Measuring Effects of Observational Learning and Social-Network Word-of-Mouth (WOM) on the Sales of Daily-Deal Vouchers

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This Version: December 2012

Abstract: This study explores how observational learning and social-network Word-of-Mouth affect shopping behaviors and sales of daily deals. Using a unique panel data set consisting of more than 500 deals from Groupon.com, we find that while both mechanisms can positively increase sales, the effect of WOM mediated via Facebook is larger than that of observational learning. All else equal, a 10% increase in past sales is associated with 1.4 more vouchers sold in the next hour, whereas a single click on Facebook “Like” for a deal is associated with 4.5 additional voucher sales, equivalent to an increase in revenue of $468. However, we do not find consistent evidence of Twitter-mediated WOM having an effect on sales. More importantly, we find that observational learning and Facebook-mediated WOM are complements, as they reinforce each other in increasing sales. Furthermore, we find WOM valence, as measured by average review ratings from Yelp/Citysearch, moderates the effects of observational learning and Facebook-mediated WOM. Valence serves as a complement with Facebook-mediated WOM when ratings are moderate but as a substitute when ratings are extreme.

Keywords: Observational learning; Word-of-mouth (WOM); Social media; Review rating; Online marketing.

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1 Introduction

Marketing practitioners and entrepreneurs have been abuzz about the explosive growth of daily-deal sites, such as Groupon.com and LivingSocial.com. Using these platforms, sellers can advertise their products by offering deep-discounted vouchers. Dholakia (2011) finds, based on his survey, that about 80% of daily-deal buyers are new customers, indicating perhaps daily-deal sites are an effective marketing vehicle for local businesses to acquire new customers. The popularity of using daily deals has increased since. As of April 2012, consumers in North America have spent approximately $7 million a day and more than $2.5 billion a year on daily deals\(^1\), and this number is expected to reach $4 billion a year by 2015.

Despite the increasing popularity, few papers have examined the economics of daily deals (Dholakia, 2011; Edelman et al., 2010; Byers et al., 2012; Kumar and Rajan, 2012). These studies investigate daily deals from a conventional perspective, such as couponing (Dholakia, 2011) and price discrimination (Edelman et al., 2010). We argue that daily deals differ from traditional marketing vehicles in at least two important ways and deserve to be investigated separately. First, daily-deal sites explicitly highlight the total number of vouchers sold in real-time. By allowing a potential buyer to observe past purchasing decisions, this practice can create information cascade, driving even more sales for popular deals (Zhang and Liu, 2012). Second, daily-deal sites facilitate a word-of-mouth (WOM) effect via social-networking sites, such as Facebook and Twitter. By clicking on the Facebook “Like” or Twitter button on a deal’s webpage, users can endorse the deal on their Facebook or Twitter profiles, simultaneously advertising and endorsing the deal to their friends and followers. This social word-of-mouth effect can have positive impact on voucher sales.

The extant literature has documented that observing past decisions helps customers update their belief about whether a product is of high quality, especially when their prior knowledge of the product is imperfect (Cai et al., 2009). On the other hand, online WOM can advertise the product to potential buyers (Chen et al., 2011a) and also update a consumer’s

\(^1\)http://savvr.com/2012/04/top-10-highest-grossing-daily-deals-of-all-time/
belief about the product quality (Liu, 2006). However, very few prior empirical studies have measured both observational learning and online WOM, perhaps because the two are rarely implemented together. Fortunately, by showing how many vouchers are sold in real time and allowing users to share the deal via social media, daily-deal sites provide an ideal context to study how observational learning and social-network WOM affect online shopping behaviors.

Prior studies show that the action-based information provided in observational learning (e.g., realized sales volume) is more credible than online WOM that comes from anonymous strangers. Thus, observational learning should have a larger effect on sales, because “actions speak louder than words” (Liu, 2006; Cheung et al., 2012). However, with the rise of social media, WOM often comes from friends via online social networks, such as Facebook or Twitter. As friends are more likely to have similar tastes (homophily) or know about a person’s idiosyncratic tastes (tie strength), social media enabled WOM may be more effective than traditional online WOM in influencing purchase decisions. Therefore, it is interesting to explore the relative strength of action-based observational learning and social-network WOM in affecting sales. For example, if action-based influences (e.g., realized sales volume) is more likely to affect future sales, the strategy would be to increase sales as early as possible, because earlier sales can have a “social multiplier” effect on later sales such that the elasticity of aggregate demand is larger than the elasticity of individual demand (Moretti, 2011). In such case, advertising early (e.g., targeting celebrities whose messages can reach a large number of people, or applying deep discounts to earlier buyers) is more beneficial. By contrast, if social-network WOM is more prominent, generating buzz via social-networking sites (e.g., creating incentives for users to “like” a product on Facebook or “tweet” it on Twitter) would be more effective in driving sales than early promotions.

Further, we investigate how observational learning and social-network WOM, when implemented together, interact with each other in driving sales, because misperceiving interaction effects would result in detrimental organizational consequences (Siggelkow, 2002). As WOM has the dual role of advertising to potential buyers and updating consumers’ beliefs about
the product, it can serve either as a complement or a substitute to observational learning. Acting as an advertising vehicle informing potential buyers about the deal, it complements observational learning, because after hearing it from social-network WOM, people are more likely to buy it when many others have already bought it, thus reinforcing the advertising effect. By contrast, when there are only a few sales, people may simply forgo the purchase, thus rendering advertising ineffective. Social-network WOM can also be a substitute for observational learning when serving as an information signal that updates consumers’ beliefs about the product. When a friend’s endorsement provides enough information for a consumer to make a decision, other information signals about the product (such as through observational learning) would be redundant.

Similar to observational learning and WOM mediated via social media, WOM valence (e.g., whether the opinion is positive or negative) can also be important for updating consumer beliefs and thus affecting product sales (Liu, 2006; Chevalier and Mayzlin, 2006; Chintagunta et al., 2010). Customer reviews, such as the average ratings from Yelp.com and Citysearch.com, provide a great way to measure valence, allowing us to explore how it can interact with observational learning and social-network WOM. Providing information that is helpful for consumers to update their beliefs about the product, valence can act as a substitute for observational learning. Similarly, valence can also substitute for social-network WOM when its primary mechanism in affecting sales is to provide signals that increase consumers’ information set. Nonetheless, valence can also be a complement when the primary mechanism of social-network WOM is through advertising.

Based on our analysis, we find both observational learning and Facebook-mediated WOM have a positive effect on voucher sales, after controlling for unobserved deal-specific heterogeneity and product diffusion and ruling out alternative explanations, such as social pressure, network effects and saliency effect. Economically, all else equal, a 10% increase in past sales is associated with 1.4 more vouchers sold in the next hour. Also, a single click on Facebook “Like” for a deal, on average, is associated with 4.5 additional voucher sales, equivalent to an
increase in revenue of $468. Interestingly, while the impact of Facebook-mediated WOM is relatively larger than observational learning, we do not find consistent evidence of Twitter-mediated WOM having an effect on sales. Perhaps the transient nature of Tweets limits the effect of Twitter in the daily-deal setting.

Besides the main effects, we find that observational learning and Facebook-mediated WOM are complements, suggesting strong advertising effect from Facebook-mediated WOM dominates the signaling effect for product quality. Interestingly, we find the opposite for product ratings that extreme ratings act as a substitute for Facebook-mediated WOM. This suggests the signaling effect for product quality from social-network WOM trumps its advertising effect, when product ratings are present. As extremely high or low ratings provide more unequivocal information about the goods, customers would then reduce their reliance on observational learning and Facebook-mediated WOM to infer product quality. Thus, combined with the advertising effect, social-network WOM complements valence in driving sales only when ratings are moderate and equivocal. These results suggest that both observational learning and product ratings complements with the advertising effect of Facebook-mediated WOM, but they also substitute for the signaling effect of social-network WOM that also update consumers’ beliefs about a product. The substitutive effect is stronger when the signal is more unequivocal, such as when ratings are extreme.

2 Related Literature

Despite the buzz about voucher promotions in mass press articles, academic publication on this growing business practice is limited. Kumar and Rajan (2012) publish one of the first articles on this topic. They consider voucher promotions as social coupons and use a conventional modeling method from the couponing literature to analyze the profitability of social coupons. However, because the unique characteristics of social coupons are not sufficiently exploited, it leaves an open question to how voucher promotions differ from tra-
ditional promotional vehicles. Despite the scant published literature, there are a growing number of unpublished working papers on daily-deal voucher promotions (Dholakia, 2011; Edelman et al., 2010; Byers et al., 2012). Edelman et al. (2010) develop a theoretical model to examine the profitability of voucher promotions and find that price discrimination and advertising are two underlying mechanisms. For empirical works, larger-scale surveys have been used to examine the performance effectiveness of voucher promotions (Dholakia, 2010). Surveying users in five major sites across 23 US markets, Dholakia (2011) finds the differentiation among voucher-selling sites is minimal. Byers et al. (2012) empirically show that the Yelp ratings of many merchants have decreased after a one-time Groupon promotion. Our work differs from these studies, because we exploit the two distinct mechanisms (observational learning and social-network WOM) that differentiate daily deals from traditional marketing vehicles to understand how they improve the effectiveness of voucher promotions.

