# Is The Daily Deal Social Shopping?: An Empirical Analysis of Customer Panel Data

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**Abstract**

Shortly after Groupon started its business in 2008, selling one deal a day with substantial price discounts, daily-deal sites became new online shopping places for many people. Starting with Groupon, most daily-deal sites required that voucher sales be higher than a predetermined number before deals become active. This feature, known as the "tipping point," was a unique characteristic of the daily-deal business and is identified as one of the most prominent features of social shopping. Most daily-deal sites also required that a redemption period start after a deal was over and be fixed, usually 90 days, presumably to maximize the promotional effect of deals by encouraging rapid voucher redemption. The question remains, however, whether such features actually contributed to the success of the daily-deal industry. Using individual-level panel data from a major daily-deal site in Korea, we analyze whether consumers' purchase and redemption behaviors were affected by these features and how consumers changed their behaviors as they continued to purchase and redeem vouchers over time. We find that the presence of the tipping point did not boost voucher sales and likely deterred new customers from buying deals right away. We also find that new customers tended to redeem their vouchers quickly, and this likely caused the small businesses that offered deals to become overwhelmed. It is not surprising, given our findings, that both Groupon and the Korean daily deal site abandoned the use of the tipping point and modified redemption rules.

*Key words*: Social Shopping, Online Platform, e-Commerce

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## Introduction

In 2008 Groupon, an Internet startup company, enjoyed instant success by selling daily deals in a voucher format with heavy discounts, usually 50 percent or more. In addition to offering heavy price discounts, every Groupon deal required a predetermined minimum of sales to be active. If this minimum, which the literature calls a tipping point or threshold, was 100, for example, the deal would not be activated until at least 100 vouchers were sold. Once a deal became activated, the same discount rate applied to everyone who bought it, but if a deal failed to reach the minimum sales level by the deadline, it became void and those who had committed to buy the deal would receive their money back.

The tipping point is an example of a social shopping feature, where social shopping is roughly defined as a method of e-commerce that involves other people in a person's shopping experience, and Groupon relied on it to make their voucher business successful.[1] Andrew Mason, Groupon's first Chief Executive Officer, stated in a 2009 interview with Reuters, "The idea … was to organize action around a tipping point .... If you can give people a way to take action where they feel it's actually going to make a difference, they'll do it."[2]

A number of daily-deal sites such as WagJag, BuyWithMe, and LivingSocial quickly entered the market in 2009, and many, if not all, of them used some sort of social shopping feature.[3] The first two companies adopted the tipping point feature, while LivingSocial, instead of using the tipping point, provided free vouchers when consumers sent a link to an offer to their contacts and

[1] See http://en.wikipedia.org/wiki/Social_shopping for details and see also Yadav et al. (2013) for discussions on the meaning and domain of social commerce.

[2] Andrew Mason, "Virtual 'Tipping Point' Leverages Group Deals," Reuters, June 10, 2009, http://www.reuters.com/article/2009/06/10/us-groupon-idUSTRE5592K720090610, accessed July 26, 2015.

[3] The business model of BuyWithMe is explained in a news article by Sam Oches entitled, "Coupon Companies Ditch Standard Format with Internet's Help," QSR, August 6, 2009, http://www.qsrmagazine.com/news/coupon-companies-ditch-standard-format-internets-help, accessed July 26, 2015. The business model of WagJag is explained in a news article at TechVibes.com entitled, "WagJag.com looks to leverage social media and save you money," TechVibes.com, March 31, 2010, http://www.techvibes.com/blog/wagjagcom-looks-to-leverage-social-media-and-save-you-money, accessed July 26, 2015.

three of those contacts bought the offer through the link. The daily-deal industry grew rapidly after 2009 with the annual growth rate close to 150 percent. As of 2014, more than 300 daily-deal sites were competing vigorously in the US market with total market revenue reaching 3.4 billion dollars (Carter 2014). However, the social shopping features that characterized early start-ups like Groupon began to disappear from these companies' business models, and as of 2012, Groupon was no longer using the tipping point in selling vouchers (Subramanian 2012).

It is debatable how much the tipping point contributed to Groupon's success and why this feature was ultimately eliminated. Some researchers claim it was essential, arguing that consumers enjoyed having an active part to play in making deals active and that this caused consumers to send links to their friends or even buy deals that they would not have otherwise. Wu, Shi, and Hu (2014), for example, analyze Groupon sales data and find that the number of voucher purchases rapidly increased as deals approached the tipping point. They interpret this as consumers behaving in a frenzy to "beat the threshold". Other researchers, however, provide different perspectives on the role of the tipping point. Subramanian (2012), for example, uses an analytical model to show that the tipping point does not always benefit the daily-deal business. Edelman, Jaffe, and Kominers (2015) also question the role of the tipping point in the growth of the daily deal business.

In this paper we analyze some key features of Groupon-like daily deal sites, asking whether consumer behaviors are affected by these features and whether their behaviors change as they become more familiar with these features. In particular, we focus on two features. One is the tipping point, one of the most prominent social shopping features in the early daily-deal industry, and the other is a predetermined period for redeeming vouchers. The predetermined redemption period is not a social shopping feature *per se*, but it is one of the daily deal's important characteristics and closely related to its social shopping features. If a redemption period is 90 days, for example, a voucher loses its value if it is not redeemed in 90 days.[4] When the fixed redemption period is paired with the group buying feature of the daily deal business, i.e., inducing a mass of consumers to buy vouchers on the same day, an unpleasant redemption experience can result as multitudes try to redeem vouchers in a short period of time. Moreover, an unpleasant redemption experience is more likely to occur when a deal is offered by a small business. There are anecdotes about retailers complaining about dealing with "too many" customers right after deals are sold and consumers complaining about receiving poor service due to retailers trying to serve more customers than they can handle. For example, a consumer purchased a voucher for a spa from Groupon and then attempted to book a spa treatment, but she was told that there were no more spots left as too many people had already scheduled appointments. This customer could not use her voucher after all.[5]

In our analyses we use individual-level data from one of the major daily-deal sites in Korea.[6] This company adopted the Groupon model, including the tipping point and the fixed redemption period features, and grew rapidly to become one of the largest daily-deal sites in Korea. Like Groupon this company also eliminated the tipping point feature a few years after its inception. For the tipping point effects, also known as the threshold effects, we first test whether and how the presence of the tipping point affects voucher sales. Using data on over 2,500 deals sold over a year we analyze the sales patterns 30 minutes before and 35 minutes after deals are activated. In our data set we observe, among many other things, the exact purchase time of each consumer, and thus know exactly when deals were activated. For each deal we divide this 1 hour and 5

[4] See the Daily-deal Industry section for a discussion of how the policy regarding unused vouchers has changed over time.
[5] Anonymous, "Groupon Complaint/Voucher Redemption," Measuredup.com, [2011], http://groupon-reviews.measuredup.com/Complaint-Voucher-Redemption-40928, accessed July 26, 2015.
[6] A disclosure agreement prevents us from revealing the name of the company or the specific periods we have data on.

minute period into thirteen 5 minute intervals with a "threshold interval" in the middle. The threshold interval is a five minute interval that begins when deals reach the tipping point. If a deal reached the tipping point at 8:03:00 am, for example, the threshold interval is from 8:03:00 am to 8:07:59 am and we include six 5 minute intervals before and after that interval. The dependent variable in this analysis is the log of the number of vouchers sold in each interval.

Knowing the exact times of the tipping points gives us at least two advantages over analyses that use data collected by "data crawlers" visiting company websites every five or ten minutes. First, we can test if any changes in sales patterns occur right before or after the tipping point rather than around the tipping point. In the example above we know this deal was activated at 8:03:00 am, while the data collected by the crawler only show that the deal was activated between 8:00:00 am and 8:05:00 am. Wu et al. (2014), for example, find higher voucher sales around the tipping point but they cannot pinpoint whether the higher sales happen right before or after the tipping point. Implications differ drastically depending on which is the case.

[Insert Figures 1 & 2 about here]

Second, we can control for the time effects of voucher sales, separately from the tipping point effect, using the clock interval. During the day there are time periods when a lot of people visit the daily-deal site and make purchases. This is clearly illustrated in Figure 1, which shows the frequency of purchase times for deals that were sold for 24 hours in our data set, and in Figure 2, which shows the frequency of times when those deals were activated. These figures show that consumers in our data bought vouchers most actively between 9 am and 11 am and between midnight (when deals are posted online) and 1 am. These figures also show that a majority of deals reached the tipping point during these time slots with over 40 percent of the deals being activated in the first hour. Because the first hour, for example, is when many consumers bought vouchers and as a result when most of the deals reached the tipping point, we need to control for the effects associated with the first hour of deals being online to identify any effects resulting from reaching the tipping point.

In our first analysis we test if there is any significant change in the number of vouchers sold either right before or right after the tipping point. We control for the time effects using the clock interval dummies (30-minute or 10-minute interval dummies), and we also control for deal heterogeneity using the deal fixed effects. Controlling for deal heterogeneity is also crucial in identifying the tipping point effect, because we rarely see exactly the same deal twice or more. We do have some information on deal characteristics such as the discount rate, business type, the maximum vouchers available, etc., but they are not sufficient. With the deal fixed effect we test if there are any noticeable jumps or drops in voucher sales of a given deal around the tipping point.

We find that sales are higher in the threshold interval, the five minute interval right after deals are activated, than in any other interval. This result is statistically and economically significant and does not disappear even with the 10-minute clock interval dummies. Our results suggest that there is no frenzy effect to beat the threshold and that there are some consumers who would wait for deals to reach the tipping point before they buy.

This result is intriguing because there is no risk in buying deals that fail to be activated other than wasting a few minutes and almost all deals included in our data set reached the tipping point. We ask, therefore, if those who buy deals after they are activated do not have much experience with daily-deal purchases. It may be that consumers prefer deals that have been activated when they buy their first daily deal, but care less about it as they become more experienced with daily-deal shopping. Or it may be that consumers pay more attention to whether deals have been activated as they become more experienced. Of course, it is also possible that their purchase time does not systematically change with their past experiences.

To answer this question we test if purchase times change as consumers buy more deals using a subsample of the data on deals sold in a three month period. About 500 deals were sold during this period, generating over 370,000 voucher sales. While we analyze all deals sold for one year for the first analysis, we focus on the three month period for the individual consumer analysis mainly because the daily-deal market became very competitive in the later part of the sample period and we believe that consumers increasingly were buying deals from multiple deal sites towards the end of the sample period. It would be ideal if all consumers in our data set gained their shopping experience only from the daily-deal site we have data on. We try to be close to the ideal situation by selecting a period before the market became hot.

Because about 40 percent of consumers bought multiple times during this three-month period, we can control for each consumer's purchase experience separately from their characteristics (such as gender, age, location, etc.) and deal characteristics. Using the number of past purchases as a proxy for experience, we analyze whether and how online shoppers' past experience affects their current purchase time. We find that consumers typically buy deals that are already activated in their first and second purchase experience. "Experienced" shoppers are more likely to buy deals before they reach the tipping point but we do not find evidence that they do so to help deals reach the tipping point; rather, they tend to buy deals right after they are posted. Our findings suggest that the presence of the tipping point is likely to deter "inexperienced" shoppers from buying deals early on, rather than encouraging them to do so. As they buy more deals, however, they seem to figure out that there is no cost associated with buying deals before they reach the tipping point and that almost all deals reach the tipping point and, hence, buy deals as early as they can.

With respect to the fixed redemption period, another feature of the daily-deal industry we focus on, we ask who redeems vouchers during peak redemption periods and whether they move away from these periods as they redeem more vouchers. It is widely understood that peak redemption periods are right after a voucher is released or just before its expiration date, and this is consistent with what our data show, although the first peak is much higher than the second one.[7] These questions are especially important if overcrowding or congestion is a common problem at businesses following successful voucher sales. We analyze the redemption time of more than 250,000 redemptions for the deals sold during the same three-month period we analyze for the purchase time. We do find that consumers typically redeem their first few vouchers right after their purchases but tend to wait longer as they redeem more vouchers. Our finding provides evidence that inexperienced shoppers drive congestion at participating businesses right after deals are sold.

When all these findings are put together, it is hard to claim that the success of the daily-deal business was due to its social shopping features; the presence of the tipping point seems to deter new customers from buying deals right away, and the predetermined redemption period does not seem to help merchants, especially small businesses, who are forced to handle an unusually large number of customers during the peak redemption periods. As of 2014, Groupon as well as the Korean daily-deal site we have data on were no longer using the tipping point and all deals could be redeemed right away without waiting for voucher sales to end. As a large portion of deals are

[7] Margie Fishman wrote on September 19, 2011: "[LivingSocial] staffers assist small business owners during peak redemption periods, such as right after a voucher is released or just before its expiration date." But she did not explain how LivingSocial staffers provided this help. (http://www.openforum.com/articles/the-top-5-group-buying-sites-love-em-or-hate-em).

sold over a few days nowadays, the instantaneous redemption may alleviate the congestion problem. And the fact that major daily-deal sites no longer use the tipping point suggests that this feature does not help their long-run growth.

