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Consumers' purchase decisions can be influenced by others' opinions, or word of mouth (WOM), and/or others' actions, or observational learning (OL). Although information technologies are creating increasing opportunities for firms to facilitate and manage these two types of social interaction, to date, researchers have encountered difficulty in disentangling their competing effects and have provided limited insights into how these two social influences might differ from and interact with each other. Using a unique natural experimental setting resulting from information policy shifts at the online seller Amazon.com, the authors 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 OL information significantly increases sales, but negative OL information has no effect. This suggests that reporting consumer purchase statistics can help mass-market products without hurting niche products. The results also reveal that the sales impact of OL increases with WOM volume.

Keywords: social interactions, social influences, observational learning, word of mouth, natural experiment

Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning

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 example, when choosing between two restaurants, a person might be heavily influenced by the opinions and experiences of his or 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 marketing literature (e.g., Arndt 1967) defines the former type of opinion- or preference-based social interaction as word of mouth (WOM). The psychology and economics literature (Bandura 1977; Bikhchandani, Hirshleifer, and Welch 1998, 2008) defines the latter type of action- or behavior-based social interaction as observational learning (OL).

Although such social channels have influenced consumers since the advent of trade, recent technological advances have significantly increased the importance of consumer social interactions as a market force. Not only are consumers now better able to exchange information through online forums, chat rooms, and blogs, but firms are gaining increasing capacity to initiate and manage consumer social interactions directly (Godes et al. 2005), tasks either impossible or too

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costly in the past. For example, the Internet, e-commerce, and information technology have created opportunities for firms to effectively facilitate WOM communication by allowing buyers to post consumer reviews based on their personal experiences on firms' Web sites or licensing consumer reviews from third-party sites, such as Epinions.com (Chen and Xie 2008). New technology has also created opportunities for firms to directly facilitate consumer OL by reporting past buyers' purchase actions on their Web sites. For example, on each product's home page, Amazon.com provides OL information under the section "What do customers ultimately buy after viewing this item?"[1] Thus, online consumer social interactions, which firms often initiate or facilitate, have increasingly significant roles in consumer purchase decisions. One recent survey reported in the *Wall Street Journal* finds that 71% of U.S. adults who purchase online use consumer product reviews for their purchases, and 42% 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 OL. For example, an online seller manages WOM through its policies on consumer-generated product reviews but manages OL through its policies on firm-reported consumer actions based on the firm's sales data. The seller can choose to facilitate WOM, OL, or both simultaneously. A good understanding of the competing impacts of each type of social interaction over product lifetime and 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 Godes et al. (2005) propose and focus on two common types: WOM and OL.[2] First, we develop theoretical propositions pertaining to three essential issues regarding the impacts of these two types of social interaction: (1) whether and how WOM and OL create different effects, (2) how these effects vary over product lifetime, and (3) how WOM and OL interact with each other to influence sales.

Then, we address these issues using a unique data set collected from Amazon.com. During the period 2005–2007, Amazon.com first removed and then reintroduced the OL information section in its digital camera category. This OL policy shift provides a unique natural experimental setting to test our theoretical propositions. Using this unique setting, we designed three longitudinal, quasi-experimental field studies that include the combination of both treatment-removal and treatment-reintroduction studies. This combination design enables 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 us to investigate the lifetime effects of WOM and OL with a high validity.

Our longitudinal studies lead to several significant results. First, our data reveal that WOM and OL differ in their impacts on sales. Specifically, negative WOM information has a greater impact on product sales than positive WOM information. However, the opposite holds for OL. These findings underscore the importance of separating the effects of the two types of social interaction. The asymmetric effect of OL can be encouraging for online infomediaries between buyers and sellers. Note that the popular (niche) products tend to attract more (fewer) purchases and thus have a positive (negative) OL 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 it may expected 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 OL 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, we detected no significant interaction between OL and WOM valence (i.e., we find no clear evidence that the impact of others' purchase actions increases or decreases when consumer ratings increase).

We organize the rest of this article as follows: Next, we present the theoretical background and conceptual development. 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 begin by defining the concepts of WOM and OL studied here. Then, we discuss why WOM and OL might produce different effects, how they might influence sales over a product's lifetime, and how these two types of information might interact with each other.

WOM Versus OL

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) through communication among people. The two most important WOM attributes studied in the literature are valence (i.e.,

[1]For example, on the page of the digital camera HP Photosmart R707 on September 21, 2005, the OL section lists how many consumers purchased this and two other cameras in decreasing order of the purchase 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 2009; Miller 2000). However, information technology makes this decision much easier and more cost efficient for the seller.

[2]We define "social interactions" broadly as any actions a nonselling party takes that affect 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 2008) than the sociology and psychology literature (e.g., Bagozzi, Dholakia, and Pearo 2007; Cialdini and Trost 1998; DeLamater 2004). Some other terms 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).

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). Previous research has indicated that WOM valence can influence product sales by changing consumer valuation of the products (e.g., Chevalier and Mayzlin 2006; Mizerski 1982), 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).

In contrast, the second form of social interaction we examine here, OL, is less explored in the marketing literature. The concept of OL can be traced back to social learning studies in psychology (Bandura 1977). How OL 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, OL 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 consumers, 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 OL using a model of consumer product adoption decision making, in which a consumer adopts (rejects) a product if he or 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 he or she observes that both previous consumers adopt (reject) the product, regardless of his or her private information. The consumer will rely on his or her own information only when one consumer adopts and another rejects. Whether a person will follow previous choices largely depends on the percentage share of previous choices (Bikhchandani, Hirshleifer, and Welch 1998, p. 156). This simple case helps illustrate the concept of OL valence. The valence of OL is determined by the percentages of adoptions or the share of choices among all previous actions. Conceptually, the OL signal is more positive (negative) if the percentage of cumulative purchases among the choices made by all previous informed consumers is larger (smaller). In general, the information cascade theory conjectures that the positive and negative OL signals both affect adoption behavior but in opposite directions; that is, the former motivates but the latter discourages adoption. Although OL 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 OL

The first issue we explore involves the possible differences between the impact of WOM and OL 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 researchers have found it to have a greater impact on consumers' adoption decisions than positive WOM information (e.g., Mizerski 1982). However, much less is known about the impact of OL valence. Although the information cascade theory suggests that positive (negative) OL can potentially increase (decrease) adoption (Bikhchandani, Hirshleifer, and Welch 1992; Bikhchandani and Sharma 2001; Welch 1992), the literature has provided few insights into whether the valence of OL has an asymmetric effect.

