January 2015

ESSAYS ON NUDGING CUSTOMERS’ BEHAVIORS: EVIDENCE FROM ONLINE GROCERY SHOPPING AND CROWDFUNDING

Na Zhang
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By Na Zhang

Entitled
ESSAYS ON NUDGING CUSTOMERS’ BEHAVIORS: EVIDENCE FROM ONLINE GROCERY SHOPPING AND CROWDFUNDING

For the degree of Doctor of Philosophy

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Head of the Departmental Graduate Program Date
ESSAYS ON NUDGING CUSTOMERS’ BEHAVIORS: EVIDENCE FROM ONLINE GROCERY SHOPPING AND CROWDFUNDING

A Dissertation
Submitted to the Faculty of
Purdue University
by
Na Zhang

In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

December 2015
Purdue University
West Lafayette, Indiana
To my father, Fangbin Zhang, my mother, Xinmei Lu, my husband, Xiaojia Zhao
and my son, Kevin.

Your love, support and encouragement, never ceases to inspire me.
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ABSTRACT


The dissertation consists of three essays that employ predictive analytics, structural modeling techniques and field experiments to understand and nudge customers’ behaviors in two types of online engagement platforms. The first one is customers’ purchase behaviors in an online grocery store and the other is customer’ contribution behaviors in a reward-based crowdfunding platform. In both contexts, we study how to actively nudge their behaviors. In Chapter 2, we investigates how, when dealing with products that are available in limited quantities, customers may be nudged to purchase them. Specifically, our main problem is to identify targeted customers to receive the limited number of coupons. We develop a Support Vector Machines (SVM) based approach to rank order customers. We conduct a field experiment in an online grocery store to evaluate how well the identified customers are nudged through information and/or couponing. We find that, in terms of the successful nudges, our SVM-based approach performed better than other approaches.

We are not just focusing on nudging customers to purchase but also on nudging them to contribute. In Chapter 3, we examine how to leverage the project reward structure (PRS) to nudge backers to contribute on reward-based crowdfunding platforms.
We develop a structural model of the backer’s dynamic pledging and learning behaviors. We use it to test a variety of behavioral theories of how PRS and intertemporal changes in the PRS influence backers’ pledging decisions over the course of a project’s funding period. We also use the model to run market simulations and shed lights on how to offer the PRS changes and what is the optimal timing to make such changes.

Coupons often act as price discrimination tools to nudge low willingness-to-pay customers to purchase. However, in our context where there is limited product availability, strategies other than just sending coupons may be desirable. For some customers, it is sufficient that we provide information alone but no coupons. Also coupons of different discount depths might play a different role as customers might update their expectations. Particularly, in Chapter 4, we investigate the impact of different nudging strategies on customers’ purchase behaviors. We evaluate the effectiveness of those different nudging strategies via a randomized field experiment. Consistent with the prior literature, we found coupons could serve as a form of “advertisement”. Furthermore, our findings show that coupons with a low discount rate could have a longer information carryover effect than those with a higher discount one. The experiment also generated insights about when couponing as opposed to information is more effective when nudging.
CHAPTER 1. INTRODUCTION

With the increasing importance of big data and business analytics in the business area and predictive analytics in the academic world (Shmueli & Koppius 2011), our research pays close attention to leveraging vast amount of data to learn and predict customers’ online behavior, provide insights to business managers and contribute to academic research as well. Much of the information systems and operation management literature appears to treat the end-customer demand to be exogenous (Bernstein and Federgruen, 2005; Cachon and Lariviere, 2005). However, there are many real world examples in which customers’ demand can be nudged using information technology. Zara is an example of a firm where consumer demand is nudged by limiting production even if it meant leaving demand unsatisfied (Ghemawat and Nueno, 2003). Shaping the consumer demand is more easily accomplished in the Internet channel given the store’s ability to adapt the offering as well as track individual consumers’ behavior. In this dissertation, we explore different ways and strategies that companies could employ to nudge customers’ behaviors in two types of online engagement platforms, such as an online grocery store and a reward-based crowdfunding platform.

In Chapter 2, we investigates how, when dealing with products that are available in limited quantities but still exceeds the current demand, customers may be nudged to purchase them. Specifically, our main problem is to identify targeted customers to
receive the limited number of coupons. This implies that we have to be able to rank order customers based on their purchase potential, an issue that is non-existent in most recommendation systems. We develop a Support Vector Machines (SVM) based approach to rank order customers. The underlying notion is that Type I errors in our classifier are not necessarily problematic but are potential nudging targets. Also, as a consequence, traditional ways of evaluating classifiers (with Type I and Type II errors) are not appropriate. Therefore, we conduct a field experiment to evaluate how well the identified customers are nudged through information and/or couponing. We find that, in terms of the successful nudges, our SVM-based approach performed better than other approaches.

We are not just focusing on nudging customers to purchase but also on nudging them to contribute, such as on reward-based crowdfunding platforms. In Chapter 3, we collect data from Kickstarter, a funding platform for creative projects, and examine how to leverage the project reward structure (PRS) to nudge consumers to contribute. Our preliminary analysis reveals that PRS does matter in determining the success of the projects. Furthermore, we have developed a structural model of the backer’s dynamic pledging decision and learning behaviors. We use it to test a variety of behavioral theories of how PRS and intertemporal changes in the PRS influence backers’ pledging decisions over the course of a project’s funding period. Furthermore, we also use the model to run additional market simulations and shed lights on how to offer the PRS changes over the course of the funding period and what is the optimal timing to make such changes.
Coupons often act as price discrimination tools to nudge low willingness-to-pay customers to purchase. However, in our context where there is limited product availability, strategies other than just sending coupons may be desirable. For some customers, it is sufficient that we provide information alone but no coupons. Also, when a coupon is provided, customers may perceive the product to be unpopular and therefore may anchor their valuations for the product lower. Coupons of different discount depths might play a different role when the anchoring effects are considered. So it is valuable to understand the effects of coupons versus information on nudging customers to purchase the product. Particularly, in Chapter 4, we investigate the impact of different nudging strategies, such as information only, low discount, high discount, on customers’ purchase behaviors. We evaluate the effectiveness of those different nudging strategies via a randomized field experiment. Consistent with the prior literature, we found coupons could serve as a form of “advertisement”. Furthermore, our findings show that coupons with a low discount rate could have a longer information carryover effect than those with a higher discount one. Furthermore, the experiment also generated insights about when couponing as opposed to information is more effective when nudging different types of customers.

Our research is of great significance to both academic research and industry practice. Our work contributes to the literature of predictive analytics, machine learning, recommender systems, email targeting, crowdfunding and consumer behaviors in different online contexts. Meanwhile, we offer useful big data analytics tools for managers to identify targeted customers for products with limited availability. Also we offer insights regarding the type of customers to target with information and coupons.
Moreover, we provide guidelines to entrepreneurs about leveraging the project reward structure to nudge backers to contribute on crowdfunding platforms. Our work also provide new paths for groundbreaking research in the future.
CHAPTER 2. A RECOMMENDER SYSTEM TO NUDGE CUSTOMERS IN A CAPACITY CONstrained SUPPLY CHAIN

2.1 Introduction

Traditional models in the supply chain literature (e.g., Bernstein and Federgruen, 2005, Cachon and Lariviire, 2005) have treated the end-customer demand to be exogenous. However, allowing for shaping customer behavior gives the firm another degree of freedom to improve its supply chain efficiency. For example, Zara offers products only over a limited duration, creating a sense of urgency amongst its customers. This urgency implicitly goads the customer to purchase the products immediately. Zara takes advantage of this shaped behavior and has built its supply chain to benefit from it (Petro, 2013). Internet technologies and availability of plethora of data enables firms to more effectively shape customers. Perhaps, because of that motivation, many firms have brought in-house the order fulfillment of their electronic channels, which they had originally outsourced (Duhigg 2012). In this paper, we investigate one possible way of firms nudging customers by taking into account the supply chain constraints.

