event threat could "come and go on the same schedule as treatment introduction and removal" (Shadish, Cook and Campbell 2002, p.113). However, such combination design data are rarely available to researchers using a natural experimental approach. Fortunately, during our

[7] A potential concern of the treatment-removal study is that the observed results could be simply due to the reversion to mean after random shocks. We can rule out this possibility using two sets of evidence. First, the random shock argument would predict a symmetric pattern for positive and negative observational learning signals, while our results show an asymmetric pattern. Second, the random shock argument would predict an opposite result in our treatment-reintroduction study.

18-month data collection period, Amazon.com reintroduced the observation learning information on its website. This allows us to add a treatment-reintroduction Study 2 in our study (see Figure 1). As a unique feature of our study, the combination of the treatment-removal Study 1 and treatment-reintroduction Study 2 provides greater internal validity and increases the robustness of our findings.

All digital cameras newly reviewed by CNET.com from September 2005 to March 2006 were initially considered as the independent new sample for Study 2. Of these cameras, 41 were available at Amazon.com in both Periods 2 and 3. However, no reviews were available for two cameras in at least one period. As a result, 39 cameras were chosen as the final sample for Study 2 (see descriptive statistics in Table 1).

Study 2 has the same model specification as Study 1, but differs in the interpretation of the two observational learning coefficients, α_1 and α_2, which capture the impacts of *removing* observational learning signals in Study 1 and the impacts of *reintroducing* observational learning signals in Study 2. As shown in Table 5, the coefficient of the negative observational learning, α_2, is not significant, but the coefficients of positive observational learning, α_1, is significantly negative in both Models (1) and (2) of Study 2. The latter suggests a positive sales impact of positive observational learning signals in Study 2 because, with a treatment reintroduction design, the significantly negative sign of α_1 means that the reintroduction of positive observational learning signals significantly reduces the magnitude of sales decline over Periods 2 and 3. In addition, in Model (2), the coefficient of the negative WOM, β_4, is significant, but the coefficient of the positive WOM, β_3, is not significant. Therefore, the treatment reintroduction Study 2 presents the same pattern of asymmetric effects of WOM and observational learning found in the treatment removal Study 1.

[INSERT TABLE 5 ABOUT HERE]

It is important to note that the coefficient of positive observational learning, α_1, is significant, but has an opposite sign in the treatment-removal Study 1 and the treatment-reintroduction Study 2. This result significantly increases the robustness of our findings, and reduces concerns regarding possible threats to its internal validity. One such concern, for example, is the possible effect of sales rank information. Specifically, one might argue that product sales rank information at Amazon.com might also convey previous purchase information and thus impact consumer purchase decision-making. Therefore, the identified asymmetric effect of observational learning might be caused by the impact of sales ranks. However, sales rank information is present in both treatment-removal and treatment-reintroduction studies. If the observed effects of observational learning resulted from sales ranks, thus, they should have the same (positive or negative) impact in both treatment-removal and treatment-reintroduction studies. The significant but *opposite* signs of α_1 in Studies 1 and 2 helps to reduce this concern. In the Appendix A3, we conduct additional analyses to show how our results are robust to sales rank information, and discuss why our observational learning measure is more diagnostic than sales rank for consumers.

The Lifetime Effects of WOM and Observational Learning

To examine the second research issue, i.e., the lifetime effects of WOM and observational learning, a new Study 3 is conducted (see Figure 1). Among the 90 cameras of Study 1 (i.e., cameras available in both Periods 1 and 2), 61 are also available at Amazon.com in Period 3. Study 3 includes these cameras over Periods 2 and 3 (i.e., before and after the reintroduction of the observational learning information). As shown in Table 1, the product ages for the sample in Study 3 are significantly older than those in Study 1 and Study 2 ($p < .01$).

The lifetime effects of WOM and observational learning are investigated through a two-step analysis. First, we conduct a *within-subjects* comparison between Studies 1 and 3. Note that

Study 3 includes cameras in Study 1 that are still available on Amazon.com in Period 3, and uses data at a later stage in the product life cycle than Study 1. A comparison of these two studies can provide insights as to how WOM and observational learning influence sales over product lifetime. Second, we also conduct a *between-subjects* comparison between Studies 2 and 3 to increase the validity and robustness of the product lifetime effects of WOM and observational learning uncovered in the *within-subjects* comparison. Note that Study 2 deploys the same treatment-reintroduction design as Study 3, but has an independent sample with significantly younger products. Therefore, comparing the results of Studies 2 and 3 allows us to provide further evidence of the lifetime effects of WOM and observational learning.

