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

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Abstract

In recent years, daily-deal sites that help sellers offer deep-discounted vouchers have become an increasingly popular marketing vehicle. To investigate their effectiveness on sales, this study hypothesizes two different mechanisms, i.e., observational learning and Word-of-Mouth (WOM) via online social networks, affect shopping behaviors and sales of daily-deal vouchers. Using a unique panel data set consisting of accurate sales data of more than 500 deals from Groupon.com, this study empirically tests saliency of the two mechanisms. The findings indicate that while both mechanisms have a significantly positive association with voucher sales, the effect is stronger for Facebook-mediated WOM than for observational learning. We find that one Facebook Like on a deal, on average, is associated with two additional voucher sales and thus an increase of $215 in revenue. However, we do not find consistent evidence that Twitter-mediated WOM has any impact on the voucher sales.

1. Introduction

In recent years, marketing practitioners and entrepreneurs have been buzz about the explosive growth of daily-deal sites, such as Groupon.com, LivingSocial.com, Bloomspot.com, etc. Using these platforms, sellers can advertise their products by offering deep-discounted vouchers (often 50-80% off). Based on a survey, Dholakia (2011) finds about 80% of the voucher buyers are new customers, indicating that daily-deal sites are an effective marketing vehicle for local businesses [1]. The popularity of using daily-deals as a marketing vehicle has only increased since then. As of April 2012, consumers in North America have spent approximately $7 million a day (more than $2.5 billion a year) on thousands of different daily-deal sites and many big market players, such as Facebook, Amazon, Google and AT&T, have launched or announced their own daily-deal sites [1].

Despite its increasing popularity, few papers have examined the use of daily-deal sites [1-4]. Furthermore, most of these studies [1-4] focus on how daily deals improve the effectiveness of existing marketing vehicles, such as couponing [1] and price discrimination [3]. We argue daily deals differ from these traditional marketing vehicles in at least two important ways and deserve to be examined separately:

(i) Daily-deal sites explicitly highlight the total number of vouchers sold in real-time. By allowing new buyers to observe purchasing decisions made by prior others, daily-deal sites can create herding behavior, generating even more sales for popular vouchers [5].

(ii) Daily-deal sites facilitate the word-of-mouth (WOM) effect via social-networking websites, such as Facebook and Twitter. By clicking the Facebook “Like” or the Twitter button on a deal’s website, social-network users can post the deal on their Facebook or Twitter profiles, allowing their friends and followers to view their endorsement. This word-of-mouth effect can significantly increase sales [6].

The extant literature suggests two distinct mechanisms (i.e., observational learning [5, 7] and social-network WOM [6]) can affect online shopping behaviors and product adoption. Daily-deal sites are thus an ideal context to examine how these two distinct mechanisms affect marketing and sales.

Observational learning is likely to help online users update their valuations for a product when their prior knowledge of the product is imperfect. On the other hand, social-network WOM can increase the

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1 http://savvr.com/2012/04/top-10-highest-grossing-daily-deals-of-all-time/
awareness of the product among potential buyers via online social networking sites, such as Facebook and/or Twitter. Further, the action-based information provided in observational learning (e.g., realized sales volume) may be more credible than WOM from public others, because “actions speak louder than words” [8]. On the other hand, the theory of social ties [9] predicts that social-network WOM can also influence customers’ purchase decisions, because people tend to trust their Facebook friends and/or people they follow on Twitter. Therefore, while both observational learning and social-network WOM may affect online users’ shopping behaviors, how they affect these behaviors can differ. For example, if action-based influences, such as past realized sales, were more likely to affect future sales, the strategy would be to increase sales as early as possible, because earlier sales can have a stronger multiplier effect on later sales. In such case, advertising early (e.g., targeting celebrities whose messages can reach a large number of people, or heavily discounting to earlier buyers) is more beneficial. However, if word of mouth were the more salient mechanism, generating buzz via social-networking sites, such as incentivizing users to “like” a product online, would be more effective to drive sales than early promotions. Thus, understanding the two competing mechanisms is important for firms to develop effective strategies for online marketing and advertising [10].

