Impulse Buying in Online Sales

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Abstract

This paper discusses a randomized experiment regarding impulse buying in online sales. We ask the question: “does incentivizing impulse buying increase profits in online sales?” To answer this question, we partnered with independent consultants from the online clothing retailer LuLaRoe and offered their customers an incentive to encourage impulse buying. Our study focused on the causal effects of this incentive on the consultants' profits. Though this study involved approximately 35,000 individual customers of two different consultants, we did not detect any statistically significant difference in profits between the treatment and control groups. This may be due in part to the small effect size that we were attempting to detect with our experiment. This paper details our experiment and offers suggestions on improvements for future studies.

Background

Does incentivizing impulse buying increase profits in online sales? This question may have material benefits for small businesses that are hosting online sales. In order to study this question, we partnered with a direct sales clothing company called LuLaRoe. LuLaRoe operates through individual retailers called 'consultants' hosting online sales of clothing items via Facebook groups.

During a typical sale, which run for 1-2 days, one ‘hostess’ invites her friends and family to join a private Facebook group. At the start time of the event, the consultant posts pictures of their inventory and prices to the Facebook group and potential buyers comment “sold” on the photo to claim an item. After the sale closes, the consultant sends an invoice to the buyer for the claimed items and ships the merchandise to them. The hostess will earn rewards such as free items or discounts based on her friends’ and family members’ purchases. Since each private Facebook group is limited to a particular social network, there is unlikely to be any overlap between separate events within a short period of time. One individual will typically not be a member of separate private sales at the same time, though it is not impossible.

Each LuLaRoe consultant manages their own inventory and marketing and is responsible for maximizing their own profit margins. As such, consultants are looking for actions that could increase their profit margins. The question of the effect of incentivizing impulse buying on profits is an interesting one that may have a direct impact on the consultant’s income.

In our construction of this study, we proposed incenting customers to purchase quickly rather than waiting until the end of the sale with a limited time offer discount on free shipping. The theory behind this offer is that if a potential customer sees the benefit of buying an item quickly, then they do not have time to reconsider their purchase and they may be more likely to buy the item on impulse. If other customers see inventory being purchased earlier in the sale, there could be additional effects where other customers may feel they need to purchase before other items are sold out.

We determined that the best way to measure the impact of this limited-time offer would be to run an experiment. In this experiment some subjects would receive the incentive and others would not. If done well, we could measure the average treatment effect by comparing the differences in profit between subjects in treatment and subjects in control.

Experiment Design

The treatment that was delivered to the individual customers within our experiment was an offer for free Priority shipping if any items were claimed within the first hour of the sale event. We had considered applying this treatment randomly to individuals in a sale, but were concerned that there would have been a high potential for spillover effects. Spillover was a risk as these sale events are intended to be interactive and social. It is likely that one customer receiving the offer would mention it within the Facebook group, thereby influencing other customers' potential outcomes. In addition, it would have been logistically challenging to deliver individual treatment via private Facebook messages to 35,000+ customers.

For these reasons, a clustered design was necessary. Each sale event hosted by a particular consultant and starting on a particular date was considered a cluster in our experiment. In order to account for consultant fixed effects, we blocked first on consultant, and then assigned each cluster (i.e., each event date) to either treatment or control. All customers who were in the Facebook group at the start of a particular event were either all assigned to treatment or all assigned to control. Since there is little to no overlap between individual events, this clustered design mitigated the risk of spillover effects. The experiment flow diagram below shows our design.

