International Journal of Research in Marketing 34 (2017) 120–136

Contents lists available at ScienceDirect

IJRM

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

The “tipping point” feature of social coupons: An empirical investigation☆

Mantian (Mandy) Hu [a,*], Russell S. Winer [b,1]

[a] Chinese University of Hong Kong Business School, Hong Kong
[b] New York University Stern School of Business, United States

ARTICLE INFO

Article history:
First received on June 16, 2015 and was under review for 5½ months
Available online 6 June 2016

Area Editor: Sandy Jap

Keywords:
Social coupon
Daily deal
Assurance contract
Clickstream data
Data augmentation

ABSTRACT

Groupon has pioneered a new business model that combines the features of daily deals and group buying. Utilizing a large proprietary dataset of Groupon users, the authors formulate three hypotheses about the effects of the tipping point (i.e., whether enough people have purchased the deal before it can be redeemed) on consumer behavior. The results indicate that (1) surprisingly, the tipping point does not stimulate consumers to refer the deal to others, (2) after controlling for detailed deal characteristics, information about the tipping point increases deal purchase probability and accelerates deal purchase speed by removing consumers' uncertainty about whether the deal will eventually tip, and (3) through a comparison of the different effects of prior purchases on purchase likelihood before and after a tipping point, conformity rather than social learning is identified as playing the dominant role in contagious purchases. Taken together, our results support the fact that the tipping point can alter consumer behavior and affect sales. However, recent changes made by Groupon are inconsistent with our empirical results and keeps the company from fully utilizing its potential. This study also provides an example of using web analytics tools to augment clickstream data and consolidate information from other sources.

Since the founding of Groupon in 2008, the company has generated a large buzz in the global marketplace. The CEO appeared on the cover of *Forbes* and was described as “the next web phenom.[2]” Groupon was not the first company to provide coupons with great discounts, but it pioneered a new business model that combined two features: daily deals and group buying. This so-called social coupon has become an important part of marketing programs of numerous local retailers (Kumar & Rajan, 2012). By the end of 2011, over 50 million Americans had signed up with social coupon vendors, such as Groupon and LivingSocial, and the annual revenue of the social coupon sector had reached $1 billion. Despite the recent onset of daily deal “fatigue,” during the first quarter of 2014, Groupon generated global revenues of more than $757 million (Groupon, 2014). A total of 51.8 million unique customers have bought at least one deal from Groupon during the preceding 12 months (Groupon, 2014).

☆ We would like to thank Yuanyuan Man for her excellent job as the RA for this project. We also want to thank Irwin King, Xueming Luo and seminar participants at Fudan Big Data Marketing Analytics: Greater-China Symposium 2014 Shanghai for their helpful comments. This work was supported by grants from the Research Grants Council of the Hong Kong SAR (Project No. 24500214).

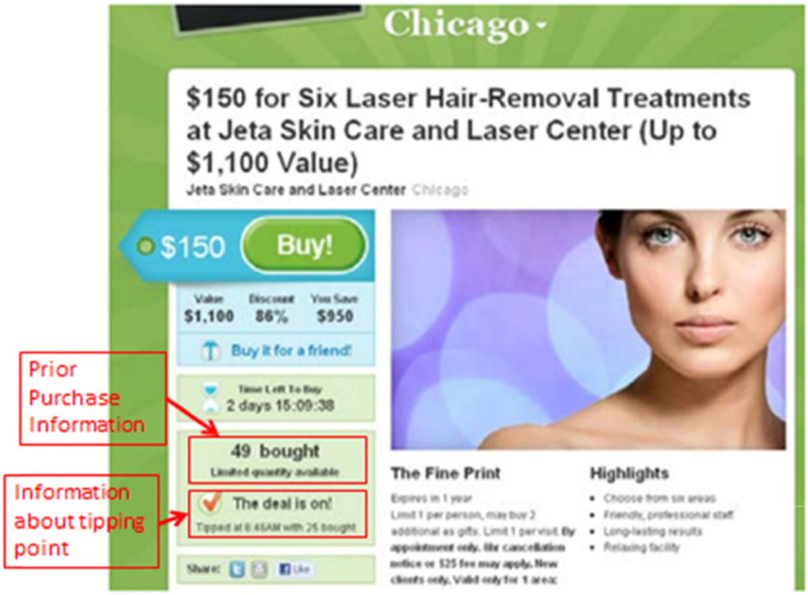
* Corresponding author at: Room 1105, Cheng Yu Tung Building, No. 12, Chak Cheung Street, The Chinese University of Hong Kong, Shatin N.T. Hong Kong. Tel.: +852 3943 5908.

E-mail addresses: mandyhu@baf.cuhk.edu.hk (M.(M.) Hu), rwiner@stern.nyu.edu (R.S. Winer).

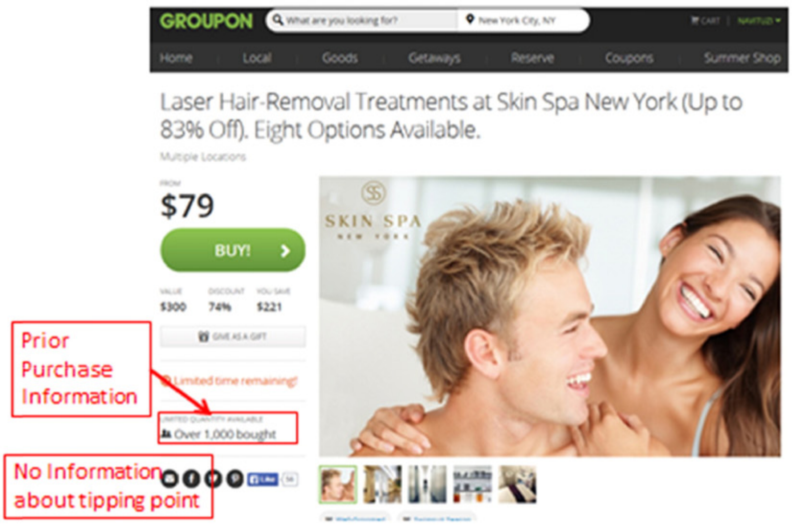
1 Tel.: +1 212 998 0540.

2 http://www.forbes.com/global/2010/0913/entrepreneurs-andrew-mason-groupon-bargains-web-sensation.html.

http://dx.doi.org/10.1016/j.ijresmar.2016.05.001



a Comparison of Groupon web pages (a web page in 2011)



b Comparison of Groupon web pages (a web page in 2014)

Fig. 1. a: Comparison of Groupon web pages (a web page in 2011) b: Comparison of Groupon web pages (a web page in 2014).

Groupon innovated the collective buying model suggested by its name: group plus coupon. A certain number of people need to buy into any given deal before it can be redeemed, or “tipped” in Groupon parlance.[3] If the deal is not tipped, no one can redeem the coupon. This group-buying feature differentiates Groupon from the old models and helps build its name. To enforce this approach, Groupon adopted the following strategies:

1) Tipping point: Information about the tipping point, such as whether and when the deal is tipped and the tipping point value, are displayed instantaneously right below the prior purchase numbers (see Fig. 1). Consumers can receive a separate email notifying them whether the deal is “on” or not after they receive the email confirming their coupon purchases.

[3] “Groupon's $6 Billion Gambler.” Dec. 20, 2010, Wall Street Journal.

2) Prior purchase: On Groupon's web pages for deals, the exact number of individuals who have purchased each deal is included in a salient position.
3) Referral links: Recommending the deals to friends is easy thank to an extensive list of tools such as emailing the uniform resource locator (URL) and clicking "Like" on Facebook and Twitter.

Over time, however, Groupon has changed the three aforementioned strategies and the amount of information provided to potential consumers. The most significant change has been the tipping point. Now, although the tipping point remains in effect, as shown in Fig. 1b, the detailed related information has been removed[4] and the exact prior purchase number has been replaced by an approximation. These changes prompt one to wonder whether the group-buying strategy was just a marketing "gimmick" without substance or did the strategies, in particular the tipping point, significantly affect consumer behavior?