Our paper contributes to the daily-deal business literature that has been growing rapidly. In addition to Wu et al. (2014) mentioned above, there are a number of empirical studies that analyze sales patterns across deals and shed light on how consumers purchase daily deals. Ye et al. (2011), for example, use data obtained from the websites of Groupon and LivingSocial and compare the dynamics of purchasing times on these two deal sites. Byers, Mitzenmacher, and Zervas (2011) use similar data to analyze the relationship between deal sales and deal characteristics. Li and Wu (2013) and Luo, Andrews, Song, and Aspara (2014) test if there is observational learning by analyzing the relationship between the number of cumulative (committed) purchases and current purchases. As far as we know, Luo et al. (2014) is the only other study that analyzes consumer-level data, but their focus is not on the threshold effects.

There are also studies that focus on other aspects of the daily-deal industry. Dholakia and Kimes (2011) use survey data from daily-deal users and non-users to examine consumer perceptions about daily deals. Kumar and Rajan (2012) investigate whether merchants benefit from selling goods and services on daily-deal sites and show that offering deals does not necessarily yield profits for merchants. Edelman et al. (2015) use a theoretical model to show that offering deals is more profitable for merchants who are relatively unknown or for merchants with low marginal costs. Dholakia (2011) examines the determinants of profitable Groupon promotions using survey data from merchants. Kim, Lee, and Park (2013) analyze daily-deal sites' entry strategies into local markets using data from Groupon and LivingSocial.

The rest of the paper is organized as follows. We first provide an overview on the daily-deal industry both in the US and Korea, and describe the data used in this paper. Then we present our analyses of purchase time and redemption time.

## The Daily-deal Industry

Daily-deal sites provide platforms that bring merchants, especially small businesses, and online shoppers together. On its website Groupon used to describe its business model as follows. "Groupon negotiates huge discounts—usually 50-90% off—with popular businesses. We send the deals to thousands of subscribers in our free daily e-mail, and we send the businesses a ton of new customers. That's the Groupon magic."[8] Daily-deal sites make money by keeping approximately half of the money customers pay. For example, suppose a daily-deal site offers an $80 massage at 50 percent discount and equally splits the revenue with the merchant. The consumer pays $40 to the daily-deal site and gets a massage valued at $80 from the massage shop, while the shop gets $20 from the daily-deal site.

Especially early on, the social shopping aspect distinguished daily-deal sites from other discount sites such as Restaurant.com, which merely functioned as platforms in the two-sided market context, and was often identified as the main factor behind the success of the daily-deal business. A Forbes article published right after Groupon's initial public offering in 2011 said, "Groupon's offerings create Word-of-Mouth and buzz for new products and services, helping them reach the "tipping point—" a very important factor for marketing new products and services."[9]

[8] This description can no longer be found on the Groupon website but can be found on other websites that explain Groupon's business model. For example, visit http://www.cbcwebcollege.com/groupon.htm

[9] Panos Mourdoukoutas, "Groupon's Advantage," Forbes.com, Nov. 4, 2011, http://www.forbes.com/sites/panosmourdoukoutas/2011/11/04/groupons-advantage/, accessed July 26, 2015.

The daily-deal industry achieved a remarkable growth in the five years leading up to 2014; the total U.S. market revenue reached $3.4 billion with the number of the daily-deal site reaching over 300. The participation of technology firms such as Amazon and Google intensified competition. Amazon acquired a large stake in LivingSocial, while Google launched Google Offers in 2011 after it failed to acquire Groupon (Carter 2014). Despite a high level of entry and intense competition, Groupon's remarkable growth continued; in the first quarter of 2011, it had revenue of over $644 million, which was about 200 times its revenue in the same quarter of 2009. Groupon's subscriber base grew from about 2 million in the beginning of 2010, to over 83 million by March 2011.[10] In 2014 Groupon was still the most dominant daily-deal site with its market share over 50 percent, followed by a distant second, LivingSocial, which had only about a 9 percent market share.

While the industry was experiencing explosive growth, a number of daily-deal sites including Groupon and LivingSocial evolved over time, experimenting with new features and rendering obsolete some of social shopping features such as the tipping point. One of the new "products" that Groupon experimented with was a real-time based deal called GrouponNow which gave business owners the ability to offer deals at specific times of the day while allowing consumers to find a nearby deal using mobile technology and geolocation and redeem it right away. Although Groupon phased out these deals, the geolocation technology is now a standard feature of the Groupon mobile app with which consumers can search for nearby deals.

Changes in redemption policies are worth noting too. In 2009 the US Congress passed the Credit Card Accountability Responsibility and Disclosure (CARD) Act, which included a provision that gift cards cannot expire within 5 years from the date they were activated. As a

[10] See Groupon's S-1, Registration Statement, http://sec.gov. Amy Lee provides a nice summary (Huffington Post, June 2, 2011, http://www.huffingtonpost.com/2011/06/02/groupon-ipo_n_870652.html, accessed July 28, 2015).

result, consumers only lose the promotional value of a voucher after the redemption period is over but they can still redeem the value that they paid for within 5 years.[11]

As of 2015 all Groupon deals are available for a limited time but a large portion have more than one day of sales period. Although GrouponNow was phased out, almost all deals can be used immediately after purchase. Some deals show a clock counting down until the deals close but many deals show only “limited time remaining,” which effectively means that they can sell out at any moment. Although the tipping point no longer exists, consumers can still see how many people have purchased deals so far. All deals display “limited quantity available” but do not provide information on the maximum number of available vouchers.[12]

The Groupon-like daily deal business did not exist in Korea until March 2010 when a start-up company launched a daily-deal site copying Groupon’s business model.[13] Shortly afterwards a series of daily-deal sites quickly sprang up by adopting the identical business model and the industry revenue reached 50 billion Korean Won (KW) by the end of 2010.[14,15] The daily-deal industry continued to grow rapidly in Korea with the total annual revenue surpassing KW 3 trillion in 2013.[16] It is estimated that the number of daily-deal sites went over 500 in 2011, but three sites dominated the market.[17] According to a report by Rankey.com, these three sites were among the top 10 e-commerce websites in Korea as of August 2013.

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[11] The entire text of the CARD Act can be found at http://www.gpo.gov/fdsys/pkg/PLAW-111publ24/html/PLAW-111publ24.htm

[12] LivingSocial also went through similar changes such as not showing the counting-down clock and extending the sales period but they still give a free voucher for three successful referrals.

[13] Anonymous, “Wipon: a unique shopping mall where one cannot buy alone”, Newswire.co.kr, March 15, 2010, http://www.newswire.co.kr/newsRead.php?no=461581, accessed July 28, 2015.

[14] 1,200 Korean Won is approximately equal to one US dollar.

[15] Hyun-chae Chung, “Social Commerce Sites in Chicken Game,” The Korea Times, November 17, 2013, http://www.koreatimes.co.kr/www/news/nation/2013/11/602_146382.html, accessed July 28, 2015.

[16] Anonymous, “Will Wemakeprice Cause Change in Dynamics of Open Market beyond Social Commerce?” BusinessKorea.co.kr, May 29, 2014, http://www.businesskorea.co.kr/article/4837/market-changer-will-wemakeprice-cause-change-dynamics-open-market-beyond-social, accessed July 28, 2015.

[17] The combined revenue of the top three accounted for over 85 percent of the industry revenue in 2013. See “Local Social Commerce Firms Enjoyed Over 50% Growth Last Year,” BusinessKorea.co.kr, January 7, 2014, http://www.businesskorea.co.kr/article/2855/social-commerce-market-local-social-commerce-firms-enjoyed-over-50-growth-

The Korean daily-deal industry has been following the US business model closely since its inception. For example, the tipping point was one of the key features at many Korean daily-deal sites early on but it disappeared, including from the site we have data on. In an earlier period consumers could not redeem vouchers beyond the expiration date, but starting in 2012 they could partially recover the value that they paid, usually 70 percent.[18] At least one daily-deal site introduced a real-time based deal that copied GrouponNow, but it was also phased out.[19]

[Insert Table 1 about here]

## Data

We have detailed information on deals as well as registered customers from one of the major daily-deal sites for the first year of its business. The data set includes 2,617 deals that generated about 4.5 million voucher sales in total from over 1 million registered customers. Table 1 summarizes the characteristics of all the deals in our sample that we analyze in the first part of the Purchase Time section. *Product Sales* is the number of vouchers sold per deal. The mean is 1,727 with the standard deviation 8,186. The deal with the highest sales sold 300,000 vouchers. *Original Price* is the original price of deals and ranges from 0 to 1 million KW with the median 33,000 KW.[20] This large variation in prices is mainly due to the deal site selling very different "products". *Discount Rate* refers to the discount rate and varies widely, but over 95 percent of deals offer at least 50 percent discount. *Sale Periods* denotes the number of days that a deal is being sold. A majority of deals were on sale for 24 hours but some deals, mainly those that began

last-year, accessed July 28, 2015, and also see Lindsey Kim, "Top 3 Social Commerce Websites Dominate Korean Online Shopping Scene," CNN.com, July 5, 2011, http://www.cnngo.com/seoul/shop/social-commerce-sites-869074, accessed July 26, 2015.

[18] This change was made by five major daily-deal sites accepting the Korea Fair Trade Commission's 2012 guidelines for consumer protection in the social commerce industry.

[19] Yoon Ja-young, "Social Commerce Going Mobile," the Korea Times, August 4, 2011, http://www.koreatimes.co.kr/www/news/biz/2015/02/123_92217.html, accessed July 28, 2015.

[20] There are 4 deals with zero price. These are mostly free concerts or lectures, and the discount rate is zero for these deals.

Fridays, were sold for multiple days. *Tipping Point* is the number of sales required to activate a deal. The median tipping point is 50 but it can be as low as 2 and as high as 20,000. *Maximum Sale* is the number of vouchers available for each deal and ranges from 8 to 300,000 with the median 1,500. During the sample period both the tipping point and the maximum sale were predetermined and revealed to consumers when deals appeared on the site. *Redemption Periods* refers to the number of days that consumers have for redeeming vouchers they buy. This period is usually 60 or 90 days. Deals with zero redemption days are concerts or performances on fixed dates. *Soldout* indicates whether a deal was sold out, meaning the number of vouchers sold reached the maximum sale. About 18 percent of the deals in our sample were sold out. Figure 3 shows deal types in a pie chart. Restaurants make up the largest category, followed by beauty/healthcare, concert/exhibition, and so on.

[Insert Figure 3 about here]

The deal site sets the discount rate, the tipping point, and the redemption period, presumably jointly with vendors, to sell all vouchers available. A simple correlation among them, however, does not show any clear pattern in how they set these values. The most correlated characteristics are the tipping point and the maximum sale. They are positively correlated with the correlation coefficient equal to 0.60, suggesting that the tipping point is set higher for deals with more vouchers available. The original price is positively correlated with the discount rate with the correlation coefficient 0.16, suggesting that more expensive products are usually more heavily discounted. The tipping point is negatively but weakly correlated with the discount rate with the correlation coefficient -0.04. Although this number is not high, this suggests that a heavier price discount tends to accompany a lower tipping point. The correlation between the tipping point and the original price is even weaker with the correlation coefficient -0.02.

[Insert Table 2 about here]

To see whether or how these attributes are associated with voucher sales, we run a simple OLS regression with the log of sales as the dependent variable and all other attributes as covariates. In addition to the variables reported in Table 1, we include the dummy variables for the week days, 6 category dummy variables, and 13 region dummy variables. We report results in the first column of Table 2. The adjusted R-squared is 0.52, which is high considering the fact that every deal is unique. The log of the (original) price variable has a negative and statistically significant coefficient, suggesting that more expensive products are less popular. The discount rate is positive and statistically significant, suggesting that a deal with a heavier discount is more popular. The tipping point is also positive and statistically significant, suggesting that a deal with a higher tipping point is more popular. The maximum sale is positive and significant, indicating the deal site sets a higher maximum sale for more popular deals. The positive coefficients for the tipping point and the maximum sale suggest that the deal site sets them at higher levels for deals that they expect to be popular. The redemption period variable has a positive and significant coefficient, suggesting that a deal with a longer redemption period is more popular. *D_salesday* is a dummy variable for deals that lasted longer than a day, and has a positive and significant coefficient, showing that a deal that lasted longer sold more vouchers, which is not surprising. The day variables show that deals offered on Mondays, Tuesdays and Wednesdays sell fewer vouchers than deals offered on Fridays, which could be a result of deals offered on Fridays being mostly multi-day deals. However, the coefficients for the first three days of the week are not much different from each other. The category variables show positive effects for restaurants and negative effects for pubs and cafes.

These results show that despite the large degree of deal heterogeneity described in Table 1, the deal characteristics explain sales patterns across the deals reasonably well. They also show, however, that about a half of variations in sales is not accounted for even after controlling for an extensive set of covariates. Because we hardly see the same deal sold twice or more during the sample period, there is not much more we can do to control for deal heterogeneity. Note, however, that it is not an issue in analyzing sales patterns around the tipping point because we exploit sales variations within deals in identifying the tipping point effects.

For the consumer-level analyses we limit our attention to deals sold for a three-month period within the whole sample period. The three-month period we select starts in the sixth month after the daily-deal industry was born in Korea. Before this three-month period we see a lot of shoppers buy their very first deal, so the relative number of experienced shoppers is tiny. Thus, we exclude the first few months in order to obtain a large sample size of repeating purchases and redemptions. The three-month period is also before the daily-deal market became hot. Right before the three-month period there were only about 30 daily-deal sites and the company we have data on was one of the major players. Thus, we are not greatly concerned about the consumers in our sample gaining their experiences from other daily-deal sites, although this is still true to some extent. During the three-month period 679 deals were sold to 253,151 customers and the total number of vouchers sold was 508,593.