Study 3 has the same model specifications as Studies 1 and 2 (i.e., Models 1 and 2). The results for Study 3 are presented in Table 6. As shown in Models (1) and (2) of Study 3, the coefficients of all WOM and observational learning variables (α_1, α_2, β_1, β_2, β_3 and β_4) are not significant in Study 3. Comparing the results from Study 1 (Models (1) and (2) in Table 4) with those from Study 3 (in Table 6) shows the diminishing pattern of lifetime effects of WOM and observational learning. Specifically, positive observational learning and negative WOM are significant in Study 1, but not in Study 3. In addition, the coefficient of WOM volume variable, β_1, is significant in Study 1, but not in Study 3. These results show a diminishing effect of WOM and observational learning over the product lifetime.[8]

[INSERT TABLE 6 ABOUT HERE]

Comparing Study 3 with Study 2 can further strengthen the validity of the lifetime effects demonstrated in Study 3. Both Studies 2 and 3 have the same treatment design (i.e., the reintroduction of observational learning information), but they differ in the ages of the product samples: The cameras in Study 2 are significantly younger than those in Study 3. Therefore, the

[8] The results are similar when comparing the results from both studies by using the same set of 61 cameras in Study 2.

lifetime effects of WOM and observational learning can be further validated by comparing the results of the two studies. As shown in Tables 5 and 6, different from Study 3 (products in their later stages), in which the coefficients of positive observational learning and WOM valence variables, α_1, β_2 and β_4, are insignificant, they are significant in Study 2 (products in their earlier stages). These results further demonstrate a decreasing lifetime effect of observational learning and WOM.

The Interaction Effects of WOM and Observational Learning

Finally, to examine the third research issue, i.e., the possible interaction between the two types of social influence, we use data collected in Studies 2 and 3, since both studies use the treatment-reintroduction design and contain both WOM and observational learning in posttest Period 3. The data from these two studies allow direct investigation of the interactions between WOM and observational learning. To study how WOM and observational learning interact with each other, we extend Model (1) by adding two interaction terms between WOM and observational learning variables (τ_1 and τ_2 as the interaction coefficients):

$$\begin{aligned}(3)\qquad \text{D\_LNRANK}_i = {} & \eta_0 + \eta_1\text{D\_LNPRICE}_i + \eta_2\text{D\_\#SELLER}_i + \eta_3\text{QUALITY}_i + \eta_4\text{LNAGE}_i \\ & + \alpha_1\text{OL\_POS}_i + \beta_1\text{D\_LN\#CR}_i + \beta_2\text{D\_ACR}_i \\ & + \tau_1\text{OL\_POS}_i \times \text{D\_LN\#CR}_i + \tau_2\text{OL\_POS}_i \times \text{D\_ACR}_i + \varepsilon_i\end{aligned}$$

Given the insignificant impact of the negative observational learning variable detected earlier, the variable OL_NEG is not included in Model (3).[9] To reduce multicollinearity, all variables included in the interaction terms are mean-centered. We estimated Model (3) with the combined sample from both Studies 2 and 3. A total of 83 cameras are listed under their observational

[9] In addition, including the dummy variable OL_NEG in the interaction terms induces a serious multicollinearity problem. Recall that, Model (1) uses single variable (D_ACR) but Model (2) uses two separate variables (D_PER5 and D_PER1) as the measurement of WOM valence. We performed the analysis of the interaction effect by adding the interaction terms to all models. Since the models with the separate WOM valence variables have a serious multicollinearity problem, we report only the results of the model with the single WOM valence (D_ACR).

learning sections at Amazon.com in both Studies 2 and 3, and are used as the final sample in the analysis of Model (3). The VIFs for all the independent variables are below the critical value.

Note the dependent variable in our model denotes the degree of sales decline over time. As shown in Table 7, coefficient τ_1 is negative and significant, indicating that WOM volume increases the impact of observational learning on sales. This suggests a positive complementary effect between observational learning and WOM volume. However, the coefficient τ_2 is not significant, implying that there is no clear evidence in the current study that consumers would consider observational learning and WOM valence as substitutive signals.

[INSERT TABLE 7 ABOUT HERE]

In addition, the positive significant interaction between observational learning and WOM volume documented here can also help to further validate the results on the diminished impacts of WOM over product lifetime. The reduced impact of WOM volume between Studies 1 and 3 can result from the difference in the product sample ages between two studies. However, it can also result from the reintroduction of the observational learning information in Study 3 if observational learning information dampens the effect of WOM volume. The *positive* interaction effect between observational learning and WOM volume shows that the *diminished* impact of WOM volume between Studies 1 and 3 does result from the product lifetime effect.

A detailed discussion on how the quasi-experimental studies in this paper are designed to rule out various possible interval validity threats is summarized in Table 8.

[INSERT TABLE 8 ABOUT HERE]

IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

Managerial Implications

The results of this study offer some interesting implications for firms in managing consumer social interactions. First, our findings of the asymmetrical impact of observational learning information on sales suggest that a seller's decision to provide observational learning information can help mass-market products without hurting niche products and the seller's own credibility, particularly in markets where most consumers do not have sufficient prior knowledge about products. This is because a large percentage of consumers tend to purchase the former, and thus send a positive observational learning signal to future potential buyers, whereas a small percentage of consumers buy the latter products. According to Anderson's (2006) long-tail theory, there are far more niche products than mass-market goods in the market (the so-called 98 percent rule). Widespread use of the Internet and other advances in information technology increases the profitability of selling niche products designed to match the needs of a small segment of consumers. Therefore, if the sales impact of observational learning information is symmetric, the overall effect of offering observational learning information on a seller's website might not be a profitable strategy.[10] This result might partly explain why, in late 2006, Amazon.com began once again to provide observational learning information.

Second, online third-party infomediaries, who face a two-sided market (i.e., buyers and sellers), can also take advantage of the asymmetric effects of observational learning by offering information about previous buyers' purchase actions. This decision can help consumers as well as sellers of popular products without necessarily harming the sellers of niche products.