The social coupon is a relatively new business model, and thus has not been fully studied using real data. Given a unique dataset about Groupon, the current paper is the first empirical study using individual level clickstream data to investigate the group buying feature on consumer behavior. In particular, we are focusing on the effect of the tipping point on consumers' referral and purchase behavior. Previous authors have made several theoretical predictions on how group-buying would affect consumer behavior, but research in this area is lacking empirical evidence. Therefore, based on extant literature, we have developed three hypotheses and tested them using real data.

We use a large proprietary dataset supplied by a third-party online marketing research firm in the U.S. This unique dataset consists of the complete clickstream within the browsing sessions of people who logged into the Groupon website between January and March 2011 in the U.S. Certain researchers have argued that the biggest limitation of clickstream data is that the meter used to collect the data does not record the content of the page but only the URL (Montgomery, Li, Srinivasan, & Liechty, 2004). In the current study, however, we augment the behavioral information based on the URL with detailed web page contents. Based on the Groupon URLs, we use social computing techniques (Du, Li, & King, 2009) to "crawl" the detailed information on the retrieved web page. In addition, the previous empirical work on Groupon used deal level information (Li & Wu, 2013) to infer individual behavior. In the present study, we directly observe individual behavior.

We first find that, surprisingly, people are not motivated to refer Groupon deals to other consumers, even if the deal is not tipped when they purchase it. Although Jing and Xie (2011) argued that group buying could be the dominant selling strategy for companies with a moderate level of consumer information heterogeneity about the product, empirical evidence indicates that this strategy did not work in the case of Groupon. Instead, we find that information about the tipping point affects individual purchase probabilities by reducing the uncertainty about whether the deal can tip or not and simultaneously speeds up the purchase process by decreasing the consumers' consideration time. Based on prior purchase information and the status of the tipping point when the deal is being viewed, we also separately identify conformity effects, which are defined as the motive of people behaving similar to peers if enough peers are acting the same (Young, 2009), and social learning effects, where consumers use information from their peers to update their own expectations of product quality (Moretti, 2011). We find that compared to social learning, conformity plays a dominant role as the mechanism behind contagious purchases. We conclude that the tipping point is an effective strategy that can alter consumer behavior and affect sales.

The rest of the paper is organized as follows. In the next section, we discuss the three main hypotheses in detail. Subsequently, we describe the data on Groupon and the main variables. We then discuss the analysis and the empirical results. Last, we conclude the paper and suggest directions for further research.

1. Hypotheses and literature review

As proposed by Bagnoli and Lipman (1989), an "assurance contract" is a game-theoretic mechanism in which people voluntarily contribute specific amount of money or private good to a public good, and the decision to provide the public good is made if and only if contributions are sufficient to reach a minimum amount. Otherwise, the contributions are refunded.

On social coupon websites, the use of tipping points and the revelation of deal purchase status create an "assurance contract."[5] Theoretically, Jing and Xie (2011) illustrated that coupon purchasers might want the deal to reach the tipping point so that they can redeem their coupons. As a result, under certain circumstances, social coupons can motivate individuals to act as sales agents and promote the deal to others to ensure that the minimum limit is met. Moreover, as the tipping status is displayed on the web page, we would expect that if the customer notices the deal is not yet tipped when he purchases it, he is more likely to refer the deal to others than when the deal is already tipped.

Thus, our first hypothesis is about referral behavior.

H1. *Consumers are more likely to refer daily deals to others if the deals are not yet tipped when they purchase them than if they are already tipped.*

In addition to referral behavior, researchers in the micro-lending literature have found investment behavior changes before and after a similar benchmark to a tipping point, that is, the requested amount of money from the borrower (Ceyhan, Shi, & Leskovec, 2011; Herzenstein, Dholakia, & Andrews, 2011; Zhang & Liu, 2012). According to the "rule of full funding" on micro-lending

[4] Groupon's explain was that most of the deals tip within minutes of being featured; hence, the tipping information becomes useless.
[5] http://en.wikipedia.org/wiki/Groupon.

websites, if the loan is not fully funded by a pre-determined duration of time, the posted loan is voided. Once the aggregate amount of the bid exceeds the amount requested by the borrower, the loan is successful, and new lenders can keep placing bids on it until the end of the duration time. Given the absence of competition among the lenders before the list is fully funded, the strategy that the lenders use to set the interest rate differs once the point is reached.

In daily deals, consumers can only choose whether to purchase or not on a social coupon website. In addition, Groupon always has "limited quantity available" posted on the web page. Thus, competition among potential buyers should be the same before and after the tipping point. However, similar to micro-lending, deals that fail to reach the minimum purchase quantities cannot be redeemed. Although consumers are not charged, they incur opportunity costs. Furthermore, information about whether the deal is tipped when they decide to purchase it may speed up the purchasing process and make the consideration time shorter due to the removal of the uncertainty about the purchase decision.[6]

Thus, the second hypothesis is about revealing the tipping point information on the webpage.

H2a. Compared with the deals that are not yet tipped, consumers are more likely to purchase deals when they are shown as "tipped" on the web page.

H2b. Consumers' purchase decision time is faster for deals with the "tipped" sign on the web page than for those that are not yet tipped.

The last investigation is on the different effects of prior purchase information before and after the tipping point. In addition to the information about the tipping point, Groupon makes the number of coupons for each deal that have been sold very salient by using a larger font and placing it at the center. Literature in fields such as sociology, economics, and medicine has indicated that the behavior of others influences the decision of an individual on the same behavior (e.g., Christakis & Fowler, 2007; Dasgupta et al., 2008). In marketing, literature on new product/technology adoption (Van den Bulte & Lilien, 2001a, 2001b; Van den Bulte & Stremersch, 2004; Iyengar, Van den Bulte, & Valente, 2011; Aral, Muchnik, & Sundararajan, 2009) has tended to confirm the hypothesis of contagious behavior. In the context of social coupons, Hu, Shi, and Jiahua (2013) posited that the deal sales information coordinates consumer actions and increases the probability that the minimum threshold is reached. Li and Wu (2013) and Luo, Andrews, Song, and Aspara (2014) noted that more coupons purchased by others resulted in a higher the purchase likelihood for the focal customer. However, the mechanism behind it remains unclear.

In the present study, given the tipping point information, we examine the different effects of prior purchase information and differentiate the two mechanisms that explain the contagious purchase phenomenon; namely, conformity and social learning (Young, 2009). Conformity is defined as the motive that drives people to behave like their peers if enough peers are acting the same. In social learning, consumers use information from their peers to update their own expectations of product quality where quality is uncertain ex ante and individuals hold a prior notion of it (Moretti, 2011). In conformity, the purchase depends solely on the popularity of a deal, whereas social learning relies on how good or desirable the deal proves to be. Different marketing strategies are recommended based on the different mechanisms.

Thus, we formulate the third hypothesis regarding the prior purchase information.

H3. The higher the number of people who purchased the deal, the more likely it is that others encountering the deal will purchase it. The effect is more pronounced when the deals are not yet tipped.

We provide three pieces of evidence to separate the mechanisms. First, we use the deal tipping status to delineate two phases, time before tipping point and time after it. We then use the effects of prior purchase in the two phases to examine the mechanisms. Second, we confirm these findings by using the identification strategy in Zhang and Liu (2012) and by utilizing public information about the quality of the deal. Third, following Young (2009), we use graphs demonstrating purchase speed and acceleration rate to distinguish between the two explanations. Unlike the aforementioned two approaches, this approach is not an identification strategy. Instead, it provides us with a visual tool to conveniently rule out alternative explanations. Moreover, we look at temporal purchase data and the distribution of elapsed time between purchase and first viewing as they provide further evidence for our findings.

2. The data and the variables constructed

The ability of websites to track the behavior of their visitors has resulted in a large amount of available clickstream data. However, they have usually been only considered as a rich source of user behavior information (Moe & Fader, 2004). In the present study, we augment the raw data with three datasets by using web analytic tools, which contain detailed information regarding online behavior as well as deal characteristics and individual demographics (see Fig. 2).