We run the same OLS regression for the log of voucher sales with these 679 deals and report results in the second column of Table 2. The adjusted R-squared is 0.61, slightly higher, but the results are not much different from those with the whole sample. Almost all coefficients have the same sign, although some of the deal characteristics have larger coefficients. The most noticeable change is that the day effects are no longer statistically significant with the smaller sample.

[Insert Table 3 about here]

Table 3 summarizes the characteristics of the 253,151 consumers who bought deals during the three-month period. About 65 percent are female and the median age is 30. The age and gender distributions, not reported in the paper, show that people in their twenties and thirties are major customers of this site, and among those in their twenties the number of females is almost twice as large as that of males. Over 50 percent of the shoppers in our sample received either mobile texts (SMS) or e-mails about deals from the site.[21] Although not reported in the table, we also know when they made an account on this deal site and which regions are their preferred markets.[22] The median number of purchases during the three-month period is 1 with about 40 percent of shoppers purchasing more than 1 deal and about 10 percent more than 3 deals. If a consumer buys two different deals in two different markets, we count it as two purchases. But if she purchases multiple vouchers of the same deal, we count it as one purchase. Note that only 13 percent of the 253,151 customers bought at least one deal by the first day of the three-month period with the average number of previous purchases 0.35 and the average number of previous redemptions 0.12. The distribution of purchase frequency is heavily skewed and has a long right tail. Out of the 10 percent who purchased more than 3 deals, about 40 percent bought more than 5 deals and about 7 percent bought more than 10 deals.[23]

In addition to the number of deals purchased, we also observe the time of every purchase for over 1 million registered consumers and utilize this information in two ways. First, we use this

[21] The company sends emails at 7 o'clock in the morning.
[22] Consumers indicate which region is their preferred market but do not always buy in their preferred markets.
[23] For the 1 year we have data on the median number of purchases is 4 and the mean is 6.67.

information to identify the exact time when each of the 2,617 deals was activated. Because we know the exact time when deals reached the tipping point, we can assess if and how the presence of the tipping point affects purchase decisions more reliably than other studies that use data crawlers. This is the main focus in the first part of the next section. Second, we use the purchase time information to construct purchase experience variables. Given a deal, we know how many other deals consumers bought from the time they had made their accounts to the date of the given deal. Using this information (on the 253,151 consumers), we test in the second part of the next section if consumers' purchase time changes as they become more experienced.

Lastly, we have information on when consumers redeemed the deals that they bought. Each purchase almost always leads to redemption and consumers have different patterns of redeeming vouchers. For example, some redeem their vouchers immediately after purchase, while others wait several weeks. In the Redemption Time section we use this information to analyze how consumers' redemption time changes as they become more experienced.

## Purchase Time

### *Tipping Point and Voucher Sales*

As explained above, many daily-deal sites including Groupon and the Korean daily-deal site that we have data on were distinguished from other online discount businesses by having the minimum purchase feature or the threshold feature. If a deal does not attract other consumers, one cannot buy it no matter how much he or she likes it, and this makes buying daily deals social shopping. However, it is not clear how this social shopping feature of the daily deal would affect purchase decisions. Did it encourage consumers to buy deals sooner or did it make them wait until deals passed the tipping point? One challenge in answering this question is that an exact time of the deal activation is rarely observed in data collected by data crawlers, but we overcome this challenge using the consumer-level data described in the previous section.

We first test if sales patterns significantly change around the tipping point. For each deal we take 30 minutes before and 35 minutes after deals were activated and divide them into 13 five-minute intervals. Let $t$ be a purchase time minus the time when a deal reaches the tipping point in the unit of minutes. So $t = 3.5$ indicates buying a deal (a voucher) 3 minutes and 30 seconds after the tipping point, $t = -2$ buying a deal 2 minutes before it reaches the tipping point, and $t = 0$ buying a deal-activating voucher, and so on. The first 5 minute interval is when $-30 \leq t < -25$, the second interval is when $-25 \leq t < -20$, and so on, and the seventh interval starts at the moment that deals reach the tipping point ($0 \leq t < 5$) and we call this interval the threshold interval. We count the number of voucher sold in each five-minute interval and use its log transformation as the dependent variable. A key question is whether this number significantly changes around the tipping point and if so, how it changes.

As explained above, there are specific times of the day when consumers actively make purchases, and as Figures 1 and 2 show, deals are likely to reach the tipping point at times when consumers actively make purchases. Thus, it is important to control for sales patterns associated with the time of day in our empirical analysis. Otherwise, we may mistakenly attribute high sales around the tipping point to "social shopping" phenomena while they are actually driven by high purchase activities during the most active shopping times. Because we observe the exact purchase time for each voucher sale, we can control for this time effects with the clock interval dummy variables.

[Insert Table 4 about here]

Table 4 shows the summary statistics for the number of voucher sales in each of the thirteen 5 minute intervals. Note that because the tipping point of the deals in our sample is widely distributed throughout the day and we take 30 minutes before and after the tipping point, these thirteen intervals are also at different points of time throughout the day. Note also that some deals reached the tipping point in less than 30 minutes after they were posted online, which makes the number of observations less than 2,617 for the first 5 intervals.

Table 4 also shows large standard deviations, which is expected as the total number of purchases is substantially different across the deals. The median is much smaller than the mean, showing similar skewness as that of the total sales described in Table 1. The minimum sales are 0 for all intervals except for the threshold interval (the 7th interval) which should have at least one purchase by definition. About 27 percent of the observations have 0 sales where one observation is defined as a deal and five-minute interval combination.

The mean sales show two interesting patterns around the tipping point. First, the mean sales slowly increases from 4.73 to 7.66 over the first three intervals (from 30 minutes prior to the tipping point to 15 minutes prior to the tipping point), then jumps to 12.86 in the fourth interval and steadily increases to 17.19 over the next three intervals (from 15 minutes prior to the tipping point up to the tipping point). This jump in sales in the fourth interval seems to indicate a surge of purchases as deals are approaching the tipping point. However, this jump could also result from high purchase activities at certain times of the day. Suppose consumers visit the deal site at a convenient time and buy a deal if they like it without paying attention to how far deals are from being activated. If many deals were activated at 9:15 am because the most convenient shopping time for many consumers happens to be 9 am, we would see the same sales pattern as just described.

Second, the mean sales jump to 21.08 right after deals are activated (in the 7th interval) and drop to 18.68 in the next interval and steadily decreases to 14.26 by the 13th interval. This jump right after the tipping point can be viewed as the presence of the "tipping point effect", whatever its nature may be, but again this may just capture high purchase activities at certain points of time during the day. Note that the average sales per 5 minutes throughout the day are 4.6 vouchers. So the table clearly shows that the one-hour period around the tipping point is a period of high purchase activities, and because deals do not become active until enough purchases are made, the sales pattern around the tipping point may just be an outcome of how the tipping point is defined. And this highlights, once again, the importance of controlling for the time effects in our empirical analysis.

[Insert Table 5 about here]

Using the log of the number of vouchers sold in each of the thirteen intervals as the dependent variable, we run the deal fixed-effect regression and report results in Table 5. We use three specifications and for each specification we run two regressions with different time-of-the-day dummy variables. In the first regression of each specification we use the dummy variables for every 30 minute (clock) interval from midnight, which results in 48 time dummy variables, and in the second regression we use the dummy variables for every 10 minute interval from midnight, which results in 144 time dummy variables.[24] Note that these time dummy variables barely overlap with the thirteen 5 minute intervals in Table 4 as the times that deals were activated determine when these thirteen intervals start and end.

[24] Because of a collinearity problem we drop the 10 minute dummies that have fewer than 10 observations and this reduces the number of the 10 minute dummies from 144 to 137.

In the first specification (the first two regressions in Table 5) we include the dummy variable indicating that deals are not activated ($D_{beforeTP}$) as the main explanatory variable. The equation we estimate is

$$\log(sales_{ij} + 1) = \beta_0 + \alpha D_{beforeTP} + \gamma_{time} D_{time} + \delta_j D_j + u_{ij} \tag{1}$$

Where $sales_{ij}$ is the number of deal $j$'s vouchers sold in interval $i$, $D_{time}$ is the time dummy variable (either for every 30 or every 10 minutes), and $D_j$ is the deal fixed effects. We use the log transformation as the dependent variable lest results be driven by deals with a large number of voucher sales. As explained above, controlling for the deal fixed effects is important because almost every deal is unique and the level of voucher sales is vastly different across the deals. With the deal fixed effects we identify $\alpha$ and other tipping-point related parameters from noticeable jumps or drops in voucher sales of a given deal around its tipping point.

Results show that the number of purchases is lower before deals are activated. The coefficient for $D_{beforeTP}$ is -0.3 with the thirty-minute time dummies and -0.263 with the ten-minute time dummies and both estimates are statistically significant. Because we use the log transformation as the dependent variable, the coefficient indicates a percentage difference in voucher sales when deals are activated. The estimates imply that the number of purchases is lower before deals are activated and it is lower by 30 percent or by 26.3 percent depending on which time effects are controlled for.

In the second specification we add two five-minute interval dummies, one for the five-minute interval right before deals are activated ($-5 \leq t < 0$) and another right after deals are activated ($0 \leq t < 5$). We estimate

$$\log(sales_{ij} + 1) = \beta_0 + \alpha D_{beforeTP} + \beta_5 I_5 + \beta_6 I_6 + \gamma_{time} D_{time} + \delta_j D_j + u_{ij} \tag{2}$$

where $I_5$ and $I_6$ indicate the two five-minute interval dummy variables. Results are much different depending on which time effects we use. With the thirty minute time dummies the coefficient for $D_{beforeTP}$ is -0.179, indicating that the number of purchases is still lower by 17.9 percent before deals are activated, but the coefficient for the -5 to 0 minute interval dummy ($\beta_5$) is 0.243, which implies that the number of purchases is 6.4 (=24.3-17.9) percent higher right before deals are activated, compared to that in the 5 to 35 minute period. This result seems to indicate that consumers make more active purchases as deals approach the tipping point.

However, the coefficient for the 0 to 5 minute interval ($\beta_6$) is 0.546, implying that the number of purchases right after deals reach the tipping point is higher by 54.6 percent compared to that in the 5 to 35 minute period. Combining this with the other two coefficients, we can infer that the number of purchases right after the tipping point is 72.5 (=54.6+17.9) percent higher than before deals are activated and still higher by 48.2 (=72.5-24.3) percent compared to the -5 to 0 minute interval. These estimates also suggest that high purchase activities right after the tipping point are temporary. All tipping-point related coefficients except for the coefficient $D_{beforeTP}$ are still statistically significant with the ten-minute time effects and the tipping-point effects do not change substantially. The estimates with the ten-minute time effects imply that the number of purchases right after the tipping point is 46.6 (=55.3+2.93-11.6) percent higher compared to the number of purchases in the -5 to 0 minute interval.

In the third specification we drop $D_{beforeTP}$ and put the twelve 5 minute interval dummies in order to estimate the trend of voucher sales around the tipping point in a more flexible way. We estimate

$$\log(sales_{ij} + 1) = \beta_0 + \beta_1 I_1 + \beta_2 I_2 + \cdots + \beta_{12} I_{12} + \gamma_{time} D_{time} + \delta_j D_j + u_{ij} \qquad (3)$$

We do not claim by this specification that consumers observe which time interval they are in when making purchase decisions. Consumers may know how many minutes have passed since a deal became active if they kept close track of it but would not know at what time a deal will be activated. Nevertheless, it is reasonable to assume that consumers who buy a voucher in the -5 to 0 minute interval would see current voucher sales closer to the tipping point than those who buy a voucher in the -10 to -5 minute interval.[25]

An alternative way to estimate this effect would be to use the number of voucher sales that is needed to make a deal reach the tipping point in lieu of the 5 minute interval dummies. However, in this alternative specification the way that the cumulative voucher sales affect current period voucher sales is restricted such that the cumulative voucher sales have the same marginal effect on voucher sales 20 minutes before a deal reaches the tipping point as 5 minutes before a deal reaches the tipping point. This is not suitable for testing our hypothesis because we need to test if there are jumps or drops in the sales trend. Our third specification, on the other hand, estimates the sales trend around the tipping point nonparametrically. In Appendix A, nevertheless, we estimate the tipping point effect using a variable that measures a "distance" between current cumulative sales and the tipping point, and show how results change with a more restrictive sales trend. This distance variable is a function of lagged voucher sales so we use the first difference instrumental variable estimator instead of the fixed effects estimator.[26]

The results of the third specification are consistent with those of the first two specifications. Both the results with the thirty minute time effects and with the ten minute time effects show that

[25] This specification tests whether voucher sales are constant over time once controlling for the (clock) time effects. If consumers do not pay attention to the tipping point, variations in vouchers sales over the twelve five-minute intervals should be explained only by the time-of-the-day effects.

[26] In principle we can discretize the distance variable to make a sales trend more flexible. However, because the distance variable is an endogenous variable, the discretization introduces multiple endogenous dummy variables and would make it very challenging to estimate the model consistently.

the number of vouchers sold jumps to a higher level right after deals are activated, about 50 percent higher compared to voucher sales right before deals are activated, and then immediately drops by 50 percent. A sales trend after the threshold interval (the 0 to 5 minute interval) looks slightly different depending on which time effects are controlled for. The results with the thirty minute time effects show that the voucher sales after the threshold interval are stable and about the same level as that in the -5 to 0 minute interval while the results with the ten minute time effects show that they are gradually declining and lower than that in the -5 to 0 minute interval but the difference is only 4 to 8 percent.