We collect a unique dataset from Groupon.com consisting of the accurate sales data of more than 500 daily deals. The objective of this paper is to empirically measure the effects of observational learning and social-network WOM on the sales of daily-deal vouchers, after controlling for unobserved deal-specific heterogeneity and product diffusion and ruling out alternative explanations, such as social pressure, network effects and saliency effects. With accurate sales, we are able to derive financial value of the two mechanisms. To the best of our knowledge, we are the first to empirically examine the effects of observational learning and social-network WOM using accurate sales data from a real-world business.

Using fixed-effect and dynamic panel analysis, we find that a deal with more existing sales is likely to receive more sales in the next period, supporting that observational learning has a significantly positive association with voucher sales. Also, we find online WOM via Facebook is positively associated with sales. Comparing the two, we find the relative impact of Facebook-mediated WOM is larger than observational learning. All else equal, one Facebook Like on a deal, on average, is associated with 2 additional voucher sales, equivalent to an increase of $215 in revenue. While Facebook-mediated WOM is positively associated with sales, we do not find consistent evidence that Twitter-mediated WOM has any impact on voucher sales, perhaps due to short-term nature of Twitter messages.

The reminder of this paper is organized as follows. First, we describe the related literature which serves as the theoretical background to motivate our hypotheses. Next, we describe the research context, data collection and the empirical methodology. We subsequently present our main results along with a set of robustness checks. We then conclude by discussing the results and the associated theoretical and practical implications.

2. Related literature

Despite the buzz about voucher promotions in mass press articles, the academic literature on this increasingly popular marketing vehicle is limited [2]. Kumar and Rajan (2012) published 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 other promotional vehicles in promoting sales. Despite the scant published literature, there are a growing number of unpublished working papers on this topic. 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 [3]. For empirical works, larger-scale surveys have been used to examine the effectiveness of voucher promotions [11]. Surveying users in five major sites across 23 US markets, Dholakia (2011) find that differences among voucher-selling sites are minimal [1]. Byers and Mitzenmacher (2012) empirically show that the Yelp ratings of many merchants have decreased after a one-time Groupon promotion and conduct a root cause analysis to explain such phenomenon [4]. 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 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 decisions made by prior others [5, 12]. 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 publications that empirically 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 [13]. 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 [14]. Zhang and Liu (2012) further find evidence of rational observational learning among lenders of Prosper.com; they infer the creditworthiness of borrowers by observing peer lending decisions [7].

This study also contributes to the literature on Word-of-Mouth (WOM). WOM is a well-established construct in marketing literature [15] and the volume of WOM is believed to significantly increase product awareness [8]. 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 [6]. 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 [16]. The work by Chen et al. (2011) is particularly relevant to our study. Using a natural experimental design resulting from information policy shifts of Amazon.com, Chen et al. (2011) conduct longitudinal, quasi-experimental field studies to examine the effect of observational learning and WOM (measured by customer reviews) on product sales [10]. Their findings indicate that observational learning and WOM have differential impacts on sales. Our study differs from the work by Chen et al. (2011) at three aspects. First, our study particularly focuses on the effect of WOM mediated by social-networking websites (Facebook and Twitter) where agents have some form of real-world relationships, e.g., Facebook friendship. By contrast, Chen et al. (2011) 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 [10], instead of having information simply pushed to them via social media. Third, the accurate number of sales is used in our study instead of sales ranking, thus allowing us to more accurately quantify the effects of observational learning and social-media mediated WOM on real financial metrics, like voucher sales and revenues.

3. Research hypotheses

3.1. Observational learning

Economic literature on herding [5] and observational learning [17] show that people are likely to imitate decisions (e.g., to adopt some product or dinning) made by their prior peers. This behavior is further exacerbated when they have imperfect information, because potential adopters tend to assume their peers have private (probably imperfect) information and infer the utility by observing their adoption decisions. Comparing to other social influence mechanisms (e.g., social contagion and peer pressure), observational learning is argued to be more prominent from an economic standpoint [18].