The raw data in this study come from a third-party online marketing research firm in the U.S. This company randomly recruits a representative sample of two million people and tracks their online behavior every day. The data used in the study comprise the complete clicking paths of individuals who logged onto the Groupon website between January and March 2011. Thus, we not only have the Groupon browsing behavior, but also information about the activities of consumers on other websites. We use that information to fill in missing values and to validate the information for the variables we use in the analysis.

[6] Although most of the deals on Groupon tip at the end, when people purchase the deal, they do not know if it will tip in the end.

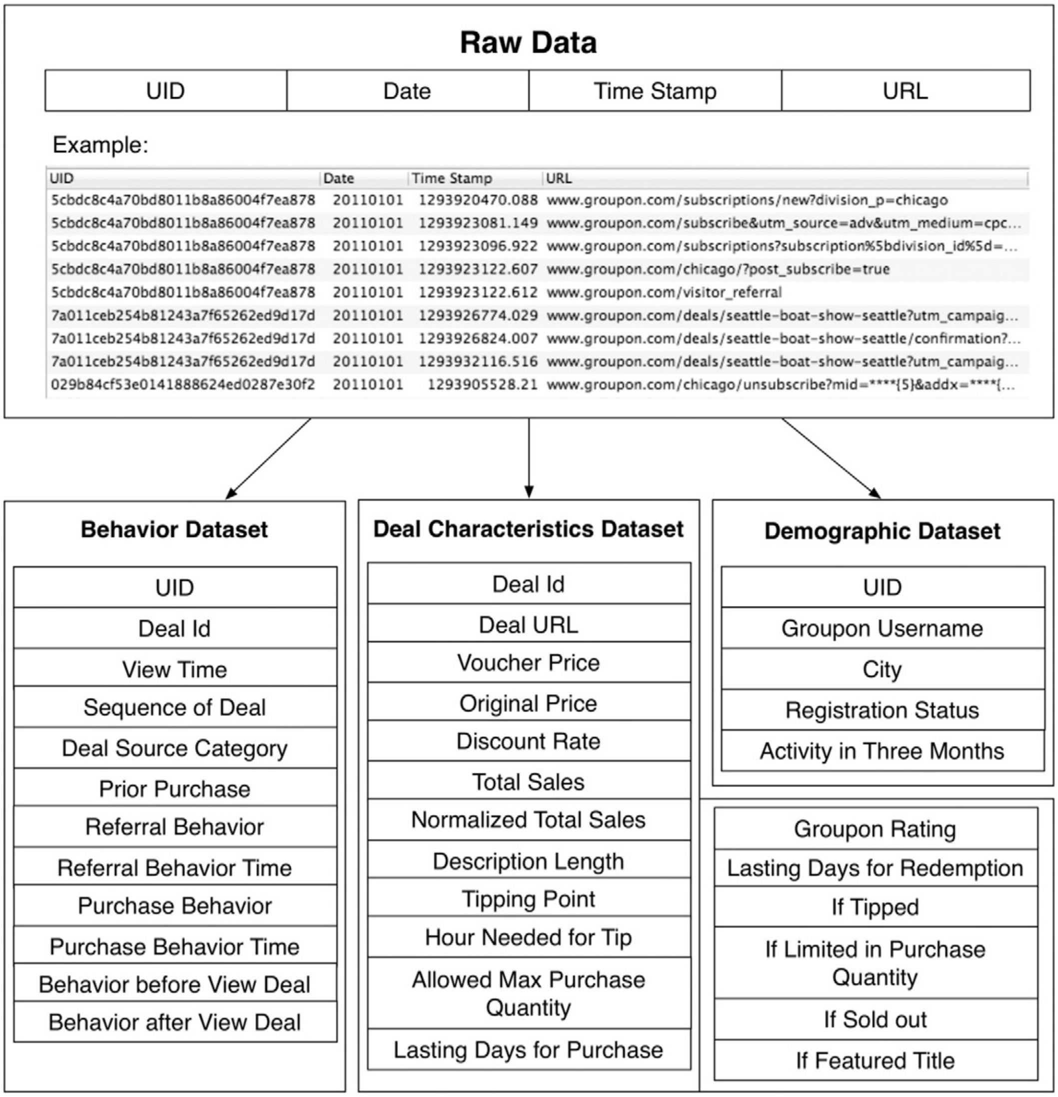


Fig. 2. Data augmentation.

There are four columns in the data: the unique individual identifier (UID), date, time stamp, and the specific URL. The date and time reveal the temporal information of the individual behavior and deal status. The URL retains the main source of the information regarding the deals. Overall, the data set is 28.2 GB in size, and it contains 156,425,702 records. A total of 186,756 unique individuals have visited Groupon at least once during the sample period.

We construct the first dataset, which is a behavior dataset, based on the URL syntax and the query strings embedded in the URL. The second dataset contains deal specific variables. By augmenting through the use of the API information provided by Groupon,[7] we extract the back-end deal characteristics. The variables and their summary statistics are shown in Table 1. We create several variables related to the tipping point. "*If tipped*," "*tipping point*," and "*hours needed to tip*" indicate the information we retrieved from the deal webpage (see Fig. 1a). Given that we know the exact time at which people viewed and purchased the deals, we can compare this information with the tipping point information to determine whether the deal had already been tipped when it was viewed or purchased. Thus, we have created two variables, namely, "*tipped status view*" and "*tipped status purchase*." The third dataset contains demographic information for each individual. We identify the location and registration status of each individual by the URLs of the deals they receive. The technique details are included in Appendix 1.

[7] https://www.groupon.com/pages/api.

Table 1
Summary statistics.

Variables	Description	Mean	Std. dev
Prior purchase	The number of deal coupons that have already been purchased by other people	1.05	4.88
Coupon price	Price after discount	37.64	117.54
Original price	Price before discount	141.67	6225.78
Discount rate	Discount	56.14	9.73
Total sales	Total number of coupons sold for the deals	472.96	1368.35
Popularity	Total sales divided by the population of the city	0.1	2
Description length	The number of words contained in the description of the deal	3132.04	801.51
Is tipped (0 = not tipped, 1 = has tipped)	Whether the deal reaches the tipping point	0.99	0.10
Tipping point	The minimum number of coupons needing to be sold	44.14	885.65
Hours needed to tip	Hours it takes to reach the tipping point	9.7	9.41
Tipped status view (0 = deal not yet tipped, 1 = has tipped)	Whether the deal is tipped on view	0.87	0.34
Tipped status purchase (0 = deal not yet tipped, 1 = has tipped)	Whether the deal is tipped on purchase	0.94	0.55
Allowed max purchase quantity	The maximum number of coupons each individual can purchase	10.15	11.78
Day type	Whether it is a 1-day deal, 2-day deal, etc	2.06	1.18
Lasting days for redemption	The days allowed for redemption	211.76	132.74
If featured (0 = not featured, 1 = featured)	If the deal is a featured deal in the newsletter	0.44	0.50
Groupon rating[a]	Ratings about the deals which are provided by Groupon	3.94	0.66
If_limited_quantity	If the deal has limited quantity for purchasing (in description)	0.37	0.48
Max_purchase_quantity	The maximum purchase quantity when users purchase the deal (in description)	8.51	11
Deal_view_sequence	The sequence of deals that have ever been viewed by the consumer	1.34	1.75
Minutes_deadline_to_purchase	The minutes between the deadline and the purchase time	1736.20	1288.38
Tenure	The difference between the date viewing the deal and the subscription date	31.75	24.27
Subscription_status	Whether is Groupon subscriber on that day	0.88	0.33
Time to the tipping point	The time difference between the first view and the time the deal tips (first_view_hour–hours needed to tip)	3.65	9.26
Deadline_first_view_min	The minutes between the deadline and the first view	1848.59	1322.18

[a] Its statistic is based on deals that have rating data.