These results show that voucher sales right after deals reach the tipping point are substantially higher than sales before the tipping point and that this effect is not driven by high purchase activities taking place at certain times of the day. Voucher sales before the -5 to 0 minute interval seem much lower than the rest but these lower sales are partially driven by deals that reached the tipping point in 30 minutes or less (see Table 4). This finding suggests that the presence of the tipping point does not encourage consumers to purchase a deal and that there are some consumers who hesitate to buy until deals pass the tipping point.

***Purchase Experience and Purchase Time***

In this section we link consumers' purchase time to their purchase experience and test if their purchase time changes as they buy more deals. As explained in the Data section we select a three-month period for this analysis. 679 deals were sold during the three-month period and among these deals we exclude deals that were sold for longer than 24 hours in order to limit consumers' purchasing time window to 24 hours.[27] After this selection we have 506 deals, 195,553 consumers, and 370,616 voucher sales left in our sample. We lose about 60,000

[27] We do not exclude deals that were sold out.

consumers by excluding multiple day deals, but the consumer characteristics remain nearly the same. The third column in Table 2 shows that the relationship between voucher sales and the deal characteristics does not change substantially by dropping these multi-day deals. The most notable change is seen in the category dummy variables; three category dummy variables including restaurants, beauty/health care, and concerts/exhibitions have larger coefficients, and the pub and cafe category variables now have positive yet statistically insignificant coefficients.

To control for purchase experience we create five dummy variables for the first purchase through the fifth purchase. Given a deal the dummy variable for the first purchase (*First Purchase*) takes 1 if the number of previous purchases is 0, the dummy variable for the second purchase (*Second Purchase*) takes 1 if the number of previous purchases is 1, and so on. These five dummy variables cover about 84 percent of all observations. Note that these dummy variables account for the number of past purchases from the date on which consumers made their accounts at the deal site. For previous redemptions we create three dummy variables for the first two redemptions. Given a deal the dummy variable for no redemption (*No Redemption*) takes 1 if a consumer did not redeem any voucher up to that point, the dummy for one redemption (*One Redemption*) takes 1 if she has redeemed one voucher before, and so on. These three dummies cover about 90 percent of all observations.

We test if the purchase experience has any effect on consumers' purchase time around the tipping point. In particular, we estimate the probability of purchasing a deal before it reaches the tipping point as a function of purchase and redemption experience. We control for consumer characteristics such as age, gender, whether they receive emails and/or text messages (*SMS*) about daily deals, how many vouchers they bought per deal (*Volume of Order*), and whether they bought deals in their preferred markets (*Preferred Area*).[28] We also include all deal characteristics variables reported in Table 1, the deal categories dummies, the weekday dummies, 13 dummies for market locations, 12 dummies for weeks that deals were sold, and 32 dummies for weeks that consumers made accounts. The 12 week dummies control for any common time trend in purchase behaviors during the sample period, and the 32 week dummies control for consumer heterogeneity associated with the time of becoming customers at the deal site.

We use both the binary logistic regression as well as the fixed effect logit regression to estimate the probability of purchasing a deal before it becomes active. Let $A_{ij}$ be the event that consumer *i* buying deal *j* before it reaches the tipping point conditional on buying deal *j*. For the binary logistic regression we estimate

$$Pr(A_{ij}) = \frac{\exp(\sum_{k=1}^{5} \gamma_k P_{ik} + \sum_{r=0}^{2} \delta_r R_{ir} + w_i \alpha + x_j \beta)}{1 + \exp(\sum_{k=1}^{5} \gamma_k P_{ik} + \sum_{r=0}^{2} \delta_r R_{ir} + w_i \alpha + x_j \beta)} \tag{4}$$

where $P_{ik}$ is the purchase experience dummy variable that takes 1 if deal *j* is consumer *i*'s *k*th purchase, $R_{ir}$ is the redemption experience dummy that takes 1 if the consumer has redeemed *r* times in the past, $w_i$ includes consumer characteristics, and $x_j$ includes deal characteristics.

For the fixed effect logit regression we estimate

$$Pr(A_{ij}) = \frac{\exp(\sum_{k=1}^{5} \gamma_k P_{ik} + \sum_{r=0}^{2} \delta_r R_{ir} + x_j \beta + c_i)}{1 + \exp(\sum_{k=1}^{5} \gamma_k P_{ik} + \sum_{r=0}^{2} \delta_r R_{ir} + x_j \beta + c_i)} \tag{5}$$

where we put a consumer-level unobserved characteristic, $c_i$, instead of $w_i$ and use consumers that change their purchase times around the tipping point over different deal purchases. With this selection rule the number of observations goes down from 370,616 to 71,402. With the fixed

[28] The preferred area variable is a dummy variable that takes 1 if consumers bought a deal in their preferred markets. About half of purchases were made for deals in their preferred markets.

effect logit regression we can control for unobserved individual heterogeneity, although we cannot learn much about the average partial effect.

[Insert Table 6 about here]

Table 6 reports results from the binary logistic regression as well as the fixed effect logit regression. In the binary logistic regression all five of the purchase experience dummies are statistically significant and negative and their absolute magnitude goes down with more purchases, indicating that the more deals consumers bought in the past, the more likely they are to buy before deals reach the tipping point. In particular, compared to those who are buying their first deal, the probability of buying a deal before it reaches the tipping point is about 30 percent higher for those who have bought one deal before, about 68 percent higher for those who have bought two deals before, and about three times higher for those who have bought five deals before.[29,30] These effects are much larger than the effects of any consumer characteristics such as age, sex, and whether they are receiving emails. In the fixed effect logit regression the coefficients of the purchase experience dummies are lower in the absolute term but the relationship among them does not change much, indicating that the main implication still holds even when accounting for individual differences.

The binary logistic regression results show that "inexperienced" shoppers tend to wait until deals pass the tipping point while "experienced" ones tend to buy before they reach the tipping point. The fixed effect logit regression results show that this difference in purchase time is not driven by intrinsic differences between heavy buyers and non-heavy buyers. In other words, consumers tend to change their purchase time as they purchase more deals over time.

[29] As above we compute the probability of the average consumer buying the average deal.
[30] The probability of buying a deal before it reaches the tipping point is 0.049 for consumers buying their first deal.

These results imply that the presence of the tipping point deters inexperienced shoppers from buying deals early on. Daily-deal sites that adopted the Groupon model may have hoped that the presence of the tipping point would trigger social interaction among online shoppers; if I see a deal that I like, I may email my friends to join me in buying it. However, the results presented in Table 5 do not support such effects and the results presented in Table 6 suggest that this social shopping feature works against its intended purpose as far as inexperienced shoppers are concerned.[31]

A follow-up question regarding purchase experience and purchase time is whether experienced buyers are the main driving force behind activating deals. In Appendix C we investigate whether experienced consumers are more likely to purchase deals right before they reach the tipping point. We find no evidence supporting this hypothesis. In fact, we find evidence that they are more likely to purchase deals right after they are posted online. These results are presented in Table C-1.

These results combined with those of Tables 6 suggest that the more deals consumers have bought in the past, the more likely they are to buy them before they are activated, and that given that they buy deals before they are activated, more experienced buyers are more likely to buy them right after they are posted online. The "typical" consumer implied by our results tends to wait until a deal passes the tipping point in their first couple of purchases but pays less attention to the activation status as she buys more deals. Then after buying several deals she tends to buy a deal right after it is posted online. It is important to note that our results are not driven by

[31] In Appendix B we use the multinomial logit model to investigate consumers' purchase time decisions in more granular time units. We find that the effect of purchase experience is most pronounced for purchases that took place between 5 and 10 minutes before deals reached the tipping point. In this time slot the probability of purchasing a voucher is 32 percent lower for consumers with no purchase experience compared to those who have bought deals more than 5 times in the past.

consumer heterogeneity but by consumers changing their purchase behaviors as they buy more deals.

One may interpret these results in the context of observational learning (Banerjee 1992; Cai, Chen, and Fang 2009), which can be used to claim that shoppers learn about the quality of deals from others. In particular, Subramanian (2012) shows that in such a situation shoppers are willing to wait until a "sufficient" number of vouchers are sold. In this perspective our results suggest that inexperienced buyers are those who wait and learn from others, while experienced ones do not care much about whether other shoppers like a deal or not. However, the observational learning motivation does not explain why buyers change their purchase times as they buy more deals or why experienced buyers no longer care about other shoppers' decisions. The deal site offers different deals every day, so buying deals in the past does not necessarily provide more information on a deal offered today. It may be that learning is not about the quality of deals but about the fact that there is no risk in buying deals before they are activated.

## Redemption Time

In this section we examine consumers' redemption behavior, another collective behavior seen in the daily-deal market. Once a deal is activated, everyone who makes a purchase has the same amount of time to redeem their vouchers. The redemption period ranges from 50 to 100 days for about 60 percent of deals in our sample and the median is 90 days. Because of this limited time window, businesses that successfully sell a lot of vouchers on the daily-deal site must serve an unusually large number of customers, and sometimes have difficulty in satisfying customers' expectations. For example, consumers may have to wait for hours to be seated at restaurants or may not be able to make a reservation at skin care shops. This "congestion" is an inevitable cost of daily deals under the fixed redemption period system and presents a challenge to the industry.

[Insert Figure 4 about here]

For this reason it is important to understand how consumers redeem vouchers, and particularly relevant questions are when they redeem vouchers and whether their redemption time changes as they redeem more vouchers. In Figure 4 we select 121 deals that have a 90 day redemption period and show the frequency of redemption time for consumers who bought those deals. The figure shows that a large number of consumers redeemed their vouchers right after they made purchases and right before redemption periods ended. Twenty eight percent of vouchers were redeemed in the first 10 days, 44 percent were redeemed in the first 20 days, and 14 percent were redeemed in the last 10 days.

For the redemption-time analysis we select from the three-month period deals whose redemption period is at least 20 days long and track redemption times for those deals. With this criterion deals that must be redeemed on fixed dates such as concerts or plays are excluded. The new sample includes 425 deals and 267,143 observations and their redemption time ranges from 1 to 183 days where 1 day means that vouchers were redeemed on the day after purchase. Note also that redemption periods for many deals in our sample, at least for deals sold in the last 20 days of our three month sample period, ended later than the end of the three-month period but we track them until all deals were expired.

We estimate two models: (1) a binary logistic model for the probability of redeeming vouchers in the first 10 days and the last 10 days of the redemption period respectively and (2) a linear regression model with the redemption time as the dependent variable.

[Insert Table 7 about here]

We first estimate the probability of redeeming vouchers in the first 10 days of the redemption period using the binary logistic regression and the fixed effect logit regression, and report results on the left panel of Table 7. We use the same regressors as in equations (4) and (5) in the previous section, but the dummy variables for days now represent days that vouchers were redeemed, not days that deals were purchased. Also, the dummy variable for the first purchase is taken out because all consumers in this sample made at least one purchase in the past. To avoid confusion, we re-label the previous purchase dummies as "One Purchase" instead of "Second Purchase", "Two Purchases" instead of "Third Purchase", etc. "One Purchase" means that consumers made one purchase up to that point, "Two Purchases" means that consumers made two purchases up to that point, etc. We also re-label the previous redemption dummies as "First Redemption" instead of "No Redemption", "Second Redemption" instead of "One Redemption", etc.

Results show that consumers are less likely to redeem their vouchers in the first 10 days as they redeem more. In the binary logistic regression the average probability of redeeming the voucher in the first 10 days is 0.32 for consumers who are redeeming for the first time. This probability goes down to 0.17 for those redeeming for the second time and 0.09 for those redeeming for the fourth time.[32] In the fixed effect logit regression the number of observations goes down to 96,892 because consumers who always redeemed in the first 10 days or those who always redeemed later than that are not used. Results show that the effect of redemption experience is now much larger.

Similarly, we estimate the probability of redeeming vouchers in the last 10 days of the redemption period and report results on the right panel of Table 7. Results show that consumers

[32] To be more specific the former probability is for those who bought two deals and are redeeming their second voucher and the latter probability is for those who bought four deals and are redeeming their fourth voucher.

are more likely to redeem their vouchers in the last 10 days as they redeem more, and this effect becomes larger in the fixed effect logit regression.[33]

[Insert Table 8 about here]

Next, we run linear regressions with the redemption time as the dependent variable. Table 8 shows both the OLS and the FE regression results. The OLS results show that consumers who are redeeming for the first time redeem about 12 days earlier than those who are redeeming for the second time and about 30 days earlier than those who redeemed more than five times. These differences become much larger in the fixed effect regression. The differences are more than 20 days between those who are redeeming for the first time and those who are redeeming for the second time and more than 90 days between the first timers and those who redeemed more than five times. These results are consistent with those presented in Table 7.[34]

All the results presented above consistently show that "typical" consumers in our data set redeem their vouchers right away after their first purchase but then wait longer as they redeem more vouchers. This implies that consumers who are redeeming their first vouchers are more likely to belong to the first peak shown in Figure 4 than experienced consumers are, and likely drive congestion right after a voucher is released. The results also show that experienced consumers are more likely to redeem vouchers at the last minute, contributing more to the second peak in Figure 4 than the first timers do.