Daily-deal sites explicitly highlight the cumulative number of vouchers sold in real-time and allow potential buyers to observe the collective decisions of prior others. Also, most of the deals sold on daily-deal sites are experience goods (like restaurants/pubs, spas, massage, etc.) and about 80% of deal users are new customers [1], suggesting most buyers are likely to have imperfect information about the deal; for example, they may have experienced similar goods but not the current good on sale. Thus, daily-deal sites are a novel context to test observational learning on product adoption for online shoppers. Buyers with uncertainty over the value of the deal would update their beliefs on the valuation by observing the total number of vouchers purchased by preceding others, because their peers may have private imperfect information about the deals (e.g., prior experience with similar goods). Intuitively, suppose there are two restaurant deals with identical characteristics (e.g., discounted voucher price, location, Yelp rating), uninformed customers may infer a higher valuation for the one that has more existing sales. This virtuous cycle can generate even more sales in subsequent periods. Therefore, we hypothesize

H1: All else equal, a deal with more existing voucher sales is likely to receive even more sales in the next period.
3.2. Social-Network WOM

Word-of-Mouth (WOM) refers to the dissemination of information through communication [10]. Valence and volume are two important WOM attributes. While valence of WOM (e.g., whether the opinions from WOM are positive or negative) affects product sales by changing customers’ valuation of the product, the volume of WOM can increase the product’s awareness among potential buyers, as more people become aware of it [8]. Also, because the theory on social ties suggests that people are more likely to trust people they know [9], WOM mediated via Facebook could be more credible than traditional WOM that often come from strangers [19]. Further, social ties via Facebook/Twitter exhibit homophily [20], suggesting that when a person likes a product and puts effort to disseminate it via social media, his/her peers are likely to prefer the product as well. Therefore, we would expect WOM mediated via social media to be more influential than traditional WOM that often comes from strangers. Accordingly, WOM is more likely to influence a person’s decision, when the information is acquired through friends via Facebook or Twitter. We conjecture

\[ H2a: \text{All else equal, more Facebook Likes on a deal are associated with more voucher sales.} \]

\[ H2b: \text{All else equal, more Twitter messages (tweets) on a deal are associated with more voucher sales.} \]

4. Research context and data

4.1. Research context

The web design of most daily-deal sites purposefully takes into account the mechanisms of observational learning and social-network WOM, providing a unique context for this study. Groupon.com, perhaps the most well-known and largest daily-deal site, went public on November 4th, 2011 and raised $700 million from IPO, valued at nearly $13 billion. Groupon features one deal everyday on its main page of each local market. Figure 1 shows a screenshot of the deal featured by Groupon on March 11th, 2011 for Chicago, a typical featured deal. In Figure 1, shoppers can see the characteristics of the deal, such as vendor, discounted voucher price, etc. In addition, the quantity of existing vouchers sold is explicitly highlighted in real-time. Immediately below the sales information, Groupon provides the Facebook “Like” and Twitter buttons, allowing shoppers to share the deal with their Facebook friends and/or Twitter followers. While the number deals sold is placed prominently on Groupon’s deal page, the number of Twitter messages (tweets) and the number of Facebook Likes are in general not displayed prominently and sometimes not displayed at all.\(^2\) We believe the primary channel for Facebook Likes and tweets to generate future sales is through influencing online social contacts and Twitter followers. For example, after one of the authors “liked” a Groupon deal, this activity is displayed on the wall of his Facebook page where all his friends can see that he has liked a Groupon deal.

![Figure 1. Screenshot of a daily deal featured on Groupon.com](image)

4.2. Data

The data in this study were all collected from publicly available sources using Cameleon Web Wrapper [29].\(^3\) Specifically, the deal characteristics and sales data were extracted from Groupon.com. Facebook and Twitter data were extracted using their public APIs. We also extracted the ratings for the deals from Yelp/Citysearch.

The data set consists of all featured deals in 6 US metropolitan cities\(^4\) from July 1\(^{st}\) to September 27\(^{th}\).

\(^2\) While the number of tweets is hidden on Groupon’s main page, the number of Facebook Likes is displayed only if Chrome and Firefox are used. This could potentially bias the estimation if one could also interpret the Facebook Like as an effect of observational learning. However, we believe the effect is minimal because it is at the bottom of the page and displayed in much smaller font than the number of voucher sales.


