For Whom the Counter Tolls

Signaling in the Economy Daily Deals

Katya Vasilaky and Blake Hall

May 6, 2012

Abstract

To evaluate the impact of the daily deals model on buying behavior, we exploit the randomized display of a purchase counter that aggregates real time purchases on a daily deals site. In particular, we look at heterogeneous effects of the purchase counter by gender, given that 60 of our users are female, and 80% of our active user base is female. Compared to females who do not see the counter, females who do see the counter are 50 % more likely to make a daily deals purchase controlling for the category, price, and user's tenure on the site, while the effects of the counter on male's purchasing behavior are not statistically significant.

JEL: O, Q

1 Intro

The flash sales or daily deals model has emerged over the last five years as a predominant model in online sales(Dholakia 2011, Ye et al 2011, Byers et. al 2011, Edelman 2011). Sites like Living Social and Groupon have dominated this market, acquiring online users in the hundreds of millions, with a higher proportion of female users. In addition to the limited time that a product is offered, a distinguishing feature of the daily deal model is the use of a purchase counter on the site, which displays the cumulative number of purchases made in real time to the buyer. The underlying behavioral assumption of displaying the counter is that customers are more likely to experience loss aversion at the tail end of a deal's life cycle. The validity and quality of an offer will increase with the number of reported purchases displayed, and the length of time that the deal has run, increasing the probability of a purchase for any given user.

Daily deals or flash sales aim to narrow the margins between what buyers are willing to pay and sellers are willing to accept through a third party online distributor, by reducing the moral hazard that businesses impose on their consumers. Purchasing from an unknown business poses a risk to consumer, because of the latter information asymmetry between the business and the consumer. And that risk is increasing in price. Unless the user is aware of the quality of the good, and the fine print around purchasing an item, price does not inherently reflect the quality of the good or service when the seller has more information than the buyer (Akerloff 1970). From the perspective of classical utility maximixation, daily deals sites minimize this risk by reducing the information gap around the good'd quality, and by decreasing the price by as much as 50 percent. From a behavioral perspective, the daily deal model increases the perception of a good or services scarcity by limiting the duration of the offer, and maximizing its perceived appeal via the deal counter. These four effects aim to increase the purchasing rate for a good above it's market equilibrium. In return for the discount, businesses gain the opportunity to market to an audience often greater than their own, where a deal site's user base can range from the tens of thousands to the hundreds of millions.

By viewing whether a critical[1] number of people purchased the deal, consumers receive real time feedback on the offer's quality. Hu et al. (2002) model this aspect of daily deals, namely that buyers sequentially view one another's cumulative purchases. They show that this "sequential buying" generates higher deal success rates compared to simultaneous buying (or no display of a counter). Varian (1994) and Gachter (2010) find reverse results in the context of publics goods contributions. Contributions are lower with a sequential mechanism due to the incentive to free ride on previous contributions. Ye et.al. (2011) simulate a model that assumes an inflection point around a deal's tipping point, which generates a linear demand curve up to the tipping point, followed by an asymptotic demand curve and then concave demand. They are able to empirically match their simulations with Groupon data with significant confidence.

This study aims to answer whether the use of sequential buying is more profitable than listing offers without any purchasing information, and whether it changes purchasing behavior. The difficulty in testing this assumption lies in the need for a simultaneous counterfactual, namely viewing the average person's choice with and without

[1] "Critical" is of course specific to the deal site and maturity of the user. A novice user may not understand whether 20 purchases is greater or less then the average number of purchases for a given category on a deal site.

his or her observance of a purchase counter. A blanket comparison of purchases before and after a counter's display will result in a biased estimated of the counter's effect. Purchases are correlated with unobservable buying habits that may be correlated with counter's effect.