A few different interpretations are possible. One may argue that consumers wait longer before redeeming their next deals because they try to avoid the "crowds" that made their

[33] Using redemption data for deals that have at least 30 days as the redemption period, we divide it into three periods: the first 10 days, the last 10 days, and the rest, and use the multinomial logit model to estimate the probability of choosing a redemption time out of these three periods. Results and implications are similar as those of Table 7.

[34] In Appendix D we use a proportional hazard model to estimate individual consumers' probability of redeeming a voucher and find similar results. Estimation results show that the hazard ratio goes down as consumers redeem more vouchers, implying that consumers tend to redeem vouchers later as they redeem more vouchers.

previous redemption experience unpleasant. Another may argue that online shoppers become better planners as they buy and redeem more deals such that they buy deals that they plan to redeem a month or two later. However, the result that experienced consumers are more likely to redeem vouchers at the last minute makes these arguments refutable and invites further investigations. Whatever the reason behind this change in the redemption time, smoothing out the redemption time is crucial for the success of the daily-deal industry and this is especially so considering the fact that small businesses are the main vendors on daily-deal sites.

## Conclusions

In this paper we empirically analyze consumers' purchase and redemption times of daily deals using consumer-level data from one of the major daily-deal sites in Korea. We first test if there exists a surge of voucher sales as deals approach the tipping point. Because we observe the exact time of each purchase, we know exactly when deals were activated. We find that voucher sales jump right after deals reach the tipping point. We next turn our attention to individual consumers and analyze how their purchase and redemption times are related to their shopping experiences. We find that typical consumers buy deals that are already activated in their first few purchases but tend to buy earlier as they buy more deals. Experienced shoppers are more likely to buy before deals reach the tipping point but we do not find evidence that they do so in order to make deals become active. Rather they tend to buy deals as soon as they are posted online. We also find that typical consumers redeem their first vouchers right after their purchases but tend to wait longer as they redeem more vouchers.

Our findings on purchase time suggest that the group shopping feature of the daily deal does not necessarily generate extra sales and may even discourage inexperienced shoppers from buying deals early on. As consumers buy more deals, however, they seem to learn that almost all deals reach the tipping point and that there is no cost to buying deals before they are activated. Our findings on redemption time provide evidence that inexperienced shoppers drive congestion right after deals are sold. When all these findings are put together, it is hard to claim that the early success of the daily-deal business was due to the group shopping features.

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**Table 1: Product Summary Statistics**

| Variable | Mean | Stdev | Median | Min | Max |
|---|---|---|---|---|---|
| Product Sales | 1,727 | 8,186 | 800 | 5 | 300,000 |
| Original Price (in KW† ) | 76,407 | 253,051 | 33,000 | 0 | 9,999,000 |
| Discount Rate (%) | 55.76 | 9.07 | 52 | 0 | 100 |
| Sale Periods (in days) | 1.59 | 1.03 | 1 | 1 | 19 |
| Tipping Point | 112 | 560 | 50 | 2 | 20,000 |
| Maximum Sale | 3,461 | 11,328 | 1,500 | 8 | 300,000 |
| Redemption Periods (in days) | 82.09 | 58.19 | 90 | 0 | 1826 |
| Soldout‡ | 0.183 | 0.386 | 0 | 0 | 1 |

†KW denotes Korean Won. 1,200 Korean Won is approximately equal to one US dollar.
‡Soldout indicates whether the number of vouchers sold reached the maximum number of vouchers available.
*Note*: The summary statistics on 2,617 deals that were sold at a daily-deal site we obtained data from. These deals include all deals that were sold for one year since the starting date of its business.

**Table 2: Sales Analysis: OLS**

| Variable | All | Subsample I | Subsample II |
|---|---|---|---|
| Discount Rate | $0.024^{**}$ | $0.021^{**}$ | $0.032^{**}$ |
| | (0.002) | (0.004) | (0.005) |
| log(Price) | $-0.664^{**}$ | $-0.613^{**}$ | $-0.553^{**}$ |
| | (0.021) | (0.038) | (0.042) |
| Tipping Point (in 100) | $0.013^{**}$ | $0.023^{**}$ | $0.024^{**}$ |
| | (0.003) | (0.011) | (0.011) |
| Max. Sale (in 1,000) | $0.025^{**}$ | $0.060^{**}$ | $0.068^{**}$ |
| | (0.002) | (0.006) | (0.007) |
| Redemption Periods | $0.001^{**}$ | $0.004^{**}$ | $0.004^{**}$ |
| | (0.000) | (0.001) | (0.001) |
| D_salesday | $0.292^{**}$ | $0.346^{**}$ | - |
| | (0.071) | (0.069) | - |
| Monday | $-0.184^{**}$ | -0.024 | -0.068 |
| | (0.075) | (0.084) | (0.087) |
| Tuesday | $-0.132^{*}$ | -0.065 | -0.141 |
| | (0.079) | (0.087) | (0.088) |
| Wednesday | $-0.187^{**}$ | 0.097 | 0.068 |
| | (0.076) | (0.086) | (0.088) |
| Thursday | -0.074 | -0.121 | -0.091 |
| | (0.079) | (0.084) | (0.087) |
| Restaurant | $0.224^{**}$ | $0.408^{**}$ | $0.693^{**}$ |
| | (0.060) | (0.109) | (0.119) |
| Pub | $-0.432^{**}$ | $-0.300^{**}$ | 0.055 |
| | (0.081) | (0.131) | (0.137) |
| Cafe | $-0.448^{**}$ | $-0.235^{*}$ | 0.117 |
| | (0.079) | (0.142) | (0.146) |
| Beauty/Health Care | -0.022 | 0.119 | $0.248^{*}$ |
| | (0.065) | (0.116) | (0.127) |
| Leisure | 0.013 | 0.104 | 0.190 |
| | (0.079) | (0.142) | (0.174) |
| Concert/Exhibition | -0.030 | $0.201^{*}$ | $0.475^{**}$ |
| | (0.070) | (0.122) | (0.139) |
| Adj. R-squared | 0.523 | 0.614 | 0.611 |
| N | 2,613 | 679 | 506 |

$^{*}$ p-value < 0.1, $^{**}$ p-value < 0.05

*Note*: The dependent variable is log(Sales). We also include the dummy variables for weeks that deals were sold and the dummy variables for market locations. Four deals that have zero price are not included in the regressions. Subsample I only includes deals that were sold during a three month period and Subsample II excludes deals that were sold for multiple days from Subsample I.

**Table 3: Consumer Summary Statistics**

| Variable | Mean | Stdev | Median | Min | Max |
|---|---|---|---|---|---|
| Gender (Male=1) | 0.36 | 0.48 | 0 | 0 | 1 |
| Age | 31.4 | 7.04 | 30 | 8 | 97 |
| SMS (Yes=1) | 0.56 | 0.50 | 1 | 0 | 1 |
| e-mail (Yes=1) | 0.52 | 0.50 | 1 | 0 | 1 |
| Purchase[†] | 1.96 | 1.94 | 1 | 1 | 158 |
| Volume of Order[‡] | 2.01 | 1.47 | 1 | 1 | 40 |

[†]Purchase indicates the number of deals that these consumers bought during the three month period.
[‡]Volume of Order indicates the number of vouchers consumers bought per deal.
*Note*: The summary statistics on 253,151 consumers who bought at least one deal for a three month period.

**Table 4: Sales around the Tipping Point**

| Interval | Time | N | Mean | Stdev | Median | Min | Max |
|---|---|---|---|---|---|---|---|
| 1 | -30 to -25 min | 2,211 | 4.73 | 27.58 | 2 | 0 | 940 |
| 2 | -25 to -20 min | 2,334 | 6.58 | 59.23 | 2 | 0 | 2,261 |
| 3 | -20 to -15 min | 2,462 | 7.66 | 58.62 | 2 | 0 | 1,998 |
| 4 | -15 to -10 min | 2,578 | 12.86 | 176.79 | 3 | 0 | 8,232 |
| 5 | -10 to -5 min | 2,609 | 15.03 | 153.08 | 3 | 0 | 5,454 |
| 6 | -5 to 0 min | 2,617 | 17.19 | 131.64 | 4 | 0 | 4,645 |
| 7 | 0 to 5 min | 2,617 | 21.08 | 141.61 | 6 | 1 | 4,502 |
| 8 | 5 to 10 min | 2,617 | 18.68 | 133.52 | 3 | 0 | 4,589 |
| 9 | 10 to 15 min | 2,617 | 17.95 | 129.50 | 3 | 0 | 4,241 |
| 10 | 15 to 20 min | 2,617 | 16.76 | 119.64 | 3 | 0 | 4,083 |
| 11 | 20 to 25 min | 2,617 | 15.83 | 112.56 | 3 | 0 | 4,226 |
| 12 | 25 to 30 min | 2,617 | 15.33 | 115.48 | 3 | 0 | 4,503 |
| 13 | 30 to 35 min | 2,617 | 14.26 | 110.71 | 3 | 0 | 4,289 |

*Note*: For each deal we take 30 minutes before and 35 minutes after deals were activated and divide them into 13 five minute intervals. The table shows the summary statistics for the number of voucher sales in each of the thirteen 5 minute intervals. Some deals reached the tipping point in less than 30 minutes after they were posted online, which makes the number of observations less than 2,617 for the first 5 intervals.

**Table 5: Linear Regressions with Deal Fixed Effects**

| Variable | Specification 1 | | Specification 2 | | Specification 3 | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | -3.432** | -3.764** | -1.265** | 1.573** | -4.017** | 0.285 |
| | (0.531) | (0.653) | (0.534) | (0.685) | (0.592) | (1.149) |
| before_TP† | -0.300** | -0.263** | -0.179** | -0.029 | | |
| | (0.012) | (0.013) | (0.015) | (0.018) | | |
| -25 to -20 min | | | | | 0.051** | 0.016 |
| | | | | | (0.020) | (0.019) |
| -20 to -15 min | | | | | 0.117** | 0.051** |
| | | | | | (0.020) | (0.021) |
| -15 to -10 min | | | | | 0.197** | 0.090** |
| | | | | | (0.021) | (0.023) |
| -10 to -5 min | | | | | 0.293** | 0.100** |
| | | | | | (0.021) | (0.026) |
| -5 to 0 min | | | 0.243** | 0.116** | 0.418** | 0.187** |
| | | | (0.015) | (0.015) | (0.022) | (0.030) |
| 0 to 5 min | | | 0.546** | 0.553** | 0.913** | 0.659** |
| | | | (0.016) | (0.015) | (0.023) | (0.034) |
| 5 to 10 min | | | | | 0.404** | 0.143** |
| | | | | | (0.025) | (0.038) |
| 10 to 15 min | | | | | 0.394** | 0.131** |
| | | | | | (0.026) | (0.043) |
| 15 to 20 min | | | | | 0.395** | 0.120** |
| | | | | | (0.027) | (0.047) |
| 20 to 25 min | | | | | 0.394** | 0.103** |
| | | | | | (0.029) | (0.051) |
| 25 to 30 min | | | | | 0.432** | 0.125** |
| | | | | | (0.030) | (0.056) |
| 30 to 35 min | | | | | 0.447** | 0.121** |
| | | | | | (0.032) | (0.061) |
| Time Effects‡ | 30 min | 10 min | 30 min | 10 min | 30 min | 10 min |
| Deal FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 33,130 | 33,130 | 33,130 | 33,130 | 33,130 | 33,130 |
| $R^2$ | 0.727 | 0.771 | 0.741 | 0.782 | 0.743 | 0.783 |

* p-value < 0.1, ** p-value < 0.05

†The dummy variable indicating that the tipping point has not been reached yet.

‡We control for the time effects using the clock interval dummies.

*Note*: The dependent variable is the log of voucher sales in each of the thirteen 5 minute intervals.