In summary, the total number of deal views was 114,459, which included 25,834 unique deals. The customers who viewed deals on Groupon looked at an average of 2.67 unique deals in three months. About half of the viewers (57.1%) only viewed one deal (see Fig. 3). Conditional on deal viewing, 10,989 purchases were made, including 6600 deals and 7600 customers. On average, each individual purchased 0.26 unique deals in three months. The majority of the people (82.3%) did not purchase any deal on Groupon during the period (see Fig. 4), 13.2% people purchased one deal, and 4.52% purchased more than two deals. The deals covered 46 states and 171 cities in the U.S., and they were concentrated in the east- and west-coast cities. Among all of the deals, 6988 deals (27.0%) were limited in purchase quantity, 443 deals (1.7%) were sold out, and 6218 deals had ratings of the product or service purchased.

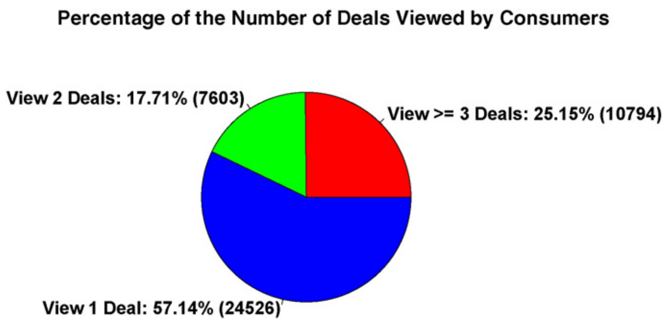


Fig. 3. Pie chart of the number of deals viewed by consumers.

Fig. 4. Pie chart of the number of deals purchased by consumers.

3. Analysis and findings

3.1. Referral behavior with a tipping point

As noted, an assurance contract makes people act as sales agents because they want the deal they are interested in to reach the tipping point so that their purchase will be valid. Thus, under certain circumstances, they should voluntarily refer deals to others thus acting as sales agents (Jing & Xie, 2011). Here, "refer" means to share the deal with other people through email, Facebook, or Twitter.[8] Surprisingly, the number of referrals for Groupon deals was not high, with only 872 referrals out of 114,459 deal view records (0.76%). Among the 10,989 purchase incidents, there were 207 referrals (1.88%) and only 92 (0.84%) of those occurred after purchases. On the other hand, among the 114,459 deals viewed by the customers, almost half of the deals (49.7%) came from a newsletter which was sent to Groupon subscribers every day by email. Only about 2% of the deals were received by individuals from the recommendations of personal email, Facebook or Twitter. This echoed the low referral behavior observed in the data.

To test H1, we run a logistic regression using individual referral behavior as a dependent variable, y^{ref}. We denote individual i referring the deal j as $y^{ref} = 1$ and 0 otherwise. The independent variables include two groups: 1) the deal characteristics X_{1j}, which include the information about the deal such as price, discount rate and category, and the measures related to the indications of its quality, such as "is tipped," "hours needed for tip," "Groupon rating," and "popularity" (i.e., total sales divided by the population of the city) and 2) the online behavior status X_{2ij}, such as the number of days since registration (i.e., *tenure*), the number of unique deals one has ever viewed before (i.e., *deal view sequence*), the number of deal coupons that have already been purchased by other people (i.e., *prior purchase*), whether the deal has tipped when it is purchased (i.e., *tipped status purchase*), the source medium of the deal, and so on. (Please refer to Table 1 for a detailed explanation and summary statistics.)

In particular, we look at the *tipped status purchase.* Consumers may worry about the tipping point not being reached, especially if they have already purchased the deal. As a result, the coefficient on *tipped status purchase* should be significant and negative as consumers want to help the deal to be active; if the deal has tipped, the consumer is less likely to refer it to someone else. In addition, this effect should be even stronger if *prior purchase* is small. So the signs of *prior purchase* and the interaction term between the two should also be negative. The error term ε_{ij} is assumed to have an extreme value distribution

$$\Pr\left(y_{ij}^{ref} = 1\right) = \frac{\exp\left(X_{1j}\beta_1 + X_{2ij}\beta_2\right)}{1 + \exp\left(X_{1j}\beta_1 + X_{2ij}\beta_2\right)}. \tag{1}$$

The estimation results are indicated in Table 2. The first column contains the results of a simple logit model on the pooled data and the second column reports the results of a logit model with fixed effects to control for individual heterogeneity as a robustness check. In both cases, *tipped status purchase* is not significant and neither of the signs are negative, indicating that in general, the deal's tipping status does not affect the individual's referral behavior. The estimate for *prior purchase* is moderately significant but the sign is positive. Along with the insignificant interaction term and the fact that the majority of deals came from newsletter, we conclude that H1 is not supported. Surprisingly, consumers are not motivated to refer deals to their friends to reach the tipping point.

There are two tentative explanations for why people do not make many referrals on Groupon. First, given the customers' knowledge that most Groupon deals do tip, they do not worry about the tipping point. Second, a referral suggests that the consumer is vouching for the deal's quality, and thus consumers may worry about referring a bad deal to their friends. Thus, we assume that the more experienced the Groupon user is and the existence of objective evidence of the quality of the deal will relieve this concern and make people more likely to refer.

8 Due to the limitation of the data, we do not observe direct communication among individuals. So our referral is restricted to use the social media icons, such as Email, Like and Twitter to recommend deals. This should be considered as the lower bound of WOM.

Table 2
Logistic regressions with referral behavior as dependent variable.

Variables	Pooled logit	Logit with fixed effects
Prior_purchase	0.011*	0.012*
	(0.006)	(0.007)
Tipped_status_purchase	0.161	0.231
	(0.283)	(0.342)
PRIOR purchase × tip status purchase	−0.001	−0.001
	(0.005)	(0.007)
Tenure	0.001***	0.002***
	(0.000)	(0.000)
Deal_view_sequence	0.002	0.005
	(0.003)	(0.005)
Minutes_deadline_to_purchase	−0.000	−0.000
	(0.000)	(0.000)
Description_length	0.000	0.000
	(0.000)	(0.000)
Discount	0.003	0.002
	(0.005)	(0.005)
Origin_price	−0.000	−0.000
	(0.000)	(0.000)
Popularity (normalized total sales)	−0.003*	−0.003
	(0.002)	(0.002)
Is_tipped	−0.185	−0.159
	(0.367)	(0.409)
Is_limited_quantity	0.144*	0.171**
	(0.077)	(0.087)
Hours needed for tip	−0.011	−0.012
	(0.007)	(0.008)
Lasting days for redemption	−0.000	−0.000
	(0.000)	(0.000)
Groupon_rating	−0.213**	−0.247**
	(0.0933)	(0.107)
If_featured	0.365**	0.291
	(0.162)	(0.183)
Source: commercial ads	−0.104	−0.139
	(0.139)	(0.157)
Source: personal email	0.721**	0.949**
	(0.364)	(0.436)
Source: Facebook	−0.355	−0.291
	(0.453)	(0.504)
Source: Twitter	2.696***	2.044***
	(0.302)	(0.481)
Source: newsletter	−0.776**	−0.693*
	(0.317)	(0.358)
Category dummies	Yes	Yes
Purchase hour dummies	Yes	Yes
Individual fixed effects	No	Yes

Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

To determine which explanation is more plausible, we look at the variable, *tenure*, which is the number of days since registration with Groupon. If the first explanation holds, we assume that the longer the tenure, the more likely that he knows that most of the deals will tip and the less likely that he would refer deals to others. In contrast, if the second explanation holds, the more experience the consumer has with Groupon, the more confident he will be about his judgment of the deals' quality making him more likely to refer the deal to others. As Table 2 shows, the coefficient of *tenure* is significantly positive, which means the longer the individual stays with Groupon, the more likely he is to refer deals. This finding supports the second explanation.[9] The longer the individual is with Groupon, the more confident he is about his judgment of the quality of the deal and the more likely it is that he would want to refer it to others. The positive coefficient of prior purchases also supports the explanation that an individual only refers if he is confident in his judgment about the deal, and that he bases his judgment on different indicators such as his own experience and other people's purchases.