This study contributes to the literature on observational learning (i.e., herding, informational cascade). The seminal work on theoretical herding research is by Banerjee (1992) and Bikhchandani et al. (1992). According to the theory, agents make decisions sequentially using their private but imperfect information, while having observed the earlier decisions that others have made. Under certain conditions, when enough prior decision makers converge on a single choice, subsequent agents can be sufficiently influenced that they simply disregard their private information and follow the converged choice. There have been a growing number of empirical papers that estimate the effect of observational learning. Duan et al. (2009) find software downloads exhibit distinct jumps and drops when the download ranking changes. A higher download rank (i.e., a lower number of downloads) at a certain week can predict a smaller download market share in the following week. Herzenstein et al. (2011) document evidence of herding among lenders on Prosper.com, whereby borrowers listings that have attracted a larger number of lenders are more likely to receive further funding. Zhang and Liu (2012) find evidence of rational observational learning among lenders of Prosper.com; lenders infer the creditworthiness of borrowers by observing peers’ lending decisions.
This study also contributes to the literature on Word-of-Mouth (WOM). WOM is a well-established construct in marketing literature and the volume of WOM is believed to significantly increase product awareness (Liu, 2006). Trusov et al. (2009) investigate the effect of WOM marketing on member growth at an internet social-networking site and further compare it with traditional marketing vehicles. Aral and Walker (2011) use a randomized field experiment to empirically test the effectiveness of WOM on the adoption of commercial applications hosted on Facebook.com. Nevertheless, empirical evidence about the effectiveness of WOM marketing, especially in terms of the monetary value, is still scant (Trusov et al., 2009). The work by Chen et al. (2011a) investigates how artists’ message broadcasting in social media affect their music sales, providing an example.

The work by Chen et al. (2011b) is particularly relevant to our study. Using a natural experimental design resulting from information policy shifts of Amazon.com, Chen et al. (2011b) conduct longitudinal, quasi-experimental field studies to examine the effect of observational learning and WOM (measured by customer reviews) on product sales. Their findings indicate that observational learning and WOM have differential impacts on sales. Our study differs from the work by Chen et al. (2011b) at the following aspects. First, our study particularly focuses on the effect of WOM mediated by social-networking sites (Facebook and Twitter) where agents have some form of real-world relationships, e.g., Facebook friendship. By contrast, Chen et al. (2011b) study the effect of WOM from Amazon’s customer reviews where Amazon customers have no established friendships. Second, Amazon customers have to actively pull information by reading the reviews, as opposed to having information simply pushed to them via social media. Third, the accurate sales data are used in our study instead of sales ranking, thus allowing us to more precisely quantify the effects of observational learning and social-network WOM using real financial metrics, like voucher sales and revenues. Lastly, we also investigate the substitute effect of product ratings on Facebook-mediated WOM in driving sales.
3 Research Hypotheses

3.1 Research Context

Daily-deal sites provide a unique context for studying the relationships between observational learning and social media enabled WOM because both mechanisms are implemented in the web design. We choose Groupon.com, the most well-known and largest daily-deal site, as the research setting of this study.

Everyday, Groupon features a single deal on the main page of each local market. Figure 1 shows a screenshot of a typical featured deal, from which shoppers can see the characteristics of the deal, such as deal description, vendor, discounted voucher price, and if applicable, the average rating from Yelp/Citysearch. The total number of vouchers sold is prominently highlighted in *real-time*. Immediately below the sales information, the Facebook “Like” and Twitter buttons are displayed, allowing shoppers to share the deal with their Facebook friends and/or Twitter followers. While the number of vouchers sold is placed prominently on Groupon’s deal page, the number of Tweets and Facebook Likes is not generally displayed.\(^2\) Furthermore, even when the number of Facebook Likes is displayed in some cases, it is always at the bottom of the deal page in a much smaller font than the display for the number of vouchers sold. Because people often neglect information that is visually unnoticeable (Nisbett et al., 1980), we assume the primary channel for Facebook Likes to affect future sales is through sharing deals with Facebook friends as opposed to observing the number of Facebook Likes.

In the following sections, we theorize the research hypotheses and organize them in the conceptual framework illustrated in Figure 2.

\(^2\)The total number of Facebook Likes is generally not displayed. However, in some web browsers, they are displayed, albeit in the smallest font possible on the website at the bottom of the webpage. When they are displayed, it could potentially bias the estimation if one also interprets the effect of Facebook Likes as a type of observational learning. Based on our trials, users of Internet Explorers cannot see the number of Facebook Likes, accounting for slightly over 40% of Web browsers (based on the statistics by September, 2011, see [http://www.tomshardware.com/news/browsers-ie-chrome-firefox-mozilla,14410.html](http://www.tomshardware.com/news/browsers-ie-chrome-firefox-mozilla,14410.html)). Thus, we could expect about 40% Groupon shoppers would not be able to observe the number of Facebook Likes. In such case, the effect of Facebook Likes is merely through online WOM.
3.2 Observational Learning

Economic literature on herding (Banerjee, 1992) and observational learning (Cai et al., 2009) suggests that people are likely to imitate others’ behaviors when they are able to observe the decisions of preceding others and make their decisions sequentially after. This phenomenon is particularly prominent when they have imperfect information, because potential adopters could infer their own utility by observing others’ adoption decisions (Duan et al., 2009). Comparing to other types of social influence mechanisms (e.g., social contagion and peer pressure), observational learning is argued to be more prominent from an economic standpoint, because “it has firm decision-theoretic foundation: agents are assumed to make rational use of information generated by prior adopters in order to reach a decision” (Young, 2009).

Daily-deal sites explicitly highlight the cumulative number of vouchers sold in real-time and allow customers to observe the collective decisions of prior buyers (see Figure 1). Also, most of the deals sold on daily-deal sites are experience goods, whose value is hard to ascertain before consumption. Furthermore, about 80% of deal users are new customers (Dholakia, 2011). These facts suggest that most buyers have, at best, imperfect information about whether the deal is of high quality and fits their preference. Thus, observing the total quantity of the vouchers sold can provide a useful signal, because prior purchases in aggregate could provide useful inferences about the good. Intuitively, suppose there are two restaurant deals with identical characteristics, such as discounted voucher price, location, Yelp rating, uninformed customers may infer a higher valuation for the deal that has more existing voucher sales and consequently choose to buy it. Therefore, we hypothesize

**Hypothesis H1**: All else equal, a deal with more existing sales is likely to receive more sales in the next period.
### 3.3 Social-Network WOM

Word-of-Mouth (WOM) refers to the dissemination of information among individuals (Chen et al., 2011b). Valence and volume are two important attributes of WOM. While WOM valence (e.g., a positive or negative sentiment) affects product sales by changing customers’ beliefs, the volume of WOM can drive sales through increasing product awareness. Although both the valence and volume of WOM can influence product sales (Chevalier and Mayzlin, 2006; Chintagunta et al., 2010), some prior empirical studies show that the volume of WOM is more effective than the valence (Liu, 2006). Thus, in the context of our study, we focus on the volume of WOM mediated by Facebook and Twitter.

As shown in Figure 1, Groupon provides the Facebook “Like” and Twitter buttons that allow people to share the deal with their Facebook friends and/or Twitter followers. For example, after clicking on the Facebook “Like” button, users are directed to log onto their Facebook accounts. Afterward, the activity that the users have “liked” the Groupon deal would be placed on their Facebook Wall, where all their friends could see they have endorsed a deal (see Figure 3). The friends could then click on the link and go to the Groupon’s deal page. Accordingly, clicking on the Facebook “Like” button could spread information about the deal as well as provide a personal endorsement to one’s Facebook friends. Both of these two effects can potentially generate new voucher sales. Fortunately, Facebook recorded the sharing activity and allows us to retrieve the total number of Facebook Likes using Facebook’s public API. Similarly, Twitter also allows people to share the deal with their followers by clicking the Twitter button (see Figure 4) and provides the total number of Tweets about the deal through its public API.