Another logistical issue in measuring the counter's effect is that while the counter is assumed to be profitable for a business, it exposes a company's sales or performance data to its competitors. That companies like Groupon have obfuscated their purchase count by only displaying a minimum number purchased after a period of time, while Yipit (a daily deals aggregator) has hidden it entirely. Contrasted against previous disclosures of information, these actions suggest that companies are aware that exposing social data to consumers has a positive effect on purchases but a negative effect on preventing competitors from copying their deals, particularly if those competitors previously lacked information about market conventions and margins.

This phenomenon of quantifying and displaying online content consumption and purchasing is not novel. Early web sites frequently employed a traffic counter on the home page to signal popularity, but the purchase counter takes this a step further by monetizing that popularity. Displaying purchasing behavior in real time encourages users to both learn and follow form the behavior others, analogous to well known theories on herd behavior and information cascades (Bikhchandani et. al,1998).

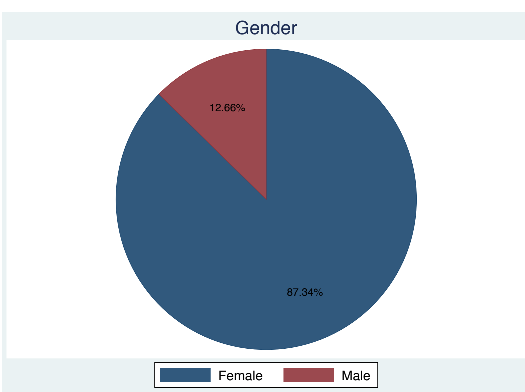
Quantifying signaling effects, however, is a challenge. By using our own data from a currently active daily site, and randomly assigning the counter to only some users, we are able to circumvent the endogeniety of the counter's effect, and can verify the number of purchases. In addition, we can look at heterogeneous effects across gender and user type. While the Economics literature has studied herd behavior at large, the Marketing literature points to considerable differences in consumer behavior across gender. Women comprise a majority of daily deal purchases on our own site as well as sites like Groupon (TechCrunch, 2011). But do women respond any differently to external consumer stimuli of herd behavior?

In the following sections, we look describe the population, data collected, experimental design, estimation, and results.

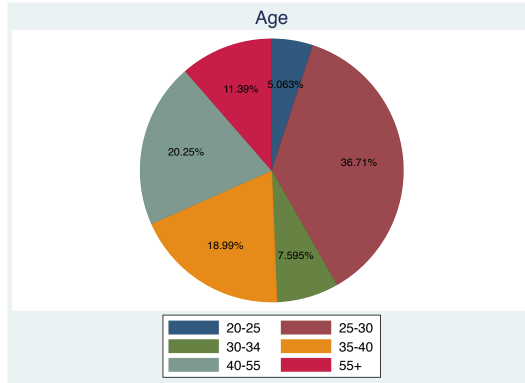
2 Data Description

Data are collected from a daily deals site across three separate US locations on the East and West Coast. Deals range in category from experiential deals–adventures, vacations, restaurant offers, spas–to necessary goods and services–home cleaning, home appliances, dental and eye care services. The typical discount is fifty percent off the average retail price. Upon subscription, the user begins to receive offers via email at daily or near-daily frequency that are specific to their locale. These emailed offers drive consumers to the deal site to check on its popularity with the deal counter.

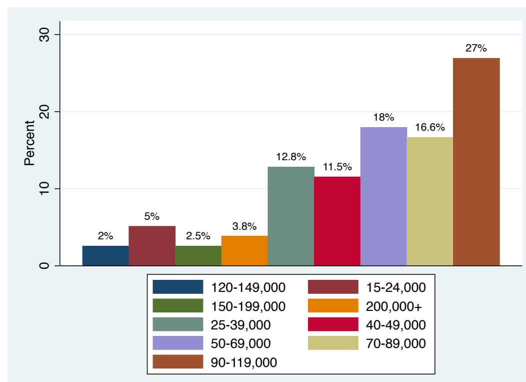
Demographically, 80 percent of our sample is female. This is true both from a survey of randomly sampled subset of our population, and with the current sample of users who participated in the experiment.