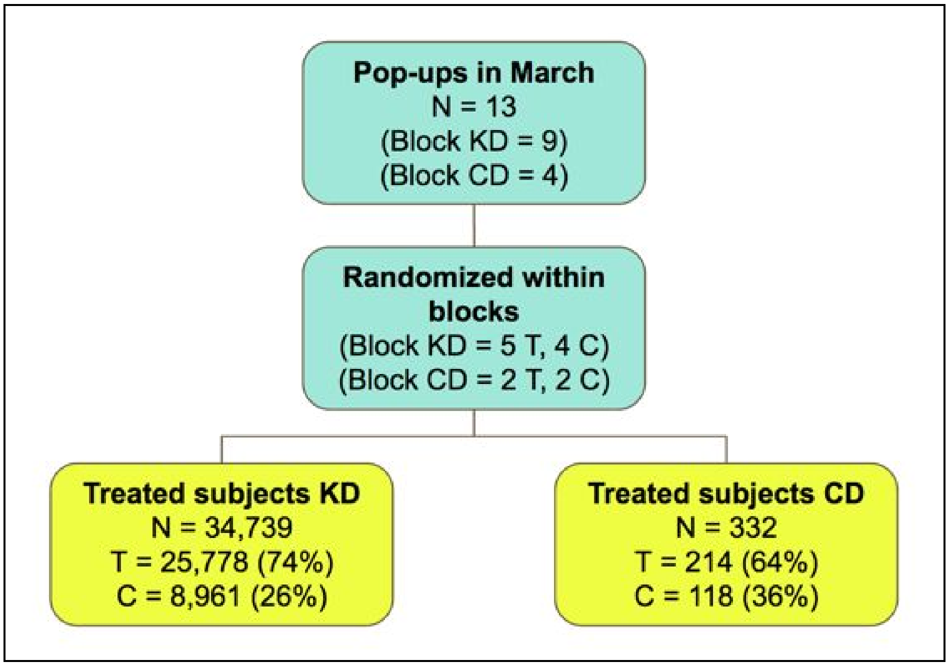

Figure 1: Experiment Flow Diagram

This clustered design also more accurately reflects the typical mechanism of consultants offering special discounts or giveaways. If they were to make this type of offer on a regular basis, it would not be delivered through private Facebook message, which customers often do not see if it is not sent from a friend. Consultants typically make special offers via a post on the Facebook wall, as they did in our experiment. Therefore, this clustered design is the most appropriate way to measure the effectiveness of the offer within this context.

Subject Recruitment and Retention

It was necessary to recruit LuLaRoe consultants to act as confederates in this experiment. They would be the ones to apply the treatment (the free shipping offer) to the subjects (their customers). In order to recruit consultants, we reached out to our personal networks and obtained contact information for approximately 20 active LuLaRoe consultants. Of those 20, four agreed to participate in the study. Two of the four scheduled private Facebook events and provided all necessary data. One of the four consultants had no private events scheduled, but had four public events scheduled, meaning that the same group of people were in all four events. This would have introduced spillover effects and essentially been a within-subjects design. Since she notified us of this irregularity from the outset, we planned to still conduct the experiment, but analyze her results separately from the other consultants. However, this consultant did not provide any sales data after her events. The last of the four consultants was a new consultant and did not schedule any events in time to participate in the experiment. Therefore, she was excluded from this study. For the two consultants who did participate fully, we received excellent cooperation and have confidence that the data provided was complete and accurate. In addition, they invited one of the researchers to the Facebook groups so that we could monitor whether the treatment was applied or withheld as instructed. While pleased with the cooperation we received from our consultants, in future studies it would be beneficial to recruit more consultants to participate in order to generalize the results to a wider population.

Randomization

In order to randomize events between treatment and control, an online application was used.[1] Blocking was done at the consultant level so that each consultant would have half of their events in treatment and half in control. We confirmed that this randomization was effective by a covariate balance check (Figure 2). As expected given the random assignment, there were no statistically significant differences between treatment and control groups on the pre-treatment

[1] We use an online randomization tool at https://www.randomresult.com/tournament.php. The randomization algorithm of this implementation is Mersenne Twister Algorithm.

covariates. Large events (250 people or more) were somewhat more likely to be assigned to treatment, but this is likely due to chance ($p < 0.43$).