It is worth noting that WOM mediated via Facebook/Twitter can be very different from traditional online WOM. The literature on social ties suggests that people are likely to think recommendations more reliable if they come from established social relationships (Granovetter, 1973), perhaps due to homophily or social influence. Thus, WOM via Facebook friends and Twitter followees could be more effective than traditional online WOM that
comes from anonymous strangers (Bapna et al., 2011). Therefore, we expect WOM mediated via social-networking sites (Facebook, Twitter) to be more influential than traditional WOM, such as Yahoo discussion messages (Liu, 2006) or Amazon customer reviews (Chen et al., 2011b), that rely primarily on opinions from anonymous strangers. Herein, we conjecture

**Hypothesis H2:** All else equal, more Facebook Likes and/or Twitter messages (Tweets) on a deal are associated with more voucher sales.

### 3.4 Complementarity between Observational Learning and Social-Network WOM

Research has shown evidence that dissimilar signals on product quality often interact with each other to affect product perception and sales (Kirmani and Rao, 2000). For example, Basuroy et al. (2006) find advertising expenditures and sequels are complements in driving box office revenue. Chen et al. (2011b) find a positive interaction between the sales of digital cameras and the number of customer reviews. Consistent with the theory and empirical evidences, we argue that observational learning and social-network WOM may also interact to increase sales, because they provide different types of information to consumers.

Through observational learning, the total number of vouchers sold provides information signal for consumers to update their beliefs about the product. Accordingly, once people heard about a deal, they are more likely to buy if others have already bought it. While observational learning adds information by aggregating adoption among a group of anonymous buyers, social media enabled WOM can provide fundamentally different types of information. First, social-network WOM has an advertising effect by disseminating information about the deal to friends and followers via social media. Through advertising alone, social-network WOM increases the total number of potential buyers. For example, people may not be aware of the product and they would have bought the product had they known about it earlier. People may also pay particular attention on deals endorsed by their friends, because they are simply curious about their friends, even though they may have no prior interests for
the product. Consequently, we would expect that social media enabled WOM is an effective advertising vehicle in attracting more potential buyers to Groupon’s deal page (Tucker, 2011; Chen et al., 2011a).

After arriving at the deal page, a potential buyer is more likely to make a purchase if many others have already bought the product, because information through observational learning helps consumers update their beliefs about the product. However, without advertising through WOM, a potential buyer may not have heard of the deal and thus would not have had the chance to buy, regardless of observational learning. Similarly, absent of other information signals, a low existing sales would not have persuaded a potential buyer to make the purchase even after they became aware of it via social media or elsewhere. Thus, acting as a vehicle to disseminate information to potential buyers, advertising via WOM complements the quality signal derived from observational learning in affecting sales.

Similar to observational learning, social-network WOM can also provide information that helps consumers update their beliefs about the product. While observational learning gleans information by aggregating preferences from anonymous strangers, WOM enabled through social media provides information by using friends’ recommendations. People are likely to pay particular attention to and hence buy the product when a friend recommends it, because they may find their friends’ opinion to be more reliable than an anonymous stranger’s (Granovetter, 1973). As friends are more likely to know a person’s idiosyncratic tastes (tie strength) and they are also more likely to have similar preferences (homophily), a reliable recommendation from a friend could be enough to persuade a potential buyer into buying. Thus, an endorsement from a friend could trump other information signals derived from strangers such as observational learning, suggesting that social-network WOM and observational learning are substitutes if the primary mechanism of WOM is through providing information signal about product quality.

However, when a friend’s recommendation is not reliable, it would not be enough to persuade a potential buyer. Additional signals derived from observational learning can be
helpful. When many have already bought the product, a potential buyer is more likely to believe in the endorsement from the friend that the product is of high quality. On the other hand, when only a few have bought the product, a potential buyer would question the friend’s endorsement especially if the friend’s opinion is not always reliable.

Thus, whether observational learning and WOM are complements or substitutes is an empirical question. Serving as an advertising vehicle, WOM complements observational learning in driving sales. However, serving as an information signal that helps consumers update their beliefs about the product, WOM is a substitute for observational learning, especially when both mechanisms provide strong signals of information. Since online friends tend to be weaker ties (Bapna et al., 2011) and that observational learning provide information through strangers, both are not strong enough to replace the other. Therefore, we hypothesize that the advertising effect of social-network WOM could dominate its signaling effect and thus it serves as a complement to observational learning.

**Hypothesis H3:** All else equal, the effects of observational learning and WOM mediated via Facebook/Twitter complement each other in affecting sales.

### 3.5 Moderating Effect of Valence

WOM Valence, which indicates whether the sentiment of the message is positive or negative, can influence customers’ perceptions and thus product sales (Liu, 2006). As a result, the average product ratings from customer reviews has received considerable attention in recent empirical studies (Anderson and Magruder, 2012; Luca, 2011). For example, Anderson and Magruder (2012) show that an extra half-star increase in Yelp rating causes restaurant to sell out 49% more often. This effect is especially prominent when other available information is scarce. Serving as an informational signal on quality, product ratings from Yelp.com or Citysearch.com are also displayed on Groupon’s deal page. Because high product ratings are shown to lead to higher product sales (Anderson and Magruder, 2012; Luca, 2011), Groupon sales could also increase when ratings for the good is high. Furthermore, we explore how
product ratings and other available information, such as observational learning and social media enabled WOM, interact to affect sales. Depending on the nature of the information signal and their relative informational strength, product ratings could either serve as a complement or substitute to these mechanisms.

3.5.1 Valence and Observational Learning

When agents have perfect information about the good, no additional signals are needed to make an informed decision. However, when armed with imperfect information, agents can benefit from additional signals such as from product ratings and observational learning. Observational learning can help consumers update their beliefs by aggregating preferences of the earlier buyers. When many people have bought the product before, it sends a strong signal that the quality and appeal for the product are likely to be high. Product ratings can also offer similar information and thus increase consumers’ information set especially when ratings are extremely high or extremely low, because the ratings average votes from anonymous strangers who have had experienced the products before. For example, Forman et al. (2008) find that customers view extreme ratings of books as a more helpful signal than modest ratings because extreme ratings are more unequivocal. Because product rating and observational learning offer similar information helping consumers to update their beliefs, they can act as substitutes. Information derived from observational learning is less useful when informational signals from product ratings are strong, especially when the rating is unequivocal (either extremely high or low). On the other hand, moderate ratings indicate ambiguity over the quality and can thus increase consumers’ reliance on other information signals, such as ones derived from observational learning. Therefore, we hypothesize that observational learning is a complement for moderate product ratings but a substitute for extreme ratings.

**Hypothesis H4**: All else equal, observational learning complements with moderate product ratings and substitutes with extreme product ratings in affecting sales.
3.5.2 Valence and Social-Network WOM

Similarly, product ratings could also moderate the impact of social WOM on sales. Acting as an advertising vehicle to disseminate information about the product, social-network WOM increases user engagement on the deal’s webpage. Once potential buyers are at the deal page, they are more likely to buy when the product has a high quality and is a good fit. Because high ratings serve as a more unambiguous signal that updates consumers’ belief about the product, it can complement the advertising aspect of social-network WOM.

On the other hand, social-network WOM can also provide information about the product to consumers because a friend has recommended it. All else equal, a person is more likely to rely on friends’ recommendation than a stranger’s. Product ratings offer similar information that can help consumers update their beliefs through collecting votes on ratings among anonymous individuals who have used the product before. When two signals provide similar inferences about the product, they can be redundant. As a high product rating provides a clear signal for quality, a person may choose to buy regardless of whether a friend has endorsed it, especially if the friend’s opinion is not always reliable. When a friend’s endorsement is reliable, people may buy despite a low product rating, because friends may have better information than strangers about product quality and whether it is a good fit. Hence, providing similar inferences about product quality, social-network WOM and product ratings can act as substitutes. On the other hand, when one of the information signal is not strong enough to persuade a person from making a decision, another similar signal could be useful to reinforce a consumer’s belief about the product. For example, mediocre ratings, which does not provide clear informational signal about the product, can benefit from a friend’s endorsement via social media in increasing sales.

Thus, while the advertising aspect of WOM can complement product ratings, social-network WOM can act as a substitute when used as a informational signal about product quality and fit. When both social-network WOM and product ratings provide strong information signals about the product, they substitute each other because information derived
from one signal is sufficient to make a decision, rendering the other redundant. However, when both signals are not strong enough, they could complement in increasing consumers’ information set. For example, when ratings are moderate, their impact on consumers’ information set is small and can thus benefit from additional signals from a friend’s recommendation. Together with the complementarity effect from advertising, WOM can complement moderate ratings in affecting sales.

**Hypothesis H5**: All else equal, the effect of WOM mediated via Facebook/Tweets increases when deals have moderate ratings from Yelp/Citysearch.

## 4 Data and Empirical Methodology

### 4.1 Data Collection

All our data come from public sources, collected using Cameleon Web Wrapper (Firat et al., 2000). For information about deal characteristics and sales, we extract them directly from Groupon.com. We use public API provided by Facebook and Twitter to extract the number of Facebook Likes and Tweets associated with each deal. When available, we also gathered product ratings from Yelp.com and Citysearch.com.