Third, our results reveal some interesting interactions between WOM and observational learning information, which suggest that firms should design their WOM and observational learning strategies jointly. Our results show that WOM volume strengthens the impact of observational learning information (i.e., they are complementary). An important implication of this finding is that the seller offering observational learning information may also need to pay attention to the volume of WOM. The seller can increase the effectiveness of observational

[10] The seller can decide to offer observational learning information only on products where that information is positive. However, this strategy is not sustainable because it will hurt the seller's credibility in the long term.

learning information posted on its website by encouraging more consumers to post product reviews. Note that websites with heavy traffic tend to attract more consumer review postings (Chen and Xie 2008). This finding also suggests that observational learning will be most influential to product sales when such information is offered on the most heavily used websites. Hence, these popular websites may need to seriously consider investing in technology that facilitates observational learning information. However, less popular online sellers might benefit less from such an investment.

Finally, this study finds that the impacts of both WOM and observational learning diminish over product lifetime, which suggests that, to increase the effectiveness of social interactions, a firm should focus on the earlier stages of a product's life cycle (i.e., the period of product introduction) despite the fact that social interaction activities increase over time.

Theoretical Implications, Limitations and Future Research

The findings from this study raise some interesting theoretical and empirical issues concerning consumer social interactions. First, our results provide new insights into the impacts of observational learning. The extant literature suggests that both positive and negative observational learning information influence individual decision-making. However, neither theoretical work nor empirical evidence has shown the possible asymmetric effect of observational learning information. Our study provides some evidence for an interesting asymmetric effect: Positive observational learning information is more influential in purchase decision-making than negative observational learning information. One plausible reason we propose for this effect is that, in a product market where both quality and product match are important for consumers, negative observational learning information may be less diagnostic than positive observational learning information. Future research might develop formal theoretical models to investigate this asymmetric impact.

Second, like WOM, observational learning is a major category of social interaction. It is natural to expect that the effect of the two types of social interaction follow the same pattern; however, our study provides evidence for opposite patterns: Positive observational learning is more influential than negative observational learning, while negative WOM is more influential than positive WOM. The difference between WOM and observational learning found in this study suggests that, when social influences are studied, it is necessary to determine whether they result from WOM or from observational learning.

Third, very few extant studies investigate how WOM and observational learning jointly influence consumers. Our study demonstrates a positive complementary interaction between observational learning and WOM volume, but does not find clear evidence of the interaction between observational learning and WOM valence. Further research may well develop formal theoretical models to examine these interaction effects, identify the possible boundary conditions, and conduct further empirical testing within the laboratory or through field studies.

One limitation of our study is that, due to the data constraint, we have a relatively small sample size. To examine the sensitivity of our results to sampling variations, we have conducted a bootstrapping analysis (Davison and Hinkley 1997, pp. 264-269). The results of the bootstrapping analysis show that our results for all studies are robust to sampling variations. Future studies can examine similar issues in field studies with larger scales.

In sum, the unique natural experimental setting identified in this paper presents an unusual opportunity for us to make an initial effort toward exploring the possible differences and interactions between two important types of social influence. We hope that the conceptual development and empirical results presented in this paper will stimulate more research in this area and help firms to initiate/facilitate consumer social interactions more effectively.

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TABLE 1: DESCRIPTIVE STATISTICS

	Study 1 (OL-Removal)		Study 2(OL-Reintroduction)		Study 3(OL-Reintroduction)	
	Period 1 September 2005	Period 2 March 2006[a]	Period 2 March 2006	Period 3 March 2007[b]	Period 2 March 2006	Period 3 March 2007[b]
Sample Size	90	90	39	39	61	61
Product Age (Days)[c]	307.90.93 (146.23)	482.99 (153.99)	227.64 (102.14)	595.64 (102.14)	448.93 (146.23)	816.93 (146.23)
Sales Rank (in Camera & Photo)	761.74 (1248.94)	1506.88 (1783.46)	795.74 (1505.13)	1742.54 (1802.35)	1001.26 (1090.04)	2038.75 (1420.86)
Lowest Price (US$)	368.43 (289.90)	364.34 (272.27)	541.89 (1100.73)	515.98 (1136.27)	301.56 (163.62)	313.65 (238.88)
Number of Sellers	10.02 (7.65)	7.99 (8.49)	17.79 (13.00)	6.36 (5.59)	10.29 (9.28)	4.80 (4.00)
Quality (CNET Editor's Rating)	6.79 (.68)	6.79 (.68)	6.79 (.77)	6.79 (.77)	6.75 (.71)	6.75 (.71)
Number of Reviews for Each Camera[d]	25.49 (25.70)	35.99 (33.63)	18.44 (14.34)	47.10 (50.84)	41.98 (39.53)	60.13 (64.97)
Average Consumer Ratings	4.20 (.42)	4.13 (.42)	4.17 (.71)	4.12 (.47)	4.12 (.38)	4.06 (.38)
% of 5 star reviews	56.5% (21.6%)	55.2% 19.3%)	58.7% (26.3%)	56.9% (18.9%)	54.7% (17.8%)	53.5% (15.2%)
% of 1 star reviews	6.1% (7.0%)	7.1% (7.3%)	7.3% (17.1%)	7.2% (7.1%)	6.9% (6.5%)	7.7% (6.8%)
% of Cameras without OL signal	17.8%	100%	100%	5.1%	100%	13.1%
% of Cameras with positive OL signal	28.9%	0%	0%	87.2%	0%	78.7%
% of Cameras with negative OL signal	53.3%	0%	0%	7.7%	0%	8.2%

[a] The review data are collected on February 15, 2006 for this period (i.e., one month before Period 2).
[b] The review data and observational learning (OL) percentage data are collected on February 18, 2007 for this period (i.e., one month before Period 3).
[c] The product ages for the sample in Study 3 are significantly older than for the samples in Study 1 and Study 2 ($p < .01$).
[d] All cameras in the final sample have consumer review postings in three periods.
Note: Means are primary entry, and standard deviations are in parenthesis.