\(^4\) We sampled the 6 US metropolitan cities across East Coast, West Coast and Middle West, including Boston, New York City, Los Angeles, San Francisco, Chicago, and Houston.
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. A total of 526 deals were collected, among which 26 (4.9%) are associated with erroneous data of key variables. It seems that the erroneous deals randomly occurred during the observation period and thus we removed them, resulting in a set of unbalanced panel data consisting of 500 daily deals with at most 24 hour periods. We also collected various deal characteristics, including the discounted voucher price, the original/face price, product category, quality rating from Yelp/Citysearch, the minimum requirement for the deal to be live, etc.

4.3. Descriptive statistics

Table 1 presents the descriptive statistics of the deal characteristics from 468 deals for which the final sales at the end of the day (11:59pm) are collected in the dataset. In this sample, 105 deals are related to restaurants and pubs, and 328 are other experience goods, like spas and massage. Thus, experience goods account for 92.5% of the overall deals. On average, the discounted voucher price is $107.86 with a face value of $278.54, resulting in an average discount rate of 57.33%. The average total number of vouchers sold on the first day is 936.66. The total number Facebook Likes and tweets received in the first day are 106.08 and 10.46, respectively.

5. Empirical methodology and results

5.1. Estimation specification

Given the panel structure of the dataset, we use fixed effect models as the main estimation specification in the analysis. Because it can eliminate any time-invariant unobserved heterogeneity, fixed-effect models has become one of the three main approaches to identifying the effect of observational learning in empirical studies [7, 13, 17].

We denote the cumulative sales of a deal \( Y_{i,t} \) up to the \( t^{th} \) clock hour by \( Y_{i,t} = Y_{i,t} - Y_{i,t-1} \) is the incremental sales occurred during the \( t^{th} \) hour of the day. According to the estimation specification suggested by Zhang and Liu (2012) [7], 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 effects.

We denote the incremental Facebook Likes and tweets of a deal \( i \) occurring during the \( t^{th} \) hour of the day by \( x_{i,t}, z_{i,t} \), respectively. Therefore, the coefficients of \( x_{i,t}, z_{i,t} \) on \( Y_{i,t} \) estimate the effects of the number of Facebook Likes and tweets in the current hour on the current sales. Both coefficients indicate the effects of social-network WOM.

Specifically, the estimation specification used in this study is as follows:

\[
Y_{i,t} = \alpha \log(Y_{i,t-1}) + \beta_1 x_{i,t} + \beta_2 z_{i,t} + \mu_i + \nu_i + \epsilon_{i,t}
\]  

(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. \( \mu_i \) is a deal fixed effect that controls for deal-specific time-invariant unobservables. \( \nu_i \) is the time fixed effect that controls for common shocks at different hours in 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 makes the estimates more robust [13]. Using

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Table 1. Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voucher price</td>
<td>107.86</td>
<td>360.67</td>
<td>2</td>
<td>2999</td>
</tr>
<tr>
<td>Original price</td>
<td>278.54</td>
<td>854.08</td>
<td>5</td>
<td>7900</td>
</tr>
<tr>
<td>Discount rate</td>
<td>57.33</td>
<td>10.94</td>
<td>33.33</td>
<td>95.00</td>
</tr>
<tr>
<td>Total sales</td>
<td>936.66</td>
<td>1829.77</td>
<td>0</td>
<td>28569</td>
</tr>
<tr>
<td>Total FB clicks</td>
<td>106.08</td>
<td>217.27</td>
<td>0</td>
<td>2612</td>
</tr>
<tr>
<td>Total tweets</td>
<td>10.46</td>
<td>30.32</td>
<td>0</td>
<td>460</td>
</tr>
</tbody>
</table>

Note: The descriptive statistics are based on 468 deals for which the final sales at the end of the day are collected in the dataset. 380 out of the 468 deals have rating data from Yelp or Citysearch.