We sampled 6 metropolitan areas across the entire United States, including East Coast (Boston, New York City), Central (Chicago, Houston) and West Coast (Los Angeles, San Francisco) from July 1st to September 27th, 2011. We discontinued our data collection on September 27, 2011, because Groupon.com had stopped displaying the accurate number of voucher sales. Accordingly, the data set includes 526 deals featured in the 6 metropolitan cities during the data collection period. For each deal, we collected the number of voucher sales, the number of Facebook Likes and Tweets hourly (from 1:00am to 11:59pm) during the first day when the deal was featured. Also, we collected the discounted voucher price.

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the original/face value, the product category, and the average rating from Yelp/Citysearch. 26 (about 4.9%) out of the 526 deals have errors. Results from the t-test and Chi-square test show these errors are not systematically different from the valid deals.\footnote{The only exception is the rating: the average ratings of erroneous deals and valid deals are 4.34 (sd=0.56) and 3.88 (sd=0.75), respectively.} Therefore, we can safely remove the erroneous deals from the data set, resulting in an unbalanced panel data set consisting of 500 deals with at most 24 hour periods.

### 4.2 Descriptive Statistics

Table 1 presents the descriptive statistics for various deal features. In our data, 113 deals are related to restaurants and pubs, and 351 are other experience goods, such as spas, massage, and cleaning services. Overall, experience goods account for 92.8% of all the deals in our data set. The remaining 36 deals are tangible products, like glasses and shoes. On average, the discounted voucher price is $103.92 with an average discount rate of 57.05%. The variance of the discount rate is small. The average number of vouchers sold in the first day is 936.66, generating an average revenue of $97,338 for a typical featured Groupon deal on that day. The average numbers of Facebook Likes and Tweets in the first day is 106.08 and 10.46, respectively, and they are statistically different ($t = 9.43, p < 0.001$). This suggests that Groupon shoppers are more likely to share the deals via Facebook than via Twitter. More than 80% of the deals have ratings from Yelp and/or Citysearch, with an average rating of 3.88 (sd=0.75).

### 4.3 Estimation Specification

Given the panel structure of the data, we use fixed-effect specification as the main model in the analysis. Because it can eliminate any time-invariant unobserved heterogeneity, fixed-effect specification has become a main approach for identifying the effect of observational learning in empirical studies (Duan et al., 2009; Zhang and Liu, 2012).
We denote the cumulative sales of a deal $i$ up to the $t^{th}$ hour by $Y_{i,t}$, $t = 1, 2, ..., 24$. As the cumulative sales are explicitly highlighted in real-time on Groupon.com (see Figure 1), the lagged cumulative sales $Y_{i,t-1}$ reflects the aggregate purchases before the $t^{th}$ hour and thus can be used to operationalize the measurement of observational learning. $y_{i,t} = Y_{i,t} - Y_{i,t-1}$ is the incremental sales occurring during the $t^{th}$ hour. According to the estimation specification used by Zhang and Liu (2012), the effect of observational learning can be estimated by the coefficient of $Y_{i,t-1}$ on $y_{i,t}$, after controlling for deal-specific heterogeneity and other time-varying variables.

The number of new Facebook Likes and Tweets associated with deal $i$ during the $t^{th}$ hour are denoted by $fb_{i,t}$, $tw_{i,t}$, respectively. Accordingly, the coefficients of $tw_{i,t}$, $fb_{i,t}$ on $y_{i,t}$ estimate the direct effect of WOM mediated via Facebook and Twitter on sales in the present hour. Specifically, the estimation specification is as follows:

$$y_{i,t} = \alpha \log (Y_{i,t-1}) + \beta_1 fb_{i,t} + \beta_2 tw_{i,t} + \mu_i + \nu_t + \epsilon_{i,t} \quad (1)$$

In Equation (1), we use the log-transformed $Y_{i,t-1}$ to operationalize the measurement of observational learning, because $Y_{i,t-1}$ is substantively skewed and has a much larger mean than other explanatory variables. $\mu_i$ controls for deal-specific time-invariant heterogeneity, and $\nu_t$ controls for common shocks at different hours over a day. $\epsilon_{i,t}$ is the unobserved disturbance term. Fixed-effect estimation allows $\epsilon_{i,t}$ to be arbitrarily correlated with explanatory variables and thus make the estimates more robust (Duan et al., 2009). Using Equation (1), the effects of observational learning (estimated by $\alpha$) and WOM mediated via Facebook and Twitter (estimated by $\beta_1$, $\beta_2$) are identified based on the within-deal variations. By design, this controls for any observable and unobservable time-invariant deal characteristics, such as voucher price, quality of the good, and location of the deal. Particularly, the unobserved

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$^6$The effect of social-network WOM can also be estimated by using one-hour lagged $fb_{i,t-1}$, $tw_{i,t-1}$, so that the reverse causality can be avoided. In such case, the coefficients of $fb_{i,t-1}$, $tw_{i,t-1}$ on $y_{i,t}$ estimate the effects of Facebook Likes and Tweets on sales in the next hour rather than the present hour. The main results remain qualitatively the same when we use $fb_{i,t-1}$, $tw_{i,t-1}$. 

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quality of a deal should be time-invariant during the day and thus controlled by the fixed effect. The common time shocks over the day are controlled using the time fixed effect. For example, if customers’ online shopping behaviors are more active in the later afternoon than in the early morning, the time dummies control for this variation.

Table 2 presents the overall mean and standard deviations of the time-varying variables in the data set. The average hourly voucher sales are 41.46 (sd=117.84). During a typical hour, there are, on average, 4.60 Facebook Likes and only 0.36 Tweets. The t-test indicates that the average hourly numbers of Facebook Likes and Tweets are significantly different ($t = 31.8, p < 0.001$), again suggesting that Groupon shoppers are more likely to share the deals via Facebook than via Twitter. The Pearson correlation coefficients among the key explanatory variables are all small ($< 0.27$), indicating multicollinearity is less likely to be an issue in the data set.

4.4 Alternative Explanations

To identify the effect of observational learning, we need to rule out several alternative explanations.

The first is social pressure: people adopt when they feel the pressure to conform, as many of their peers have already adopted (Young, 2009). While this would have been a significant concern if adopting the goods is easily observed (e.g., fashion items), the deals in our context are often personal experience goods, such as meals at restaurants, spas, massages, cleaning services, etc. Because they are highly personalized and less observable/verifiable, social pressure is less likely to explain the herding behavior if detected.

The second is positive network effects or payoff externalities. Network effects refer to that the value of a product increases as more people are using it (Katz and Shapiro, 1994). While network effects often occur with IT products (Brynjolfsson and Kemerer, 1996) (such as fax machines or microcomputers), they are less plausible in the context of daily deals for personal experience goods, because one person’s consumption does not directly increase
the value of the good for others. In fact, for experienced goods (e.g., restaurants, spas, massages), the opposite can be true due to capacity constraint; people may assume that the quality of the services to suffer, when many vouchers were already sold. Especially when there is an expiration date in the near future, customers are likely to infer that the venue may be too crowded. In this case, the positive effect of observational learning, if detected, would be there despite of capacity constraint.

The third alternative explanation is *saliency effect*: when consumers are not aware of their entire choice set, the difference in the saliency of the products may affect adopters’ decisions (Cai et al., 2009). That is, instead of observational learning, people may follow others’ choice simply because the products are more salient/noticeable. Cai et al. (2009) point out the caveat that saliency effect often confounds the empirical test for observational learning. For instance, when software on CNET.com are sorted by the number of downloads, the software with more downloads become more prominently displayed on the website. As a result, the observational learning effect estimated based on the ranking of software downloads may be partly explained by the saliency effect. The deals in our data set are purposefully collected such that all of them are the featured deals and placed at the same location on Groupon’s page (see Figure 1). Thus, saliency is less likely to confound the effect of observational learning in our study.