We develop a recommendation system that takes into account product availability constraints, implement it in an online grocery store context, and evaluate the implementation. The grocery firm we work with acts as an intermediary between local farms, food partners, and customers. The motivation for the recommendation system is
that the firm faces availability constraints for some of its products (because they are sourced from small farms) but the available quantities still exceed the current demand. Therefore, the firm has the motivation to identify the targeted customers for the unused though limited supply, instead of simply blanketing all customers with coupons. Our objective is to promote limited quantities of a high-margin product in the presence of limited availability. For this purpose, we develop an SVM-based approach. Our technique is different from those in typical existing recommendation systems such as content-based filtering and collaborative filtering because the feature set in the grocery context is not as comprehensive as in other contexts (for details about the differences, see Section 2.2). Our main objective with the proposed technique is to identify a subset of Type I error records that can potentially be nudged and evaluate the strength of identification using an experiment.

There are two ways in which we conduct the evaluations. First, we compare the SVM-based approach against other standard techniques such as logit regression, and k-Nearest Neighbors (kNN) using the historical dataset. We split the historical data into training and testing periods on a rolling time window. After training, we analyze how well the predictions are about customers’ future purchasing habits, and we find the SVM-based approach to perform better. Since evaluations based only on the historical data cannot measure the effectiveness of nudging, we also conduct a field experiment, which becomes the second manner of evaluation. In the experiment, subjects are nudged using a) information only; b) low discount; or c) high discounts. We study the impact of the different forms of nudging strategies on the nudging outcomes.
In short, we believe that our work provides both academic rigor and practical relevance. We contribute to the literature on supply chain, predictive analytics, and recommender systems. To the best of our knowledge, none of the prior works have considered a recommendation system that considers the supply chain constraints. We develop and demonstrate the effectiveness of the recommendation system through a combination of analysis and experiment. The analysis of data from our experiment also provides useful managerial insights.

This paper is organized as follows. Section 2.2 provides an overview of the related literature. Section 2.3 presents our SVM-based approach. In Section 2.4, we describe the data and research context. In Section 2.5, we evaluate our proposed approach using historical transaction data. Section 2.6 describes the field experiment we conducted. Finally, we conclude in Section 2.7 by discussing the theoretical and managerial implications.

### 2.2 Overview of the Related Literature

There is an increasing interest in predictive analytics in the information systems (IS) community recently (Sahoo et al. 2012; Shmueli and Koppius 2011; Wang et al. 2013; Zheng and Padmanabhan 2006). In our context, we use predictive analytics instead of explanatory statistical models. Predictive models are designed to predict customers’ out-of-sample behaviors while explanatory models are better suited to provide in-sample model fit. In the following, we survey prior literature on recommender systems.
2.2.1 Recommender System Techniques

Note that there are two widely adopted recommender system techniques: content-based filtering and collaborative filtering. For detailed literature review, refer to Koren et al. (2009), Sahoo et al. (2012) and Adomavicius and Tuzhilin (2005). The content-based filtering technique in general has highly demanding data requirements. It requires that the properties of product items, such as genres of movies and music, be specified. Also, it needs customers’ explicit preferences, such as user ratings (i.e., after experiencing this product, the user tells us whether he/she liked or disliked it, and how much, by providing a rating on a scale of, for example, 1 to 5). Possibly due to the data requirements, this method is not widely adopted.

The collaborative filtering technique, in contrast, has less demanding data requirements, and is widely incorporated in recommender engines (Koren et al. 2009). In general, there are two main approaches to collaborative filtering: the neighborhood method and the latent factor model (Koren et al. 2009). The neighborhood approach may be either user- or item-oriented, and is based on similarity measures such as Pearson correlation coefficient (Hu et al. 2008). In the user-oriented implementation, which is its original form, the neighborhood approach estimates unknown ratings based on recorded ratings of users. The item-oriented implementation, which has become popular due to its easy interpretability, predicts unknown ratings based on items most similar to the focal item. Note that the both implementations are based on explicit feedback from users, such as ratings.

The latent factor approach is used to uncover underlying factors that could explain the observed explicit feedback from users. Matrix factorization is widely used in
characterizing the latent factors of users and items (Bell et al. 2007; Paterek 2007). The traditional form of those latent factor models is also based on explicit feedback, such as ratings.

Of late, there is a growing interest in developing collaborative filtering algorithms for situations where only the implicit feedback is available. For example, Hu et al. (2008) developed a model based on the matrix factorization technique to account for implicit feedbacks based on the frequency of people watching TV shows. One key feature of the matrix factorization technique is that it requires characterization of a reasonable set of latent factors that can capture the product characteristics. For the aforementioned study, the TV genre set (such as comedy, action, horror, etc.) is small but comprehensive.

There has been some recent effort to design the collaborative filtering technique when preferences dynamically change. Sahoo et al. (2012) characterize a Hidden Markov Model (HMM) and compare the HMM-based algorithm to other algorithms in dynamic settings.

We evaluated the applicability of the aforementioned techniques to the online grocery context. First, as we detail later, we do not have explicit feedback about customer preferences. We only have data about their purchase history. Second, neither do we have the comprehensive feature set that characterizes customers’ decision-making processes. For example, different products (e.g., tomatoes and onions) have different feature sets. The decision to consume a particular product not only depends on the individual’s taste preference for the product but also on additional processing that may be done before consumption. It is natural for us not to be aware of those details. Third, the dynamic user preference assumption is not pertinent in our grocery shopping context. So,
the HMM-based approach that we discussed earlier is not relevant to our context. For these reasons, we develop an SVM-based recommender system.

SVM, with origins in machine learning, transforms the original feature space into a higher-dimensional feature space via the kernel trick (Vapnik 2000). The SVM technique has been found to be robust in various contexts. Prior literature has found that SVM performs better than multinomial logistic regressions in marketing (Cui and Curry 2005) and that SVM outperforms several other techniques, such as neural networks etc. in forecasting stock market movement direction in finance (Huang et al. 2005). Another salient feature of our paper is the managerial insights we generate from the experiment to evaluate our approach. For this reason, we briefly survey the work on the impact of recommender systems.

### 2.2.2 Impact of Recommender System

At the aggregate level, prior research has found that recommendations can have a positive effect on sales and web impressions (Ansari et al. 2000; Das et al. 2007; Bodapati 2008; De et al. 2010). There is a broader set of papers (Fleder and Hosanagar 2009; Oestreicher-Singer and Sundararajan 2012; Hervas-Drane 2013) that have studied when products gain as opposed to lose sales because of recommendations; or whether recommendations increase the market for niche goods as opposed to “long tails.” For example, Fleder and Hosanagar (2009), show that counter to popular perception, recommendations can lead to a reduction in sales diversity.

Prior research has also studied the impacts of the recommender systems at the individual level. Senecal and Nantel (2004) experimentally compare the human expert-
based (salesperson, independent experts), other humans (such as friends and acquaintances), and an online recommendation. They conclude that online recommendations could be more effective when compared with humans’ recommendations. Some studies corroborate that providing customers with a predicted system rating introduces anchoring biases that significantly influence customers’ preference ratings (Cosley et al. 2003; Adomavicius et al. 2011). Adomavicius et al. (2014) study the impact of recommender systems on customers’ willingness to pay in the context of purchasing digital songs. Hosanagar et al. (2013) found that personalization brought by recommender systems helps widen users’ interests and thus creates commonality among users. Even though our paper is mainly focused on developing a recommendation system, we also evaluate the effectiveness of the recommendation system to various types of forms of nudging (information, low-discount, or high-discount).

2.3 Our SVM-Based Recommender System

SVM is called the “maximum margin classifier”. It is based on maximizing the margins between two classes of an output to identify a separating hyperplane in a higher-dimensional space (Refer to Appendix A for details about SVM). SVM with a Gaussian kernel is recommended in scenarios similar to ours where the number of data points is rather not huge (Hsu et al. 2010). Specifically, we develop a non-linear SVM based recommender system that uses the Gaussian kernel transformation to identify the targeted customers who are among the people with high propensity of purchasing the focal product.
We would like to highlight the differences in processes associated with a standard classification task and ours. In general, classifiers are trained using the training dataset and tested on the test dataset. The testing involves evaluating the correctness of the classification, i.e., analyzing the number of Type I and II errors, in the testing dataset. In scenarios where costs associated with Type I and II errors are different, and when testing on the testing dataset, those variations in costs are also considered to infer the expected cost incurred by the classifier (Witten et al. 2011). Therefore, the choice of the classifier is often based on the expected cost measures.