TABLE 2: SALES CHANGE COMPARISON BETWEEN THE TREATMENT-REMOVAL GROUP AND THE CONTROL GROUP IN STUDY 1

Treatment-removal Group	**Positive Observational Learning Items** (N = 26)	**Negative Observational Learning Items** (N = 48)
	1.449 (1.222)	.699 (1.125)
Control Group (N = 16)	.849 (.464)	.849 (.464)
Two Group *t*-test	2.252**	-.751

** p < .05

Notes: The sales change measure is $\text{D\_LNRANK}=\ln(\text{Rank}_{i,2})-\ln(\text{Rank}_{i,1})$. The table lists the means with standard deviations in parentheses.

TABLE 3: LIST OF VARIABLES USED IN THE ANALYSIS

Variable Name	Meaning
D_LNRANK	Difference of sales ranks (in natural log) between the two periods
D_LNPRICE	Difference of lowest prices (in natural log) between the two periods
D_#SELLER	Difference of the number of sellers between the two periods
QUALITY	CNET Editor's Ratings (1~10)
LNAGE	Age of the product (days in natural log)
OL_POS	The ratio of a camera's purchase percentage to the highest percentage in its observational learning section
OL_NEG	Whether a camera fails to be listed under its observational learning section
D_LN#CR	Difference in the number of consumer reviews (in natural log) between the two periods
D_ACR	Difference in the average consumer ratings between the two periods
D_PER5	Difference in the percentage of 5-star reviews between the two periods
D_PER1	Difference in the percentage of 1-star reviews between the two periods

Note: All difference variables are the subtractions of variables in pretest period from the variables in the posttest period in each study.

TABLE 4: THE SALES EFFECTS OF WOM VERSUS OBSERVATIONAL LEARNING

	Study 1		
	Model (0)	Model (1)	Model (2)
D_LNPRICE (η_1)	.715 (.453)	.690 (.419)	.609 (.409)
D_#SELLER (η_2)	-.057** (.016)	-.047*** (.016)	-.053*** (.015)
QUALITY (η_3)	-.082 (.159)	-.196 (.150)	-.188 (.146)
LNAGE (η_4)	.056 (.338)	-.540 (.387)	-.649* (.376)
OL_POS (α_1)		1.101*** (.411)	1.099*** (.399)
OL_NEG (α_2)		.081 (.254)	.109 (.246)
D_LN#CR (β_1)		-1.045*** (.358)	-1.051*** (.328)
D_ACR (β_2)		-.233 (.480)	
D_PER5 (β_3)			-.165 (1.034)
D_PER1 (β_4)			1.354** (.564)
Sample Size	90	90	90
Adjusted R-squared	.175	.299	.336
Model Fit F	5.712**	5.736***	6.001***

*p < .1, **p < .05, *** p < .01, NS: not significant

Notes: The dependent variable is D_LNRANK=$\ln(\text{Rank}_{i,2}) - \ln(\text{Rank}_{i,1})$. The table lists the unstandardized coefficients with standard errors of parameter estimates in parentheses. There is an intercept in the regression.

TABLE 5: THE RESULT ROBUSTNESS OF THE SALES EFFECTS OF WOM VERSUS OBSERVATIONAL LEARNING

	Study 2	
	Model (1)	Model (2)
D_LNPRICE (η_1)	1.015* (.512)	1.076* (.531)
D_#SELLER (η_2)	-.051*** (.013)	-.047*** (.013)
QUALITY (η_3)	.176 (.227)	.186 (.238)
LNAGE (η_4)	.447 (1.188)	.843 (1.249)
OL_POS (α_1)	-1.241** (.584)	-1.310*** (.613)
OL_NEG (α_2)	.066 (.828)	.058 (.839)
D_LN#CR (β_1)	.353 (.374)	.410 (.384)
D_ACR (β_2)	-1.237** (.464)	
D_PER5 (β_3)		-1.859 (1.221)
D_PER1 (β_4)		3.253** (1.454)
Sample Size	39	39
Adjusted R-squared	.529	.523
Model Fit F	6.345***	5.623***

*p < .1, **p < .05, *** p < .01

Notes: The dependent variable is $\text{D\_LNRANK}=\ln(\text{Rank}_{i,3})-\ln(\text{Rank}_{i,2})$. The table lists the unstandardized coefficients with standard errors of parameter estimates in parentheses. There is an intercept in the regression.