Table 1: Covariate Balance Check

	Dependent variable:	
	Treat_offer	
	(1)	(2)
Large_event	0.238	
	(0.293)	
ConsultantKD		0.056
		(0.325)
Constant	0.429*	0.500*
	(0.199)	(0.271)
Observations	13	13
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 2: Covariate balance check

Experiment Procedures

The random assignments of treatment and control events were applied to the all the planned sales events of two consultants who participated in our experiment. For each event selected for treatment, the consultant would post our treatment message and offer the incentive. At the end of the event, we would observe outcomes. For each control event, we would simply observe outcomes at the end of the event with no treatment applied. This was repeated throughout the month of March for all events. The Research Design Diagram below illustrates our experiment procedures described.

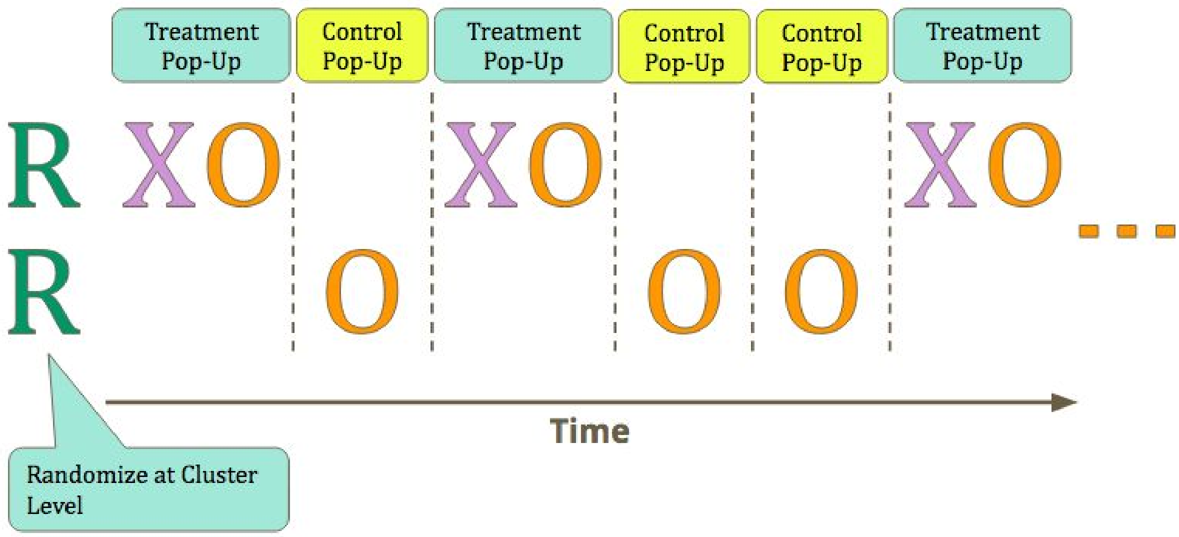

Figure 3: Research Design Diagram

Existing Literature and Hypothesis

Our hypothesis regarding this experiment was that customers who are offered the incentive for free shipping for any item claimed within the first hour of the sale would spend more money, resulting in higher profits for the consultants. This hypothesis was based on several studies, surveys, and trade articles that discuss the impact of free shipping on online commerce. Rejoinder.com has an excellent summary of two studies related to this topic.[2] The first is AlixPartners who conducted a survey asking customers what their top reasons for not choosing to order were. The number two item was “cost of delivery was too high.” The second is

[2] Putnam, Joe. "What Impact Does Free Shipping Have on Online Retail Sales?" Rejoiner. April 07, 2016. Accessed May 04, 2017. http://rejoiner.com/resources/free-shipping-online-retail-sales/.

a UsabilitySciences study on cart abandonment that showed that the second most common reason customers abandon their carts is due to unacceptable shipping costs. Another article, this time from Inc.com, cites various surveys and studies that discuss the positive impacts of offering free shipping to online customers.[3] With such a focus on free shipping and its impact on the online commerce experience, we felt a study to measure its impact on impulse purchases would be interesting.

Data Collection

Each LuLaRoe consultant collected the data for our experiment. We gave them specific instructions as to what to record and then each was provided with a dedicated Google sheet. This sheet was private to each consultant and contained a tab for each of the scheduled pop-ups. In each pop-up sheet, the consultant recorded the total purchase amount per subject. Those that didn't purchase anything were not included in the sheet. We also had the consultant record how many items were purchased, whether or not the subject took advantage of our treatment, and whether the customer had purchased with this LuLaRoe consultant before. Lastly, the consultant recorded whether the subject received any other discounts or incentives through the normal incentive programs the consultant offers.