Recall that our objective is not to simply train the classifier and evaluate them based on the testing dataset. We are interested in identifying a restricted number of target customers to be nudged. The underlying notion in our approach is that Type I errors in our dataset are not necessarily problematic but potentially involve customers who have not purchased the focal product because they are unaware of the product’s availability. In an abstract sense, we are seeking to identify a subset of records with Type I errors to nudge. Of course, the cardinality of the subset is based on the restriction from the online grocer. Then, our focus is to develop a rank order for the Type I errors to choose the top ranked records for nudging.

2.3.1 Steps

Even though we maintain our focus on the SVM approach, we also compare it against other classifiers. Given that our objective is different from other prediction tasks studied in general, the steps below to identify the customers to be nudged are agnostic to the classifier technique.
Step 1: We use the entire sample as the training set. We train the classifier on the training set and obtain the best parameters by maximizing the cross-validation accuracy. Such a process is recommended for SVM by Chang and Lin (2011). Obviously, we extend the approach to other classifiers also and the best parameters obtained depend on the technique adopted.

Step 2: The classifier is implemented with the best parameter combination from the previous step on the entire training set (not just on the subset as we do in the n-fold cross validation).

Step 3: Type I errors from the Step 2 implementation is considered for rank ordering. The way in which the customers are ranked ordered may differ across the techniques. The top-ranked customers that are obtained as a consequence are selected for further analysis.

Step 4: We evaluate the output from Step 3 in two ways: (1) passively, we use the historical data to evaluate how well the identified customers performed in the following periods; (2) more actively, we conduct a field experiment where the identified customers are nudged through information and/or couponing. The first way is indicative of the natural process of discovery of the focal product by the customers. The second way is a more useful test of our technique.

In the SVM approach, we are interested in the regularization and variance parameters of the kernel function for Step 1. Specifically, we initially use a coarse grid-search method, followed by a better-region-only grid-search to obtain the optimal parameter combination. At each stage, we use the sequential minimal optimization (refer to Hsu et al., 2010, for details) to identify the separating hyperplane. In Step 3
corresponding to the SVM approach, we rank order the Type I “errored” records according to their corresponding distance from the separating hyperplane. As we discuss later, we compare our SVM-based approach to other approaches as well. In one alternate approach, we estimate a logit model that is a model in marketing to study customers’ discrete choices. The categorical variable in the SVM approach is treated as the response variable in logit model and the feature set correspond to the predictor variables. Similarly, the potential customers are rank ordered according to the fitted probability of purchasing this product. The higher probability the customers have, the higher rank they receive in Step 3. In yet another approach we study the kNN technique, which is widely used in collaborative filtering. We rank order potential customers based on the mean distance of them from surrounding grass-fed customers among k neighbors (k=10, 20). Finally, we also compare against a random selection strategy by randomly drawing M (for different values M=100, 200,… 1000) customers, calculating the number of successes, and redoing the process 20 times to compute the average.

2.4 Research Context and Data Source

We evaluate our technique in an online grocery store, where the firm acts as an intermediary between local farms, food partners, and customers. The purchase-to-delivery process works as follows: (1) customers place orders online and specify the pickup location (usually a meeting place such as schools, churches, etc.); (2) the firm picks up the order from local farms and food partners; (3) the firm takes its delivery trucks to the pre-destined sites; (4) the last mile problem is usually handled by customers who drive to the pre-destined site to pick up the groceries.
We intend to evaluate the nudging of customers to purchase grass fed beef. The product choice is ideal in many regards. First, the margins are high for this product and the firm prefers that high potential customers be exposed to it soon. So, the firm was willing to send out limited number of coupons to expose customers. Second, grass-fed appears to be a healthy option for customers (Cross 2011). Third, there appears to be quite a bit of variation in customers’ knowledge about this product. So, it is possible for customers, who have not purchased the product because of the lack of information, may be nudged to shape their behavior. Fourth, the product was introduced in 2009. Thus, as researchers, we have sufficient data for our analysis.

2.4.1 Overview of the Data Set

Our dataset includes all transactions from this online grocer since its launch until December, 2013. There are in total around 100,000 orders placed by almost 18,000 users on around 40,000 product offerings (We cannot provide specific numbers because of confidentiality). The data consists of orders, order details, anonymized customer information, and product details. For grass-fed beef, which is the focal product, the first order was placed in January 2009. Our analysis only focuses on customer behavior transactions since that time.

It turns out that the information about the nature of the products (whether it is meat, organic, etc.) had to be manually categorized in our dataset. For this purpose, we recruited 15 students to do the classification on a list of grocery products and were paid $10 per hour for their effort. The list was prepared such that each product had classification inputs from three students. For 92.27% of the products, the three inputs
concurred. For those that did not have concurring results (4.82%), the product was classified based on the majority of inputs. If there was no majority, for example due to missing data, researchers’ input was used to determine the majority.

2.4.2 Features Set for the Classifiers

Consider t+1 as the time period over which we are interested in understanding a customer’s interests in purchasing the focal product. The categorical binary variable, i.e. the classifier label, is whether the customer purchased grass fed beef or not (1 if purchased, and -1 if not purchased yet). The feature set for the classifiers – independent of whether we use SVM, Logit, or KNN models – includes information from period t. One of the features is the purchase expenditure measured as the average dollar amount per order spent by the customer in t. Another is the purchase count defined as the total number of orders placed by the customer in t.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
<th>We Measure:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat type</td>
<td>Affinity to different meat types, such as beef, pork, other red meat, poultry, seafood, other meat, dairy products, not meat</td>
<td>the number of the corresponding meat type products purchased by a customer in t</td>
</tr>
<tr>
<td>Organic</td>
<td>Affinity to organic products</td>
<td>the number of organic products purchased by a customer in t</td>
</tr>
<tr>
<td>Non-organic</td>
<td>Affinity to non-organic products</td>
<td>the number of non-organic products purchased by a customer in t</td>
</tr>
<tr>
<td>Grass-fed</td>
<td>Affinity to grass-fed products</td>
<td>the number of grass-fed products purchased by a customer in t</td>
</tr>
<tr>
<td>Non-grass-fed</td>
<td>Affinity to non-grass-fed products</td>
<td>the number of non-grass-fed products purchased by a customer in t</td>
</tr>
<tr>
<td>Price</td>
<td>Average expenditure</td>
<td>the average dollar amount spent in orders in t</td>
</tr>
<tr>
<td>Purchase</td>
<td>Purchase count</td>
<td>the total number of orders placed by a customer in t</td>
</tr>
</tbody>
</table>
Some of the manually identified categories mentioned earlier are also considered as a part of the feature set. As grass-fed beef is a form of red meat, we count the number of red meat purchases in t as a feature. Given that grass-fed beef is viewed as being natural, we believe that customers’ affinity to organic products can also affect purchases. So, we include in the feature set the number of organic products purchased by a customer in t. Simply keeping track of the number of organic products purchased may not truly capture the customer’s interest in grass-fed beef. So, it is important to consider the proportion of organic products also. Therefore, we account for it by including in the feature set the number of non-organic products purchased in t. Grass-fed products are not limited to beef. There are other products available with grass-fed options, such as cheese, milk etc., The affinity towards such products is defined in the feature set as the number of other types of grass-fed products purchased. Table 2.1 summarizes features used in the classifiers (we cannot provide descriptive statistics because of confidentiality concerns but we have provided for a shorter duration in Table 2.2).

2.5 Results and Discussion

From a prediction standpoint, the online grocer is interested in planning for a three month period. Such a timeframe accounts for seasonal variations in grocery shopping. The question is: how long of a history do we analyze for predicting the purchase in the following three months?
2.5.1 Choosing the Training Window-Length

An individual’s consumption pattern, with groceries in particular, is well-known to change across time. Obviously, a longer history leads to non-stationarity of data but provides richer information because of the larger sample size. So, choosing the window length involves a trade-off between non-stationarity and the sample size. We evaluate how well different history window lengths – the previous three-, six-, nine-, or twelve-months – are for predicting behaviors in the following three month period. The metric for comparison is, among a certain number of M top predictions, how many purchase the product in subsequent test window of three months. We also study the performance with respect to varying M (i.e., M = 100, 200 … 1000). Note that we intend to use the best window from these choices when we conduct the subsequent analysis. Since the window length may be different for different classifiers, we execute the same process for the classifiers we evaluate – SVM, Logit models and kNN.