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

According to the accessibility–diagnosticity model (Feldman and Lynch 1988), whether consumers will use any accessible information 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 OL carry a limited amount of information on the reasons behind others' actions, negative OL can be relatively less diagnostic compared with positive OL 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 narrow product positioning (i.e., offering unique features that only a small market segment appreciates). Thus, a product with a negative OL signal (i.e., a relatively small percentage of purchase actions) might not be perceived unfavorably by 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. Therefore, a product with positive OL 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 a person's taste). For example, a mono classical music CD may have a small purchase percentage (negative OL 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 OL information) is of poor quality is low. Therefore, a positive OL signal (a product with a relatively large purchase percentage) is more diagnostic for consumers than a negative OL signal (relatively small percentage of purchase actions) because 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 OL can reduce its use in consumers' purchase decision making. Furthermore, although both positive and negative OL information are generally perceived as credible signals, such high credibility is more likely to strengthen the impact of positive OL but offers little help to the negative OL 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 greater impact of negative than positive signals found in WOM may not apply to OL. Rather, the opposite pattern (i.e., the greater impact of positive than negative signals) might hold.

The Lifetime Effects of WOM and OL

Our second issue involves the dynamics of the two types of social interaction. We identify two factors that affect the sales impact of WOM and OL 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 OL information than experts. As a result of these consumer segment dynamics, both WOM and OL can have 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 because of 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 OL (Bikhchandani, Hirshleifer, and Welch 1992). Similar effects also apply to WOM impact, because in the later stages of the product life cycle, consumers are more informed and may have formed their attitudes toward a product on the basis of information from other channels. As a result of this information substitution dynamic, the impact of both WOM and OL 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. Thus, we conclude that the direction of the overall effect is an empirical issue that should be tested using real market data.

The Interaction Effects of WOM and OL

The third issue we explore is the possible interaction effect between WOM and OL 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, we might expect a complementary effect between WOM volume and OL information. The information cascade theory argues that the likelihood of an information cascade and the impact of OL 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, he or she can be indirectly informed by the volume of WOM because the more people who have evaluated the product, the more WOM information is generated. As a result, a person is more likely to act according to the information conveyed by previous actions if he or she perceives a greater volume of WOM information. In other words, a positive complementary effect might exist: The volume of WOM can strengthen the impact of OL signals. Moreover, we might also expect a substitution effect between WOM valence and OL information because both types of information reveal the desirability of the product. Thus, they may weaken each other's effect.

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

METHODOLOGY: A NATURAL EXPERIMENT

Because of limited data availability, to date, researchers have encountered difficulty in disentangling the competing effects of WOM and OL and have provided limited insights into 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 through 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 OL, but not both (e.g., Chevalier and Mayzlin 2006; Dholakia and Soltysinkski 2001; Godes and Mayzlin 2004a, b; Hanson and Putler 1996; Liu 2006; Salganik, Dodds, and Watts 2006; Tucker and Zhang 2009; Zhang 2010). However, in reality, consumers are usually subject to the influences of both WOM and OL simultaneously. To examine how WOM and OL jointly influence product sales, the following criteria must be met for our empirical research design:

- The design must be able to separate the two types of social interaction and decompose the impacts of OL from WOM.
- It must investigate the impacts of WOM and OL over product lifetime.
- The design must examine how WOM and OL influence product sales jointly and how they interact with each other.
- It must 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 researchers cannot manipulate (e.g., government interventions, policy changes; Shadish, Cook, and Campbell 2002). Over the past decade, the natural experimental approach has gained considerable attention in economics, though it is still relatively rare in marketing (Meyer 1995; Moorman 1996). A major advantage of a natural experiment is that it can provide greater validity on causal inferences than purely statistical adjustments (Shadish, Cook, and Campbell 2002). This is particularly important when studying social interactions, in which it is difficult for researchers to conclude using econometric models that their observations result from social interactions rather than unobserved individual preferences (Manski 2000).

The online seller Amazon.com provides an ideal setting for our empirical study because it was the pioneer in allowing consumers to post product reviews and facilitate WOM interactions on its Web site. In recent years, in addition to offering consumer review information, Amazon.com has provided OL information for each product on that product's home page 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 OL construct suggested in the theoretical literature and defined in the theoretical section here. However, in early November 2005, Amazon.com removed the purchase percentage section and stopped providing this information for all digital cameras, though 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 again provided OL information for the digital camera category. Throughout this 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, but 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 OL information. As a result, these models provide an untreated control group for our study.

The OL policy shifts at Amazon.com provide a unique natural experimental setting with both treatment and control groups. It enables us to disentangle two types of social influence and examine the causal inferences regarding the sales effects of WOM and OL information. The control group enables us to control for the time trend and rule out the history threat to internal validity. More important, it can help determine whether the possible correlation between the OL signals and sales is the result of the impact of OL signals or 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 OL in this natural setting, we adopt a longitudinal, quasi-experimental approach in which the treatment assignment might be nonrandomized (Shadish, Cook, and Campbell 2002). Because researchers have no control over information policy changes at Amazon.com, the quasi-experimental approach enables us to control the data collection schedule without having control over the scheduling of experimental stimuli (Moorman, Du, and Mela 2005; Shadish, Cook, and Campbell 2002). The experimental stimuli here are the information policy changes at Amazon.com (i.e., the removal and later reintroduction of OL information). The policy changes at Amazon.com imply three periods in which the firm adopted different information policies—Period 1: before the removal of OL information; Period 2: after the removal of OL information; and Period 3: after the reintroduction of OL 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 OL than the nonpaid 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. The following subsections elaborate on the specific data 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. Then, Amazon.com 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 Chevalier and Mayzlin (2006), data on two different measures: the average customer rating (ACR) for each camera and the percentages of five-star (PER5) and one-star (PER1) reviews for each camera. We used the second measure to examine the potential difference in sales impact between positive and negative WOM.