**Table 6: Purchase Before Deals are Activated**

| Variable | Binary Logistic | FE Logit |
|---|---|---|
| First Purchase | $-0.987^{**}$ | $-0.487^{**}$ |
| | (0.028) | (0.054 ) |
| Second Purchase | $-0.697^{**}$ | $-0.307^{**}$ |
| | (0.027) | (0.048) |
| Third Purchase | $-0.465^{**}$ | $-0.187^{**}$ |
| | (0.027) | (0.044) |
| Fourth Purchase | $-0.361^{**}$ | $-0.143^{**}$ |
| | (0.028) | (0.041) |
| Fifth Purchase | $-0.280^{**}$ | $-0.113^{**}$ |
| | (0.030) | (0.034) |
| No Redemption | $-0.201^{**}$ | $-0.097^{*}$ |
| | (0.028) | (0.054) |
| One Redemption | $-0.234^{**}$ | -0.052 |
| | (0.026) | (0.046) |
| Two Redemptions | $-0.169^{**}$ | 0.010 |
| | (0.027) | (0.042) |
| Volume of Order | $-0.051^{**}$ | $-0.037^{**}$ |
| | (0.006) | (0.010) |
| Age | $-0.019^{**}$ | |
| | (0.001) | |
| Male | $0.219^{**}$ | |
| | (0.013) | |
| e-mail | $-0.118^{**}$ | |
| | (0.020) | |
| SMS | $-0.083^{**}$ | |
| | (0.018) | |
| e-mail · SMS | $0.107^{**}$ | |
| | (0.026) | |
| Preferred Area | -0.009 | $0.081^{**}$ |
| | (0.014) | (0.026) |
| N | 370,616 | 71,402 |

$^{*}$ p-value < 0.1, $^{**}$ p-value < 0.05

*Note*: We estimate the probability of buying deals before they are activated, conditional on buying deals. In addition to the variables reported in the table, we also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

**Table 7: Redemption Time**

| | First 10 Days | | Last 10 Days | |
|---|---|---|---|---|
| **Variable** | **Binary Logistic** | **FE Logit** | **Binary Logistic** | **FE Logit** |
| One Purchase | 0.205** | 2.284** | 0.682** | -4.287** |
| | (0.023) | (0.091) | (0.031) | (0.254) |
| Two Purchases | -0.070** | 1.121** | 0.664** | -2.542** |
| | (0.022) | (0.070) | (0.028) | (0.196) |
| Three Purchases | -0.161** | 0.557** | 0.583** | -1.539** |
| | (0.022) | (0.059) | (0.027) | (0.162) |
| Four Purchases | -0.168** | 0.279** | 0.455** | -0.908** |
| | (0.023) | (0.052) | (0.026) | (0.138) |
| Five Purchases | -0.162** | 0.074 | 0.319** | -0.545** |
| | (0.024) | (0.048) | (0.027) | (0.116) |
| First Redemption | 1.898** | 7.253** | -2.094** | -7.890** |
| | (0.027) | (0.072) | (0.031) | (0.094) |
| Second Redemption | 1.334** | 5.561** | -1.468** | -5.788** |
| | (0.026) | (0.062) | (0.028) | (0.077) |
| Third Redemption | 0.966** | 4.280** | -1.027** | -4.273** |
| | (0.026) | (0.055) | (0.026) | (0.065) |
| Fourth Redemption | 0.666** | 3.198** | -0.668** | -2.993** |
| | (0.028) | (0.051) | (0.026) | (0.057) |
| Fifth Redemption | 0.481** | 2.300** | -0.482** | -1.973** |
| | (0.032) | (0.050) | (0.028) | (0.050) |
| Volume of Order | 0.138** | 0.129** | -0.169** | -0.214** |
| | (0.004) | (0.010) | (0.006) | (0.015) |
| Age | -0.008** | | 0.007** | |
| | (0.001) | | (0.001) | |
| Male | 0.198** | | -0.123** | |
| | (0.010) | | (0.012) | |
| e-mail | -0.046** | | 0.101** | |
| | (0.015) | | (0.019) | |
| SMS | 0.015 | | 0.061** | |
| | (0.014) | | (0.017) | |
| e-mail · SMS | 0.022 | | -0.056** | |
| | (0.020) | | (0.024) | |
| Preferred Area | 0.087** | 0.024 | -0.176** | -0.121** |
| | (0.011) | (0.030) | (0.013) | (0.034) |
| N | 267,143 | 96,892 | 267,143 | 68,867 |

* p-value < 0.1, ** p-value < 0.05

*Note*: We also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

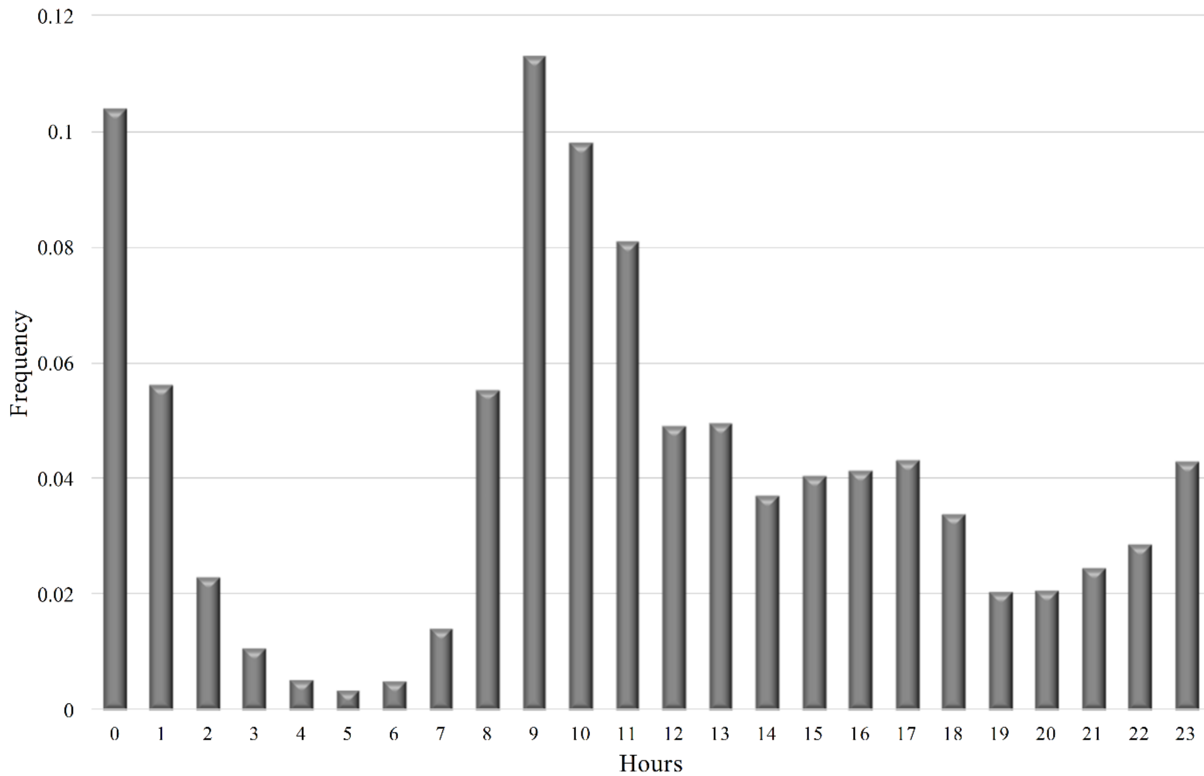
**Table 8: Redemption Time: Linear Regression**

| Variable | OLS | Fixed Effect |
|---|---|---|
| One Purchase | 8.376** | -6.399** |
| | (0.296) | (0.535) |
| Two Purchases | 9.764** | 0.113 |
| | (0.275) | (0.446) |
| Three Purchases | 9.052** | 3.163** |
| | (0.269) | (0.394) |
| Four Purchases | 7.383** | 3.759** |
| | (0.272) | (0.362) |
| Five Purchases | 5.710** | 3.187** |
| | (0.282) | (0.345) |
| First Redemption | -39.816** | -85.460** |
| | (0.308) | (0.320) |
| Second Redemption | -28.918** | -64.943** |
| | (0.288) | (0.286) |
| Third Redemption | -20.694** | -48.577** |
| | (0.282) | (0.266) |
| Fourth Redemption | -14.176** | -35.131** |
| | (0.292) | (0.261) |
| Fifth Redemption | -9.754** | -24.175** |
| | (0.323) | (0.270) |
| Volume of Order | -2.388** | -1.784** |
| | (0.054) | (0.067) |
| Age | 0.113** | |
| | (0.009) | |
| Male | -2.769** | |
| | (0.126) | |
| e-mail | 1.163** | |
| | (0.191) | |
| SMS | 0.072 | |
| | (0.177) | |
| e-mail · SMS | -0.332 | |
| | (0.250) | |
| Preferred Area | -2.466** | -1.185** |
| | (0.136) | (0.181) |
| Adj. $R^2$ | 0.199 | 0.106 |
| N | 267,143 | 267,143 |

* p-value < 0.1, ** p-value < 0.05

*Note*: We also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

**Figure 1: At What Time Consumers Buy Deals**



## Figure 2: When Deals Reach the Tipping Point

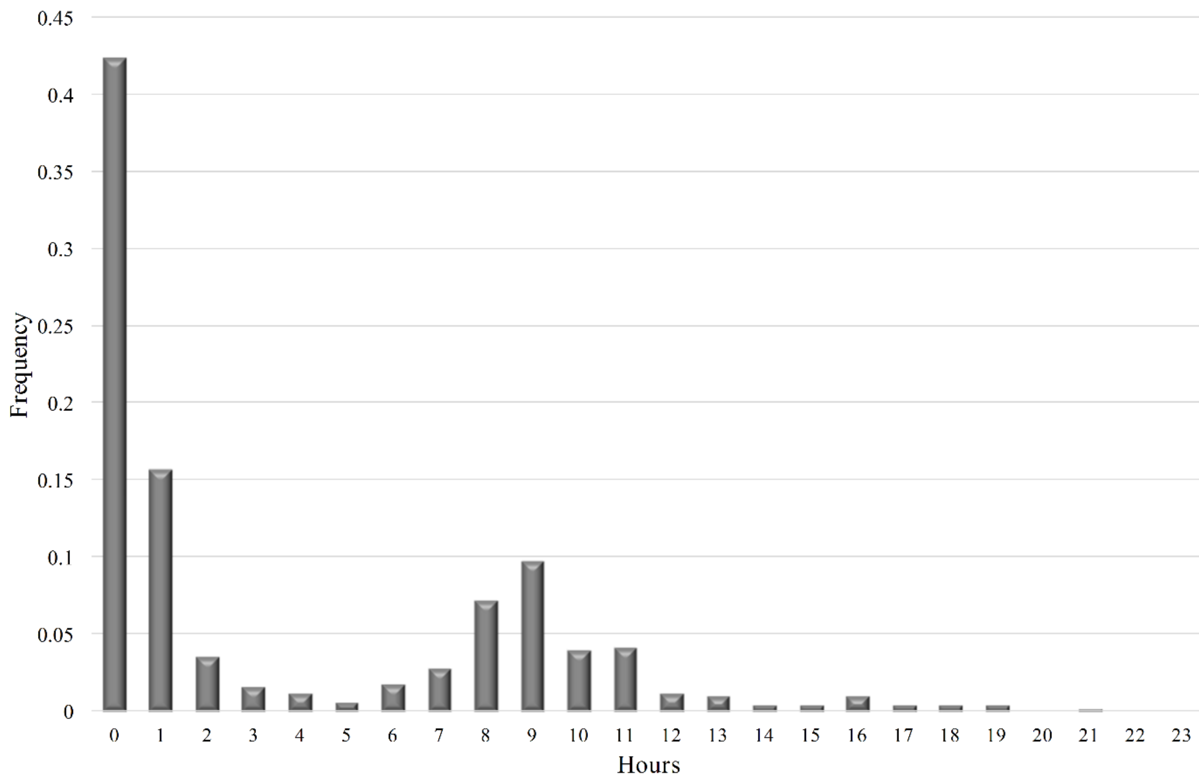
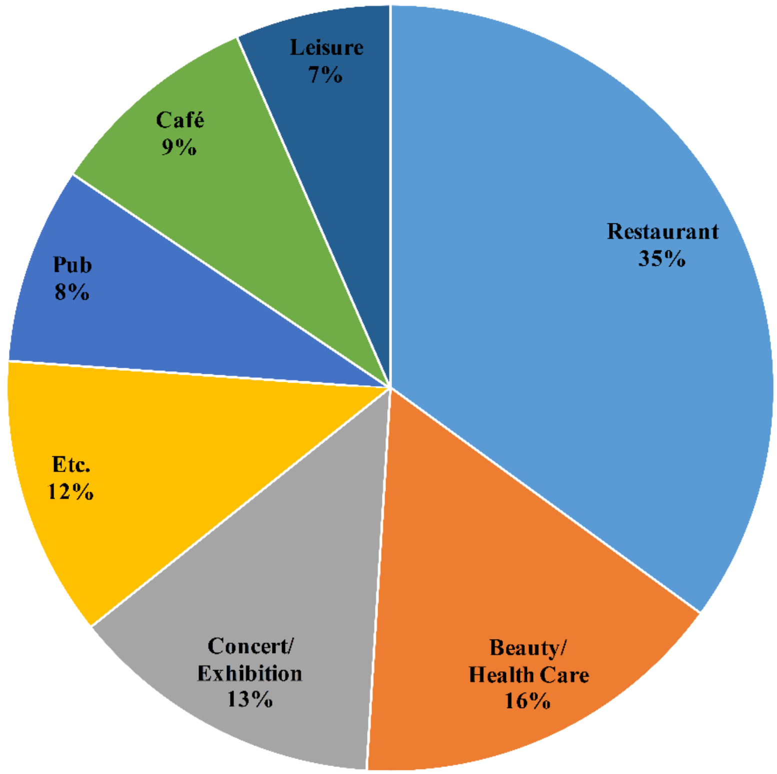
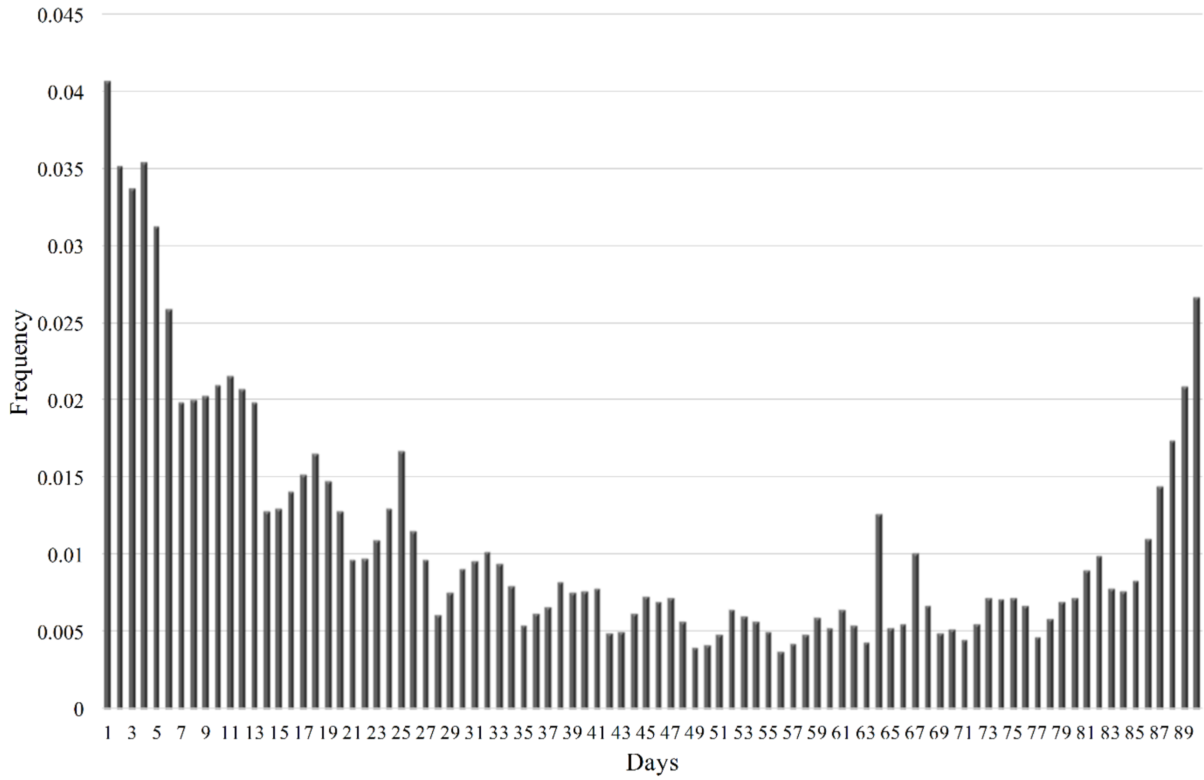