TABLE 6: THE LIFETIME EFFECTS OF WOM AND OBSERVATIONAL LEARNING

	Study 3	
	Model (1)	Model (2)
D_LNPRICE (η_1)	.795 (.485)	.869* (.491)
D_#SELLER (η_2)	-.039** (.017)	-.040** (.017)
QUALITY (η_3)	.162 (.210)	.160 (.212)
LNAGE (η_4)	-1.845** (.907)	-1.966** (.921)
OL_POS (α_1)	-.235 (.413)	-.283 (.423)
OL_NEG (α_2)	-.843 (.585)	-.925 (.596)
D_LN#CR (β_1)	-.059 (.473)	-.137 (.469)
D_ACR (β_2)	.188 (.753)	
D_PER5 (β_3)		1.350 (1.540)
D_PER1 (β_4)		1.056 (3.858)
Sample Size	61	61
Adjusted R-squared	.196	.192
Model Fit F	2.833**	2.589**

*p < .1, **p < .05, *** p < .01

Notes: The dependent variable is $D\_LNRANK = \ln(Rank_{i,3}) - \ln(Rank_{i,2})$. The table lists the unstandardized coefficients with standard errors of parameter estimates in parentheses. There is an intercept in the regression.

TABLE 7: THE INTERACTIONS BETWEEN WOM AND OBSERVATIONAL LEARNING

	Studies 2&3
	Model (3)
D_LNPRICE (η_1)	1.091** (.426)
D_#SELLER (η_2)	-.043*** (.011)
QUALITY (η_3)	.028 (.169)
LNAGE (η_4)	-.797 (.709)
OL_POS (α_1)	-.913* (.487)
D_LN#CR (β_1)	. 359 (.353)
D_ACR (β_2)	-1.054* (.634)
OL_POS $\times$ D_LN#CR (τ_1)	-1.674* (1.041)
OL_POS $\times$ D_ACR (τ_2)	2.078 (1.981)
Sample Size	83
Adjusted R-squared	.301
Model Fit F	4.921***

*p < .1, **p < .05, *** p < .01

Notes: The dependent variable is $\text{D\_LNRANK} = \ln(\text{Rank}_{i,3}) - \ln(\text{Rank}_{i,2})$. The table lists the unstandardized coefficients with standard errors of parameter estimates in parentheses. WOM and observational learning variables and their interaction terms are mean-centered. There is an intercept in the regression.

TABLE 8: AN EXAMINATION OF INTERNAL VALIDITY THREATS TO QUASI-EXPERIMENTS*

Description of the threat	How eliminated from the current study
(1) Selection bias: Observed effect results from the sample selection.	• Product specific factors (age, quality, marketing variables) are controlled in the study. • First-difference model controls potential self-selection problem due to unobserved effects (Woodridge 2002). • The definition of observational learning signals is based on the purchase percentages among those who viewed the same item instead of the dependent variable, sales rank (see details in Appendix A1). • Results are robust to different observational learning measures (see details in Appendix A1).
(2) Selection maturation: Observed effect is due to experimental groups maturing overtime.	• Product age is controlled in the study. • The lifetime effects are specifically examined.
(3) Mortality: Observed effect is due to sample attrition.	• The sample is confined to the products available in both pretest and posttest periods. • The sales ranks are not significantly different between the attrition products and the retained products (see details in Appendix A2).
(4) History: Observed effect is due to an event, which occurs concurrently with the stimulus.	• Combing with the treatment reintroduction design, the removed-treatment design can rule out the potential contamination from history threat. • Results are robust to the analysis adding lagged sale-rank independent variable (see details in Appendix A3). • Control group is used. The sales ranks are not statistically different between the control group and treatment group (see details in Appendix A4).
(5) Testing: Observed effect results from familiarity induced by testing.	It is not an issue in this study since the subjects are the same cameras over the periods.
(6) Statistical regression: Observed effect is attributed to regression to the mean.	The WOM and observational learning statistics in this study should be less susceptible to this type of error.
(7) Ambiguity about the direction of causal influence: Causality of observed effect cannot be detected.	It is not an issue in this study given the time sequences of the stimuli.

* The list of threats here is following Moorman, Du and Mela (2005). A complete list can be found at Shadish, Cook, and Campbell (2002).

FIGURE 1: A NATURAL EXPERIMENT: THE LONGITUDINAL QUASI-EXPERIMENTAL DESIGN

Study 1		
O_1	~~X~~	O_2
O_1		O_2
09/2005		*03/2006*

Studies 2 and 3*		
O_2	X	O_3
O_2		O_3
03/2006		*03/2007*

Theoretical Issues	Quasi-experimental Studies
1. Sales Effects of WOM versus Observational Learning	• Study 1 (observational learning treatment-removal study) • Robustness check: Study 2 (observational learning treatment-reintroduction study)
2. Lifetime Effects of WOM and Observational Learning	• Within-subjects cross-time comparison (same products in different product life stages: Study 1 vs. Study 3) • Robustness check: Between-subjects cross-time comparison (same observational learning treatment with products in different age groups: Study 2 vs. Study 3)
3. Interaction Effects of WOM and Observational Learning	• Study 2 and Study 3 (observational learning treatment-reintroduction studies)

Notes: O_t: the observation in period t

~~X~~: the observational learning treatment removal; X: the observational learning treatment reintroduction

* Studies 1 and 3 examine the same product samples over product lifetime under different treatment designs; Studies 2 and 3 replicate the same treatment design for two independent samples with significantly different product ages.