OL data. For each camera at Amazon.com, the OL section is presented under the "What do customers ultimately buy after viewing this item?" section. This section reports the aggregate sales statistics based on previous buyers actions. Specifically, it lists the purchase percentages of 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, he or she can find the purchase percentage of camera i in the OL 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 OL 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] Thus, we consider the OL signal of a product negative if its purchase percentage is too small to be

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

listed in its OL section. In contrast, we consider the OL signal 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 also use several alternative OL measures and show that our findings are robust (for detailed analyses and discussion, see Appendix A).

Sales data. Several recent studies using 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). These researchers have used this measure 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 study of the effects of social interactions on sales.

Note that the sales ranks at Amazon.com might reflect some recent sales up to a month (for a detailed discussion, see Chevalier and Goolsbee 2003; Chevalier and Mayzlin 2006). To eliminate the possible simultaneity between the review/OL information and sales rank in that month, following Chevalier and Mayzlin's (2006) practice, we examined the log-sales-rank change by time t relatively to the review/OL changes up to one month before time t in each study.

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, we collected data on two product-specific variables, product quality (QUALITY) and age (AGE), from the leading consumer technology product Web site, 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. Therefore, 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 allowed us to calculate the product age of each camera. Because 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 needed 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]

[4]Amazon.com lists hundreds of different cameras. For example, 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 enable 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.

EMPIRICAL ANALYSIS AND RESULTS

The Sales Effects of WOM Versus OL

We examine the first research issue (i.e., whether and how WOM and OL differentially affect consumer purchase decisions) using a quasi-experimental Study 1. Figure 1 depicts the quasi-experimental design, which we created using Shadish, Cook, and Campbell's (2002) notation. Here, O_t denotes the measurement observation in period t, and $\cancel{X}$ and X denote the removal and reintroduction of the OL treatment, respectively. The dashed line distinguishes the treatment and the control groups. Study 1 includes Periods 1 and 2 (i.e., before and after the removal of OL 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 2004a; 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). We detected the impact of OL 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 OL available to consumers in Period 1, but only WOM in Period 2) is affected by the removal of its OL signal and the changes in its WOM information.

The initial sample in Study 1 includes all 120 digital cameras that were both available for sale on Amazon.com and reviewed by CNET.com from June 2004 to September 2005. These cameras were newly reviewed models at CNET.com and tended to be in the early stage of product lifetime (i.e.,

Figure 1

A NATURAL EXPERIMENT: THE LONGITUDINAL QUASI-EXPERIMENTAL DESIGN

Study 1			*Studies 2 and 3*		
O_1	$\cancel{X}$	O_2	O_2	X	O_3
O_1		O_2	O_2		O_3
09/2005		03/2006	03/2006		03/2007

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

Notes: O_t = the observation in period t, $\cancel{X}$ = the OL treatment removal, and X = the OL 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.

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), we confined the final sample for Study 1 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 and retained products (for details on sample attrition, see Appendix B). Table 1 presents the descriptive statistics of the overall data generated in the current study.

Before presenting the formal analysis, we first examine some descriptive statistics. Table 2 presents the sales change comparison between the treatment and control groups in Study 1. Among the 90 cameras in Study 1, Amazon.com presented 26 (28.9%) of the cameras with positive OL information and 48 (53.3%) with negative OL information in Period 1. The other 16 (17.8%) cameras were not supplied with OL 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., D_LNRANK = $\ln[\text{Rank}_{i,2}] - \ln[\text{Rank}_{i,1}]$). It is linearly correlated with the real sales change over time, because $\ln(\text{Rank}_{i,2})$ is linearly correlated with $-\ln(\text{Sales}_{i,2})$ (Chevalier and Goolsbee 2003; Chevalier and Mayzlin 2006).[5] As Table 1 shows, the sales ranks slide (i.e., the rank numbers are increasing) over time for products in our data set. Thus, we can interpret D_LNRANK as the degree of the sales decline between the two periods. As Table 2 shows, after removing the OL information, the degree of sales decline is significantly larger for the cameras with positive OL 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 OL information in Period 1 and the control group (t = –.751, $p > .45$). These statistics provide some preliminary empirical evidence of an asymmetric sales effect of OL, in which positive OL information is more influential on sales than the negative OL signal. This finding is opposite to the asymmetric pattern of the WOM effect shown in the literature (e.g., Chevalier and Mayzlin 2006).

Model specification. To examine the sales effects of WOM versus OL thoroughly, we estimated two "first-difference" econometric models to control for a potential endogeneity issue and alternative explanations (Wooldridge 2002). Specifically, we estimate the following two separate models, which differ in the measures of WOM valence used (for the variable definition, see Table 3):

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

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

In both models, D_LNRANK_i is the difference of sales ranks (in natural log) between the two periods for a camera i, D_LNRANK_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 cam-

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

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]	307.93	(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 & Video)	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)
Percentage of five-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%)
Percentage of one-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%)
Percentage of cameras without OL signal	17.8%		100%		100%		5.1%		100%		13.1%	
Percentage of cameras with positive OL signal	28.9%		0%		0%		87.2%		0%		78.7%	
Percentage of cameras with negative OL signal	53.3%		0%		0%		7.7%		0%		8.2%	

[a]The review data were collected on February 15, 2006, for this period (i.e., one month before Period 2).
[b]The review data and OL percentage data were 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.
Notes: Means are primary entry, and standard deviations are in parentheses.