Here is an example of one of the Google sheets used in our study:

[3] Roesler, Peter. "Why Free Shipping Is a Must." Inc.com. November 24, 2014. Accessed May 04, 2017. https://www.inc.com/peter-roesler/why-free-shipping-is-a-must.html.

Date of Pop-Up:	3/12/17	Consultant Name:			
Total number of Facebook group members at the start of the pop-up:					6243
Customer # (indicate the pop-up hostess with an asterisk)	Total Purchase Amount (excluding taxes and shipping)	Number of Items Purchased	Did this customer receive free shipping for items claimed within the first hour? (Yes/No)	Has this customer made a LuLaRoe purchase with you before this pop-up? (Yes/No)	Notes (optional):
1*	$0.00	0	No	No	won 3 items as hostess rewards
2	$60.00	2	Yes	No	
3	$35.00	1	Yes	No	
4	$25.00	1	Yes	No	
5	$120.00	4	No	No	free shipping for spending over $100
6	$55.00	1	Yes	No	
7	$61.00	1	No	No	
8	$35.00	1	No	No	
9	$15.00	1	No	No	won $10 LuLaCash

Figure 4: Sample Google sheet used for data collection

Covariates

For our experiment we considered four primary covariates: consultant fixed effects, consultant inventory size, size of event, and customer's previous purchases. We felt each of these might be able to tell us something interesting about our subjects and, if possible, we wanted to control for each of them.

Our first covariate of interest was consultant fixed effects. This covariate is trying to capture the possibility that the customers or the sale techniques of one consultant are somehow not representative of the population of consultants. We were concerned that these fixed effects might affect our ability to detect responsiveness to our treatment. Fortunately, we already had an easy way to measure consultant fixed effects: we were blocking our randomization at the consultant level.

The second covariate of interest was consultant inventory size. If there was a large variance in inventory size between consultants, our study might be dramatically impacted by the opportunity our subjects had to purchase clothes that interested them. When we investigated this concern with our LuLaRoe consultants, we learned that each event always had the same inventory no matter who was selling. Every event had approximately 1,200 items for sale. As a result we did not need to include inventory size as a covariate of interest.

One covariate that we did not consider until we were in the midst of the experiment was the number of subjects in each event. We had assumed that the number of subjects in each event would be relatively small, maybe a few dozen. When we started conducting the study we found that while some events only had a few dozen of customers, other events could have thousands of customers in them. This variance concerned us: large events are less personal, less engaging. Also, with large events, there is a potential for higher volume sales and a lower proportion of potential customers who make purchases. Concerned by this and the potential for skew in our analysis, we created a covariate that would measure whether or not an event was large. We set the threshold for a large event at 250 customers.

The last covariate we considered was whether a customer had made a LuLaRoe purchase in the past. We thought that that information could be predictive of the customer making a future purchase. In pursuit of this information we asked each consultant if they would be able to give us information about their customer's purchase history. Unfortunately, all we could capture was the purchase history status of a customer if they had purchased an item in the event we were studying. This meant we were unable to access information about all the customers in each event that did not purchase anything. The lack of this information prevented us from performing any useful analysis around this covariate.

Outcome Measures

There were two outcome measures of interest for our experiment. The most important measure was whether or not our treatment affected the profit our consultants received at the event level. Giving away free shipping could decrease profits since the shipping cost would be absorbed by the consultant instead of the customer. Alternatively, customers might find the promotion so attractive that the offer could have a net increase in sales and thus, through volume, the consultant would make more money overall. Whether our treatment increased or decreased profits was a major focus of our study. The challenge we had with this measure is that we did not have access to each consultant's true profit. Since this data was not available, we created our own measure of profit. We settled upon the following formulation for this measure:

Profit **= *PurchaseAmount* – *WholesalePrice* – (*FreeShipping* x *CostOfShipping*)**

- *WholesalePrice* = (*PurchaseAmount* + *Discount*) x 45%
- *FreeShipping* = 1 if the customer received free shipping, 0 otherwise
- *CostOfShipping* = $6.50 for USPS Priority mail
- *Discount* = any discount applied by the seller for an individual sale

Our profit formula was driven off of the purchase amount for each item sold minus a wholesale price. From that figure we subtracted the shipping cost if that event was selected for treatment. The wholesale price is our proxy for the costs incurred by the consultant for acquiring the item sold. For this we used the purchase amount, plus any discounts times 45%. The 45%

represents a 55% profit margin on each item sold by the LuLaRoe consultant. We validated this estimate with one of our consultants and she confirmed that it was an appropriate estimate.

The second measure was whether our treatment affected the purchase amount within each sale. Not only did we need this measure for our profit calculation, but we also conjectured that the dollar amount of product purchased by customers might be impacted by our treatment. This measure was obtained from each consultant after they completed an event.

Models and Results

We first constructed a full specification model using selected covariates. The *consultantKD* is a binary variable (1 for consultant KD, 0 for consultant CD) for blocking. Because only consultant KD has large event, there is no interaction between *LargeEvent* and *ConsultantKD*. The full specification regression equation is

$$Profit = \beta 0 + \beta 1 Treatment + \beta 2 LargeEvent + \beta 3 ConsultantKD + \beta 4 LargeEvent*Treatment + \beta 5 ConsultantKD*Treatment + \varepsilon$$

The coefficients can be interpreted as the following:

- *$\beta 1$:* the treatment effect of time based freeshipping incentive
- *$\beta 2$:* the effect of a large event where subjects may have different online shopping behavior from a small event
- *$\beta 3$:* the effect of consultant KD's sales event regardless of treatment
- *$\beta 4$:* the treatment effect of large Events (of consultant KD)
- *$\beta 5$:* the treatment effect of consultant KD's event

Figure 5 shows the outcome of the full specification model. The effect is in the unit of profit in dollar amount per subject. The treatment effect is -0.196 with a cluster standard error of 1.701

which is statistically insignificant. The large event has negative impact of -7.032 on the profit with cluster standard error of 4.179. Overall, the model indicates that the time-based, free-shipping incentive neither increases or decreases profit.

Table 3: Fully Specified Model

	Dependent variable:
	Profit All Events
Treat_offer	−0.196
	(1.701)
Large_event	−7.032*
	(4.179)
ConsultantKD	5.461
	(4.433)
Treat_offer:Large_event	4.036
	(4.179)
Treat_offer:ConsultantKD	−3.816
	(4.512)
Constant	1.580
	(1.478)
Treat p value	0.91
Observations	35,071
R^2	0.049
Adjusted R^2	0.049
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 5: The full specification model for our experiment

We also built three smaller regression models which we believe are more intuitive to interpret. The three models are the treatment effects of consultant KD's large events, consultant

KD's small events, and consultant CD's small events. The effects are also in the unit of profit in dollar amount per subject. By using simplified models, the regression equations are in the following form:

$$Profit = \beta 0 + \beta 1 Treatment + \varepsilon$$

- $\beta 1$: The treatment effect of time based free-shipping incentive

Figure 6 shows the side-by-side comparison of the three models. KD large events model shows positive treatment effect 0.024 with cluster standard error of 0.035. KD smaller events, on the other hand show negative treatment of -4.012 with cluster standard error 4.931. And CD small events has a treatment effect of -0.196 and a cluster standard error of 1.890. All three models show statistically insignificant outcome. Thus, we reached the same conclusion: our experiment treatment of time based free-shipping incentive neither increase or decrease profit for online sales.