APPENDIX

A1. The Results Robustness to Alternative Measures of Observational Learning

It is important to note that the definition and measures of observational learning (OL) signals are based on the purchase percentages among those who viewed the same item instead of sales rank. In other words, our selection of different observation learning signals is not based on the dependent variable, sales rank. A product with a top sales rank could still have a very low purchase percentage and thus be categorized in the group with negative OL signals (OL_NEG =1). For example, in our data, Canon PowerShot A520 has a top sales rank 5 in Period 1. However, its purchase percentage is so small that it is not even listed among the cameras in its purchase percentage section (i.e., most consumers viewing this camera bought other even more popular cameras; OL_NEG=1). Meanwhile, a product with a high purchase percentage (i.e., OL_POS =1) could still have a very low sales rank (a large rank number). For instance, in the example we provided in footnote 1, HP Photosmart R707 was the most purchased model among all consumers who viewed this item (OL_POS=1). However, its sales rank was only 720. In fact the overall correlations between OL variables and sales ranks are significant (from zero), but very low (-.26 between OL_POS and sales rank, and -.30 between OL_NEG and sales rank). Furthermore, as shown in Appendix A3, when both variables are incorporated into the model, our OL variable (purchase percentage statistics) has a significant effect on sales change but sales rank (lagged) does not. These statistics suggest that our results on the impacts of OL on sales change over time are less likely to be the artifacts of how we define or select OL signals. Sales ranks include information from consumers who may never be interested in or have not considered the focal product. They are based on a comparison of all possible products in the market, even though many of them are not relevant to a consumer's interest. However, the OL data we focus on here are based on a set of products in which a consumer may have strong interest. This information may well be more diagnostic because these products are listed on the basis of the behaviors of consumers with similar preferences (i.e., they have all viewed and considered the focal product).

To further show that our main findings are robust to alternative OL measures, we conduct several additional analyses. First, as pointed out in the paper, the simplest measure of the positive OL signal is to treat the signal as positive only if a camera *i*'s purchase percentage is the highest in display (i.e., using observations with *extreme* positive signal only rather than using *all* observations with positive signal as in Table 4). In addition, since generally three or four cameras are listed in the OL section (i.e., four or five choice alternatives regarding the focal product), another alternative measure uses 1/5 or 20 percent as the cutoff point for positive/negative OL signals. Specifically, the OL signal is negative if a camera's percentage is not the highest and is less than 20 percent, and positive otherwise. Table A1 presents results based on these two alternative measures, which reveal the same asymmetric effect of observational leaning as that reported in Table 4. Hence, our main results on the asymmetric effect of observational leaning are robust to this measure.

[INSERT TABLE A1 ABOUT HERE]

Second, our analysis uses the purchase percentage information of a given product on its own web page. It is possible for a consumer to find a product's sales percentage on other products' pages (i.e., A's sales percentage may appear in B's page if A is among the top products purchased by consumers who have viewed B). To allow for this possibility and test the robustness of our main findings, we incorporate this information and run additional analyses. Specifically, for each camera *i,* in addition to the purchase percentage information for all listed cameras in *i*'s own OL section, we also collect the purchase percentage information from the home page of each of those listed cameras. For each camera *i,* we use three alternative OL measures: (1) the average, (2) the maximum, and (3) the minimum of all purchase percentage ratios from different product pages, including its own page. Specifically, OL_POS is the average, maximum or minimum of all purchase percentage ratios from different product pages including camera *i*'s own page. Correspondingly, OL_NEG indicates if the camera *i* is absent in the OL sections of all product pages (for the average and maximum ratios) or absent in the OL section of one product page (for the minimum ratio). We rerun the analysis in Study 1 by using three alterative measures (the model specifications of all three models are the same as Model (2) in the paper. They only differ in the measurement of OL information). As shown in Table A2, our results are robust for all three measures: The impact remains significant for positive but not for negative OL signals.

[INSERT TABLE A2 ABOUT HERE]

In addition, the results in Table A2 can also help to reduce one potential confounding, due to the way of measuring OL, behind the insignificant effect of negative OL signals we observed. Specifically, if a camera *i* is not listed on its own OL section, it may get the positive inflow of search from other pages given that *i* may be listed in the OL section of other items. As a result, the insignificant effect of negative OL signal we identified may be the combined results of the negative OL on one's own page and the positive inflow of search from other pages. One way to address this concern is to check if our result can still hold if we strictly focus on the negative OL signals when such positive inflow is less likely to occur. For the average and maximum ratio measures in Table A2, camera *i*'s OL signal is classified as negative only if camera *i* is neither listed in its own OL section nor in the OL section of all other listed products' homepages. The positive inflow of search is less likely to occur for these restricted cases. Our main results remain similar (see the average and maximum ratio columns in Table A2): the negative OL signal (under the more restricted measurement) still has no significant impact on sales. This suggests the insignificant result of negative OL in our data is less likely the result of the confounding from the positive inflow of search or the result of the way we measure the OL signals.