Table 2

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

	Positive OL Items (N = 26)	*Negative OL Items (N = 48)*
Treatment-removal group	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 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 OL section
OL_NEG	Whether a camera fails to be listed under its OL 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 five-star reviews between the two periods
D_PER1	Difference in the percentage of one-star reviews between the two periods

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

era i, and AGE_i is the number of dates (in natural log) from the product launch to Period 2 in Study 1. Because unobserved product characteristics can influence both product sales and social interactions, given the nature of the current data, we adopted a first-difference model to circumvent this endogeneity problem (Mouw 2006; Wooldridge 2002). Specifically, the sales differences over time eliminate all unobserved time-invariant fixed effects. In addition, we use the control variables to control for possible time-variant effects related to the constant variables over two periods (Wooldridge 2002).[6]

We included two variables to measure the impacts of positive and negative OL information. The variable OL_NEG_i measures the impact of removing negative OL signals in Study 1. This is a dummy variable, such that $OL\_NEG_i = 1$ if, in Period 1, Amazon.com provided camera i's OL section (i.e., it does not belong to the control group) but its purchase percentage is too low to be listed; otherwise, $OL\_NEG_i = 0$. The variable OL_POS_i measures the impact of removing the positive OL signals in Study 1. There are several ways to code this variable; the simplest 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 OL signal) and excludes all observations for which a camera's purchase percentage is high enough to be listed as a popular model (but not the most popular) under the OL section. An alternative way to code this variable is to include all positive OL observations and use the ratio of camera i's purchase percentage to the highest percentage in its OL section to capture the 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 OL 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 $OL\_POS_i = 0$ if otherwise. This more general measure has the advantage of including all cameras with different degrees of positive OL signals and examining their impacts. We performed our empirical analysis using both the simplest and the general measures of OL_POS_i discussed previously (and some additional alternative measures of the OL signal) and reached the same conclusions. We report our results using the general ratio measure of the positive OL signal here and our results using other alternative measures in Appendix A (see Tables A1 and A2).

In summary, in Models 1 and 2, the coefficient of OL_POS, a_1, captures the effects of the removal of various degrees of positive OL information, and the coefficient of OL_NEG_i, a_2, reflects the potential effects of the removal of negative OL information. The estimates of a_1 and a_2 are the difference-in-differences estimators (Wooldridge 2002), which capture the sales effects of positive and negative OL information relative to no OL signals (i.e., the control group).

To show that the effects of OL are robust to different measures of WOM, consistent with the extant literature (e.g., Chevalier and Mayzlin 2006), we used two 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 five-star (D_PER5_i) and one-star (D_PER1_i) reviews, which helps 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 WOM volume over the two periods. We tested multicollinearity 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. Model 0 presents results for a regression in which we included no social interaction variables, and Models 1 and 2 present results of the two models

[6]We conducted a Hausman test to ensure that $D\_LNPRICE_i$ and $D\_\#SELLER_i$ are exogenous in the model (Hausman 1978; Wooldridge 2002). In our first-difference model, $QUALITY_i$ and AGE_i are the difference of the interaction variables between time t and $QUALITY_i$ and AGE_i, which control for the time-varying effects related to quality and age. (We canceled out the time-invariant effect of quality and age by taking the first difference.)

Table 4
THE SALES EFFECTS OF WOM VERSUS OL

	Study 1		
	Model 0	*Model 1*	*Model 2*
D_LNPRICE (η_1)	.715	.690	.609
	(.453)	(.419)	(.409)
D_#SELLER (η_2)	–.057**	–.047***	–.053***
	(.016)	(.016)	(.015)
QUALITY (η_3)	–.082	–.196	–.188
	(.159)	(.150)	(.146)
LNAGE (η_4)	.056	–.540	–.649*
	(.338)	(.387)	(.376)
OL_POS (α_1)		1.101***	1.099***
		(.411)	(.399)
OL_NEG (α_2)		.081	.109
		(.254)	(.246)
D_LN#CR (β_1)		–1.045***	–1.051***
		(.358)	(.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^2	.175	.299	.336
Model fit F	5.712**	5.736***	6.001***

*$p < .1$.
**$p < .05$.
***$p < .01$.
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, and there is an intercept in the regression.

specified previously. Consistent with Table 2's results, for both Models 1 and 2, the coefficient for negative OL, α_2, is insignificant, but the coefficient for the positive OL variable, α_1, is highly significant and positive. The insignificant result for negative OL implies that the sales change is not significantly different between the control group and the cameras from which negative OL information is removed. In other words, compared with the cameras without OL signals, the presence of negative OL 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 OL signals intensifies product sales decline over Periods 1 and 2, suggesting the converse (i.e., that the presence of positive OL signals led to higher product sales before the removal of OL 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 one-star reviews worsens the sales decline over Periods 1 and 2, but an increase in the percentage of five-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).

Robustness of the results. Study 1 shows that both WOM and OL 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 OL 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 OL information was removed and if this event also affected sales, 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 18-month data collection period, Amazon.com reintroduced the OL information on its Web site. This enables us to add a treatment-reintroduction Study 2 in our study (see Figure 1). 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.

Initially, we considered all digital cameras newly reviewed by CNET.com from September 2005 to March 2006 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, we chose 39 cameras as the final sample for Study 2 (for descriptive statistics, see Table 1).

Study 2 has the same model specification as Study 1 but differs in the interpretation of the two OL coefficients, α_1 and α_2, which capture the impacts of removing OL signals in Study 1 and the impacts of reintroducing OL signals in Study 2. As Table 5 shows, the coefficient of the negative OL, α_2, is not significant, but the coefficients of positive OL, α_1, is significantly negative in both Models 1 and 2 of Study 2. The latter finding suggests a positive sales impact of positive OL signals in Study 2 because, with a treatment reintroduction design, the significantly negative sign of α_1 means that the reintroduction of positive OL 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_4, is not significant. Therefore, the treatment-reintroduction Study 2 presents the same pattern of asymmetric effects of WOM and OL we found in the treatment removal Study 1.

It is important to note that the coefficient of positive OL, a_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. For example, one such concern is the possible effect of sales rank information. Specifically, it could

[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 OL signals, and our results show an asymmetric pattern; second, the random shock argument would predict an opposite result in our treatment-reintroduction study.

Table 5

THE RESULT ROBUSTINESS OF THE SALES EFFECTS OF WOM VERSUS OL

	Study 2	
	Model 1	*Model 2*
D_LNPRICE (η_1)	1.015*	1.076*
	(.512)	(.531)
D_#SELLER (η_2)	–.051***	–.047***
	(.013)	(.013)
QUALITY (η_3)	.176	.186
	(.227)	(.238)
LNAGE (η_4)	.447	.843
	(1.188)	(1.249)
OL_POS (α_1)	–1.241**	–1.310***
	(.584)	(.613)
OL_NEG (α_2)	.066	.058
	(.828)	(.839)
D_LN#CR (β_1)	.353	.410
	(.374)	(.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^2	.529	.523
Model fit F	6.345***	5.623***

*$p < .1$.
**$p < .05$.
***$p < .01$.
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, and there is an intercept in the regression.

be argued that product sales rank information at Amazon.com might also convey previous purchase information and thus affect consumer purchase decision making. Therefore, the identified asymmetric effect of OL 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 OL resulted from sales ranks, they should have the same (positive or negative) impact in both treatment-removal and treatment-reintroduction studies. The significant but opposite signs of a_1 in Studies 1 and 2 help reduce this concern. In Appendix C, we conduct additional analyses to show how our results are robust to sales rank information and discuss why our OL measure is more diagnostic than sales rank for consumers.