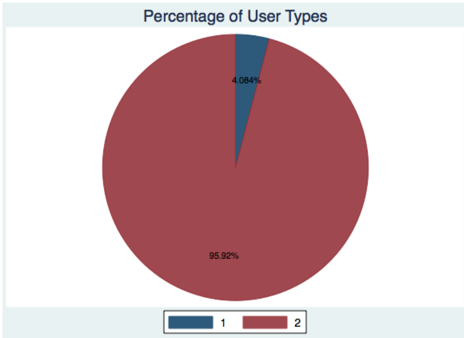
Users' ages range between 25 and 35.



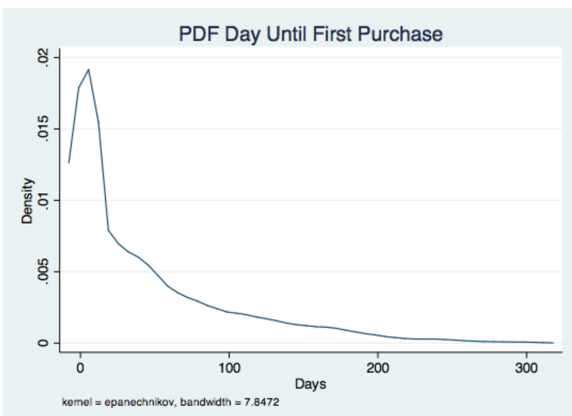
Income is evenly distributed across a range of twenty-five thousand dollars per annum to one hundred and twenty thousand dollars per annum.



User types in this sample are predominantly those who have already made a purchase on the site, as they are users who tend to frequent the site in any given week.



Purchasing the same day or a day after registering has the highest probability in terms of time to first purchase.



The difficultly in testing whether the counter's display has a positive effect on conversions is the inability to compare the same individual's purchasing behavior with and in the absence of the counter without order effects. A blanket comparison of two different groups who view and do not view the counter would lead us to the traditional pitfall of biased results. The effects of the counter on purchasing behavior are correlated with individual's unobservable characteristics that may also drive purchasing behavior: attention to one's social network's, computer saviness, differences in discretionary income, etc. Randomization of the counter's visibility to a user provides a simple solution to this endogeneity. Because viewing the counter is randomly assigned, users will be identical on average, in terms of unobservable as well as observable characteristics. Consequently, a simple difference of observed purchasing outcomes between users who can view and cannot view the counter will produce a consistent estimate of the impact of the counter, the social observation it enables, and the increased purchasing rate that it is deemed to generate.

3 Experiment

From February 9th to February 16th, every other user that visited the website was shown the counter. Once assigned or labeled counter or no counter, that label remained with the user, identified by log in, regardless of whether he or she left the site and came back. In order to purchase an item the user must complete a two step process:

Two step action:

Step 1: View deal site

Step 2: Click "Buy Now"

Step 3: Enter credit card number and click submit

The data are an unbalanced panel of purchase amounts ranging from zero to eleven purchases or those users who visited the site during the duration of the experiment. We tracked whether the individual clicked on the "Buy Now" button and whether he or she proceeded to make the purchase. This second step, purchasing, required the user to enter credit card information and then click submit. Some users had signed up for the service prior to the initiation of the experiment and some users signed up for this daily deals site while the experiment was being conducted. All of the users in the former group had seen the counter during previous site visits.

Preliminary results suggest that the presence of the counter has a significant and positive impact on the average number of purchases made by a visitor to the site, doubling the average number of purchases with a greater than 99 percent significance. As such, the counter appears to be a profitable mechanism as has a statistically significant impact on purchase against the one time cost of establishing its presence.

Total Purchased

	No Counter	Counter	p-value
Total purchases	99	220	
Avg purchase	1.2	2.3	0.002

4 Estimation

A logical estimation for estimating the impact of the experiment's is a Heckman selection model, where the Bernoulli decision of viewing making a purchase is estimated by a selection equation where the login count is excluded from the main equation determining total purchased. Namely, the user first selects into purchasing based on her past activity. This is followed by the decision of how much to purchase, where the counter's effect is anticipated to have an effect.