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5 Groupon started no longer displaying the accurate number of voucher sales around September 28th, 2011, forcing the observation period of our study to cease on September 27th, 2011. Please see: http://allthingsd.com/20111010/groupon-makes-it-less-possible-to-track-how-well-it-is-doing;
Equation (1), the estimated coefficient \( \alpha \) measures the effect of log-transformed past cumulative sales on incremental sales in the present hour. The estimated coefficients \( \beta_1 \) and \( \beta_2 \) measure the effects of contemporaneous Facebook Likes and tweets on the current sales. Therefore, the effects of observational learning (measured by \( \alpha \)) and social-network WOM (measured by \( \beta_1 \) and \( \beta_2 \)) are identified based on the within-deal variations over the 24 hours of the day. By design, this rules out unobserved time-invariant deal characteristics, such as discounted voucher price, quality of the good, and location of the deal, etc. For example, the popularity of a deal should be time-invariant during the day and thus controlled by the deal fixed effect. The common shocks over the day are controlled by the time fixed effect. For instance, if buyers’ purchasing activities are more active in the later afternoon than in the early morning, time dummies can control for this variation. While there could still be unobserved time-varying factors that may affect past and current sales, we use dynamic GMM with lagged dependent variables as a robustness check and find that it did not change our estimation.

5.2. 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 adopt, because many of their peers have already adopted [18]. While this would be a significant concern if most of the goods are easily observed, such as fashion items, the deals in our context are often personal experience goods, such as meals at restaurants, spas, massages, etc. Because they are less observable or verifiable, social pressure is less likely to explain the observed herd behavior.

The second is the positive network effects or payoff externalities. Network effects refer to the value of a product increases as its user base expands [21]. While network effects often occur with IT products [22] (such as fax machines or microcomputers), they are less plausible in the context of daily deals for personal experience goods, because one’s utility of using the deal does not directly affect others.

The third alternative explanation is saliency effect: when consumers are not aware of their entire choice set, the difference in the saliency for the products may affect adopters’ decisions [17]. That is, people may follow others’ adoption decisions simply because the products are more salient instead of observational learning. For instance, when software on CNET.com are sorted by ranks of number of downloads, the software that have been downloaded more often become more salient on the website. As a result, the herding behavior observed by Duan et al. (2009) may be partly explained by the confounding saliency effect. Since all the deals in our data set are featured at the same location on Groupon’s webpage (see Figure 1), 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 [18]. The adoption rate increases as the user base grows but may decrease when the product starts to saturate the market. Thus, to take product diffusion into account, we added the linear and quadratic terms of product age into the estimation specification, as the extant literature suggests [13, 23]. 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 vary across different cities but remain constant for deals in the same city. Therefore, 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 \( y_{1j} \), \( y_{2j} \) are the coefficients of linear and quadratic deal ages, controlling for the effect of product diffusion.

\[
y_{ijt} = \alpha \log(y_{ij,t-1}) + \beta_1 y_{ij,t} + \beta_2 y_{ij,t}^2 + y_{1j} + y_{2j} t^2 + \mu_t + \nu_t + \epsilon_{ij,t} \tag{2}
\]

5.3. Results of fixed effect estimation

5.3.1. Fixed effect with clustered standard errors.

We first use the standard fixed effect estimation with robust standard errors clustered at the deal level to estimate the effects. Table 2 reports the estimation results, in which Columns (1)–(4) are estimated using Equation (1) and Column (5) is estimated using Equation (2), controlling for city-specific linear and quadratic time trends (i.e., product diffusion). The estimated coefficients across Columns (1)–(5) are very consistent when adding more explanatory variables, indicating that multicollinearity is less likely an issue in the analysis. The single variable of Facebook Likes itself explains a large part of within \( R^2 \) of the model, indicating a strong effect of Facebook Likes. According to Column (5) of Table 2, the coefficient of log past sales, log\((y_{ij,t-1})\), is
positive and statistically significant at the $p<.001$ level. The results support Hypothesis $H1$, indicating a positive observational learning effect. Both of the coefficients of Facebook Likes and tweets are positive and statistically significant at the $p<.01$ level, supporting Hypothesis $H2$ that social-network WOM (via Facebook and Twitter) has positive effect on the voucher sales. Based on the estimates in Column (5), with all else equal, a 10% increase in past sales of a deal is associated with 1.41 additional voucher sales in the next hour. Also, one Facebook Like or tweet on a deal is associated with 4.48, 1.56 additional sales, respectively.