Table 3: Profit Amount Models

	Dependent variable:		
	Profit		
	KD Large Events	KD Small Events	CD Small Events
	(1)	(2)	(3)
Treat_offer	0.024	−4.012	−0.196
	(0.035)	(4.931)	(1.890)
Constant	0.009	7.041	1.580
	(0.015)	(4.931)	(1.642)
Treat p value	0.5	0.42	0.92
Observations	34,562	177	332
R^2	0.0001	0.018	0.0002
Adjusted R^2	0.0001	0.012	−0.003
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 6: Simplified models

Problems and Challenges

We faced several challenges during our project. First, we could not recruit enough LulaRoe consultants to obtain sufficient effect size. Despite our best effort, we were only able to recruit 4 out of 20 consultants to participate in our experiment. Among the 4 participants, only 2 provided quality data for our analysis. The small effect size greatly impacted the statistical power of our models.

Second, we did not anticipate the disparity in sizes of sales events. Our initial estimation of a LulaRoe sales event size is less than 100 people because a sales event is typically organized by one person and its participants are his or her families and friends. We significantly underestimated the social networking size of some LulaRoe organizers. The largest event of Consultant KD had more than 10,000 people. Because we conducted randomization at the sales event level in the very beginning, we ended up with more large events in the treatment group than in the control group. The imbalance of treatment subject size versus control subject size did not impact our model thanks to the block randomization approach of our experiment. We learned a good lesson on how one should carefully plan the strategy of an experiment based on attributes of subjects and mechanics of data generation.

Third, the actual sales volume in each sales event is very low (below 1%), which we also did not anticipate. This may be common for online sales at a social media platform such as Facebook. It is possible that some consultants decided not to participate our experiment because offering free shipping is not the right incentive if they have even lower sales volume.

Lastly, there could be potential intertemporal substitution effect in our experiment. If a buyer made a purchase because of the free shipping incentive, he or she may not make another purchase in the subsequent events. Our treatment could have merely moved their purchases from latter events to earlier ones.

Additional Considerations

Our experiment did not have differential attrition problems. There was only one consultant who failed to produce data for us. We did not need to do anything special for that consultant because we would have had to analyze her data separately anyway due to her sales events not being private. The event setup would be different. For the two consultants who provided data, they applied treatment to their sales events based on our instruction. From an individual buyer's' perspective, as long as she enters a LulaRoe Facebook sales event, she is either treated or not treated (control) because the freeshipping message is part of the event invite.

We also do not need to worry about issue of non-compliance. Our research question of incentivised impulse buying focuses on intent to treat (ITT) effect because our research goal is to determine what sellers want to learn on impulse buying knowing there will be a certain percentage of people who will not take any incentive treatment. We considered many Facebook users who had received the LulaRoe sale invites, but decided not to attend the events as non-compliance subjects. But it did not impact our analysis.

We do have a problem of external validity. Based on our model analysis, we cannot generalize our result to all LulaRoe consultants, nor can we generalize to similar online sales. Our outcome measures are not statistically significant due to our small effect size. We also learned from the project that LulaRoe consultants can have very different event size and frequency.

Lastly, we faced an unique issue of “Late arriving subjects” in the treatment groups. Those are the people who entered a event later than 1 hour and missed the opportunity to take the incentive because our free-shipping incentive has 1 hour limit. Conceptually these subjects are different from those who joined the event on time. Although they are treated by the event invitation with the free-shipping offer, they can not contribute to the outcome even if they wanted to. But since intent to treat (ITT) effect is the goal of our experiment, we can still put them in the same category as those who arrived on time for the event but decided not to take the incentive. From the perspective of ITT, these two groups of people are the same -- buyers who did not go for the incentive. Therefore, we believe this will not affect our analysis results.

Conclusion

In summary, although free shipping is a well-known powerful profit generator for online sales, our treatment of offering free shipping on a limited-time basis did not show any effect on profit. More specifically, our analysis showed that this incentive neither increased nor decreased the profit of online sales for LulaRoe sales events. As a result, we do not recommend LulaRoe consultants use limited-time based free shipping as an incentive method. A LulaRoe consultant may consider the first-hour free shipping offer as a giveaway similar to the other activities they use to increase engagement during their sales. But we have no experimental basis for saying this technique with affect profits at this time. This can be a topic of a new experiment.