Finally, the literature on social contagion and product diffusion suggests that people adopt when they come in contact with others who have already adopted, spreading like epidemics (Young, 2009). The adoption rate increases as the user base grows but may decrease when the product starts to saturate the market. Thus, it is important to control for product diffusion. The extant literature suggests that adding the linear and quadratic terms of product age into the estimation specification can address the issues raised from product diffusion (Duan et al., 2009; Carare, 2012). In our context, the age of the deal is operationalized as the number of hours since the deal has been featured. To maintain enough degrees of freedom for the estimation, we adopt an approach, suggested by Duan
et al. (2009), that allows the coefficients of the deal age and its quadratic term to vary across different cities but remain constant in the same city. Accordingly, we can use the following Equation (2) in which $j$ is the index for the 6 metropolitan cities, $t$ is the number of hours as the deal age, and $\gamma_{j1}$, $\gamma_{j2}$ are the coefficients of linear and quadratic deal ages, controlling for city-specific product diffusion pattern and common time trends.

$$y_{ij,t} = \alpha \log (Y_{ij,t-1}) + \beta_1 f_{ij,t} + \beta_2 t w_{ij,t} + \gamma_{j1} t + \gamma_{j2} t^2 + \mu_i + \nu_t + \epsilon_{ij,t}$$ (2)

## 5 Results

### 5.1 Main Effects

We first use the standard fixed-effect estimation with robust standard errors clustered at the deal level to estimate the main effects of observational learning and social-network mediated WOM.\footnote{Allowing for any arbitrage form of serial correlation, robust standard errors clustered at the panel level consistently converge to the true standard errors, as the number of clusters approaches infinity (Wooldridge, 2010). The number of deals in our data is 500, much larger than the usual criteria 50. Therefore, the clustered standard errors used in this study are reasonably close to the true standard errors.} Table 3 reports the estimation results, in which Columns (1)-(3) are estimated using Equation (1) and Column (4) is estimated using Equation (2), controlling for city-specific linear and quadratic time trends. The estimated coefficients across Columns (1)-(4) are very consistent, suggesting that multicollinearity is not an issue.

According to Column (4) of Table 3, the estimated coefficient of past sales, $\log (Y_{ij,t-1})$, is positive and statistically significant at the 0.001 level, suggesting a positive effect of observational learning and supporting Hypothesis $H1$. Both coefficients of Facebook Likes and Tweets are positive and statistically significant at the 0.01 level, supporting Hypotheses $H2$. Thus, WOM mediated via Facebook and Twitter are positively associated with voucher sales. Based on the estimates in Column (4), all else equal, a 10% increase in existing total sales of a deal is associated with 1.41 additional voucher sales in the next hour. While one extra Facebook Like is associated with 4.48 additional sales in the present hour, Tweets have
relatively lower impact that one extra tweet is associated with 1.56 more sales.

To precisely compare the relative impacts of observational learning and social-network WOM, we centered each key independent variable by subtracting the overall mean and then dividing it by the standard deviation. We find that a one standard-deviation increase in the past sales is associated with 30.59 additional sales. Similarly, we find that a one standard-deviation increase in the number of Facebook Likes is associated with additional sales of 59.19, but the same increase in the number of Tweets is only associated with only 5.49 additional sales. The result from the one-tailed Wald test \( F_{1,495} = 2.14, p = 0.07 \) suggests that the Facebook Likes have a greater effect than both past sales and Twitter.

Note that although the estimated coefficient of Tweets is positive and statistically significant in Column (4) of Table 3, the result is not robust when we use the dynamic Generalized Method of Moments (GMM). Based on the estimates from dynamic GMM reported in Columns (5) and (6), we do not find a clear evidence that Twitter-mediated WOM has any impact on voucher sales. Detailed robustness checks will be presented in Section 5.4. Thereafter, we focus on WOM mediated via Facebook (Facebook Likes, \( fb_{ij,t} \)) in the remaining part of this paper and therefore use the number of Tweets (\( tw_{ij,t} \)) as a time-varying control variable, making our estimates more robust.

### 5.2 Complementarity between Observational Learning and Facebook-Mediated WOM

After identifying the main effects of observational learning and WOM mediated via Facebook, in this section we investigate the complementarity effect between the two.\(^8\) Specifically, we include the interaction term of log past sales and the number of Facebook Likes in Equa-

\(^8\)Because in the robustness checks we do not find consistent evidences that Twitter-mediated WOM has any impact on voucher sales, we do not consider the interaction or moderating effects associated with Twitter-mediated WOM.
tion (2), leading to the following specification:

\[ y_{ij,t} = \alpha \log (Y_{ij,t-1}) + \beta_1 f_{bij,t} + \eta_1 \log (Y_{ij,t-1}) \times f_{bij,t} + \beta_2 t w_{ij,t} + \gamma_{j1} t + \gamma_{j2} t^2 + \mu_i + v_t + \epsilon_{ij,t} \] (3)

To reduce multicollinearity, we mean-centered the variables in the interaction term of Equation (3). The uncentered variance inflation factors (VIFs) of all the key independent variables are below the critical values, indicating multicollinearity is not an issue. The estimates are reported in Column (2) of Table 4, while Column (1) of Table 4 reproduces Column (4) of Table 3 for the readers’ convenience. The estimated coefficients of past sales and Facebook Likes remain positive and significant, suggesting that the effects of observational learning and Facebook-mediated WOM are positive. More importantly, the estimated coefficient of the interaction term between the two effects is also positive (\( \hat{\eta}_1 = 1.08 \)) and statistically significant at the 0.10 level, after controlling for deal-specific heterogeneity, common time shocks, city-specific time trends and the time-varying number of Tweets. The positive interaction effect suggests that the advertising effect from Facebook-mediated WOM trumps its signaling effect of updating consumers’ belief. As a vehicle for advertising the product to potential buyers, WOM mediated via Facebook attracts more potential consumers to Groupon’s deal page and its effect on sales is magnified when the product has a more favorable quality signal as approximated through higher past sales.

5.3 Moderating Effect of Rating

In order to explore the moderating effect of rating on observational learning and test Hypothesis \( H4 \), we need distinguish between deals with moderate ratings and those with extreme (high/low) ratings. Considering in our sample the mean of ratings is 3.88 (sd=0.75), we create a dummy variable to indicate the rating of deal \( i \) (\( r_i \)) as moderate if \( r_i \in (3.0, 4.75) \).\(^9\)

\(^9\)We can also choose other cutoffs for extremely high rating (\( \geq 4.5 \)) and extremely low rating (\( \leq 2.5 \) or \( \leq 2 \)). Estimates from these alternative cutoffs remain qualitatively identical.
Using this definition, we classified 291 (58%) out of the 500 deals to have moderate ratings. Therefore, we use the following Equation (4) to estimate the data.

\[
y_{ij,t} = \alpha \log (Y_{ij,t-1}) + \beta_1 f b_{ij,t} + \eta_2 \log (Y_{ij,t-1}) \times \mathbb{1}_{\text{moderate}} \\
+ \beta_2 tw_{ij,t} + \gamma_{j1} t + \gamma_{j2} t^2 + \mu_i + v_t + \epsilon_{ij,t}
\] (4)

The estimates are reported in Column (3) of Table 4. The estimated coefficient \( \hat{\eta}_2 \) is 3.76 and statistically significant at the 0.01 level, supporting Hypothesis \( H4 \) that observational learning does complement with moderate ratings and substitute with extreme ratings. That is to say, when the rating from Yelp/Citysearch is just moderate and equivocal, the effect of observational learning is amplified, because consumers have to rely more on observing their peers to infer the product quality.

To explore the moderating effect of rating on Facebook Likes and test Hypothesis \( H5 \), we use the following Equation (5) to estimate the data.

\[
y_{ij,t} = \alpha \log (Y_{ij,t-1}) + \beta_1 x_{ij,t} + \eta_3 x_{ij,t} \times \mathbb{1}_{\text{moderate}} \\
+ \beta_2 z_{ij,t} + \gamma_{j1} t + \gamma_{j2} t^2 + \mu_i + v_t + \epsilon_{ij,t}
\] (5)

The results are reported in Column (4) of Table 4. The estimated coefficient \( \hat{\eta}_3 \) is 4.45 and statistically significantly at the 0.05 level, supporting Hypothesis \( H5 \). Therefore, the results suggest that while a unequivocal rating substitutes the signaling effect of Facebook-mediated WOM, the effect of Facebook-mediated WOM increases when the deal is of a moderate (equivocal) rating. We also added interactions with Twitter and find that the coefficients are largely statistically insignificant. This result reinforces our finding on Facebook because we may expect any unobserved variables to affect Facebook and Twitter similarly as both have similar capabilities to advertise and to provide endorsements to friends. The fact that interactions with Facebook is statistically significant but not ones with Twitter suggests that the interaction comes from Facebook-mediated WOM as opposed to omitted variables.
5.4 Robustness Checks

In this section, we conduct a set of robustness checks to verify if the findings are robust with respect to alternative specifications.