To compare the relative impacts of these effects, we centered each key independent variable by subtracting its overall mean and then divided by its overall standard deviation. Reporting in Column (6) of Table 2, we find the effect of Facebook Likes is larger than that of observation learning and tweets. Specifically, a one standard deviation increase in Facebook Likes is associated with 59.19 (std. dev.=6.43, $p<.001$) additional voucher sales, while the same increase in observational learning is associated with 30.58 (std. dev.=17.74, $p<.001$) additional sales.

### 5.3.2. Fixed effect with AR(1) serial correlation.

One identification assumption behind the standard fixed effect model is that the unobserved disturbance terms $\epsilon_{ij,t}$ in Equation (2) are serially uncorrelated (i.e., $\epsilon_{ij,t}$ and $\epsilon_{ij,t-1}$ are uncorrelated). If not, the usual standard errors from fixed effects can be misleading, especially when the number of time periods $T$ is large [24]. In our case $T=24$. We conduct the Wooldridge test with the null hypothesis that there is no first-order autocorrelation [24]. The test strongly rejects the null and thus we need to verify if the findings are biased because of serial correlation. Assuming unobserved disturbance terms $\epsilon_{ij,t}$ are first-order autoregressive, we estimate the data using fixed effect with AR(1) serial correlation. The results are reported in Table 3. The estimated coefficients across Columns (1)-(5) are also very consistent when adding more explanatory variables. Again, the variable of Facebook Likes explains a large part of within $R^2$ of the model, indicating a strong effect of Facebook Likes. According to Column (5) of Table 3, the coefficient of log past sales, $\log(Y_{l,t-1})$, is positive but not statistically significant, thus failing to support Hypothesis $H1$.

The coefficient of Facebook Likes is still positive and statistically significant, but the coefficient of tweets is no longer significant. Thus, Hypothesis $H2$ is partly supported in that the effect of WOM via Facebook is positive and statistically significant, but the effect of WOM via Twitter is not different from zero. According to Column (6) in Table 3, while that of log past sales and tweets are insignificant, the standardized coefficient of Facebook Likes is substantial. That is, one standard deviation increase in Facebook Likes is associated with 28.94 additional voucher sales, suggesting that Facebook-mediated WOM has the stronger impact on the sales than observational learning. Note that although observational learning is not statistically significant in predicting sales in this model with specific assumption of AR(1), this result alone is not sufficient to prove the effectiveness of observational learning without further robustness checks.

### 6. Robustness checks

The robustness checks are conducted with respect to Equation (2). The results of robustness checks are reported in Table 4. For comparison, Column (1) and (2) of Table 4 replicate Column (5) of Table 2 and 3.

#### 6.1. Dynamic GMM

While fixed effect estimation is more efficient when the disturbance terms $\epsilon_{ij,t}$ are serially uncorrelated, the first-differencing estimation is more efficient when $\epsilon_{ij,t}$ follow a random walk [24]. Wooldridge (2010, pp.321) write that “in many cases, the truth is likely to be lie somewhere in between.” Considering there are $T=24$ time periods in our data (longer than the usual panel data used in standard fixed effect estimation), first-differencing estimation is necessary to be conducted as a robustness check. The first-differencing specification, corresponding to Equation (2), is as follows:

$$\Delta y_{ij,t} = \alpha \Delta \log(Y_{ij,t-1}) + \beta_1 \Delta x_{ij,t} + \beta_2 \Delta z_{ij,t} + \gamma_1 \Delta y_{ij,t-2} + \Delta v_{ij,t} + \Delta \epsilon_{ij,t} \quad (3)$$

Note that the deal fixed effect $\mu_i$ disappears in Equation (3). First-differencing estimation requires a different assumption of strict exogeneity (i.e., the first-differencing variables are exogenous) and the corresponding disturbance terms $\Delta \epsilon_{ij,t}$ are serially uncorrelated.