The Lifetime Effects of WOM and OL

To examine the second research issue (i.e., the lifetime effects of WOM and OL), we conducted Study 3 (see Figure 1). Among the 90 cameras available in Study 1 (i.e., cameras available in both Periods 1 and 2), 61 were 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 OL information). As Table 1 shows, the product ages for the sample in Study 3 are significantly older than those in Studies 1 and 2 ($p < .01$).

We investigated the lifetime effects of WOM and OL using a two-step analysis. First, we conducted a within-subject comparison between Studies 1 and 3. Note that Study 3 includes cameras in Study 1 that were still available on Amazon.com in Period 3 and uses data at a later stage in the product life cycle than Study 1. Comparing these two studies can provide insights into how WOM and OL 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 OL uncovered in the within-subject 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 enables us to provide further evidence of WOM and OL's lifetime effects.

Study 3 has the same model specifications as Studies 1 and 2 (i.e., Models 1 and 2). Table 6 presents the results. As Models 1 and 2 of Study 3 show, the coefficients of all WOM and OL 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 OL. Specifically, positive OL 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 OL over the product lifetime.[8]

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

Table 6

THE LIFETIME EFFECTS OF WOM AND OL

	Study 2	
	Model 1	*Model 2*
D_LNPRICE (η_1)	.795	.869*
	(.485)	(.491)
D_#SELLER (η_2)	–.039**	–.040**
	(.017)	(.017)
QUALITY (η_3)	.162	.160
	(.210)	(.212)
LNAGE (η_4)	–1.845**	–1.966**
	(.907)	(.921)
OL_POS (α_1)	–.235	–.283
	(.413)	(.423)
OL_NEG (α_2)	–.843	–.925
	(.585)	(.596)
D_LN#CR (β_1)	–.059	–.137
	(.473)	(.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^2	.196	.192
Model fit F	2.833**	2.589**

*$p < .1$.
**$p < .05$.
Notes: The dependent variable is 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, and there is an intercept in the regression.

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 OL 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, we can further validate the lifetime effects of WOM and OL by comparing the two studies' results. As Tables 5 and 6 show, in contrast to Study 3 (products in their later stages), in which the coefficients of positive OL 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 OL and WOM.

The Interaction Effects of WOM and OL

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

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

Given the insignificant impact of the negative OL variable detected previously, we did not include the variable OL_NEG in Model 3.[9] To reduce multicollinearity, we mean-centered all variables included in the interaction terms. We estimated Model 3 with the combined sample from both Studies 2 and 3. A total of 83 cameras are listed under their OL sections at Amazon.com in both Studies 2 and 3; these make up the final sample in our 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 Table 7 shows, coefficient τ_1 is negative and significant, indicating that WOM volume increases the impact of OL on sales. This suggests a positive complementary effect between OL and WOM volume. However, the coefficient τ_1 is not significant, implying that there is no clear evidence in the current study that consumers would consider OL and WOM valence as substitutive signals.

In addition, the positive, significant interaction between OL and WOM volume documented here further validates 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 OL information in Study 3 if OL information dampens the effect of WOM volume. The positive interaction effect between OL and WOM volume shows that the diminished impact of WOM volume between Studies 1 and 3 results from the product lifetime effect. Table 8 summarizes how we designed the quasi-experimental studies to rule out various possible interval validity threats.

Table 7

THE INTERACTIONS BETWEEN WOM AND OL

	Studies 2 and 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)
D_ACR (β_2)	.188
	(.753)
OL_POS × D_LN#CR (τ_1)	–1.674*
	(1.041)
OL_POS × D_ACR (τ_2)	2.078
	(1.981)
Sample size	83
Adjusted R^2	.301
Model fit F	4.921***

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: The dependent variable is 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 OL variables and their interaction terms are mean-centered, and there is an intercept in the regression.

IMPLICATIONS, LIMITATIONS, AND FURTHER RESEARCH

Managerial Implications

The results of this study offer some noteworthy implications for firms in managing consumer social interactions. First, our finding of the asymmetrical impact of OL information on sales suggests that a seller's decision to provide OL information can help mass-market products without hurting niche products and the seller's own credibility, particularly in markets in which 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 OL signal to future potential buyers, whereas a small percentage of consumers buy the latter

[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. Because 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).

Table 8

AN EXAMINATION OF INTERNAL VALIDITY THREATS TO QUASI-EXPERIMENTS

Description of the Threat	*How We Eliminated It 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 (Wooldridge 2002). •The definition of OL 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 A). •The results are robust to different OL measures (for details, see Appendix A).
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 (for details, see Appendix B).
4. History: Observed effect is due to an event that occurs concurrently with the stimulus.	•Combining with the treatment reintroduction design, the removed-treatment design can rule out the potential contamination from history threat. •The results are robust to the analysis adding lagged sale-rank independent variable (for details, see Appendix C). •We use a control group. The sales ranks are not statistically different between the control group and treatment group (for details, see Appendix D).
5. Testing: Observed effect results from familiarity induced by testing.	It is not an issue in this study because the subjects are the same cameras over the periods.
6. Statistical regression: Observed effect is attributed to regression to the mean.	The WOM and OL 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.

Notes: The threats listed here follow Moorman, Du, and Mela (2005). Shadish, Cook, and Campbell (2002) present a complete list.

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% rule). Widespread use of the Internet and other advances in information technology increase the profitability of selling niche products designed to match the needs of a small consumer segment. Therefore, if the sales impact of OL information is symmetric, the overall effect of offering OL information on a seller's Web site might not be a profitable strategy.[10] This result might partly explain why, in late 2006, Amazon.com began again to provide OL information.