[9] We are not arguing that the existence of the overall certainty-in-tipping in the population is not a factor. With the data we have, we just want to show that the second explanation of the "judgment exposure to peers" also plays a significant role.

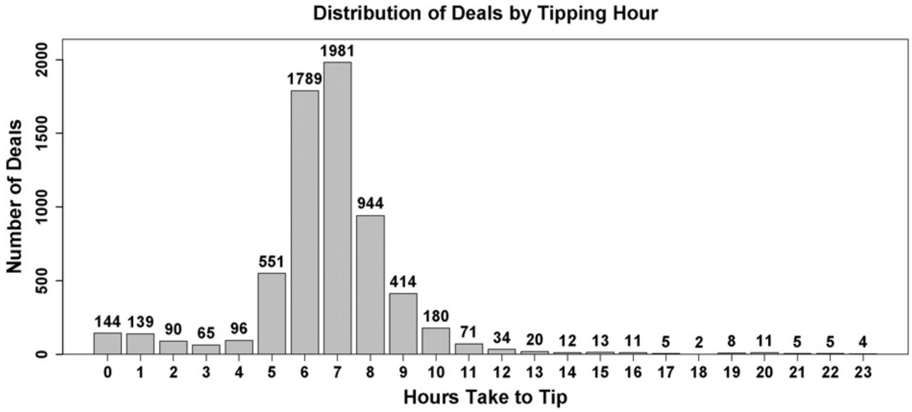


Fig. 5. Distribution of deals by tipping hour.

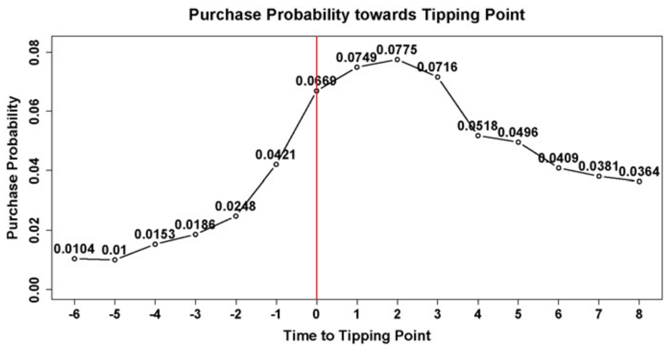


Fig. 6. Distribution of purchase probabilities by time to tipping point.

From the analysis, we also learn what deals are more likely to be referred. The answer is featured deals with limited quantity. That also explains why the variable *popularity* is negative. *Popularity* is calculated as the total sales/local population. Thus, if the quantity is limited, this number should be small, with the negative sign indicating that higher scarcity results in more referrals. In terms of the source, the deals that come from personal recommendations and Twitter are more likely to be referred, and those from the newsletter are less so. This is probably because a personal recommendation is more trustworthy, leaving the individual more confident in referring it. This is also consistent with our explanation of consumers' confidence in judgment.[10]

3.2. Purchase behavior with a tipping point

In the early days of Groupon, people could easily monitor the status of deals' tipping point through the real-time updated window (see Fig. 1a). But Groupon later removed this information, identifying it as redundant due to most deals' tendency to tip anyway. H2a and H2b examine the effectiveness of such information on people's purchase behavior to determine whether Groupon should have kept the tipping information available or not. Previous literature on peer-to-peer lending (Ceyhan et al., 2011; Herzenstein et al., 2011; Zhang & Liu, 2012) revealed dramatic behavior changes among lenders around the tipping point, indicating that it may be a reference point around which there could be substantial changes in behavior. But in that context, the interest rate awarded by the project changes before and after the tipping point, providing enough incentive for consumers to alter their behavior. However, in the context of Groupon, nothing about the deal attributes changes. Furthermore, Subramanian (2012) predicted theoretically that having or not having a tipping point may both be profitable for the company in different situations. Thus, the answer to whether Groupon should keep the information about the tipping status or not on the webpage is uncertain. To examine H2a and H2b, we study two important possible changes in behavior–the purchase probability and purchase speed before and after the tipping point.

Fig. 5 presents the distribution of hours that elapse before a deal tips (all of the deals start at midnight). Among the 6594 tipped deals, 144 (2%) tipped in the first hour after the deal starts. About 86% of the deals reached the tipping point within five to 9 h (i.e., 5 am to 9 am). Only 2% of the deals tipped after noon.

[10] A caveat here is that this finding is correlational, so it can also be explained by individual heterogeneity. That is, certain people refer more and they also receive more deals from email or Twitter.

To first provide some empirical evidence, we study the purchase probabilities during each hour before and after the tipping point (see Fig. 6). Following Ceyhan et al. (2011), we normalize the time so that 0 indicates the tipping point and the positive and negative numbers are the hours after and before the tipping point, respectively. We calculate the purchase probability by the number of people who have purchased the deal divided by the number of people who have viewed it and then averaged across all of the deals for that particular period. For example, the deal "Blockbuster-Express" was tipped at 7:30 am, which we normalize to 0. In the hour directly following the tipping point, from 7:31 to 8:31, 7 customers viewed the deal and 2 purchased it. Thus, the purchase likelihood of that deal in that hour is 2/7. We then take an average of all of the deals as the average purchase probability for that hour (.0749). Based on the figure, the average purchase probability steadily increases until it reaches the peak at about two hours after the tipping point; it then decreases, but it is maintained at a higher level than before the tipping point.

To test H2a and H2b, we run a logistic regression with fixed effects[11] using *if purchased* as the dependent variable. We denote $y_{pur} = 1$ if individual i purchased deal j and 0 otherwise. The independent variables are similar to Eq. (1). The panel structure of the data allows us to capture unobserved individual heterogeneity by decomposing its error term to $\alpha_i + \varepsilon_{ij}$, where ε_{ij} is assumed to have an extreme value distribution.[12]

$$\Pr\left(y_{ij}^{pur} = 1\right) = \frac{\exp\left(X_{1j}\beta_1 + X_{2ij}\beta_2 + \alpha_i\right)}{1 + \exp\left(X_{1j}\beta_1 + X_{2ij}\beta_2 + \alpha_i\right)}. \tag{2}$$

Column (1) of Table 3 reports the estimation results of Eq. (2). *Tipped_status_view* has a significant and positive main effect supporting H2a and confirming that consumers are more likely to purchase the deal if it is already tipped when they view it. *Prior_purchase* also has a significant and positive main effect. Thus, more previous coupon purchases attract a higher purchase probability later. In addition, the interaction term *prior_purchase* × *tipped_status_view* is negative. This term was called payoff externalities in Zhang and Liu (2012). When viewing the deal before it has tipped (i.e., *tipped_status_view* = 0), the consumer may assess the chances that the deal will tip. The greater the number of prior purchases, the less the risk that the deal may fail. Thus, the negative interaction term confirms that access to the tipping status information removes the risk component in the consideration process, which increases purchase probability.[13] This term, together with the variable *prior_purchase*, also provides a clean way to identify the mechanisms of the prior purchase information on an individual's purchase likelihood. We discuss this more in the next section.

The results indicate that deals that are cheaper and featured in newsletters with fewer restrictions in terms of purchase quantities and redemption days attract more consumers. The effect of *deal_view_sequence* is negative indicating that the more unique deals a consumer has viewed, the less likely he would purchase the current one.