A2. Sample Attrition

One potential concern regarding our results is that sample attrition might explain the asymmetric effects of OL because such attrition could occur based on the dependent variable (sales). To address this concern, first we conduct a *t*-test on the sales rank between the attrition models and the final retained sample, and find that the sales ranks are not significantly different between the two. In the treatment-removal Study 1, 16 cameras overall are available for sale at Amazon.com in period 1 but not in period 2 (i.e., the attrition models). Among the 16 attrition models, 13 cameras still have sales rank information available in period 2. The sales ranks of these 13 attrition models in period 2 do not differ significantly from the 90 cameras in our final retained sample ($t = 1.127$, $p > .282$). In the treatment-reintroduction Study 2, among the 4 attrition models, three cameras still have sales rank information available in period 3. The sales ranks of these three cameras in period 3 are not significantly different from the 39 cameras in the final sample ($t = .417$, $p > .679$) either. Second, a detailed investigation of the data further suggests that the availability of a camera at Amazon.com does not seem to depend on product sales. On any given day, a specific camera may not be available simply because none of the sellers at Amazon.com carries that particular model that day. However, this model would be available the next day if one (or more) seller were to offer the product again. This can be shown in our data. In our initial camera sample, of all cameras available in period 1 (09/21/2005), 16 are not available for sale in period 2 (03/15/2006) at Amazon.com (i.e., the attrition models). However, although these 16 cameras are not available in period 2, some of them still have sales rank information available in period 2. Almost half of the 16 attrition models (7 cameras) became available again in period 3 (3/18/2007). Finally, an examination of our data shows that, in the final retained sample, a majority of the treatment group, i.e., 48 out of 74 cameras (65%), carry negative OL signals in the early period. This further suggests that the observed asymmetric effect of OL is less likely to be explained by the sample attrition from negative OL signals.

A3. The Robustness of the Results to Potential Impact of Sales Ranks

We explain in the paper why our unique combination design of treatment-removal and treatment-reintroduction can help to reduce the concern that the identified results on the asymmetric sales effects of OL might result from sales rank information. To further reduce this concern, we extend our models by including lagged sales rank as an independent variable, and to check whether or not the asymmetric effects of OL, identified in both the treatment-removal Study 1 and the treatment-reintroduction Study 2, are robust to the new analysis. We are able to obtain the lagged sales rank data in the treatment-reintroduction Study 2 (the data on the lagged sales rank for the treatment-removal Study 1 were not available for collection), and conduct a new analysis by adding the one-month lagged sales-rank difference, D_RANK_LAG, in Models (1) and (2). As shown in Table A3, first, our main findings are robust to this new analysis: The impact remains significant for positive OL signals but not for negative OL signals. Second, the coefficient of the newly added lagged sales-rank difference variable is not significant. Third, the new models have lower adjusted R-squared values compared with our original models (see Table 5). These results further reduce the concern of the potential impacts from sales ranks, and increase the robustness of our findings.

[INSERT TABLE A3 ABOUT HERE]

There are different plausible reasons why consumers are affected by the purchase percentages of those who viewed the same item but not by sales rank while both information sources are available on Amazon.com. First, the former information is much easier to obtain because sale rank information is buried in the middle of a page with all other product details, while the purchase percentage information is listed at the top of the page in proximity to the camera picture. Second, rank number of product *i* may be less relevant for consumer decision making because such information is based on thousands of models in the digital camera category, and consumers may not be aware of or be interested in most of the models. However, purchase percentages at Amazon.com are based on the decisions of other consumers who have viewed the same camera *i*. These consumers were all aware of and interested in the camera *i*, and, thus, their actions are more comparable for any consumer considering the product and the information on their purchase percentage or choice share is more diagnostic. This information is also more aligned with the OL construct defined in the literature (e.g., Bikhchandani, Hirshleifer and Welch 1992).

A4. Information Policy at Amazon.com and Control Group

The exact reasons for the information policy changes and treatment group assignments at Amazon.com are unknown to the researchers. We made a number of different efforts to contact Amazon.com and also searched all news releases, but were not able to find information on the reason for these changes. One potential concern regarding the treatment group assignment is that Amazon.com did not provide OL data for some cameras (i.e., the control group) because these were low-sales items for which the OL signals would have been negative. We take several steps to address this concern. First, we conduct a *t*-test on the sales ranks between the control group and the treatment group in our data prior to the policy change. The sales ranks between two groups are not significantly different ($t = 1.183$, $p > .25$). This result suggests that the decision by Amazon.com to provide OL information does not seem to depend on product sales. Second, the control group in our study does not include only low-sales cameras. Half of the cameras in the control group are among top 250 items in the Camera & Photo section, which includes thousands of items (e.g., 2556 items on 03/15/2006). Almost one quarter of the cameras in the control group are among the top 100 items in the Cameras & Photo section. In addition, 48 out of 74 cameras (65%) in the treatment group carry negative OL signals in our study. This also suggests that the concern about displaying the negative OL signals of low sales does not seems to play a major role here for Amazon.com's decision to provide observational data. Finally, as documented in the literature, many other researchers studying natural experiments have encountered a similar difficulty. In policy/program evaluation studies, for example, researchers often do not have sufficient information on the reasoning behind policy implementation, and policy makers often assign subjects into different policy conditions based on characteristics that the researchers cannot observe (Wooldridge 2001, p. 254). In this study, following the methods in this literature (Wooldridge 2001), we use the panel data and the first-difference model to control for this unobserved effect and address this concern.