5.4.1 Dynamic GMM

While fixed effect estimation is more efficient when the disturbance terms $\epsilon_{ij,t}$ are serially uncorrelated (i.e., $\epsilon_{ij,t}$ and $\epsilon_{ij,t-1}$ are uncorrelated), the first-differencing estimation is more efficient when $\epsilon_{ij,t}$ follow a random walk (i.e., the first difference of $\epsilon_{ij,t}$ are independently random residuals) (Wooldridge, 2010). Wooldridge (2010, pp. 321) notes that “in many cases, the truth is likely to be lie somewhere in between.” Considering there are $T = 24$ time periods in the data, first-differencing estimation is necessary to be conducted as a robustness check. The first-differencing estimation specification, corresponding to Equation (2), is:

$$\Delta y_{ij,t} = \alpha \Delta \log (Y_{ij,t-1}) + \beta_1 \Delta fb_{ij,t} + \beta_2 \Delta tw_{ij,t} + \gamma_{j1} + \gamma_{j2} \Delta t^2 + \Delta v_t + \Delta \epsilon_{ij,t} \tag{6}$$

Note that the deal fixed effect $\mu_i$ disappears in Equation (6). First-differencing estimation requires a different assumption of strict exogeneity (i.e., the first-differencing variables are strictly exogenous) and the corresponding disturbance terms $\Delta \epsilon_{ij,t}$ are serially uncorrelated. In Equation (6), the dependent variable $\Delta y_{ij,t} = y_{ij,t} - y_{ij,t-1} = (Y_{ij,t} - Y_{ij,t-1}) - (Y_{ij,t-1} - Y_{ij,t-2})$ and the explanatory variable $\Delta \log (Y_{ij,t-1}) = \log (Y_{ij,t-1}) - \log (Y_{ij,t-2})$. Hence, the estimated coefficient of $\Delta \log (Y_{ij,t-1})$ in Equation (6) may be biased due to a potential endogeneity problem. To address this concern, we use the dynamic Generalized Method of Moments (GMM) to estimate Equation (6).

Specifically, we use Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. This estimation method instruments the lagged dependent variables and any other endogenous variables using second- and/or higher-order lags, while addressing the fixed effects using first-differencing. Two-step robust system GMM estimation
with corrected standard errors is more efficient than difference GMM and using orthogonal deviations can deal with the unbalanced panel data (Arellano and Bover, 1995; Blundell and Bond, 1998). Considering $T = 24$ is relatively large in our data set, we choose to use 18th-order and deeper lags of $\log(Y_{ij,t-1})$ as instruments,\(^{10}\) because deeper lags are likely to satisfy the IV assumptions of relevancy and exogeneity. We also treat $fb_{ij,t}$ and $tw_{ij,t}$ as endogenous variables and instrument them using their 18th-order and deeper lags, so that the potential endogeneity between $y_{ij,t}$ and $fb_{ij,t}$, $tw_{ij,t}$ are addressed. Whenever an interaction term (say, the interaction between $\log(Y_{ij,t-1})$ and $fb_{ij,t}$) is examined, we also include it (e.g., $\log(Y_{ij,t-1}) \times fb_{ij,t}$) as an endogenous variable in the estimation.

Column (2) of Table 5 reports the system GMM estimates. The Arellano-Bond test for AR(2) in first differences cannot reject the null hypothesis that there is no second-order serial correlation in the residuals of the first-differencing equation ($p = 0.27$). Thus, serial correlation is not an issue in the GMM estimation. Neither Hansen $J$ statistic (over-identification test) ($p = 0.10$) nor difference-in-Hansen test ($p = 0.93$) rejects the null hypothesis that the instruments are uncorrelated with the disturbance terms, ensuring the validity of the instruments used in the GMM estimation (Roodman, 2007). The number of instruments used is 93, much less than the number of panels ($N = 496$), eliminating the concern of “instrument proliferation” (Roodman, 2007, 2009). All these post-estimation diagnostics satisfy the criteria of system GMM estimation suggested by Roodman (2009), ensuring the set of instruments used in the analysis is valid and the estimates are consistent. As we can see, the estimates in Column (2) of Table 5 are qualitatively similar to Column (1). The only difference is that now the estimated coefficient of Tweets changes its sign to negative but far from statistically significant. Therefore, the results support Hypothesis $H1$ at the 0.001 level. Also, Hypothesis $H2$ is supported at the 0.01 level that the effect of Facebook Likes is positive, but the effect of Tweets is minimal.

Column (3) of Table 5 reports the estimates when the interaction between past sales

\(^{10}\)We also use other sets of deep lags and get qualitatively similar results.
and number of Facebook Likes is included. Again, all the post-estimation diagnostics satisfy the criteria of system GMM estimation. The estimated coefficient of the interaction term \( \log (Y_{ij,t-1} - 1) \times fb_{ij,t} \) is 1.60 and significant at the 0.10 level. Thus, Hypothesis \( H3 \) is supported that the effects of observational learning and Facebook Likes positively interact with each other; the two effects are complements.

When too many instruments are used in the estimation, the Hansen test of over-identification can be weakened, threatening the validity of the GMM estimators. Roodman (2009) suggests that “Researchers should be aggressively tested for sensitivity to reductions in the number of instruments.” One way is to use deeper lags as instruments and the other is to collapse the instruments. Thus, we use 20\textsuperscript{th}-order and deeper lags as instruments and collapse them in the GMM estimation. The results are reported in Columns (4) and (5) of Table 5. As can be seen, the number of instruments are substantially reduced. All the post-estimation diagnostics satisfy the criteria of system GMM estimation, ensuring the instruments used are valid. The results in Columns (4) and (5) of Table 5 are qualitatively similar to Columns (2) and (3), respectively.

Overall, the estimates in Table 5 suggest that both the effects of observational learning and Facebook-mediated WOM are positive and statistically significant, whereas there is no clear evidence about the impact of Twitter-mediated WOM. Further, the effects of observational learning and Facebook-mediated WOM complement each other in driving sales.

We also use system GMM to estimate the moderating effect of rating. The results are reported in Table 6. Column (1) of Table 6 reproduces Column (4) of Table 3 for readers’ convenience. The estimated coefficient \( \hat{\eta}_2 \) in Column (2) is 3.01 and statistically significant at the 0.10 level, supporting Hypothesis \( H4 \) that the effect of observational learning is larger for deals with moderate ratings. Column (3) of Table 6, similar to Column (4) of Table 4, shows that the estimated coefficient \( \hat{\eta}_3 \) is 4.18 and statistically significant at the 0.10 level. This estimate supports that the effect of Facebook-mediated WOM increases when the deal is of a moderate (equivocal) rating. Column (4) of Table 6 includes all the interaction and
moderating terms. The estimates in Column (4) are qualitatively consistent with previous estimates, although the estimated coefficient $\tilde{\eta}_2$ is not significant.

Note that dynamic GMM is most suitable for panel data with “small $T$, large $N$” and Roodman (2007) notes “If $T$ is large, dynamic panel bias becomes insignificant, and a more straightforward fixed effects estimator works”. Since the number of instruments tends to explode with the number of time periods $T$, the relatively large $T = 24$ in our data indicates that the standard fixed effect estimation with clustered standard errors is reasonably valid to be used as the main estimation method.

5.4.2 Fixed-Effect Count Model

Since the dependent variable $y_{ij,t}$ is the number of voucher sales of deal $i$ in the $t^{th}$ hour (nonnegative integer values), we are able to use fixed effect count model to estimate the data as another set of robustness checks. The most widely-used count model is the Poisson model. The idea is to consider buying a voucher as an event. Specifically, the number of deal $i$ purchased within the $t^{th}$ hour is assumed to be drawn from a Poisson distribution with a mean parameter $\lambda_{ij,t}$, where $\lambda_{ij,t}$ is the conditional mean of $y_{ij,t}$ (i.e., $\lambda_{ij,t} = E(y_{ij,t}|.)$). Note that fixed effect Poisson estimator produces consistent estimates under very general conditions and is very flexible to fit many nonlinear models (Wooldridge, 2010). Therefore, it is necessary to test if the findings are robust with respect to fixed effect Poisson model. Herein, we use the following estimation specification.

$$\log(\lambda_{ij,t}) = \alpha \log (Y_{ij,t-1}) + \beta_1 f_{b_{ij,t}} + \beta_2 t w_{ij,t} + \gamma_{j1} t + \gamma_{j2} t^2 + \mu_i + \nu_t + \epsilon_{ij,t}$$  \hspace{1cm} (7)

Column (1) of Table 7 reports the fixed effect Poisson estimators. Results are qualitatively similar to the estimates from the main specification, i.e., Column (4) of Table 3. Both the estimated coefficients of log past sales and Facebook Likes are positive and statistically significant at the 0.001 level, supporting Hypotheses $H1$ and $H2$. However, the estimated
The coefficient of Tweets now becomes negative and statistically significant at the 0.05 level. Together with the estimates of Tweets in Columns (2) and (4) of Table 5, we conclude there is no clear evidence for the impact of Twitter-mediated WOM on voucher sales.

The Poisson model imposes a restrictive assumption on the conditional moments of \( y_{ij,t} \), that is, \( \lambda_{ij,t} = Var(y_{ij,t}) = E(y_{ij,t}) \). This assumption, so-called Poisson variance assumption by Wooldridge (2010), is often violated in applications. Considering in Table 2 the standard deviation (117.84) of \( y_{ij,t} \) is much larger than its mean (41.46), the Poisson variance assumption is likely to be violated in the data. To address this over-dispersion issue, we use fixed-effect Negative Binomial regression model to analyze the data as another robustness check. The results are reported in Column (2) of Table 7, which is very similar to Column (1). The only difference is that the estimated coefficient of Tweets is now not significantly different from zero.