Because we have data between 2009 and 2013, we have 14 pairs of training and testing datasets, where the training window is three months. The descriptive statistics of the features for one three month window (April, 2011 to June, 2011) are presented in Table 2.2. Specific numbers for purchase expenditure and frequency are not provided to maintain confidentiality. Also for the same reason, meat products are aggregated and one single measure is shown in the table.
Table 2.2  Descriptive Statistics for a Typical Season

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat Products</td>
<td>2.43</td>
<td>3.71</td>
<td>36</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dairy</td>
<td>2.22</td>
<td>3.58</td>
<td>26</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Not Meat (NM)</td>
<td>3.19</td>
<td>4.23</td>
<td>32</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Non-organic (NOrg)</td>
<td>5.70</td>
<td>7.36</td>
<td>57</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Organic (Org)</td>
<td>2.31</td>
<td>4.01</td>
<td>31</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Non-grassfed (NGF)</td>
<td>7.63</td>
<td>10.67</td>
<td>86</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Grass-fed (GF)</td>
<td>0.24</td>
<td>0.45</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Categorical Dependent Variable</td>
<td>0.22</td>
<td>0.41</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 2.1 shows the average number of successes across the 14 pairs as M varies. Note that, for the SVM approach, the training period of 3 months generated the best predictions. We also performed same analysis for other methods but found the same three-month window to also be the best for kNN and Logit classifier models. Therefore, we choose three months as the training window length for all subsequent analyses.

![Figure 2.1 History window length vs. Non-stationarity](image_url)
2.5.2 Comparisons

As shown in Figure 2.2, our proposed SVM method appears to consistently perform better than other methods. In the lower range, logistic regression is better than kNN. However, kNN outperforms the logit model if we choose more than top 200. The effect of the value of k in kNN is not significant. Random selection as expected is the worst. We have not shown its performance in the figure as the number of successes is very small. In the following subsection, we explore in detail the results obtained using our (SVM-based) approach.

![Figure 2.2 Method Comparisons for Average Number of Success](image)

2.5.3 Evaluation of the SVM Approach without Active Nudging

We are next interested in investigating how well the customers identified by our approach perform in the absence of any nudging interventions. Specifically, (1) how far
ahead can our approach identify customers who purchase the product; and (2) how frequent do those identified customers purchase the product thereafter? The objective of such analyses is to identify the value from nudging the customers to purchase earlier. Next, we define metrics for the analyses.

2.5.3.1 Conversion Rate

Recall that our SVM approach performs the estimation on a rolling window basis. Given the rolling window, this subsection characterizes a structured way of computing the conversion rate for customers identified by the SVM when there is no nudging. Suppose $r$ is the training-window index and $s$ indexes the future time-periods thereafter. Then, based on the top 1000 SVM predictions for the training window $r$, we can count the number of customers who actually bought the focal product between periods $s$ and $r$ and denote it by $n_{rs}$, where $s > r$. By re-indexing $n_{rs}$ such that $t = s - r$, we obtain $n_{rt}$ as the number of customers within the future $t$ periods identified by SVM when the training window is $r$.

Figure 2.3 shows the variations with respect to $t$, the averages and variances of $n_{rt}$ (An example of analysis in this section could be found at Appendix B). Observe that the variation is non-monotonic and one of the reasons is that the denominator to compute the averages is not the same. When computing the average for large $t$ values, the number of available training windows is small and vice-versa. An interesting aspect about the figure is that as much as 20% of the identified customers eventually purchase the product without any intervention by the retailer. Also, observe that a large number of customers arrive quite late relative to when the SVM identifies them. In that regard, recall that each
period marked along the x-axis corresponds to a three-month frame. It appears from this analysis that both in terms of the number of customers as well as the time periods there appears to be significant advantage if the firm were to nudge.

![Graph showing means of accumulative number of success in lifetime prediction.](image)

**Figure 2.3** Means of Accumulative Number of Success in Lifetime Prediction

### 2.5.3.2 Units Purchased by Converted Customers

Instead of simply considering the number of customers who bought the focal product, we consider here the number of units of the focal product bought. Similar to the previous section, we denote $m_{rt}$ as the total number of units customers purchased the focal product in the future $t$ periods when the training window is $r$. The averages are computed as before. Interestingly, in Figure 2.4, we find that the SVM-identified customers purchased the focal product 800 times. It appears that nudging is valuable for the firm when considering the frequency of purchase.
2.5.4 Motivation for Nudging Customers to Convert Earlier

According to analysis from previous subsections, we found that SVM-selected customers do not all immediately convert to purchase the product and it could take some of those top predicted customers two or three years to begin consuming this product. Conditional on a customer buying the product subsequent to a specific training window, we compute the average time before which the customer buys.\(^1\) In Figure 5, the blue line shows the average number of periods customers take to purchase for the various \(r\). Note that the data is right censored. It implies that the actual averages are larger than those in

\[^1\] Using the definition of \(n_{rt}\) from Section 5.3.1, for a given time window \(r\), we compute the average number of periods customers take to convert as \(\frac{1}{T} \sum_{t=1}^{T} (n_{r(t+1)} - n_{rt}) * (t + 1)\), where \(T\) denotes the largest available \(t\) for \(r\).
the plots. Even then, we observe that average time it takes to convert customers is as much as one year.

Next, conditional on the customer purchasing the focal product in a period subsequent to a specific training window, we compute the average number of units purchased per customer. In Figure 2.5, the dashed line shows the average number of units purchased by the customers as $r$ varies. The figure shows that the average number of grassfed beef purchases by the customers per period can be as high as 2 units. Again, as mentioned before, the data is right censored.

Figure 2.5 Average Number of Waiting Periods and Repeat Purchase of Identified Customers
2.6 The Field Experiment

The previous section highlights the importance of expediting the purchase of the focal product. So, in this section, we conduct an experiment with the same objective. The additional purpose of the experiment is also to validate the modified SVM technique we propose. Recall that, unlike the traditional machine learning literature, our focus is not to evaluate Type I and II errors but to employ the Type I errors to nudge the customers. The experiment offers the means to evaluate the nudging. Fortunately, the same online grocery store evaluated was willing to conduct a field experiment to evaluate our proposed approach. As Harrison and List (2004) point out, field experiments are ideal to study since subjects do not perceive any of the controls as they do in lab experiments. The following subsection details the experimental design.

2.6.1 Experiment Design

We gained access to run the experiment in January 2014. So, we used winter 2013 as the training data period to implement our modified SVM approach. Our SVM approach identified and rank ordered the top 1000 customers. As a control group against which SVM will be evaluated, we randomly choose 1000 customers for nudging. Note that such would be the policy if there was no clear way to rank order the customers. Within each group of 1000 customers, they are randomly assigned to one of the four information treatments: (a) Info_only, sending out emails including only information of grass-fed beef, such as nutritional values; (b) Low_Coupon, sending out emails including both information and a 25% off coupon; (c) High_Coupon, sending out both information and a 50% off coupon; and (4) No treatment where no nudging is imposed. Table 2.3
shows the different information treatments as well as the number of customers assigned
to each treatment within each group. Note that the discounts are available only for
purchase of the focal product and the coupons expired one week after the customer
receives the coupons.

The customers in each of the three information treatments were reached via an
email. The text within the email, except for the discount details, is identical so that the
outcome differences can be attributed to the treatments. The coupon was designed such
that link within the email offered the coupon instead of an explicit code, which could
have been shared in deal aggregator websites. Also, it was indicated in that email that it
was a limited-time offer valid for one week.