Second, online third-party infomediaries, which face a two-sided market (i.e., buyers and sellers), can also take advantage of OL's asymmetric effects 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 OL information, which suggest that firms should design their WOM and OL strategies jointly. Our results show that WOM volume strengthens the impact of OL information (i.e., they are complementary). An important implication of this finding is that the seller offering OL information may also need to pay attention to the volume of WOM. The seller can increase the effectiveness of OL information posted on its Web site by encouraging more consumers to post product reviews. Note that Web sites with heavy traffic tend to attract more consumer review postings (Chen and Xie 2008). This finding also suggests that OL is most influential to product sales when such information is offered on the most heavily used Web sites. Therefore, these popular Web sites should seriously consider investing in technology that facilitates OL information. However, less popular online sellers might benefit less from such an investment.

Finally, this study finds that the impacts of both WOM and OL 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) even though social interaction activities increase over time.

Theoretical Implications, Limitations, and Further Research

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

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

Second, like WOM, OL 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 OL is more influential than negative OL, while negative WOM is more influential than positive WOM. The difference between WOM and OL found in the current study suggests that when social influences are studied, it is necessary to determine whether they result from WOM or OL.

Third, few extant studies investigate how WOM and OL jointly influence consumers. Our study demonstrates a positive complementary interaction between OL and WOM volume but does not find clear evidence of the interaction between OL and WOM valence. Further research might 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.

A limitation of our study is that because of the data constraint, our sample size was relatively small. To examine the sensitivity of our results to sampling variations, we conducted a bootstrapping analysis (Davison and Hinkley 1997, pp. 264–69). The results of the bootstrapping analysis show that our results for all studies are robust to sampling variations. However, future studies could examine similar issues in field studies with larger scales.

In summary, the unique natural experimental setting identified here 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 here will stimulate more research in this area and help firms to initiate and/or facilitate consumer social interactions more effectively.

APPENDIX A: THE RESULTS' ROBUSTNESS TO ALTERNATIVE MEASURES OF OBSERVATIONAL LEARNING

It is important to note that the definition and measures of OL signals are based on the purchase percentages among people who viewed the same item instead of sales rank. In other words, our selection of different OL 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 had a top sales rank of 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 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 example, recall that in n. 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. 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 Appendix C shows, 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 could 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 conducted several additional analyses. First, as we pointed out previously, 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 only observations with extreme positive signal rather than all observations with positive signal, as in Table 4). In addition, because in general 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 one-fifth, or 20%, 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%, and positive otherwise. Table A1 presents results based on these two alternative measures, which reveal the same asymmetric effect of OL as that reported in Table 4. Therefore, we conclude that our main results on the asymmetric effect of OL are robust to this measure.

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 incorporated this information and ran 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 collected 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) maximum, and (3) 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 reran the analysis in Study 1 using three alternative measures. (The model specifications of all three models are the same as Model 2 in the study; they differ only in the measurement of OL information.) As Table A2 shows, our results are robust for all three measures: The impact remains significant for positive but not negative OL signals.

In addition, the results in Table A2 can help reduce one potential confounding, due to the way of measuring OL,

Table A1

THE RESULT ROBUSTNESS TO ALTERNATIVE OL MEASURES

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

*$p < .1$.
**$p < .05$.
***$p < .01$.

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

[b]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 if otherwise.

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

Table A2

THE RESULT ROBUSTNESS TO ALTERNATIVE OL MEASURES: INFORMATION FROM DIFFERENT WEB PAGES

	Study 1 (Model 2)		
OL Measure	*Average Ratio[a]*	*Maximum Ratio[a]*	*Minimum Ratio*
D_LNPRICE	.492	.379	.691
	(.397)	(.400)	(.417)
D_#SELLER	–.053***	–.056***	–.054***
	(.015)	(.015)	(.016)
QUALITY	–.259*	–.268*	–.161
	(.144)	(.144)	(.147)
LNAGE (η_4)	.056	–.540	–.649*
	(.338)	(.387)	(.376)
LNAGE	–.391	–.434	–.509
	(.366)	(.365)	(.385)
OL_POS[b]	1.109***	.877***	.857**
	(.382)	(.305)	(.441)
OL_NEG[b]	–.198	–.132	–.072
	(.232)	(.245)	(.259)
D_LN#CR	–.943***	–1.037***	–.917***
	(.310)	(.309)	(.333)
D_PER5	–.028	–.204	–.172
	(.994)	(.998)	(1.047)
D_PER1	1.205**	1.307**	1.204*
	(.545)	(.544)	(.441)
Sample size	90	90	90
Adjusted R^2	.380	.379	.314
Model fit F	7.064***	7.037***	5.528***

*$p < .1$.
**$p < .05$.
***$p < .01$.

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

[b]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).

Notes: The dependent variable is 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.

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 the camera's own page and the positive inflow of search from other pages. One way to address this concern is to check whether our result still holds 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, we classified camera i's OL signal as negative only if it is neither listed in its own OL section nor in that of all other listed products' home pages. 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 that 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.

APPENDIX B: SAMPLE ATTRITION

A potential concern regarding our results is that sample attrition might explain the asymmetric effects of OL because such attrition could occur because of low (high) sales ranks. To address this concern, 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 were available for sale at Amazon.com in Period 1 but not 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, 3 cameras still had sales rank information available in Period 3. The sales ranks of these 3 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. Our data demonstrate this. In our initial camera sample, of all cameras available in Period 1 (September 21, 2005), 16 are not available for sale in Period 2 (March 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 (March 18, 2007). Finally, an examination of our data shows that in the final retained sample, a majority of the treatment group (i.e., 48 of the 74 cameras, or 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.

APPENDIX C: THE ROBUSTNESS OF THE RESULTS TO POTENTIAL IMPACT OF SALES RANKS

We explain in the body of our article why our unique combination design of treatment removal and treatment reintroduction can help reduce the concern that the identified results on the asymmetric sales effects of OL might result from sales rank information. To reduce this concern further, we extend our models by including lagged sales rank as an independent variable and to check whether 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 were 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 Table C1 shows, 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-square values than 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.

There are different plausible reasons that consumers are affected by the purchase percentages of those who viewed the same item but not sales rank, even though 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 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 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).