In Equation (3), the dependent variable $\Delta y_{ij,t}$ is $\Delta y_{ij,t} = Y_{ij,t} - Y_{ij,t-1} = (Y_{ij,t} - Y_{ij,t-1}) - (Y_{ij,t-1} - Y_{ij,t-2})$ 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 $\Delta \log(Y_{ij,t-1})$ may be biased due to a
Table 2. 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 sales, log($Y_{t-1}$)</td>
<td>18.58*** (4.00)</td>
<td>-</td>
<td>-</td>
<td>14.86*** (3.02)</td>
<td>14.77*** (3.11)</td>
<td>30.58*** (6.43)</td>
</tr>
<tr>
<td>FB clicks, $x_{i,t}$</td>
<td>-</td>
<td>4.54** (1.34)</td>
<td>-</td>
<td>4.47** (1.34)</td>
<td>4.48** (1.34)</td>
<td>59.19** (17.74)</td>
</tr>
<tr>
<td>Tweets, $z_{i,t}$</td>
<td>-</td>
<td>-</td>
<td>2.22** (0.71)</td>
<td>1.50* (0.59)</td>
<td>1.56** (0.59)</td>
<td>5.49** (2.07)</td>
</tr>
<tr>
<td>Deal-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>No. of obs.</td>
<td>9987</td>
<td>10550</td>
<td>10550</td>
<td>9987</td>
<td>9987</td>
<td>9987</td>
</tr>
<tr>
<td>No. of groups</td>
<td>496</td>
<td>500</td>
<td>500</td>
<td>496</td>
<td>496</td>
<td>496</td>
</tr>
<tr>
<td>Within $R^2$</td>
<td>0.172</td>
<td>0.371</td>
<td>0.163</td>
<td>0.385</td>
<td>0.389</td>
<td>0.389</td>
</tr>
</tbody>
</table>

Note: Standard errors are clustered for each deal level and reported in parentheses. Columns (1)-(4) are estimated using Equation (1). Column (5) is estimated using Equation (2), controlling for city-specific linear and quadratic time trends. Column (6) is standardized coefficients estimated using Equation (2). * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 3. Fixed-Effect Estimation with AR(1) Serial Correlation

<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 sales, log($Y_{t-1}$)</td>
<td>2.82 (2.62)</td>
<td>-</td>
<td>-</td>
<td>3.16 (2.52)</td>
<td>3.08 (2.53)</td>
<td>6.37 (5.23)</td>
</tr>
<tr>
<td>FB clicks, $x_{i,t}$</td>
<td>-</td>
<td>2.18*** (0.07)</td>
<td>-</td>
<td>2.17*** (0.08)</td>
<td>2.17*** (0.08)</td>
<td>28.64*** (1.02)</td>
</tr>
<tr>
<td>Tweets, $z_{i,t}$</td>
<td>-</td>
<td>-</td>
<td>0.03 (0.12)</td>
<td>0.06 (0.12)</td>
<td>0.06 (0.12)</td>
<td>0.21 (0.43)</td>
</tr>
<tr>
<td>Deal-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>No. of obs.</td>
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<td>10050</td>
<td>9491</td>
<td>9491</td>
<td>9491</td>
</tr>
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<td>No. of groups</td>
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<td>498</td>
<td>498</td>
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<td>495</td>
<td>495</td>
</tr>
<tr>
<td>Within $R^2$</td>
<td>0.100</td>
<td>0.171</td>
<td>0.095</td>
<td>0.175</td>
<td>0.178</td>
<td>0.176</td>
</tr>
<tr>
<td>Autoreg. coef.</td>
<td>0.82</td>
<td>0.79</td>
<td>0.82</td>
<td>0.79</td>
<td>0.79</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Note: Standard errors are reported in parentheses. Columns (1)-(4) are estimated using Equation (1). Column (5) is estimated using Equation (2), controlling for city-specific linear and quadratic time trends. Column (6) is standardized coefficients estimated using Equation (2). * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4. Robustness Checks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past sales, log($Y_{t-1}$)</td>
<td>14.77*** (3.11)</td>
<td>3.08 (2.53)</td>
<td>10.54*** (2.91)</td>
<td>4.69* (2.41)</td>
</tr>
<tr>
<td>FB clicks, $x_{i,t}$</td>
<td>4.48** (1.34)</td>
<td>2.17*** (0.08)</td>
<td>2.06*** (0.45)</td>
<td>2.30** (0.88)</td>
</tr>
<tr>
<td>Tweets, $z_{i,t}$</td>
<td>1.56** (0.59)</td>
<td>0.06 (0.12)</td>
<td>-2.96 (3.01)</td>
<td>-0.40 (15.97)</td>
</tr>
<tr>
<td>Deal-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time-fixed controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>No. of obs.</td>
<td>9987</td>
<td>9491</td>
<td>9987</td>
<td>9987</td>
</tr>
<tr>
<td>No. of groups</td>
<td>496</td>
<td>495</td>
<td>496</td>
<td>496</td>
</tr>
</tbody>
</table>