Table 2.3  Experiment Design

<table>
<thead>
<tr>
<th>Name</th>
<th>Treatments</th>
<th>Random group</th>
<th>SVM group</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>High_Coupon</strong></td>
<td>Send out information + high discount coupons 250 (R1) 250 (S1)</td>
<td>250 (R1)</td>
<td>250 (S1)</td>
</tr>
<tr>
<td><strong>Low_Coupon</strong></td>
<td>Send out information + low discount coupons 250 (R2) 250 (S2)</td>
<td>250 (R2)</td>
<td>250 (S2)</td>
</tr>
<tr>
<td><strong>Info_only</strong></td>
<td>Send out information 250 (R3) 250 (S3)</td>
<td>250 (R3)</td>
<td>250 (S3)</td>
</tr>
<tr>
<td><strong>NT</strong></td>
<td>No treatment 250 (R4) 250 (S4)</td>
<td>250 (R4)</td>
<td>250 (S4)</td>
</tr>
</tbody>
</table>

2.6.2  Experiment Procedures

After we selected the 1000 SVM- and the 1000 randomly-identified customers,
we found some overlap across the two sets. So, we continued to draw from the customer
lists until we obtained 2000 unique customers. 250 customers are randomly selected from
the list and assigned to each treatment and the control group. The campaign was alive
from January 13 to 26. In order to increase customers’ engagement, emails are sent to each customer a day before the time they usually get their order. The last date a user would be able to use the coupon was February 2.

2.6.3 Analysis and Discussion

In this section, we present the results of the experiment. We first focus on the aggregate performance comparisons among different techniques, followed by a discussion about the impact of different treatments, and some final analysis on the nature of customer behaviors on outcomes.

We study the impact of the treatments as of April 2, 2014. All transactions from January 13 to April 2, 2014 are used for the analysis. In that timeframe, 1680 customers purchased the product. Of them, 988 are first-time purchasers and the rest of them had repeatedly purchased the product. Of the first-time purchasers, 235 (24%) have previously shopped here.

Table 2.4 Method comparisons of Conversion Rates

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>Logit</th>
<th>Random</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active nudging (Treatment groups) *</td>
<td>16.75%</td>
<td>10.28%</td>
<td>7.14%</td>
</tr>
<tr>
<td>Natural progression (No Treatment)</td>
<td>6.80%</td>
<td>2.45%</td>
<td>1.60%</td>
</tr>
</tbody>
</table>

Table 2.4 characterizes how customers converted under different treatments. Note that, the number of customers who converted to purchasing the product is significantly better under our approach than the random selection (6.8% versus 1.6%). To focus on the effect of information, we do not consider the subjects to whom the email
was sent but restrict our attention only to subjects whom we have tracked as having opened the email.\textsuperscript{2,3} Even among those customers, responses are significantly better under our approach. Further, the information treatments were better than the no information treatment. Thus, the table provides evidence that customers are not only better identified by our approach but also they are also more likely to be nudged. Interestingly, around 30% (68) of the 235 customers who purchased in the quarter were also subjects in our information treatments\textsuperscript{4}.

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>Random</th>
<th>Total</th>
<th>SVM</th>
<th>Random</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Coupon</td>
<td>146</td>
<td>7</td>
<td>153</td>
<td>Q1</td>
<td>206</td>
<td>7</td>
</tr>
<tr>
<td>Low Coupon</td>
<td>156</td>
<td>12</td>
<td>168</td>
<td>Q2</td>
<td>153</td>
<td>12</td>
</tr>
<tr>
<td>Information</td>
<td>149</td>
<td>8</td>
<td>157</td>
<td>Q3</td>
<td>172</td>
<td>8</td>
</tr>
<tr>
<td>NT</td>
<td>151</td>
<td>16</td>
<td>167</td>
<td>Q4</td>
<td>74</td>
<td>16</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>Random</th>
<th>Total</th>
<th>SVM</th>
<th>Random</th>
<th>Total</th>
</tr>
</thead>
</table>
\hline
High Coupon | 146 | 7      | 153   | Q1  | 206    | 7     | 213   |
Low Coupon  | 156 | 12     | 168   | Q2  | 153    | 12    | 165   |
Information | 149 | 8      | 157   | Q3  | 172    | 8     | 180   |
NT         | 151 | 16     | 167   | Q4  | 74     | 16    | 90    |

Our experimental design considered only our approach and the random selection. However, we are also interested in understanding how our approach compares against the Logit-based one. We used the intersection of the top 1000 ranked customers from the Logit approach and the 2000 subjects in our experiment. We found 648 such customers –

\textsuperscript{2} Email is in general recognized as a poor marketing campaign approach due to its low open rates from customers (http://www.smartinsights.com/email-marketing/email-communications-strategy/statistics-sources-for-email-marketing/). Fortunately, we have the ability to track the opening of the email using the software that the company uses to manage the campaigns. This allows us to focus on consumers conditional on opening the email.

\textsuperscript{3} In some cases, when consumers scroll down in their inboxes, the emails may get “opened” even if they have not been actively read upon. So, our measures are only conservative.

\textsuperscript{4} We examined the weighted average number of previous orders for customers (i.e. the number in the following parentheses) in different rank ranges: top 1000 (10.9), top 1000-5000 (3.88), beyond top 5000 (2.83). We found that the missing 70% are mostly customers with fewer purchase experience and we do not have enough information to learn and predict their behaviors. This is consistent with the cold start problem in traditional recommender systems.
605 of them overlapped with the SVM-based approach and the rest with the random selection. Note from Table 2.5 that the number of subjects in each treatment is roughly the same across both Logit and SVM. From a rank standpoint, again as expected, there is a larger overlap with the top 250-ranked customers (Q1), the next 250 (Q2), the next 250 (Q3), and the final 250 (Q4). Even then, we find that overall SVM does better than the Logit model in terms of the effectiveness of nudging conditional on customers opening the emails (10.45% versus 16.45%). Extrapolating our observations we conclude that even if there will be no differences with respect to the subjects in the various treatments, our approach appears to perform better than the Logit-based model. In Chapter 4, we further analyze the behaviors of customers identified by our approach when they are subjected to the different information treatments.

2.7 Conclusions and Implications

This paper investigates how, when dealing with products that are available in limited quantities but may still exceed the current demand, customers may be nudged to purchase them. Specifically, our main problem is to generate a rank order list of customers to be nudged to purchase the product. Existing recommender system techniques do not typically deal with generating such a list. Accordingly, we developed a Support Vector Machine (SVM) based approach that allows us to rank order customers based on their propensity to purchase the product.

Without any nudges, we first evaluated how well our SVM based approach performs compared to standard ones (such as logit regression, kNN etc.) in predicting future purchases of consumers. Specifically, we impose a rolling time window on the
historical transaction data from an online grocery store. We find that up to 20% of the top predictions from SVM eventually become consumers who subsequently purchase the product. This measure is found to be significantly better than existing standard techniques. It surprisingly turns out that our approach can predict the purchasing consumer one year ahead when it happened in reality. This motivated us to consider active nudging strategies that we implement with an experiment.

In the experiment, we subject customers to information versus coupons treatments and analyze the differences in their behaviors. We find that, as before, our SVM based approach performed better than other techniques. In summary, our work relates to various domains. As mentioned earlier, traditional supply chain models focus on optimizations assuming exogenous customers’ demand. Our paper allows for taking into account behavioral aspects of customers when dealing with supply chain constraints. Our work also contributes to the predictive analytics and recommender system literature. We, to our best knowledge, are the first to propose a recommender system for products available in limited quantities. One of the salient features of our technique is that we identify customers marked as Type I errors as the ones to be nudged. In line with that, we rank order potential customers for nudging. Our analysis is also distinctive in the manner in which we use the experiments. Also, our results from the experiments are useful actionable insights.

There are some limitations in our research. Firstly, features used in training our SVM approach are limited. Due to privacy issues, we do not have access to customers’ demographic information, such as income. Secondly, our analysis lies in the online
grocery context. If we had access to data from other contexts, the applicability of our approach can be better investigated.