**Figure 3: Deal Categories**



## Figure 4: When Vouchers are Redeemed



## Appendix A: Alternative Specifications for Table 5

In Table 5 we use the 5 minute interval dummy variables to show that voucher sales temporarily jump right after deals reach the tipping point. In this section we estimate the tipping point effect using alternative specifications. In particular, we use the number of voucher sales that is needed to make a deal reach the tipping point in lieu of the 5 minute interval dummies. We create a "distance" variable that measures a gap between current cumulative sales and the tipping point. For example, if the tipping point for a deal were 100 voucher sales and the cumulative sales at time *t* (say 10 minutes before the deal reached the tipping point) were 80, the distance variable would be 20. One advantage of using the distance variable is that it is a variable that consumers observe at the time of purchase. However, the distance variable has the same marginal effect on voucher sales in any time period, say 20 minutes before a deal reaches the tipping point or 5 minutes before a deal reaches the tipping point, and this is not suitable for testing our hypothesis because we need to test if there are jumps or drops in the sales trend around the tipping point. Nevertheless, we show here how results differ from those in Table 5.

Consider

$$\begin{aligned} &log(sales_{ij}+1) \\ &= \beta_0 + \alpha_1 dist_{i,TP} D_{beforeTP} + \alpha_2 dist_{i,TP}(1 - D_{beforeTP}) + \gamma_{time} D_{time} + \delta_j D_j + u_{ij} \end{aligned} \quad \text{(A.1)}$$

where $dist_{i,TP} = log\left(\left|TP_i - \sum_{s=1}^{s=j-1} sales_{is}\right| + 1\right)$ and $TP_i$ denotes the voucher sales that activate deal *i* . The coefficients, $\alpha_1$ and $\alpha_2$, measure how voucher sales change around the tipping point. The negative sign of $\alpha_1$, for example, implies that voucher sales increase as a deal becomes closer to the tipping point while the negative sign of $\alpha_2$ implies that voucher sales decreases as a deal moves away from the tipping point after reaching it. Notice, however, that

$dist_{i,TP}$ is a function of voucher sales in the past time periods, and as a result the strict exogeneity condition needed for the fixed effects estimator does not hold any more.

An estimator commonly used in such a situation is the first difference instrumental variable estimator.[35] Thus, we take the first difference, denoted Δ, for all variables except for the time dummies and estimate.

$$\Delta log\left(sales_{ij}+1\right) = \alpha_1 \Delta dist_{i,TP} D_{beforeTP} + \alpha_2 \Delta dist_{i,TP}(1-D_{beforeTP}) + \gamma_{time} D_{time} + \Delta u_{ij} \tag{A.2}$$

where $\Delta dist_{i,TP}$ is still an endogenous variable and we use three and four periods lag sales, i.e., $log(sales_{i,j-3}+1)$ and $log(sales_{i,j-4}+1)$, as instruments. Note that because we use the lag sales as instruments, we cannot use voucher sales in the first four 5 minute intervals, i.e., $-30 \leq t < -10$, in estimating this model.

[Insert Table A-1 about here]

The first two columns of Table A-1 show estimation results for the first differencing estimator without using the instruments. The two columns differ by whether the 30 minute clock dummies or the 10 minute clock dummies are included to control for the time-of-the-day effect. Results show that (the log of) the distance variable prior to the tipping point, $\alpha_1$, is not statistically significant at the 10 percent level and its sign changes depending on which time dummies are used, while the distance variable post the tipping point, $\alpha_2$, is negative and statistically significant at the 1 percent level. Columns 3 and 4 of Table A-1 show that these estimates change with the instruments with $\alpha_1$ being negative and statistically significant at the 5

[35] See chapter 11 of Wooldridge (2010) for details.

percent level and $\alpha_2$ positive but not statistically significant.[36] An estimate for $\alpha_1$ is -0.36 with the 30 minute dummies and -0.44 with the 10 minute dummies, implying that voucher sales go up by 0.36 or 0.44 percent when the distance to the tipping point goes down by 1 percent. However, this implied change is restricted to be constant no matter how close a deal is to the tipping point.

In order to test if there is any significant departure in voucher sales from this linear trend around the tipping point, we add the first difference of two 5 interval dummies, one for $-5 \leq t < 0$ and another for the threshold interval, i.e., $0 \leq t < 5$. Columns 5 and 6 of Table A-1 show estimation results with the 30 minute dummies and the 10 minute dummies respectively. Results show that $\alpha_1$ is still negative but no longer statistically significant while $\alpha_2$ is still not statistically significant. The coefficient for the threshold interval is positive and statistically significant at the 1 percent level while the coefficient for the $-5 \leq t < 0$ interval is positive but significant (at the 10 percent level) only with the 30 minute dummies. Moreover, when the estimates for these two coefficients are both significant, i.e., the specification with the 30 minute dummies, they imply that voucher sales are about 10 percent higher during the threshold interval than right before a deal reaches the tipping point. These results show that the tipping point effect reported in Table 5 - that voucher sales jump right after deals reach the tipping point - is robust to these alternative specifications and that a simple sales trend cannot fully account for this effect.

## Appendix B: The Multinomial Logit Model for Purchase Time

In the Purchase Experience and Purchase Time section we use the binary logistic model and the fixed effect logit model to show that inexperienced shoppers tend to wait until deals pass the tipping point while experienced ones tend to buy before deals reach the tipping point. In this

[36] The model is exactly identified as we use two instrumental variables for two endogenous variables and the first-stage F statistics on the two instruments are higher than 10 for both $\Delta dist_{i,TP} D_{beforeTP}$ and $\Delta dist_{i,TP}\,(1 - D_{beforeTP})$. See Table A-1 for details.

section we use the multinomial logit model to investigate customers' purchase time decisions in more granular time units. In particular, we focus on the same time span as in the Tipping Point and Voucher Sales section and estimate the conditional probability of consumer *i* buying a deal in one of the 5 minute intervals around the tipping point. There are 35,323 consumers who bought at least one deal in one of the thirteen 5 minute intervals during the three-month period.

With t defined in the same way as in the Tipping Point and Voucher Sales section, we consider 7 events: (1) buying a deal when $-30 \leq t < -10$ , (2) buying a deal when $-10 \leq t < -5$ , (3) buying a deal when $-5 \leq t < 0$ , (4) buying a deal when $0 \leq t < 5$ , (5) buying a deal when $5 \leq t < 10$ , (6) buying a deal when $10 \leq t < 15$ , and (7) buying a deal when $15 \leq t < 35$ . Note that we do not divide events 1 and 7 into multiple five-minute intervals in order to focus on the time span close to the tipping point.

[Insert Table B-1 about here]

We report the summary statistics of purchase experience for these 7 intervals in Table B-1. Note first that the number of consumers who bought deals in the threshold interval ($0 \leq t < 5$) is highest among the other five-minute intervals. This is consistent with our finding in the Tipping Point and Voucher Sales section that voucher sales go up right after deals are activated. The table also shows that the average number of previous purchases is higher before deals reach the tipping point, which implies that those with little experience are less likely to buy deals before they become active and is consistent with the results in Table 6. The average previous purchases is 4.48 for $-10 \leq t < -5$ while it is 4.09 for $5 \leq t < 10$. The difference is less substantial between right before deals reach the tipping point (4.21) and right after the tipping point (3.96) but the latter is still lower, and the average previous purchase is the lowest (3.72) 10 minutes after deals are activated.

[Insert Table B-2 about here]

Table B-2 show results from the multinomial logit regression with event 7 ($15 \leq t < 35$) as the base outcome. The first purchase dummy is statistically significant in all of the first four events, the second purchase dummy is significant in the first, the second, and the fourth events, the third and the fourth purchase dummies are significant only in the second event, and the fifth purchase dummy is significant in the first two events. The table also shows that none of the redemption experience dummies have significant coefficients. Using these estimates we calculate the probability of buying a deal in each time slot for consumers with different degrees of purchase experience.[37]

The estimated probabilities show that consumers with little purchase experience are less likely to buy deals that have not reached the tipping point. For example, if consumers have no purchase experience, their probability of buying a deal sometime between 5 and 10 minutes before it reaches the tipping point ($-10 \leq t < -5$) is about 11 percent lower compared to those who have bought one deal in the past and about 32 percent lower compared to those who have bought deals more than 5 times in the past.

However, the relationship between purchase experience and purchase time is less pronounced within the 5 minute boundary around the tipping point. The probability that the first-time buyer purchases a deal right before the tipping point is only 9.6 percent lower compared to those who have made more than 5 purchases in the past, and her purchase probability at $-5 \leq t < 0$ is not much different from her purchase probability at $0 \leq t < 5$ . This is not surprising considering the small difference in the average number of previous purchases shown in Table B-1. It may be that

[37] We use the mean value for all regressors except for the experience variables in calculating the probability.

consumers with no purchase experience try to avoid buying deals close to the tipping point whether they have reached the tipping point or not.

Table B-2 also shows that the coefficient on the second purchase dummy for $0 \le t < 5$ is slightly more negative than that of the first purchase dummy (the fourth column of the table). The estimates imply that the probability that first-time buyers purchase a deal right after the tipping point is about 6 percent higher than second-time buyers. Moreover, the second-time buyer's probability of buying a deal right after the tipping point is about 20 percent lower than her probability of buying a deal right before the tipping point. Although these results are not as strong as those in Table 6, they provide consistent evidence that consumers pay less attention to deals' activation status as they gain more experience.

## Appendix C: Purchase Time Before Deals Reach the Tipping Point

In this section we investigate whether experienced buyers are the main driving force behind activating deals. The results presented in Tables 6 and B-2 show that the more deals consumers have bought in the past, the more likely they are to buy their next deal before it becomes active. Do these results suggest that experienced buyers are the main driving force behind activating deals? One may interpret these results as experienced shoppers buying deals that they would not normally purchase for the sake of deal activation because they receive so much utility from activating deals. However, the same results can be interpreted as experienced consumers not paying attention to the tipping point as they have "learned" that almost all deals pass the tipping point and that they do not lose a penny even if a deal they are committed to buy fails to reach the tipping point. In this interpretation experienced shoppers' early-purchase behavior is not necessarily associated with social shopping behavior.

In order to shed more light on purchases prior to the tipping point, we focus on 32,076 voucher sales that took place prior to the tipping point during the three-month period and estimate the multinomial logit model for the probability of the following three events: (1) being part of the first 10 percent purchases, (2) being part of the last 10 percent before deals reach the tipping point, and (3) being part of the middle 80 percent. If a deal needs 100 voucher sales to be activated, for example, event 1 is to buy one of the first 10 vouchers, event 2 is to buy one of the last 10 vouchers, and event 3 is to buy one of the middle 80 vouchers.[38] Note that we estimate the probability conditional on buying deals before they reach the tipping point.

[Insert Table C-1 about here]

The left panel in Table C-1 shows results from the multinomial logit regression with event 3 as the base outcome. We use the same regressors as in Table 6. The table shows that the first three purchase experience dummies are negative and statistically significant for event 1, suggesting that consumers with more purchase experience are more likely to buy deals right after they are posted online. Given that they buy deals before they are activated, the probability that consumers with no prior purchase experience will buy the first 10 percent of the minimum voucher sales is about 43 percent lower compared to those who have bought at least 5 deals in the past. If consumers had bought one or two deals in the past, the probability is about 22 percent lower. The table also shows that the purchase experience dummies are positive but not statistically significant for event 2. The one with the largest magnitude is the first purchase dummy but it is significant only at a 20 percent significance level.

[38] The deal site we have obtained data from displayed the number of purchases in real time during the sample period.