Second, we study the purchase speed, which is defined as the time difference between the first view and the purchase. We note that among all of the 10,989 purchases, consumers take an average of approximately 109 min to purchase the deal after the first view, and in 90% of the purchases, the elapsed time is shorter than 123 min. Fig. 7 illustrates the average purchase speed against the normalized time to the tipping point. Before the tipping point, the average number of view-purchase minutes is 11.4, which drops to 9.1 after the tipping point. To test the purchase speed statistically, we use a linear regression model with fixed effects. The dependent variable is the purchase speed, y^{speed}. The independent variables are similar to those in Eq. (1), with the exception of three terms. *Time to the tipping point* is the time difference between the first view and the time the deal tips. The interaction between the *tipped status view* and the *time to the tipping point*. To control for the deadline effect, we also include the time difference between people who viewed the deal and the deadline of the deal, *deadline_first_view_min*:

$$y_{ij}^{speed} = X_{1j}\beta_1 + X_{2ij}\beta_2 + \mu_i + v_{ij}. \tag{3}$$

Based on the regression results in Table 4, the difference in purchase speed for tipped and untipped deals is significant ($\beta = -62.264$, s.e. = 29.695, p-value < 0.05)and the interaction term significantly negative ($\beta = -7.319$, s.e. = 3.713, p-value < 0.05). Thus, after the tipping point, people generally spend less time from the first view until they purchase the deal. Hence, tipping point information speeds up the purchase process, which supports H2b. We also note that the more deals people have previously viewed, the less time they spend purchasing. People also tend to spend more time on deals with higher prices, and less on deals with limited quantities.

Summarizing, although the tipping point does not change consumers' referral behavior, access to information about it encourages purchasing and decreases consumers' consideration time. Thus, H2a and H2b are supported.

[11] We also ran a random effects model as a robustness check. The key findings remained, although the estimates were different in magnitude. The results are available from the authors upon request.

[12] As a robustness check, the results of a simple logit model are available upon request. One thing worth noting is that unlike grocery shopping data, in our data, we know exactly what deals people viewed and what they purchased, so the deal view is informative in addition to the purchase information. Each individual has multiple records that include viewed and purchased deals, so the identification is clear even when the purchase number is low.

[13] The results were robust even when we included the quadratic term of *prior_purchase* to control for the nonlinearity between *prior_purchase* and purchase likelihood.

Table 3
Regression of contagious purchase with purchase as DV.

Variables	(1) Tipping point	(2) First 3 h	(3) Learning
Prior_purchase	0.309*		0.45***
	(0.162)		(0.1311)
Tipped_status_view	0.115**		0.025
	(0.0493)		(0.0331)
Tip hours from start	−0.0561***	−0.1334***	−0.067***
	(0.00503)	(0.0205)	0.0036
Subscription_status	2.782***		5.629***
	(0.629)		(0.410)
Deal_view_sequence	−0.00339*	−0.0154***	−0.020**
	(0.00197)	(0.00525)	(0.00127)
Groupon_rating	−0.0761**	−0.234	
	(0.0377)	(0.240)	
Discount	0.00578***	−0.0019	
	(0.00180)	(0.0073)	
Current_price	−0.0109***	−0.0092***	
	(0.000756)	(0.0028)	
If_limited_quantity	−0.238***	−0.2265*	
	(0.0334)	(0.1275)	
Max_purchase_quantity	−0.00344**	−0.0042	
	(0.00166)	(0.0067)	
Day_type	−0.0707***	0.1224***	
	(0.0151)	(0.0514)	
Lasting_days_for_redemption	0.000943***	0.0015***	
	(0.000115)	(0.000372)	
If_featured	1.043***	1.431***	
	(0.0695)	(0.2930)	
Prior_purchase × tipped_status_view	−0.294*		−0.3842***
	(0.162)		(0.111)
Prior purchase × Groupon rating			0.0394***
			(0.0157)
Prior purchase × discount			−0.0038***
			(0.00073)
Prior purchase × current price			0.0000325
			(0,004,618)
Prior purchase × limited quantity			−0.0379***
			(0.0117)
Prior purchase × max purchase quantity			0.0022***
			(0.00064)
Prior purchase × day type			0.005
			(0.0041)
Prior purchase × if_featured			0.0011
			(0.0041)
Prior purchase × expire_day			−0.000024
			(0.0000252)
Pop (normalized total sales)		−0.00614	−8.163***
		(0.00476)	(0.412)
Constant		0.3745	
		(0.904)	
Source medium dummies	Yes	Yes	Yes
Category dummies	Yes	Yes	Yes
Time of day dummies	Yes	Yes	Yes
Individual fixed effects	Yes	No	No
Observations	114,432	4.979	114,432
Log likelihood	−11,528.067	−1319.4887	−11,999.381

Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

3.3. Contagious purchase mechanisms

We examine how the real-time progress bar with prior purchase information facilitates contagious purchase behavior. In particular, we study the effects of prior purchases before and after the tipping point. There is a large body of literature on how the behavior of others influences individual decision making and a variety of mechanisms have been proposed; two of the most popular are conformity and social learning. In this section, we provide three pieces of evidence to separate them. First, we use the deal

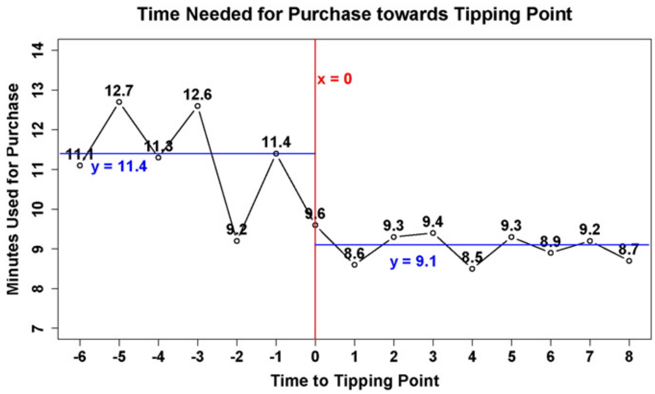


Fig. 7. Distribution of time needed for purchase toward tipping point.

tipping status to separate two phases; namely, the time before and after the tipping point. We then use the effects of prior purchases in the two phases to examine the mechanisms. Second, we confirm the finding using the identification strategy proposed in Zhang and Liu (2012) in the case of peer-to-peer lending. Third, we follow Young (2009) and use the "footprints" of different mechanisms on purchase rates. As the author states, this approach is not a true identification strategy, but it provides a quick diagnosis and a visual tool to conveniently rule out alternative explanations. Then, we provide a general picture of the customer temporal purchase pattern on Groupon as further evidence.

Conformity here is defined as a type of social influence, such that people behave similarly to their peers if enough of the peers are acting the same. It has also been called irrational herding or the bandwagon effect. Why do people conform? One of the five main motivational reasons for conforming is the desire to be correct (Nail, MacDonald, & Levy, 2000). People strive to be accurate and correct in their judgments and observations and they often rely on the social cues around them to help them make decisions. Thus, in the Groupon context, when they are uncertain about how good the deal is, they may take comfort in agreeing with a large number of other people. As for social learning, a consumer may decide to purchase if he has reason to believe that doing so will improve his current situation compared with not purchasing, with the evidence coming from directly observing the outcomes among prior adopters. In conformity, the purchase depends solely on the popularity of the deal, whereas learning relies on how good or desirable the deal proves to be.

First, we separate the two mechanisms using the effects of prior_purchases on purchase likelihood before and after the tipping point. According to the regression results from H2a on purchase likelihood, the main effect of prior purchases is significantly positive ($\beta = 0.309$, s.e. $= 0.162$, p-value $= 0.056$) and the interaction term of prior purchase and the tipping status when a person

Table 4
Fixed effect logistic regression with purchase speed as dependent variable.