Table C1

THE RESULT ROBUSTNESS TO SALES RANK INFORMATION

	Study 2	
	Model 1	*Model 2*
D_LNPRICE	.928*	.936*
	(.523)	(.562)
D_#SELLER	–.052***	–.049***
	(.013)	(.014)
QUALITY	.158	.194
	(.229)	(.240)
LNAGE	.558	.894
	(1.199)	(1.258)
OL_POS	–.946*	–1.051*
	(.674)	(.697)
OL_NEG	.374	.321
	(.901)	(.931)
D_LN#CR	.460	.505
	(.394)	(.404)
D_ACR	–1.160**	
	(.474)	
D_PER5		–1.325
		(1.397)
D_PER1		3.324**
		(1.466)
D_RANK_LAG[a]	.112E-03	.115E-03
	(.127E-03)	(.143E-03)
Sample size	39	39
Adjusted R^2	.526	.517
Model fit F	2.833**	2.589**

*$p < .1$.
**$p < .05$.
***$p < .01$.
[a]D_RANK_LAG is the sales-rank difference between Period 2 (February 15, 2006) and February 18, 2007 (one month before Period 3).
Notes: The dependent variable is 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, and there is an intercept in the regression.

APPENDIX D: INFORMATION POLICY AT AMAZON.COM AND CONTROL GROUP

We do not know the exact reasons for the information policy changes and treatment group assignments at Amazon.com. We made several efforts to contact Amazon.com and also searched all news releases but were not able to find information on the reason for these changes. A 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 OL signals would have been negative. We took several steps to address this concern. First, we conducted a t-test on the sales ranks between the control group and the treatment group in our data before the policy change. The sales ranks between two groups are not significantly different (t = 1.183, $p > .25$). This result suggests that Amazon.com's decision 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 the top 250 items in the Camera, Photo & Video section, which includes thousands of items (e.g., 2556 items on March 15, 2006). Almost one-quarter of the cameras in the control group are among the top 100 items in the Camera, Photo & Video section. In addition, 48 of the 74 cameras (65%) in the treatment group carried 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 in Amazon.com's decision to provide observational data. Finally, as documented in the literature, many other researchers conducting natural experiments have encountered a similar difficulty. For example, in policy/program evaluation studies, researchers often do not have sufficient information on the reasoning behind policy implementation, and policy makers often assign subjects into different policy conditions according to characteristics that the researchers cannot observe (Wooldridge 2002, p. 254). In the current study, following the methods in this literature (Wooldridge 2002), we used the panel data and the first-difference model to control for this unobserved effect and address this concern.

REFERENCES

Alba, Joseph and Wesley Hutchinson (1987), "Dimensions of Consumer Expertise," *Journal of Consumer Research*, 13 (March), 411–54.

Anderson, Chris (2006), *The Long Tail: Why the Future of Business Is Selling Less of More*. New York: Hyperion.

Anderson, Eugene (1998), "Customer Satisfaction and Word of Mouth," *Journal of Service Research*, 1 (1), 5–17.

Arndt, Johan (1967), "Role of Product-Related Conversations in the Diffusion of a New Product," *Journal of Marketing Research*, 4 (August), 291–95.

Bagozzi, Richard P., Utpal M. Dholakia, and Lisa Klein (2007), "Antecedents and Consequences of Online Social Interactions," *Media Psychology*, 9 (1), 77–114.

Bandura, Albert (1977), *Social Learning Theory.* Englewood Cliffs, NJ: Prentice Hall.

Banerjee, Abhijit (1992), "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107 (3), 797–817.

Becker, Gary (1991), "A Note on Restaurant Pricing and Other Examples of Social Influences on Price," *Journal of Political Economy*, 99 (5), 1109–1116.

Bell, David and Sangyoung Song (2007), "Neighborhood Effects and Trial on the Internet: Evidence from Online Grocery Retailing," *Quantitative Marketing and Economics*, 5 (4), 361–400.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch (1992), "Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy,* 100 (5), 992–1026.

———, ———, and ——— (1998), "Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades." *Journal of Economic Perspectives*, 12 (3), 151–70.

———, ———, and ——— (2008), "Information Cascades," in *The New Palgrave Dictionary of Economics Online*, S.N. Durlauf and L.E. Blume, eds. Basingstoke, UK: Palgrave Macmillan, [available at http://www.dictionaryofeconomics.com/article?id=pde2008_I000103].

——— and Sunil Sharma (2001), "Herd Behavior in Financial Markets: A Review," *IMF Staff Papers,* 47, 279–310.

Bowman, D. and D. Narayandas (2001), "Managing Customer-Initiated Contacts with Manufacturers: The Impact on Share of Category Requirements and Word-of-Mouth Behavior," *Journal of Marketing Research*, 38 (August), 281–97.

Cai, Hongbing, Yuyu Chen, and Hanming Fang (2009), "Observational Learning: Evidence from a Randomized Natural Field Experiment," *American Economic Review*, 99 (3), 864–82.

Chen, Yubo and Jinghong Xie (2005), "Third-Party Product Review and Firm Marketing Strategy," *Marketing Science*, 23 (2), 218–40.

——— and ——— (2008), "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix," *Management Science*, 54 (3), 477–91.

Chevalier, Judith and Alan Goolsbee (2003), "Measuring Prices and Price Competition Online: Amazon.com and BN.com," *Quantitative Marketing and Economics*, 1 (2), 203–222.

——— and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345–54.

Choi, JeongHye, Sam K. Hui, and David Bell (2007), "Spatio-Temporal Analysis of Imitation Behavior in Adoption of an Online Grocery Retailer," working paper, the Wharton School of Business, University of Pennsylvania.

Cialdini R.B. and M.R. Trost (1998), "Social Influence: Social Norms, Conformity, and Compliance," in *The Handbook of Social Psychology*, 4th ed., D.T. Gilbert, S.T. Fiske, and G. Lindzey, eds. Boston: McGraw-Hill, 151–92.

Davison A.C. and D.V. Hinkley (1997), *Bootstrap Methods and Their Application*. Cambridge, UK: Cambridge University Press.

DeLamater, John (2004), *Handbook of Social Psychology*. New York: Kluwer-Plenum.

Dholakia, Utpal and Kerry Soltysinkski (2001), "Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions," *Marketing Letters*, 12 (3), 223–35.