In general, the robustness check using fixed-effect count model again supports Hypotheses H1 and H2, ensuring that both the effects of observational learning and Facebook Likes are positive and statistically significant, while the impact of Twitter-mediated WOM is minimal. We only use the count models as a robustness check for the main effects but not for the interaction or moderating effect, because the interaction effect from nonlinear models is conditional on the independent variables and the sign of the interaction term does not necessarily indicate the sign of the true interaction effect (Norton et al., 2004).

5.4.3 Observational Learning for Experience Goods vs. Tangible Products

As we discussed in Section 3.2, one necessary condition for observational learning is that people have imperfect information about the valuation of the decision (Banerjee, 1992; Bikhchandani et al., 1992). After all, if people have perfect information about the product quality, they could make the purchase decisions certainly by themselves and do not necessarily update their beliefs based upon observation. By the same token, if customers could easily obtain the information about the product quality, they would be less likely to rely on
observation to infer their utility of the product. Since Groupon shoppers are largely new customers and it is relatively difficult and costly to obtain information about the quality of an experience good before consumption, we expect the impact of observational learning, if any, is larger for experience goods than for tangible products about which related information can be obtained relatively easily. Yet, we do not expect such differential effect of Facebook Likes for experience goods and for tangible products.

Given that the data set contains 36 tangible products (like glasses, shoes), we are able to separately test the data across the two subsamples (experience goods vs. tangible products). The results are reported in Columns (3) and (4) of Table 7. Comparing the results in Columns (3) and (4), we find that the estimated coefficient of observational learning for experience goods is large (16.07) and statistically significant at the 0.001 level, whereas the counterpart coefficient for tangible products is much smaller (5.25) and not significantly different from zero (p = 0.13). The result of t-test further suggests that the two estimated coefficients are significantly different (t = 2.22, p < 0.05). On the other hand, the difference between the estimated coefficients of Facebook Likes from the two subsamples is far from significant (t = 0.62). Consequently, the comparison supports our prediction that observational learning does exist and have a larger impact for experience goods than for tangible products, but the effect of Facebook Likes does not differ.

6 Implications and Conclusion

This study offers a number of noteworthy implications for theory on observational learning and online WOM mediated via social media.

First, perhaps due to limited data availability, prior empirical studies have measured either the effect of observational learning or online WOM, but not both; only recently a few exceptions have appeared in the literature (Chen et al., 2011b; Cheung et al., 2012). Given the unique context of daily-deal sites, we are able to collect accurate volumes of
voucher sales, Facebook “Likes” and Twitter messages, so that the financial impacts of both observational learning and social-network WOM on product sales can be directly quantified in a real business context.

Second, little research has examined the role of conversation channel in generating WOM and in impacting the effectiveness (Berger and Iyengar, 2012). Contributing to this recent research strand, our findings shed light on how the effects of social-network WOM differ across the two most popular social-networking sites (Facebook vs. Twitter). Specifically, we find Groupon shoppers are much more likely to endorse the deals via Facebook than via Twitter. More interestingly, while Facebook-mediated WOM has both statistically and economically significant impact on voucher sales, we do not find consistent evidences for Twitter-mediated WOM.

Finally, few prior studies have investigated how observational learning and online WOM interact with each other. Our study examines the interactions between observational learning and the two WOM attributes (volume and valence). We find that observational learning and the volume of Facebook-mediated WOM positively interact with each other and thus confirm there is a complementary between observational learning and WOM volume. On the other hand, WOM valence (measured by average product ratings from Yelp/Citysearch) moderates the effects of observational learning and Facebook-mediated WOM. Specifically, we find the effects of observational learning and Facebook-mediated WOM are magnified when the product rating is just moderate. Because a moderate rating just provides an equivocal quality signal and does not help increase consumers’ information set about the product, consumers have to rely more on the information signals provided by observational learning and WOM mediated via Facebook.
References


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Table 1: Descriptive Statistics

<table>
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<th>Mean</th>
<th>s.d.</th>
<th>Min</th>
<th>Max</th>
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<td>103.92</td>
<td>349.39</td>
<td>2</td>
<td>2999</td>
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<tr>
<td>Original value</td>
<td>500</td>
<td>267.21</td>
<td>827.66</td>
<td>5</td>
<td>7900</td>
</tr>
<tr>
<td>Discount rate</td>
<td>500</td>
<td>57.05</td>
<td>10.89</td>
<td>33.33</td>
<td>95.00</td>
</tr>
<tr>
<td>Rating</td>
<td>410</td>
<td>3.88</td>
<td>0.75</td>
<td>1</td>
<td>5</td>
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<tr>
<td>Total sales</td>
<td>468</td>
<td>936.66</td>
<td>1829.77</td>
<td>0</td>
<td>28569</td>
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<td>Total FB Likes</td>
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<tr>
<td>Total Tweets</td>
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<td>10.46</td>
<td>30.32</td>
<td>0</td>
<td>460</td>
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</table>

Note: The descriptive statistics of total sales, total FB Likes and total Tweets are based on 468 deals for which the observations at the end of the day (11:59pm) are collected in the data set.

Table 2: Pearson Correlations among Time-Varying Variables

<table>
<thead>
<tr>
<th>Variable</th>
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<th>s.d.</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Incremental sales (y_{i,t})</td>
<td>41.46</td>
<td>117.84</td>
<td>1</td>
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<td></td>
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<td>2. Log of past cumulative sales, (\log(Y_{i,t-1}))</td>
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<td>2.07</td>
<td>0.350</td>
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<td>3. Incremental FB Likes (fb_{i,t})</td>
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<td>13.21</td>
<td>0.576</td>
<td>0.267</td>
<td>1</td>
</tr>
<tr>
<td>4. Incremental Tweets (tw_{i,t})</td>
<td>0.36</td>
<td>3.52</td>
<td>0.151</td>
<td>0.040</td>
<td>0.100</td>
</tr>
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</table>

Note: The means, standard deviations (s.d.) and Pearson correlations are based on the pooled data set including 10,550 observations of 500 deals.
Table 3: Fixed-Effect Estimation with Clustered Standard Errors

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past total sales, log (Y_{ij,t-1})</td>
<td>18.58***</td>
<td>14.86***</td>
<td>14.77***</td>
<td>10.54***</td>
<td>9.55**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.00)</td>
<td>(3.02)</td>
<td>(3.11)</td>
<td>(2.91)</td>
<td>(2.87)</td>
<td></td>
</tr>
<tr>
<td>Facebook Likes (fb_{ij,t})</td>
<td>4.54**</td>
<td>4.47**</td>
<td>4.48**</td>
<td>2.06***</td>
<td>1.78**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(1.34)</td>
<td>(1.34)</td>
<td>(0.45)</td>
<td>(0.64)</td>
<td></td>
</tr>
<tr>
<td>Tweets (tw_{ij,t})</td>
<td>1.50*</td>
<td>1.56**</td>
<td>-2.96</td>
<td>1.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>(0.59)</td>
<td>(3.01)</td>
<td>(9.54)</td>
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<tr>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Hour FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Clustered S.E.</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td>No. of clusters</td>
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<td>500</td>
<td>496</td>
<td>496</td>
<td>496</td>
<td>496</td>
</tr>
</tbody>
</table>

Note: DV: Hourly voucher sales \(y_{ij,t}\). Standard errors are clustered at the deal level and reported in parentheses. Columns (1)-(3) are estimated using Equation (1). Columns (4)-(6) are estimated using Equation (2), controlling for city-specific linear and quadratic time trends. Columns (1)-(4) are estimated using the standard fixed-effect estimation. Columns (5)-(6) are estimated using Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. *\(p < 0.05\), **\(p < 0.01\), ***\(p < 0.001\)
Table 4: Interaction and Moderating Effects