TABLE A1: THE RESULT ROBUSTNESS TO ALTERNATIVE OBSERVATIONAL LEARNING MEASURES

OL Measures	Study 1			
	Alternative Measure 1[1]		Alternative Measure 2[2]	
	Model (1)	Model (2)	Model (1)	Model (2)
D_LNPRICE	.685 (.487)	.543 (.493)	.837** (.423)	.755* (.416)
D_#SELLER	-.027 (.023)	-.031 (.023)	-.043*** (.016)	-.049*** (.016)
QUALITY	-.094 (.168)	-.065 (.168)	-.165 (.150)	-.156 (.147)
LNAGE	-.656 (.438)	-.811* (.436)	-.549 (.388)	-.654* (.380)
OL_POS	1.041* (.534)	1.110** (.528)	.975** (.373)	.911** (.367)
OL_NEG	-.031 (.280)	.053 (.282)	-.119 (.222)	-.104 (.217)
D_LN#CR	-1.019*** (.379)	-1.103*** (.354)	-1.022*** (.357)	-1.038*** (.330)
D_ACR	.157 (.520)		-.148 (.479)	
D_PER5		.461 (1.106)		-.056 (1.042)
D_PER1		1.098 (.788)		1.217** (.570)
Sample Size	68	68	90	90
Adjusted R-squared	.162	.176	.296	.325
Model Fit F	2.615**	2.595**	5.677***	5.758***

*p < .1, **p < .05, *** p < .01

Notes: 1. For alternative OL measure 1, OL_POS=1 if camera *i* has the highest purchase percentage in display, and OL_POS =0, otherwise; OL_NEG=1 if camera *i*'s purchase percentage is too low to be listed, and OL_NEG=0, otherwise.

2. For alternative OL measure 2, OL_POS=1 if *i*'s percentage is 20% or higher or is the highest in display, and OL_POS =0, otherwise; OL_NEG=1 if camera *i*'s purchase percentage is not the highest in display and below 20%, and OL_NEG =0, otherwise.

3. The dependent variable is $\text{D\_LNRANK}=\ln(\text{Rank}_{i,3})-\ln(\text{Rank}_{i,2})$. The table lists the parameter estimates with standard errors in parentheses. There is an intercept in the regression.

TABLE A2: THE RESULT ROBUSTNESS TO ALTERNATIVE OBSERVATIONAL LEARNING MEASURES: INFORMATION FROM DIFFERENT WEB PAGES

	Study 1 (Model (2))		
OL Measure	Average Ratio[2]	Maximum Ratio[2]	Minimum Ratio
D_LNPRICE	.492 (.397)	.379 (.400)	.691 (.417)
D_#SELLER	-.053*** (.015)	-.056*** (.015)	-.054*** (.016)
QUALITY	-.259* (.144)	-.268* (.144)	-.161 (.147)
LNAGE	-.391 (.366)	-.434 (.365)	-.509 (.385)
OL_POS[1]	1.109*** (.382)	.877*** (.305)	.857** (.441)
OL_NEG[1]	-.198 (.232)	-.132 (.245)	-.072 (.259)
D_LN#CR	-.943*** (.310)	-1.037*** (.309)	-.917*** (.333)
D_PER5	-.028 (.994)	-.204 (.998)	-.172 (1.047)
D_PER1	1.205** (.545)	1.307** (.544)	1.204* (.441)
Sample Size	90	90	90
Adjusted R-squared	.380	.379	.314
Model Fit F	7.064***	7.037***	5.528***

$^*p < .1$, $^{**}p < .05$, $^{***}p < .01$

Notes: 1. OL_POS is the average, maximum or minimum of all purchase percentage ratios from different product pages including camera *i*'s own page; correspondingly, OL_NEG indicates if the camera *i* is absent in the observational learning sections of all product pages (for the average and maximum ratios) or absent in the observational learning section of one product page (for the minimum ratio).

2. Camera *i*'s OL signal is classified as negative (i.e., OL_NEG =1) only if camera *i* is neither listed in its own OL section nor in the OL section of all other listed products' home pages.

3. The dependent variable is $\text{D\_LNRANK} = \ln(\text{Rank}_{i,2}) - \ln(\text{Rank}_{i,1})$. The table lists the parameter estimates with standard errors in parentheses. There is an intercept in the regression.

TABLE A3: THE RESULT ROBUSTNESS TO SALES RANK INFORMATION

	Study 2	
	Model (1)	Model (2)
D_LNPRICE	.928* (.523)	.936* (.562)
D_#SELLER	-.052*** (.013)	-.049*** (.014)
QUALITY	.158 (.229)	.194 (.240)
LNAGE	.558 (1.199)	.894 (1.258)
OL_POS	-.946* (.674)	-1.051* (.697)
OL_NEG	.374 (.901)	.321 (.931)
D_LN#CR	.460 (.394)	.505 (.404)
D_ACR	-1.160** (.474)	
D_PER5		-1.325 (1.397)
D_PER1		3.324** (1.466)
D_RANK_LAG[1]	.112E-03 (.127E-03)	.115E-03 (.143E-03)
Sample Size	39	39
Adjusted R-squared	.526	.517
Model Fit F	5.686***	5.063***

*p < .1, **p < .05, *** p < .01;

Notes: 1. D_RANK_LAG is the sales-rank difference between Period 2 (02/15/2006) and February 18, 2007 (one month before Period 3).

2. The dependent variable is $D\_LNRANK = \ln(Rank_{i,3}) - \ln(Rank_{i,2})$. The table lists the unstandardized coefficients with standard errors of parameter estimates in parentheses. There is an intercept in the regression.