Variables	(1) Coef	(2) Se
Tipped_status_view	−62.264**,*	29.695
Time to the tipping point	−2.450	3.193
Time to the tipping point × Tip_status_view	−7.319**	3.713
Deadline_first_view_min	−0.0623***	0.0074
Deal_view_sequence	−1.257	0.854
Prior_purchase	1.407	2.437
Description_length	0.016	0.010
Discount	0.254	1.309
Origin_price	0.472***	0.121
Pop	−0.524	1.171
Is_limited_quantity	−13.598	19.061
Expire_day_after_end	0.104	0.070
Groupon_rating	−34.963	20.707
If_featured	−4.604	41.519
Constant	321.235**	128.260
Time of day dummies	Yes	
Category dummies	Yes	
Source medium dummies	Yes	
Individual fixed effects	Yes	

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

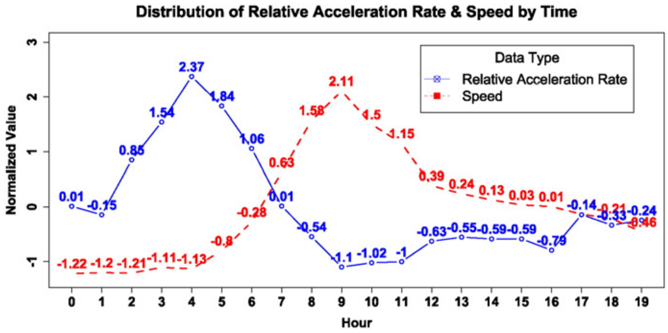


Fig. 8. Distribution of relative acceleration rate and speed by time.

views the deal is significantly negative ($\beta = -0.294$, s.e. $= 0.162$, p-value $= 0.069$). These results indicate that once the deal tips, the effect of prior purchases on purchase likelihood is significantly dampened. Thus, H3 is supported.

The only thing that changes before and after the tipping point is the uncertainty about whether enough people will purchase it. The deal attributes remain the same. As stated, in social learning, consumers use information from their peers to update their own expectations of product quality where quality is uncertain ex ante and individuals hold a prior notion of it (Moretti, 2011). So if it is the social learning mechanism at work, what they infer from the prior purchase decision before and after tipping point should remain the same given that the deal attributes do not change. That is, the way consumers update their own expectations of product quality based on prior purchases of others should not differ depending on tipping status. Observing the same amount of prior purchasing should have the same effect on the purchase decision. Conformity, on the other hand, expresses the motive of people behaving similarly to peers if enough peers are acting the same. It indicates that the purchase decision relies on the popularity of the deal. A tipping point indicates the threshold of popularity (i.e. enough people). Once the threshold is reached, the effect of more purchases is dampened. Therefore, consistent with our empirical evidence, we find that conformity behavior plays a more dominant role rather than social learning in the contagious purchase behavior.

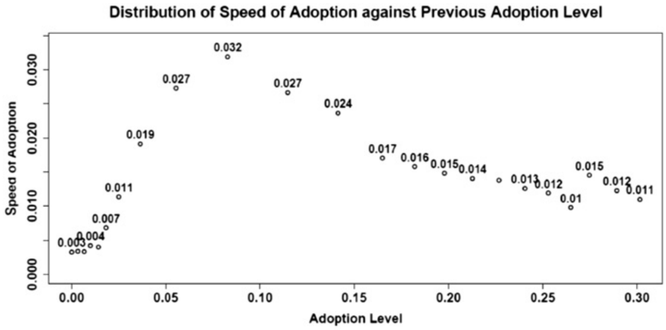
To validate these findings further, we follow the identification strategy developed by Zhang and Liu (2012) to separate conformity effects from social learning and to understand the factors that affect consumers' purchase likelihood on social coupon websites. The identification rationale is as follows. If the consumer is mimicking other purchase decisions (i.e., conformity), he ignores the observable attributes of the deal. However, if he is a rational learner, his inference from the purchase decisions of others can be affected by those attributes. For example, suppose that two similar deals from the same category receive an equivalent number of purchases in the first hour. The only difference between the two is that one deal has a longer redemption period (which is considered a favorable attribute) than the other. If a subsequent viewer is learning rather than mimicking, he can infer that people who purchase the one with a shorter redemption period in the first hour must have sufficiently positive private information to make the decision. In contrast, the decision to purchase the one with a longer redemption period does not require extra positive information. Thus, a subsequent viewer can make a positive *incremental* quality inference about the deal with a shorter redemption period. The opposite results would be expected for unfavorable attributes. Thus, we expect the effect of favorable attributes (e.g., a longer redemption period) on purchase probability to be *dampened* and *accentuated* for unfavorable ones (the less the better; e.g., price).

We implement the analysis in two steps. We first uncover the main effects by regressing the purchases in the first 3 h[14] on public deal attributes that are observable to all so we can determine which attributes are favorable or unfavorable. To address the omitted variable problem in the regression, that is, the consumer may have prior knowledge about the goods or services that are unobservable to the researchers (Zhang & Liu, 2012), we use "popularity" (i.e., normalized total sales) as a proxy for the private information that the consumers have about the deal. Popularity is defined as the number of deals sold divided by the city population. Column (2) in Table 3 presents the estimated main effects of deal attributes. Intuitively, the deals with lower prices (i.e., price is an unfavorable attribute), featured (i.e., favorable attribute) in newsletters, long expiration date (i.e., favorable attribute), and redemption period (i.e., favorable attribute) and without limited quantity (i.e., unfavorable attribute) attract more sales.

We then augment Eq. (2) with the interaction terms of the number of prior purchases and the public attributes of the deals.[15] Following the aforementioned arguments, if the main effect of the attribute is negative, in the case of social learning, the subsequent viewer extracts more favorable information from prior purchasers for that attribute and vice versa. Thus, β_3 should take

[14] As a robustness check, the results from the first hour's data are available upon request.

[15] As a robustness check, the results for the model with individual-level fixed effects are available upon request.



$$y = a + b_1 x$$

Coefficient	t-statistic
a = 0.025	1.147
b_1 = -0.184	-1.46

Fig. 9. Distribution of speed of adoption against previous adoption level.

the *opposite* sign of the main effects of the attributes of deals.

$$\Pr\left(y_{ij}^{pur}=1\right)=\frac{\exp\left(X_{1j}\beta_1+X_{2ij}\beta_2+PriorPurchase\times X_{1j}\times\beta_3+\alpha_i\right)}{1+\exp\left(X_{1j}\beta_1+X_{2ij}\beta_2+PriorPurchase\times X_{1j}\times\beta_3+\alpha_i\right)}. \tag{4}$$

Column (3) presents the results of Eq. (4). Four of the eight interaction terms between time-invariant deal attributes and prior_purchase are significant, namely, Groupon rating, discount, if limited quantity, and maximum purchase quantity. Comparing Columns (4) and (3), we do not find opposite signs between the main effects and interaction terms as predicted by social learning. The signs for limited quantity are the same. Thus, we do not have support demonstrating social learning. Subsequent deal viewers do not infer a significant amount of information regarding the attributes of deals from prior purchases. These results provide further support for the conformity mechanism. Admittedly, we cannot rule out the existence of social learning using the current analysis. We are simply arguing that in the contagious purchase situation of Groupon, conformity plays a more significant role than social learning.

We provide some further empirical evidence to illustrate the point. Young (2009) proposed that a process is characterized by conformity "if the adoption process accelerates initially, then it accelerates initially at a super-exponential rate for some period of time." Following this argument, we define the rate of change (i.e., speed of adoption) as $\Delta_{t+1} - \Delta_t$ and the relative acceleration rate as $(\Delta_{t+1} - \Delta_t) / \Delta_t$. In Fig. 8, the dotted line indicates changes in the adoption rate, whereas the solid line is the relative acceleration rate. Both numbers are standardized to fit in the figure. The change in adoption initially has a mild acceleration followed by a sharp change starting from 5 am. The relative acceleration rate rises sharply from the 1 am to 4 am, which indicates a super-exponential acceleration. The two findings combined provide strong evidence for conformity.