<table>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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</thead>
<tbody>
<tr>
<td>Past total sales, log ($Y_{ij,t-1}$)</td>
<td>14.77***</td>
<td>16.54***</td>
<td>14.89***</td>
<td>13.12***</td>
<td>14.77***</td>
<td>15.39***</td>
<td>16.05***</td>
</tr>
<tr>
<td></td>
<td>(3.11)</td>
<td>(2.89)</td>
<td>(3.10)</td>
<td>(3.09)</td>
<td>(2.85)</td>
<td>(2.72)</td>
<td>(3.54)</td>
</tr>
<tr>
<td>Facebook Likes $fb_{ij,t}$</td>
<td>4.48**</td>
<td>1.44*</td>
<td>4.47**</td>
<td>4.08***</td>
<td>1.69*</td>
<td>1.27+</td>
<td>-2.11</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(0.66)</td>
<td>(1.34)</td>
<td>(1.16)</td>
<td>(0.67)</td>
<td>(0.75)</td>
<td>(1.36)</td>
</tr>
<tr>
<td>$\log (Y_{ij,t-1} \times fb_{ij,t})$</td>
<td>1.08+</td>
<td></td>
<td></td>
<td></td>
<td>0.87+</td>
<td>0.96+</td>
<td>1.37**</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
<td></td>
<td></td>
<td></td>
<td>(0.51)</td>
<td>(0.54)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>$\log (Y_{ij,t-1} \times 1_{\text{moderate}})$</td>
<td></td>
<td></td>
<td>3.76**</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(1.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$fb_{ij,t} \times 1_{\text{moderate}}$</td>
<td>4.45*</td>
<td>3.78*</td>
<td>4.45*</td>
<td>1.39</td>
<td>2.69*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.81)</td>
<td>(1.56)</td>
<td>(1.81)</td>
<td>(1.14)</td>
<td>(1.37)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\log (Y_{ij,t-1} \times fb_{ij,t} \times 1_{\text{moderate}})$</td>
<td></td>
<td></td>
<td></td>
<td>0.97</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.90)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tweets $tw_{ij,t}$</td>
<td>1.56**</td>
<td>1.39*</td>
<td>1.56**</td>
<td>1.28*</td>
<td>1.19*</td>
<td>1.17*</td>
<td>-2.82</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.57)</td>
<td>(0.59)</td>
<td>(0.59)</td>
<td>(0.58)</td>
<td>(0.57)</td>
<td>(9.21)</td>
</tr>
<tr>
<td>Deal FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Hour FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Clustered S.E.</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td>No. of clusters</td>
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<td>496</td>
<td>496</td>
<td>496</td>
<td>496</td>
<td>496</td>
<td>496</td>
</tr>
</tbody>
</table>

Note: DV: Hourly voucher sales $y_{ij,t}$. Standard errors are clustered at the deal level and reported in parentheses. All variables used in the interaction terms are mean-centered to reduce multicollinearity. Columns (1)-(6) are estimated using the standard fixed-effect estimation. Column (7) is estimated using Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
Table 5: Robustness Checks using GMM for Main Effects and Interaction

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past total sales, log ( Y_{ij,t-1} )</td>
<td>14.77***</td>
<td>10.54***</td>
<td>20.80**</td>
<td>9.55**</td>
<td>16.57***</td>
</tr>
<tr>
<td></td>
<td>(3.11)</td>
<td>(2.91)</td>
<td>(6.29)</td>
<td>(2.87)</td>
<td>(4.20)</td>
</tr>
<tr>
<td>Facebook Likes ( fb_{ij,t} )</td>
<td>4.48**</td>
<td>2.06***</td>
<td>-4.03</td>
<td>1.78**</td>
<td>-3.05</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(0.45)</td>
<td>(3.13)</td>
<td>(0.64)</td>
<td>(2.07)</td>
</tr>
<tr>
<td>( \log (Y_{ij,t-1}) \times fb_{ij,t} )</td>
<td>1.60†</td>
<td>1.42†</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
<td>(0.82)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tweets ( tw_{ij,t} )</td>
<td>1.56**</td>
<td>-2.96</td>
<td>14.94†</td>
<td>1.49</td>
<td>-16.53</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(3.01)</td>
<td>(8.80)</td>
<td>(9.54)</td>
<td>(18.27)</td>
</tr>
</tbody>
</table>

Deal FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
Hour FEs  | ✓ | ✓ | ✓ | ✓ | ✓ |
Clustered S.E. | ✓ | ✓ | ✓ | ✓ | ✓ |
No. of obs. | 9987 | 9987 | 9987 | 9987 | 9987 |
No. of clusters | 496 | 496 | 496 | 496 | 496 |
No. of instruments | | 93 | 113 | 45 | 49 |

Note: DV: Hourly voucher sales \( y_{ij,t} \). Standard errors are clustered at the deal level and reported in parentheses. Column (1) is estimated using standard fixed-effect model. Columns (2)-(5) are estimated using Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. In Columns (2) and (3), 18th-order and deeper lags are used as instruments. In Columns (4) and (5), 20th-order and deeper lags are used as instruments and all the instruments are collapsed. The post-estimation diagnostics ensure all the instruments used are valid. †\( p < 0.10 \), *\( p < 0.05 \), **\( p < 0.01 \), ***\( p < 0.001 \)
Table 6: Robustness Checks using GMM for Moderating Effect of Rating

<table>
<thead>
<tr>
<th>Scale</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past total sales, log ($Y_{ij,t-1}$)</td>
<td>14.77***</td>
<td>7.52**</td>
<td>10.62**</td>
<td>16.05***</td>
</tr>
<tr>
<td></td>
<td>(3.11)</td>
<td>(2.36)</td>
<td>(3.12)</td>
<td>(3.54)</td>
</tr>
<tr>
<td>Facebook Likes $fb_{ij,t}$</td>
<td>4.48**</td>
<td>2.99***</td>
<td>3.60**</td>
<td>-2.10</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(0.75)</td>
<td>(1.09)</td>
<td>(1.36)</td>
</tr>
<tr>
<td>log ($Y_{ij,t-1}$) $\times fb_{ij,t}$</td>
<td>1.37**</td>
<td>1.37**</td>
<td>1.37**</td>
<td>1.37**</td>
</tr>
<tr>
<td>log ($Y_{ij,t-1}$) $\times \mathbb{1}_{moderate}$</td>
<td>3.01$^+$</td>
<td>3.01$^+$</td>
<td>3.01$^+$</td>
<td>3.01$^+$</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(1.77)</td>
<td>(1.77)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>$fb_{ij,t}$ $\times \mathbb{1}_{moderate}$</td>
<td>4.18$^+$</td>
<td>4.18$^+$</td>
<td>4.18$^+$</td>
<td>4.18$^+$</td>
</tr>
<tr>
<td></td>
<td>(2.49)</td>
<td>(2.49)</td>
<td>(2.49)</td>
<td>(2.49)</td>
</tr>
<tr>
<td>Tweets $tw_{ij,t}$</td>
<td>1.56**</td>
<td>20.01$^+$</td>
<td>10.96</td>
<td>-2.82</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(11.3)</td>
<td>(14.3)</td>
<td>(9.21)</td>
</tr>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Hour FEs</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
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<tr>
<td>No. of instruments</td>
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<td>65</td>
<td>57</td>
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</table>

Note: DV: Hourly voucher sales $y_{ij,t}$. Standard errors are clustered at the deal level and reported in parentheses. Column (1) is estimated using standard fixed-effect model. Columns (2)-(4) are estimated using Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. In Columns (2) and (3), 16th-order and deeper lags as instruments and all the instruments are collapsed. In Column (4), 20th-order and deeper lags are used as instruments and all the instruments are collapsed. The post-estimation diagnostics ensure all the instruments used are valid. $^+p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$
Table 7: Additional Robustness Checks on Main Effects

<table>
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<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past total sales, log (Y_{ij,t-1})</td>
<td>0.44***</td>
<td>0.33***</td>
<td>16.07***</td>
<td>5.25</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(3.50)</td>
<td>(3.39)</td>
</tr>
<tr>
<td>Facebook Likes (x_{ij,t})</td>
<td>2.37e-03***</td>
<td>4.25e-03***</td>
<td>4.46**</td>
<td>6.24*</td>
</tr>
<tr>
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<td>(0.65e-03)</td>
<td>(1.10e-03)</td>
<td>(1.35)</td>
<td>(2.56)</td>
</tr>
<tr>
<td>Tweets (z_{ij,t})</td>
<td>-1.98e-03*</td>
<td>-1.68e-03</td>
<td>1.55*</td>
<td>1.36</td>
</tr>
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<td>(1.03e-03)</td>
<td>(0.61)</td>
<td>(1.04)</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
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<td>✓</td>
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<td>No. of clusters</td>
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<td>496</td>
<td>460</td>
<td>36</td>
</tr>
</tbody>
</table>

Note: DV: Hourly voucher sales \(y_{ij,t}\). Standard errors are clustered at the deal level and reported in parentheses. Columns (1) and (2) are estimated based on fixed-effect Poisson model and fixed-effect negative binomial model, respectively. Columns (3) and (4) are estimated using the standard fixed effect model based on the subsamples of experience goods and tangible products, respectively. *\(p < 0.05\), **\(p < 0.01\), ***\(p < 0.001\)
Figure 1: Screenshot of a daily deal featured by Groupon.com

Figure 2: Conceptual framework of research hypotheses
Figure 3: A Groupon deal was shared on Facebook page

Figure 4: A Groupon deal was shared on Twitter