In the future, we would like to develop a model to further investigate how information and coupons interact with different types of potential customers. This would offer more insights regarding how to strategically leverage different strategies to nudge potential customers to purchase and subscribe to the product. More personalized nudging strategies could be implemented to improve the conversion rates.
CHAPTER 3. AN ANALYSIS OF INCENTIVE STRUCTURE IN COLLABORATIVE ECONOMY: AN APPLICATION TO CROWDFUNDING PLATFORM

3.1 Introduction

The collaborative economy – which includes firms like Airbnb, Kickstarter, Uber, etc. – continues to grow at a staggering 25% pace annually (Forbes, 2013). According to an article in MIT Sloan Expert, collaborative consumption is a $110 billion market (Sloan, 2013). A crucial aspect to the functioning of these collaborative economies is the incentive structure that encourages participation. For example, Uber dynamically changes the rates depending on the demand and supply of Uber cars in specific regions. Kickstarter, on the other hand, gives the leeway to the project creators to offer incentives to project backers so as to raise money for projects. While there are different forms of incentive structures that exist, the objective in this paper is to use the structural modeling approach to study one form of it.

Generally speaking, there are two forms of incentive structures in these collaborative economies: one where a non-monetary resource may be shared and the provider gains monetary incentives (e.g., Uber); and the other where money is the shared resource and the providers obtain benefits (including the psychological satisfaction) from the projects (e.g., Kickstarter). Prior research has studied the dynamic pricing model in Airbnb to explore the incentive structure of the former kind (Edelman and Luca, 2013).
In this paper, we focus on the latter kind of incentive structure. In those cases, because the rewards are non-monetary, often a menu of options is provided. Also, because these are non-monetary rewards, they are subject to information asymmetry issues. Furthermore, as in Kickstarter.com, creators are allowed to dynamically change across time the project reward structure (PRS), including the number of reward levels, their denominations, reward types, and maximum number of backers for some rewards. So, the information asymmetry and the levels of rewards offered create interesting tensions that have implications on whether the project is successfully funded. The objective of our research is to understand the impact of PRS on backers’ pledging decisions during projects’ funding period. Specifically, we analyze a project panel data to investigate the following questions. Firstly, how do various features of the PRS impact backers’ pledging decisions and how is the nature of the impact contingent on other project features? Secondly, when and how should creators strategically modify the PRS during the funding period to attract more backers?

To motivate the structural analysis, we first present a project-level reduced-form model to investigate the impact of the reward structure on project outcomes. We find that dynamically modifying reward structures during project funding process has significantly positive impacts on influencing the project outcomes. We then develop a structural model to investigate how reward structures affect the reward-level decision making process by using a panel data. We find that reward levels that have been popular options till date or that have gained recent popularity are perceived to be more favorable if they are pushed lower down the menu of options, presumably by introducing weaker or less attractive
options ahead of them in the menu. Thus we provide insights into how project creators can strategically design PRS.

Understanding this mechanism is of significant importance to both industry practitioners and academic researchers. On one hand, our research could shed light on how to leverage non-monetary incentives to distract users’ attention to risks and get them actively engaged in collaborative community. Also the findings could provide some guidelines for project creators to strategically design the reward mechanism in a more efficient way. On the other hand, our research extends previous research on how private incentives work and also contributes to the rapidly increasing literature on collaborative economy and crowdfunding.

The remainder of the paper is structured as follows. In Section 3.2, we review relevant literature in incentive design in collaborative economy, crowdfunding studies, and product line design theory in marketing. Section 3.3 describes the research context and data collection details. In Section 3.4, we present results from the reduced form logit regression analysis. Following that, Section 3.5 describes the structural model to understand the impact of PRS on contribution patterns. To account for endogeneity issues, we further present a model in Section 3.6. Empirical results are shown in Section 3.7. The counterfactual market simulations are presented subsequently. We conclude this paper with theoretical and managerial implications.
3.2 Literature Review

Our study points to three streams of literature: (1) incentive design in collaborative economy; (2) crowdfunding research in management; and (3) product line design in marketing.

3.2.1 Incentive Design in Collaborative Economy

In the collaborative economy, incentives are crucial for encouraging participation. Edelman and Luca (2013) study the dynamic pricing model on Airbnb.com and suggest the digital discrimination in online marketplaces. Meanwhile, crowdfunding is similar to the single threshold public good in the sense that people’s monetary contributions need to collectively achieve a threshold to make this project successfully funded. Prior research has investigated mechanisms that facilitate coordination among subjects’ contributions to alleviate free riding behaviors. Coordination mechanisms generally include, but are not limited to: communication, threat of punishment (Fehr and Gächter, 2002), anonymity vs. identifiability (e.g. a type of reputation), information (Hashim et al., 2012), and private incentives (e.g. a centrally provided lottery ticket for every contribution) (Fuster and Meier, 2010). Gneezy et al. (2011) further propose that the discussion should focus on when and why incentives do and do not work (Gneezy et al., 2011). The analysis that we conduct in our paper corresponds to the use of menu of non-monetary rewards as the mechanism to nudge contribution in a public good setting.
3.2.2 Crowdfunding Research in Management Studies

Prior crowdfunding studies examine users’ contribution patterns. For example, rational herding behaviors have been observed in Prosper.com, a lending-based platform (Herzenstein et al., 2011; Zhang and Liu, 2012). Burtch et al. (2013) find that crowding out may occur where contributors may experience a decrease in marginal utility from making a contribution as it becomes less important to the recipient in digitalism crowdfunding (Burtch et al., 2013).

Scholars also look into how to alleviate the information asymmetry in those crowdfunding platforms. For example, Lin et al. (2012) show that online friendship of borrowers could serve as signals of credit quality of borrowers on Prosper.com (Lin et al., 2012). Ghasemkhani et al. (2012) further empirically investigate the role of information systems in alleviating adverse selection through information availability in a P2P lending market (Ghasemkhani et al., 2013). However, to our best knowledge, there has been little research on investigating how non-monetary incentives alleviate risk and encourage participation on reward-based crowdfunding platforms.

3.2.3 Product Line Design in Marketing Research

A lot of studies examine how companies manage the product line by choosing the length and the variety of the product line in marketing. We borrow theories in this area to deepen our understanding of the reward structure including the length of the rewards and types of rewards. Firms may compete through their product lines vertically and horizontally. First, firms have the incentives to extend their product lines vertically to
attract customers of different willingness-to-pay for quality. Second, many firms may offer products that are different in characteristics such as flavor, color, or scent.

Additionally, product line design is treated as a competitive tool to compete with other companies or products (Draganska and Jain, 2005). They also find that consumers value product-line characteristics, such as quality and price, more than horizontal characteristics (Draganska and Jain, 2006). To our best knowledge, our study is the first one to bring the perspective of product line design into studying the reward structure design of crowdfunding platforms.

### 3.3 Research Context and Data Collection

The reward-based crowdfunding platform we study is Kickstarter.com, one of the largest crowdfunding websites. Kickstarter is aiming at funding creative projects, ranging from films, music, comics and dance, to video games, food-related projects and technology products. It has 13 different categories and 50 subcategories. Depending on the role, the set of tasks are different. A campaigner needs to create a project, specify the amount to raise, create the reward structure for the backers and decide the funding raising duration. As a contributor, you go through different reward levels, decide which level to contribute to and make a pledge. The funding mechanism is called fixed funding campaign, or “all or nothing”. The project gets funded only if it achieves or exceeds the goal; otherwise, money is refunded. More importantly, the reward, will be delivered only if the project is successfully funded.

We collected a panel data set from this website from March to July 2013 using a web crawler. All the active projects’ features have been collected, which include daily
information about the funding status, the reward structure, comments related to the project, and backers for each project. We have the data for all 13 categories. In the preliminary analysis, we choose games and films categories as the sample to facilitate the estimation process in the current empirical application. Games and films are among the top five most popular categories in terms of the number of projects launched and the top two popular categories in terms of the total amount of dollar donations as of August, 2014. The descriptive statistics are outlined in Table 3.1.