Feldman, Jack and John Lynch (1988), "Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention, and Behavior," *Journal of Applied Psychology*, 73 (3), 421–35.

Godes, David and Dina Mayzlin (2004a), "Firm-Created Word-of-Mouth Communication: A Field-Based Quasi-Experiment," Working Paper No. 05-023, Harvard Business School, Harvard University.

——— and ——— (2004b), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545–60.

———, ———, Yubo Chen, Sanjiv Das, Chrysanthos Dellarocas, Bruce Pfeiffer, et al. (2005), "The Firm's Management of Social Interactions," *Marketing Letters*, 16 (3–4), 415–28.

Grinblatt, Mark, Matti Keloharju, and Seppo Ikäheimo (2005), "Interpersonal Effects in Consumption: Evidence from the Automobile Purchases of Neighbors," working paper, National Bureau of Economic Research.

Guo, Liang, Hao Zhao, and Ying Zhao (2007), "Social Communication and Durable Goods Pricing," working paper, Department of Marketing, Hong Kong University of Science and Technology.

Hanson, Ward and Daniel Putler (1996), "Hits and Misses: Herd Behavior and Online Product Popularity," *Marketing Letters*, 7 (4), 297–305.

Hausman, Jerry (1978), "Specification Tests in Econometrics," *Econometrica*, 46 (6), 1251–71.

Herr, Paul M., Frank R. Kardes, and John Kim (1991), "Effects of Word of Mouth and Product Attribute Information on Persuasion: An Accessibility-Diagnosticity Perspective," *Journal of Consumer Research*, 17 (4), 454–62.

Hoch, Stephen J. and John Deighton (1989), "Managing What Consumers Learn from Experience," *Journal of Marketing*, 53 (April), 1–20.

Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, 70 (July), 74–89.

Mahajan, Vijay, Eitan Muller, and Rajendra Srivastava (1990), "Determination of Adopter Categories by Using Innovation Diffusion Models," *Journal of Marketing Research*, 27 (February), 37–50.

Manski, Charles (2000), “Economic Analysis of Social Interactions,” *Journal of Economic Perspectives*, 14 (3), 115–36.

Mason, Charlotte H. and William D. Perrault (1991), “Collinearity, Power, and Interpretation of Multiple Regression Analysis,” *Journal of Marketing Research*, 28 (August), 268–80.

Meyer, Bruce (1995), “Natural and Quasi-Experiments in Economics,” *Journal of Business & Economic Statistics*, 13 (2), 151–61.

Miller, Laura (2000), “The Best-Seller List as Marketing Tool and Historical Fiction,” *Book History*, 3 (1), 286–304.

Mizerski, R. (1982), “An Attribution Explanation of the Disproportionate Influence of Unfavorable Information,” *Journal of Consumer Research*, 9 (3), 301–310.

Moorman, Christine (1996), “A Quasi-Experiment to Assess the Consumer and Informational Determinants of Nutrition Information Processing Activities: The Case of the Nutrition Labeling and Education Act,” *Journal of Public Policy & Marketing*, 15 (Spring), 28–44.

———, Rex Du, and Carl F. Mela (2005), “The Effect of Standardized Information on Firm Survival and Marketing Strategies,” *Marketing Science*, 24 (Spring), 263–74.

Mouw, Ted (2006), “Estimating the Causal Effect of Social Capital: A Review of Recent Research,” *Annual Review of Sociology*, 32, 79–102.

Photo Marketing Association International (2001), *2000 Digital Imaging Marketing Association Digital Imaging Consumer Survey*. Jackson, MI: Photo Marketing Association International.

Raymond, Emily (2006), “Digital Cameras Among Consumer Electronics Association’s Five Hottest Markets,” *Digital Camera Info*, (April 3), (accessed November 28, 2010), [available at http://www.digitalcamerainfo.com/content/Digital-Cameras-Among-Consumer-Electronics-Association%E2%80%99s-Five-Hottest-Markets.htm].

Salganik, Matthew, Peter Sheridan Dodds, and Duncan J. Watts (2006), “Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market,” *Science*, 311 (5762), 854–56.

Scheinkman, José A. (2008), “Social Interactions (Theory),” in *The New Palgrave Dictionary of Economics Online*, Steven Durlauf and Blume Lawrence, eds. Baskingstoke, UK: Palgrave Macmillan, [available at http://www.dictionaryofeconomics.com/article?id=pde2008_T000200].

Shadish, William, Thomas Cook, and Donald Campbell (2002), *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Boston: Houghton Mifflin Company.

Simester, Duncan, John Hauser, Birger Wernerfelt, and Roland Rust (2000), “Implementing Quality Improvement Programs Designed to Enhance Customer Satisfaction: Quasi-Experiments in the United States and Spain,” *Journal of Marketing Research*, 37 (February), 102–112.

Spors, Kelly (2006), “How Are We Doing?” *The Wall Street Journal*, (November 13), R9.

Tucker, Catherin and Juanjuan Zhang (2009), “How Does Popularity Information Affect Choices? Theory and a Field Experiment,” working paper, MIT Sloan School of Management, Massachusetts Institute of Technology.

Van den Bulte, Christophe and Gary L. Lilien (2001), “*Medical Innovation* Revisited: Social Contagion Versus Marketing Effort,” *American Journal of Sociology*, 106 (2001), 1409–1435.

Weinberger, M.G. and W.R. Dillon (1980), “The Effects of Unfavorable Product Rating Information,” *Advances in Consumer Research*, Vol. 7, Jerry C. Olson, ed. Ann Abor, MI: Association for Consumer Research, 528–32.

Welch, Ivo (1992), “Sequential Sales, Learning, and Cascades,” *Journal of Finance*, 47 (2), 695–732.

Wooldridge, Jeffery (2002), *Econometric Analysis of Cross Section and Panel Data*. Boston: MIT Press.

Zhang, Juanjuan (2010), “The Sounds of Silence: Evidence of Observational Learning from the U.S. Kidney Market,” *Marketing Science*, 29 (2), 315–35.

Zhao, Min and Jinhong Xie (2010), “Effects of Social and Temporal Distance on Consumers’ Responses to Peer Recommendations,” working paper, University of Florida.