We report coefficient estimates in Table One for both stages of the estimation. Columns one through four estimate the effects of the counter on purchases in two stages. Users who entered the sign over the course of the experiment may or may not have made a purchase, but were nevertheless assigned to the treatment or control group. The selection equation estimates the individual's selection into become a purchaser. The purchase quantity equation estimates the decision to purchase based on viewing the counter, the price and category of a deal, given that the user has chosen to make a purchase. For a subsample of the population, we had first names for the user, which enable us to hand code their sex. Equations 1-2 estimate a heckman model as outlined above for females and males. Column one

VARIABLES	(1) purchase_quantity (f)	(2) select	(3) purchase_quantity (m)	(4) select
counter	0.508***	-0.0495	-0.184	-0.0675
	(0.173)	(0.164)	(0.742)	(0.292)
location	0.0189*	-0.0211***	-0.0249	-0.00914
	(0.0108)	(0.00786)	(0.0205)	(0.00869)
price	-0.0154***		-2.71e-10	
	(0.00401)		(3.15e-10)	
category	0.0558		-4.74e-09	
	(0.0516)		(4.11e-09)	
no. past logins		0.0386***		1.22e-10**
		(0.0104)		(5.88e-11)
Constant	1.094***	-0.557***	-0.534	-0.563***
	(0.360)	(0.201)	(0.779)	(0.184)
Observations	295	295	143	143

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

indicates that the marginal effect of the counter is positive and significant for females; however, it is negative and insignificant for males. For females, the seeing the counter increase the purchase quantity by 50%.

5 Discussion

The results found here all clearly point to the added benefit of displaying group buying behavior, and increasingly so for an active user base that is predominantly female. Some of the limitations of the data were imposed by the business considerations of a growing, for-profit corporation, i.e., the choice to enter one's name, the duration of the experiment, and the sample size. To further test the effect of the counter on purchasing behavior, an additional step would be to allow the counter to persist even at checkout. In addition, we would like to test whether the counter's effect is increasing within the number of purchases displayed. Are later viewers more likely to purchase than early viewers?

Additional considerations would be to test other metrics of visualizing social purchasing behavior, such as displaying the total amount saved. Further, the idea of visualizing real time group buying need not be limited to the display of simple numeric statistics. Fab.com, a popular site offering curated products via online shops, has capitalized on converting real-time Twitter streams into a real time sales stream, complete with purchasing username attached and relevant product photos. Off shoots of the twitter stream, or purchasing stream to invoke herd behavior could include featuring the activity of central players (well connected) to the site, or highly connected individuals with a user's own network.

6 References

Akerlof, George. 1970. The Market for Lemons: Quality Uncertainty and the Market Mechanism. Quarterly Journal of Economics 1970.

John W. Byers, Michalis Potamias, Michael Mitzenmacher, and Georgios Zervas. A Month in the Life of Groupon. 2011. Cornell Univeristy arXiv:1105.0903v1 [cs.SI].

Bernardo A. Huberman, Thomas Sandholm, Mao Ye, Chunyan Wang and Christina Aperjis. 2011. Collective Attention and the Dynamics of Group Deals. HP Research.

Sushil Bikhchandani, David Hirshleifer and Ivo Welch. 1998. Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades. Journal of Economic Perspectives 12:3, 151Ð170.

Dholakia, Utpal. 2011. What Makes Groupon Promotions Profitable For Businesses? Rice Unverisity.

Benjamin Edelman, Sonia Jaffe and Scott Duke Kominers. 2011. To Groupon or Not to Groupon: The Profitability of Deep Discounts. Harvard Business School 11-063.

Tech Crunch (http://techcrunch.com/2011/03/20/why-women-rule-the-internet/).