Table 3.1 Descriptive Statistics of Kickstarter Projects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project Success (1 = Success)</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Project Duration</td>
<td>32.12</td>
<td>1</td>
<td>60</td>
</tr>
<tr>
<td>Project Goal (in $)</td>
<td>37656.22</td>
<td>1</td>
<td>10000000</td>
</tr>
<tr>
<td># Reward Level Options in a Project</td>
<td>9.79</td>
<td>1</td>
<td>79</td>
</tr>
<tr>
<td>Total #Backers for a Project</td>
<td>136.75</td>
<td>0</td>
<td>66724.5</td>
</tr>
<tr>
<td>Total Donation for a Project (in $)</td>
<td>16611.74</td>
<td>0</td>
<td>5702153</td>
</tr>
</tbody>
</table>

On the reward menu, the reward options are typically sorted in ascending order based on the dollar value of the reward level. In terms of the reward descriptions, the creator could offer backers different types of rewards. Backers’ valuations toward those rewards could affect their pledging decisions. Therefore, we manually categorized reward descriptions and created several reward category variables for our model. Here are the reward categories: (1) Decorative item related to the project, such as poster, sticker, painting etc.; (2) In-kind item related to the project, such as shirt, mug, bag etc.; (3)
Tickets for early access to the product; (4) Contributor acknowledgement, such as name shown on the contributor list etc.; (5) Gratitude, such as sending out “Thank you” message; (6) product samples, such as a DVD of games; (7) backer engagement, such as personal conversations with the creator, participating in designing the product etc.; (8) other reward categories who do not follow in previous rewards. A sample of reward descriptions for a project has been offered in Appendix E. As you could see in the example, our current categorization mainly focuses on classifying the rewards into different categories. We do not consider differentiating the quantity differences in certain categories.

The categorization process works as follows. Firstly, we collected all the reward description data in a file and ran a word frequency analysis. Among the top 200 high frequent words, we identified 20 meaningful words. Secondly, based on the meaningful word list, two of the authors manually coded around 500 reward descriptions and completed the keyword list of different reward categories. Thirdly, according the keyword list, we programmed to accomplish the major part of the coding. However, for some of the reward descriptions, it could not be correctly categorized. The reason is that among some reward levels, the creator tries to employ an accumulative reward design method. For example, they will provide “all previous rewards” from a lower reward level in a higher reward level. Therefore, one of the researchers coded the rest of the reward descriptions according to the keyword list.

To facilitate our estimation, we choose a representative sample (25%) from the films and games category proportionally with 500 projects in films and 200 in games, respectively. Among those projects, the creators of 275 projects do not display their
Facebook connection on the project campaign page. And 37 projects have missing data on reward description due to missing data problem in our data collection process. Besides, we remove projects that have 0 backers on any given day. The final data for estimation include 313 projects (218 projects in film category and 95 projects in games category). Even though the number of projects in the estimation is not huge, we use the daily reward level data of each project and the data points used in the following estimation is sufficiently rich.

3.4 Reduced-Form Analysis

Before we present the analysis from the structural model, we firstly describe the reduced form analysis in understanding the effects of PRS on the funding outcome at the project level. Insights from this analysis motivate our structural analysis in section 5.

We use binary logit regression for the reduced-form analysis. The prediction variable is 1 if the project got successfully funded and 0 otherwise. The predictor variables include creator-related features, project-related features and interaction between backers and creators. Two main variables related to PRS are: (1) numRewards, which indicates the number of reward options for each project; and (2) rewardDummy, which represents if the number of rewards were modified by project creators during the funding collection period. As mentioned before, data for this reduced-form analysis is from Games, and Film categories.

The preliminary analysis of project funding data revealed two key insights about the PRS: (a) Projects that offer more reward level choices are more likely to succeed; and (b) Projects that modify the reward structure anytime during the funding period are more
likely to succeed. Results are presented in table 3.2. The significantly positive impact of PRS in the reduced form regression motivates us to develop a structural model to under backers’ dynamic decision process based on a panel data.

Table 3.2 Estimation Results of Preliminary Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate*</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.0299</td>
<td>0.1172</td>
</tr>
<tr>
<td>Games - Dummy</td>
<td>-0.4092</td>
<td>0.0752</td>
</tr>
<tr>
<td>Project Duration</td>
<td>-0.0258</td>
<td>0.00330</td>
</tr>
<tr>
<td>Project Goal (in $)</td>
<td>-6.85E-6</td>
<td>9.046E-7</td>
</tr>
<tr>
<td># Reward Level Options</td>
<td>0.0523</td>
<td>0.00675</td>
</tr>
<tr>
<td>Reward Menu Changed (Y = 1)</td>
<td>1.0081</td>
<td>0.0809</td>
</tr>
</tbody>
</table>

* Parameter estimates in bold letters are significant at least at the 99.9% confidence level.

3.5 A Structural Model of Backers’ Learning and Pledging Decisions

We develop a structural model of “Backers’ Learning and Pledging Decisions”. We consider potential backers’ daily decisions of whether to back a particular project and which reward level to choose from the available options in the PRS. The model incorporates the dynamic structure of the PRS, as well as the observable and unobservable (to the researcher) features at the project level and the reward level. Historical daily funding data for every reward level of a representative sample of projects will be used to facilitate the estimation of and the inference for this model (in the current empirical application, we used a sample of projects in two categories - Games and Films).
3.5.1 Model Specification

Let $T_j$ denote the project duration (in days) of project $j$ ($j = 1, 2, \ldots, J$) and let $R_j$ denote the number of reward level options available to backers in project $j$’s rewards menu at time $t$. The indirect utility for a backer from donating in reward level $r$ ($r = 1, 2, \ldots, R_j$) of project $j$ ($j = 1, 2, \ldots, J$) at time $t$ ($t = 1, 2, \ldots, T_j$) is specified as:

$$u_{jrt} = f(Q_j) + \alpha X_{jrt} - \beta P_r + \epsilon_{jrt}$$  \hspace{1cm} (1)

where, $Q_j$ is the latent quality or attractiveness of project $j$ which is not explained by the observable project characteristics. $f(Q_j)$ is a function through which the project quality enters the utility function. $X_{jrt}$ are observable reward and project-level characteristics that include both time-variant as well as time-invariant features that are observed by the researcher as well as the backers. $P_r$ is the dollar value or donation amount of the reward. Finally, $\epsilon_{jrt}$ is a mean-zero random shock that captures the effect of unobserved (to the researcher) reward-level features that may influence potential backers’ choice of specific reward levels in project $j$.

We assume that backers do not know the true quality of a project perfectly. That is, they have uncertainty about the true quality, $Q_j$. Due to this uncertainty, backers’ belief about the true quality of project $j$ at time $t$ is stochastic. Hence, in Equation (1), we replace $Q_j$ with $\hat{Q}_j$, which is backers’ belief about the true quality of project $j$ at time $t$.

In the next sub-section, we explain the process by which backers learn about quality.
We allow that backers may be risk averse with respect to the uncertainty in the quality belief. Specifically, we assume that \( f(\tilde{Q}_{jt}) \) takes the CARA form:

\[
f(\tilde{Q}_{jt}) = -\exp\left(-\rho_j \tilde{Q}_{jt}\right)
\]

(2)

where, \( \rho_j \) is the level of risk aversion of backers of project \( j \). Backers of project \( j \) are risk averse if \( \rho_j > 0 \), risk neutral if \( \rho_j = 0 \), and risk seeking if \( \rho_j < 0 \). If a project creator can attract several of his or her friends and acquaintances to back the project, then such backers may have a lower level of risk aversion. Hence, we allow the level of risk aversion of backers to be project specific. In particular, we allow the risk aversion level of backers of a project to depend on the size of the social network of the project creator. Specifically, the size of the creator’s social network on Facebook:

\[
\rho_j = \rho_0 + \rho_1 \ln\left(1 + \#FBfriends\right)
\]

(3)

Due to their uncertainty about project quality, backers choose the pledging decision that maximizes their expected utility:

\[
E\left[u_{rjt}\right] = E\left[f(\tilde{Q}_{jt})\right] + \alpha X_{rjt} - \beta P_r + \varepsilon_{rjt}
\]

(4)

The expected utility from not donating in the project at time \( t \) is specified as:

\[
u_{0t} = \varepsilon_{0t}
\]

(5)

### 3.5.2 Learning about Project Quality

In any period, \( t \), backers face uncertainty about the project quality. This uncertainty is signified by a prior distribution of backers’ belief about the quality of
project \( j \). We assume that backers’ prior beliefs should be right on average about the true quality of a project. That is, backers have *rational expectations* such that the mean of their prior belief is the true quality of the project. This assumption is standard in many learning models (Coscelli and Shum, 2004), and is made to address the infeasibility of identifying the risk aversion parameter separately from the prior mean. The prior belief is assumed to be a normal distribution:

\[
\hat{Q}_{j0} \sim N(Q_j, \sigma_0^2)
\]  

(6)

With aggregate data on backers’ pledging decisions, we cannot identify the prior variance, \( \sigma_0^2 \). Thus, similar to many learning models (Narayanan et al., 2005) we fix the initial prior variance to one.