Young (2009) proposed that in social learning, "initially the adoption process decelerates whereas the relative acceleration rate strictly increases. If the process begins to accelerate, and if the density is increasing at that point, then the process undergoes a period of super-exponential growth." This proposal is intuitive because to make learning happen, there should be a period for

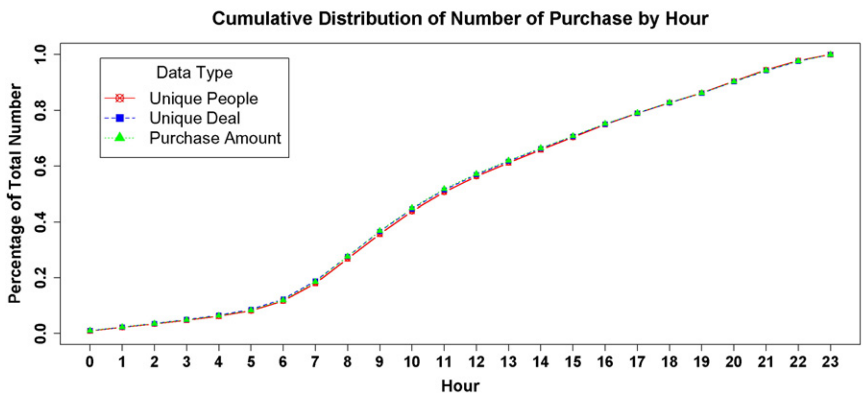


Fig. 10. Cumulative distribution of number of purchase by hour.

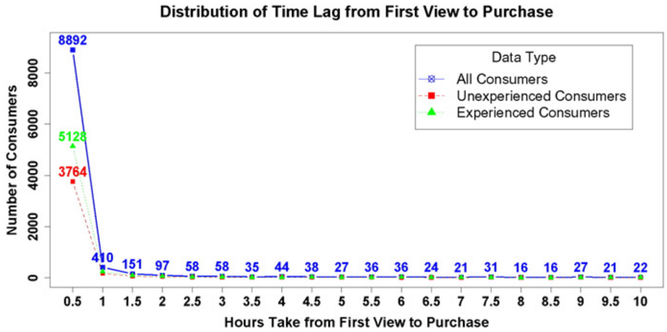


Fig. 11. Distribution of time lag from purchase to first view by hour.

accumulating information provided by prior purchasers. Thus, we observe a slow start-up. Moreover, “in a social learning model, the speed of adoption at a given point in time depends on adoption levels at earlier points in time,” which is not the case with conformity.

As presented in Fig. 8, we do not observe an initial deceleration in our data. Then, using the data from Fig. 9, we investigate whether the adoption speed depends on the adoption level. The OLS regression results indicate no significant relationship between the speed and the previous purchase proportion.

Thus, using the graphs of Figs. 8 and 9, we find evidence that also supports conformity behavior rather than social learning. This analysis is not a rigorous identification strategy, but rather empirical evidence, using the data we have to give a relatively quick assessment of the purchasing behavior.

Finally, to provide further support for the conformity mechanism, we explored the temporal purchase behavior of people on social coupon websites. Fig. 10 illustrates the cumulative distribution of purchases in terms of unique deals, individuals, and purchase occasions. The three lines are almost identical. We observe a turning point at between 5 am and 9 am, and an almost linear increase after that; 5 am to 9 am corresponds with the time people start working and checking their emails every day.

In addition, people make quick purchase decisions on social coupon websites. We illustrate the point using Fig. 11, which presents the distribution of the elapsed time between the purchase and first view. The line with squares is for all of the individuals in the sample, the line with circles is for inexperienced customers who are newly register to Groupon while purchasing, and the line with triangles is for experienced customers who register before the sample period. Using Korean data, Song, Park, Yoo, and Jeon (2012) noted that inexperienced customers tend to delay their purchase decisions, whereas experienced customers do not. However, the majority of U.S. consumers, no matter how long they have used Groupon, make their purchase decisions within 30 min of the first view.

These two graphs indicate that when people start their work day, they check the social coupon websites immediately and make quick purchase decisions. Thus, the majority of sales occur on the first half of the day when the deals are shown. If social learning played an important role, the sales should occur later on to allow the information to accumulate. This additional evidence supports rejecting the social learning mechanism as an explanation for contagious behavior.

4. Conclusion

Utilizing a large proprietary dataset of clickstream data from Groupon and augmenting it with information crawled by APIs, we investigate three hypotheses regarding the group-buying feature of social coupons. In particular, we focus on the effect of a tipping point on deal referral and purchase behavior. Previous literature has made several theoretical predictions, and our paper is the first empirical study to investigate these predictions using actual individual level online browsing data. Importantly, we found a few discrepancies between the theoretical predictions and our empirical results based on actual behavior. Understanding these differences advances our knowledge about consumer behavior in the context of collective buying environments.

Specifically, contrary to the theoretical prediction, access to information on tipping points does not affect deal referral behavior. We found evidence to show that people are more likely to refer deals if they feel confident about their judgments of their quality. As a result, Groupon should consider incentives for referring deals. In contrast, the tipping point positively affects purchase probabilities and decreases the consideration time people spend on making purchase decisions. The information removes consumers' uncertainty about whether the deal will tip or not. Hence, removing the information from the progress bar of the webpage is, unfortunately, not a good idea. The discrepancy between the effects of tipping status on referral versus purchase may due to the reason that knowing their peers are very likely to be subscribers themselves, Groupon's subscribers expect their peers to receive the same deals from Groupon every day. Therefore, they are not motivated to refer deals even for the ones not tipped yet. However, they draw inferences about the tipping status when they make decisions. Therefore, the tipping status affects purchases. The different effects of prior purchases before and after the tipping point also provide a way to differentiate between two mechanisms motivating contagious deal purchasing behavior, conformity and social learning. We further support this finding with another identification strategy and empirical evidence. The analysis reveals that conformity plays an important role in creating purchase momentum and driving sales. Based on knowledge of consumers' purchase patterns, we find that Groupon deals demonstrate a considerable amount of momentum early in the day. As a result, the company should think of means to reward people who purchase during the first few hours. Once the conformity behavior begins, the deal will be sold out quickly.

Since this is an empirical study, all of our findings are limited by the data that we utilized. We should be careful to generalize our findings about referral behavior to the general concept of WOM. What we observe is the lower bound. In addition, the findings were solely based on the Groupon website. Although Groupon is a good representative of the social coupon industry, we should be careful to generalize the findings to other companies. Another limitation is the data collection process. We have data about all Groupon visitors in the third party research company's tracking panel. This is different from placing a cookie on the Groupon website and collecting information about all customers of Groupon. As a result, the data may have some bias due to the selection of the panel. While each data collection approach has its pros and cons, an advantage of our approach is that we do observe people's online browsing behavior outside of Groupon. This information is helpful to fill in the missing information and validate the deal information. For example, using the URL that directly precedes the Groupon website allowed us to identify the source of the deals. Using the URL that directly followed the Groupon website helped us to validate some referral behavior.

The current paper studies how people learn from others' behavior on Groupon. Regarding future research, we would like to better flesh out the “conformity” mechanism. In addition, we noticed from the analysis that customers actually learn from their own experiences with Groupon. A possible future study is to focus on an individual's learning behavior with this daily deal website. It is possible to develop a structural model to study an individual's learning about deal distributions through multiple deal views and how this learning would affect their behavior.

Appendix 1. Datasets construction

Behavior dataset

We construct the behavior dataset based on the URL syntax and the query strings embedded in the URL. For example, the URL for succeeded coupon purchase is “www.groupon.com%/deals/%?post_purchase.” A typical query string consisted of a parameter, such as “utm_source,” “utm_campaign,” and “utm_medium,” and a value to the parameter. We use the pair to determine the additional information related to the behavior. For example, “utm_source” indicates the source that leads the consumer to Groupon. The value part has three options: commercial advertisements, newsletter, and personal referral. We include this information to the behavior dataset.

Deal characteristics dataset

The second dataset contains deal-specific variables. By augmenting through the use of API provided by Groupon, we extract back-end deal characteristics.

Demographic dataset

The third dataset contains demographic information for each individual. We identify the location and registration status of each individual by the URLs of the deals they receive. We can identify their cities from the URL. For example, the URL http://www.groupon.com/chicago/deals/takashi-restaurant indicates the city is Chicago. Moreover, if they receive newsletters, we know they are subscribers of Groupon.

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