In order to ascertain that these results, especially the results for event 1, are not driven by intrinsic differences between heavy buyers and light buyers we combine events 2 and 3 and estimate the binary logit model and the fixed effect logit model for the probability of buying the first 10 percent of the minimum voucher sales, conditioning on buying deals before they are activated. The right panel in Table C-1 shows results from the binary logistic regression as well as the fixed effect logit regression. The latter regression uses 1,039 consumers who changed their behaviors over time and the total number of observations used is 3,715. The table shows that both regressions confirm the results from the multinomial logit regression, and the fixed effect model shows that these results are not driven by intrinsic differences among consumers.

## Appendix D: Hazard model for voucher redemption

As an alternative model for voucher redemption we estimate a proportional hazard model for individual consumers' probability of redeeming a voucher at each time period, treating redeeming a voucher as "death". In particular, we estimate

$$\lambda(t;X) = \lambda_0(t) exp\left(\sum_{k=1}^{5} \gamma_k P_{ik} + \sum_{r=1}^{5} \delta_t R_{ir} + w_i \alpha + x_j \beta\right) \tag{6}$$

where $\lambda_0(t)$ is the baseline hazard that is common to all consumers and the exponential function captures a proportional difference as a function of the covariates. In Table D-1 we report estimated coefficients on the left panel and the hazard ratio on the right panel.[39] The table shows that the hazard ratio goes down as consumers redeem more vouchers. For example, when a consumer redeems a voucher for the first time, the hazard ratio is 2.69 (=exp(0.988)) and is 68.9 percent higher compared to a consumer who is redeeming a voucher for the third time. In Figure D-1 we divide consumers into five groups by the number of their previous redemptions

[39] The hazard ratio is defined as e to the power of a given coefficient.

($R_{ir}$) and draw the average survival rate over time with all other covariates fixed at their average value.[40]

[Insert Table D-1 & Figure D-1 about here]

The figure shows the average survival rate (the probability of not redeeming) is higher for those with more redemption experience, implying that consumers tend to redeem vouchers later as they redeem more vouchers.

[40] For this graph we estimate the same proportional hazard model using 242 deals (156,152 observations) whose redemption period is between 85 and 95 days. Estimates are similar to the ones reported in Table D-1. For example, the hazard ratio for consumers redeeming a voucher for the first time is 2.61 and is 68.0 percent higher compared to those redeeming for the third time.

**Table A-1: First Difference IV Estimator**

| Variable | Without IVs (1) | Without IVs (2) | With IVs (3) | With IVs (4) | With IVs (5) | With IVs (6) |
|---|---|---|---|---|---|---|
| $\Delta dist_{i,TP} D_{beforeTP}$ | 0.007 | -0.012 | $-0.361^{**}$ | $-0.437^{*}$ | -0.263 | -0.318 |
| | (0.008) | (0.008) | (0.158) | (0.230) | (0.161) | (0.237) |
| $\Delta dist_{i,TP}(1 - D_{beforeTP})$ | $-0.131^{**}$ | $-0.112^{**}$ | 0.188 | 0.317 | 0.225 | -0.348 |
| | (0.010) | (0.010) | (0.176) | (0.268) | (0.190) | (0.299) |
| $\Delta I_{-5 \leq t<0}$ | | | | | $0.292^{*}$ | 0.386 |
| | | | | | (0.168) | (0.268) |
| $\Delta I_{0 \leq t<5}$ | | | | | $0.395^{**}$ | $0.383^{**}$ |
| | | | | | (0.093) | (0.119) |
| Time Effects† | 30 min | 10 min | 30 min | 10 min | 30 min | 10 min |
| Deal FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 30,513 | 30,513 | 22,662 | 22,662 | 22,662 | 22,662 |
| 1st stage F stats‡ | | | 86.018 | 86.037 | 142.019 | 145.775 |
| | | | 103.552 | 94.494 | 93.289 | 80.747 |

* p-value < 0.1, ** p-value < 0.05

† We control for the time effects using the clock interval dummies.

‡ We report the first stage F statistics for testing the joint significance of the two instrumental variables. For each column the first number is for $\Delta dist_{i,TP} D_{beforeTP}$ and the second number for $\Delta dist_{i,TP}(1 - D_{beforeTP})$.

*Note*: The dependent variable is the log of voucher sales in each of the thirteen 5 minute intervals $dist_{i,TP} = log\left(\left|TP_i - \sum_{s=1}^{s=j-1} sales_{is}\right| + 1\right)$ where $TP_i$ denotes the voucher sales that activate deal $i$.

**Table B-1: Summary Statistics for the Number of Previous Purchases**

| Intervals | Time | N | Mean | Stdev | Median | Min | Max |
|---|---|---|---|---|---|---|---|
| 1 | -30 to -10 min | 7,308 | 4.44 | 6.66 | 2 | 0 | 107 |
| 2 | -10 to -5 min | 3,269 | 4.48 | 6.97 | 2 | 0 | 93 |
| 3 | -5 to 0 min | 3,621 | 4.21 | 6.72 | 2 | 0 | 103 |
| 4 | 0 to 5 min | 4,226 | 3.96 | 6.35 | 2 | 0 | 83 |
| 5 | 5 to 10 min | 3,771 | 4.09 | 6.73 | 2 | 0 | 112 |
| 6 | 10 to 15 min | 3,430 | 3.72 | 7.24 | 2 | 0 | 174 |
| 7 | 15 to 35 min | 9,698 | 3.72 | 7.37 | 2 | 0 | 176 |

*Note*: The summary statistics for the number of previous purchases for consumers who bought deals in a three month period.

**Table B-2: Purchase Time: Before and After Tipping Point**

| Variable | -30 to -10 | -10 to -5 | -5 to 0 | 0 to 5 | 5 to 10 | 10 to 15 |
|---|---|---|---|---|---|---|
| First Purchase | -0.345** | -0.402** | -0.215** | -0.217** | -0.107 | -0.074 |
| | (0.074) | (0.093) | (0.091) | (0.086) | (0.089) | (0.092) |
| Second Purchase | -0.207** | -0.247** | -0.133 | -0.228** | -0.120 | -0.027 |
| | (0.070) | (0.088) | (0.086) | (0.082) | (0.085) | (0.088) |
| Third Purchase | -0.094 | -0.287** | -0.094 | -0.109 | -0.026 | -0.019 |
| | (0.070) | (0.090) | (0.087) | (0.082) | (0.085) | (0.089) |
| Fourth Purchase | -0.091 | -0.191** | -0.087 | 0.041 | -0.069 | -0.060 |
| | (0.073) | (0.092) | (0.090) | (0.083) | (0.089) | (0.093) |
| Fifth Purchase | -0.175** | -0.187* | -0.016 | -0.048 | 0.063 | 0.037 |
| | (0.077) | (0.096) | (0.093) | (0.089) | (0.090) | (0.095) |
| No Redemption | -0.099 | 0.115 | -0.059 | -0.068 | -0.030 | 0.010 |
| | (0.072) | (0.090) | (0.088) | (0.083) | (0.086) | (0.090) |
| One Redemption | -0.079 | 0.059 | -0.077 | -0.066 | -0.070 | -0.026 |
| | (0.067) | (0.084) | (0.082) | (0.078) | (0.081) | (0.085) |
| Two Redemptions | -0.020 | 0.005 | -0.088 | -0.121 | -0.061 | -0.114 |
| | (0.068) | (0.086) | (0.084) | (0.081) | (0.083) | (0.089) |
| Volume of Order | -0.045** | -0.013 | 0.021 | 0.042** | 0.0001 | -0.017 |
| | (0.016) | (0.019) | (0.017) | (0.016) | (0.017) | (0.017) |
| Age | -0.004 | -0.002 | -0.003 | 0.0001 | 0.003 | 0.001 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) |
| Male | 0.060* | -0.038 | 0.059 | -0.025 | -0.063 | -0.060 |
| | (0.034) | (0.044) | (0.042) | (0.039) | (0.041) | (0.042) |
| e-mail | -0.068 | 0.008 | 0.006 | -0.003 | -0.121* | -0.048 |
| | (0.053) | (0.067) | (0.064) | (0.060) | (0.063) | (0.064) |
| SMS | 0.065 | 0.046 | 0.054 | -0.076 | 0.020 | -0.036 |
| | (0.050) | (0.063) | (0.060) | (0.057) | (0.058) | (0.061) |
| e-mail · SMS | 0.044 | 0.012 | -0.018 | 0.050 | -0.001 | 0.044 |
| | (0.071) | (0.089) | (0.085) | (0.080) | (0.084) | (0.086) |
| Preferred Area | 0.117** | 0.191** | 0.214** | 0.066 | 0.120** | 0.106** |
| | (0.038) | (0.049) | (0.047) | (0.044) | (0.046) | (0.047) |

* p-value < 0.1, ** p-value < 0.05

*Note*: We estimate the probability of buying deals in one of the time slots, conditional on buying deals between 30 minutes before and 35 minutes after the tipping point. We also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

**Table C-1: Purchases Prior to the Tipping Point**

| Variable | Multinomial Logit First 10%† | Multinomial Logit Last 10%‡ | Binary Logit First 10% | FE Logit First 10% |
|---|---|---|---|---|
| First Purchase | -0.423** | 0.126 | -0.720** | -0.510** |
| | (0.097) | (0.095) | (0.091) | (0.237) |
| Second Purchase | -0.240** | 0.079 | -0.394** | -0.297 |
| | (0.091) | (0.091) | (0.085) | (0.211) |
| Third Purchase | -0.293** | 0.060 | -0.38* | -0.263 |
| | (0.091) | (0.091) | (0.086) | (0.193) |
| Fourth Purchase | -0.154* | -0.026 | -0.232** | -0.308* |
| | (0.092) | (0.096) | (0.087) | (0.176) |
| Fifth Purchase | -0.161 | 0.127 | -0.212** | -0.136 |
| | (0.099) | (0.099) | (0.084) | (0.167) |
| No Redemption | 0.018 | -0.108 | 0.002 | -0.017 |
| | (0.090) | (0.094) | (0.084) | (0.230) |
| One Redemption | -0.074 | -0.061 | -0.062 | -0.085 |
| | (0.083) | (0.088) | (0.078) | (0.184) |
| Two Redemptions | -0.127 | -0.151 | -0.103 | -0.017 |
| | (0.084) | (0.092) | (0.080) | (0.168) |
| Volume of Order | -0.102** | 0.086** | -0.111** | -0.128** |
| | (0.024) | (0.018) | (0.022) | (0.049) |
| Age | 0.004 | -0.007** | -0.005 | |
| | (0.003) | (0.003) | (0.003) | |
| Male | -0.039 | 0.005 | -0.004 | |
| | (0.044) | (0.043) | (0.041) | |
| e-mail | 0.051 | -0.065 | 0.006 | |
| | (0.069) | (0.066) | (0.063) | |
| SMS | 0.007 | -0.017 | -0.050 | |
| | (0.066) | (0.061) | (0.061) | |
| e-mail · SMS | 0.026 | 0.070 | 0.085 | |
| | (0.092) | (0.087) | (0.085) | |
| Preferred Area | 0.032 | -0.019 | 0.029 | 0.183* |
| | (0.050) | (0.048) | (0.046) | (0.110) |
| N | 32,076 | | 32,076 | 3,715 |

* p-value < 0.1, ** p-value < 0.05
† First 10% indicates buying the first 10% of the minimum voucher sales. ‡ Last 10% indicates buying the last 10% of the minimum voucher sales.
*Note*: We also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

**Table D-1: Redemption Time: Cox Proportional Hazard Regression**

| Variable | Coefficient | Hazard Ratio |
|---|---|---|
| One Purchase | -0.356** | 0.701** |
| | (0.009) | (0.007) |
| Two Purchases | -0.336** | 0.715** |
| | (0.009) | (0.006) |
| Three Purchases | -0.272** | 0.762** |
| | (0.009) | (0.007) |
| Four Purchases | -0.208** | 0.812** |
| | (0.009) | (0.007) |
| Five Purchases | -0.150** | 0.860 |
| | (0.009) | (0.008) |
| First Redemption | 0.988** | 2.686** |
| | (0.010) | (0.027) |
| Second Redemption | 0.674** | 1.961** |
| | (0.009) | (0.019) |
| Third Redemption | 0.464** | 1.590** |
| | (0.010) | (0.015) |
| Fourth Redemption | 0.306** | 1.357** |
| | (0.010) | (0.013) |
| Fifth Redemption | 0.207** | 1.230** |
| | (0.011) | (0.013) |
| Volume of Order | 0.072** | 1.075** |
| | (0.002) | (0.002) |
| Age | -0.004** | 0.996** |
| | (0.0002) | (0.0003) |
| Male | 0.084** | 1.088** |
| | (0.004) | (0.005) |
| e-mail | -0.028** | 0.972** |
| | (0.006) | (0.006) |
| SMS | 0.003 | 1.003 |
| | (0.006) | (0.006) |
| e-mail · SMS | 0.008 | 1.008 |
| | (0.008) | (0.008) |
| Preferred Area | 0.079** | 1.082** |
| | (0.004) | (0.004) |
| N | 267,144 | |

* p-value < 0.1, ** p-value < 0.05

*Note*: We also control for the deal characteristics reported in Table 1, days of the week, weeks that deals were sold, deal categories, market locations, and weeks that consumers made accounts.

**Figure D-1: Kaplan-Meier curve from Cox proportional hazards model**