Note: Standard errors are reported in parentheses. Column (1) is from fixed-effect estimation with clustered standard errors. Column (2) is from fixed-effect estimation with AR(1) serial correlation. Columns (3) and (4) are estimated using the Arellano-Bond/Blundell-Bover two-step robust system GMM estimation with orthogonal deviations. Instruments are collapsed in Column (4). * $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$
potential problem of endogeneity. To address this concern, we use the dynamic Generalized Method of Moments (GMM) to estimate Equation (3). The similar method is also used by Zhang and Liu (2012) in their robustness check on the estimation of observational learning [7].

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 [25, 26]. Considering \( T=24 \) is relatively large in our data set, we choose to use 18th-order and deeper lags of \( Y_{ij,t-1}, x_{ij,t} \), and \( z_{ij,t} \) as instruments,\(^6\) because deeper lags are likely to satisfy the IV assumptions of relevance and exogeneity.

Column (3) of Table 4 reports the estimates with the standard errors are robust and clustered at the deal level, which are similar to Column (1) and (2). The only difference is that now the coefficient of tweets changes its sign to negative but far from being statistically significant. The Arellano-Bond test for AR(2) autocorrelation in first differences fails to reject the null hypothesis that there is no second-order autocorrelation in the residuals of the first-differencing equations \( (p=0.272) \). Thus, serial correlation is not an issue in the first-differencing 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 in the GMM estimation. The number of instruments used is 93, much less than the number of panels in our data \( (N=500) \), eliminating the concern of “instrument proliferation” [27, 28]. All these checks satisfy the criteria of system GMM estimation suggested by Roodman (2009) [28], ensuring that the set of instruments used in the analysis is valid and the estimates are reliable.

When the number of instrument are many, Hansen test of over-identifying can be severely weakened and thus threat the validity of the GMM estimators. Therefore, Roodman (2009) suggests that “Researchers should be aggressively tested for sensitivity to reductions in the number of instruments” [28]. A straightforward way is to collapse the instruments, as also suggested by Roodman (2009). Column (4) of Table 4 reports the results using the collapsed instruments. The number of instruments is now reduced from 93 to 51. Neither Hansen test of over-identifying \( (p=0.45) \) nor difference-in-Hansen test \( (p=0.36) \) rejects the null, again ensuring the instruments are valid. The estimates in Column (4) of Table 4 are qualitatively similar to Columns (1)-(3). The only difference is that the coefficient of log past sales, \( \log(Y_{ij,t-1}) \), is only significant at the .10 level \( (p=0.052) \).

Therefore, the results of system GMM estimation indicate the observational learning effect is positive and statistically significant, supporting Hypothesis \( H1 \). Hypothesis \( H2 \) is partly supported in that the effect of Facebook Likes is positive and significant but Twitter is not.

7. Conclusion and Discussion

In this paper, we investigate the effectiveness of daily-deal vouchers that embodies both observational learning and social-network WOM mechanisms. Extant empirical research examining both mechanisms in a same setting is scant [10]. We use fixed-effect models to analyze a panel data set consisting of over 500 daily deals from Groupon.com. Ruling out alternative explanations (e.g., social pressure, network effect, saliency effect, and product diffusion), we find supportive evidence that both mechanisms (i.e., observational learning vs. social-network WOM) are driving the voucher sales. Although traditional wisdom suggests “actions speak louder than words” [8], our analysis reveals that the relative impact of WOM via Facebook is larger than observational learning, probably because people tend to trust their Facebook friends and thus more likely to adopt the products endorsed by their friends. However, we do not find consistent evidence that WOM via Twitter has any impact, perhaps due to short-term nature of Twitter messages.

8. References


\(^6\) We also use other sets of deep lags and get similar patterns.