In each period, backers update their belief about the quality of project \( j \) based on the signals they receive through the status of the existing number of backers in the various reward levels of the project. We also assume that backers do not track reward level status daily over the project duration. Hence, at any time \( t \), backers have the same prior belief shown above, and they only use information about reward level status at time \( t \) to update their belief.

Suppose there are \( B_{jr-1} \) backers that have donated in reward level \( r \) of project \( j \) until time \( t-1 \). We assume that this reward status generates an unobserved (to the researcher) signal, \( s_{jr} \), that is normally distributed with mean equal to the true project quality, \( Q_j \), and a variance that is inversely related to \( B_{jr-1} \):
Hence, the precision of the signal, $\frac{B_{j-1}}{\sigma_r^2}$, increases with the number of existing backers for that reward level. We also allow the precision of the signal to depend on the dollar value of the reward level, $P_r$:

$$\sigma_r^2 = \exp\left(\gamma_0 + \gamma_1 \ln(P_r)\right)$$

(8)

A negative value for $\gamma_1$ would indicate that, controlling for the number of backers in the reward levels, the precision of the signals is greater for the reward levels of higher dollar value.

Backers are assumed to update their beliefs in a Bayesian manner. That is, they combine their prior belief about project quality with the quality signals from the $R_j$ reward levels and apply Bayes Rule to form the posterior belief. As the prior belief and the signals are normally distributed, the posterior belief is also a normal distribution and is given by:

$$\tilde{Q}_{j^*} \sim N\left(Q_{j^*}, \sigma_{\tilde{Q}_{j^*}}^2\right)$$

(9)

where

$$Q_{j^*} \frac{\sigma_{\tilde{Q}_{j^*}}^2}{\sigma_0^2} Q_j + \sum_{r=1}^{R_j} \frac{\sigma_{\tilde{Q}_{j^*}}^2}{\sigma_r^2} B_{j^*} * s_{j^*}$$

(10)

and
Note that the signals, $s_{j,t}$, are known to backers but are unobserved by the researcher. Hence, the mean of the posterior belief, $Q_j$, is a stochastic variable from the point of view of the researcher. Since the signals are assumed to have normal distributions, it follows that $Q_j$ is also a normal variable. In particular, by substituting Equation (7) in Equation (10), we can derive the following:

$$Q_j = Q + \eta$$

where

$$\eta \sim N(0, \sigma^2),$ \quad \sigma^2 = \sum_{r=1}^{\infty} \frac{\sigma^4_{r-1} B_{j,t-1}}{\sigma_r^2}$$

Given that the quality belief in any period is a normal distribution with mean $Q_j$ and variance $\sigma^2_{Q_j}$, we can rewrite the expected utility of backers (Equation 4) as follows:

$$E[u_{j,t}] = -\exp \left( -\rho_j \left( Q_j + \eta_jt - \frac{1}{2} \rho_j \sigma^2_{\eta,t} \right) \right) + \alpha X_{j,t} - \beta P + \epsilon_{j,t}$$

We will use the following equivalent form for the expected utility:

$$E[u_{j,t}] = Q_j + \eta_jt - \frac{1}{2} \rho_j \sigma^2_{\eta,t} + \alpha X_{j,t} - \beta P + \epsilon_{j,t}$$
3.5.3 Estimation

Let the market size of backers be denoted by \( M \). We assume a sufficiently large size of potential backers (\( M = 10,000 \)). If we assume that the unobserved shocks, \( \varepsilon \), follow an i.i.d. Type I extreme value distribution, then backers’ probability of not donating in project \( j \) at time \( t \) is:

\[
\Pr_{n_{jt}} = \frac{M - \sum_{k=1}^{R_y} B_{kjt}}{M}
\]

\[
= \frac{1}{1 + \sum_{k=1}^{R_y} \exp\left(E\left[u_{kjt}\right]\right)}
\]

\[
= \frac{1}{1 + \exp\left(Q_j + \eta_{jt} - \frac{1}{2} \rho_j \sigma_{Q_j}^2\right) \sum_{k=1}^{R_y} \exp\left(\alpha X_{kjt} - \beta P_k\right)}
\]

Hence, we get the following expression:

\[
Q_j + \eta_{jt} - \frac{1}{2} \rho_j \sigma_{Q_j}^2 = \ln\left(\sum_{k=1}^{R_y} B_{kjt}\right) - \ln\left(M - \sum_{k=1}^{R_y} B_{kjt}\right) - \ln\left(\sum_{k=1}^{R_y} \exp\left(\alpha X_{kjt} - \beta P_k\right)\right)
\]

(17)

In the first period (\( t = 1 \)) when backers make their decision based on only the prior distribution, we have:

\[
Q_j = \ln\left(\sum_{k=1}^{R_y} B_{kjt}\right) - \ln\left(M - \sum_{k=1}^{R_y} B_{kjt}\right) - \ln\left(\sum_{k=1}^{R_y} \exp\left(\alpha X_{kjt} - \beta P_k\right)\right) - \left(-\frac{1}{2} \rho_j \sigma_b^2\right)
\]

(18)

We assume that the project qualities, \( Q_j \), follow a normal distribution that is specific to the project category. That is, \( Q_j \sim N\left(\mu_c, \sigma_c^2\right)\).
For all subsequent periods \((t = 2, 3, \ldots, T_j)\), we have the following expression for \(\eta_{jt}\):

\[
\eta_{jt} = \ln \left( \frac{1}{\sum_{k=1}^{R_j} B_{kt}} \right) - \ln \left( M - \sum_{k=1}^{R_j} B_{kt} \right) - \ln \left( \sum_{k=1}^{R_j} \exp \left( \alpha X_{kt} - \beta P_k \right) \right) - \left( Q_j - \frac{1}{2} \rho_j \sigma_j^2 \right)
\]

(19)

Now, conditional on \(Q_j\) and \(\eta_{jt}\), for those who donate in project \(j\), we have the following conditional probability of choosing reward level \(r\):

\[
\Pr_{rjt} \left( Q_j, \eta_{jt} \right) = \frac{\exp \left( \alpha X_{jt} - \beta P_r \right)}{\sum_{k=1}^{R_j} \exp \left( \alpha X_{kt} - \beta P_k \right)}
\]

(20)

We use Maximum Likelihood Estimation to estimate the model parameters \(\Theta\). The parameters to be estimated include the utility function parameters \((\alpha, \beta\) in Equation 1), risk aversion parameters \((\rho_0, \rho_1\) in Equation 3), quality signal parameters \((\gamma_0, \gamma_1\) in Equation 8), and the normal distribution parameters for the quality of projects in each category \((\mu_C, \sigma_C, C = 1, 2, \ldots)\). Hence, \(\Theta = \{\alpha, \beta, (\rho_0, \rho_1), (\gamma_0, \gamma_1), (\mu_C, \sigma_C)\}\).

For a random sample of \(J\) projects, the likelihood function is given by:

\[
L = \prod_{j=1}^{J} \left[ \phi \left( Q_j, \mu_C, \sigma_C \right)^{T_j} \prod_{t=2}^{T_j} \phi \left( \eta_{jt}, 0, \frac{\sum_{r=1}^{R_j} \sigma_{Q,j}^4}{\sigma_r^2} B_{rjt-1} \right) \right]^{T_j} \prod_{r,t} \left\{ \Pr_{rjt} \left( Q_j, \eta_{jt} \right)^{B_{rjt}} \right\}
\]

(21a)
where \( \phi(Q_j, \mu_c, \sigma_c) \) is the p.d.f. of the normal distribution of project quality when the project is in category \( C \), \( \phi(\eta_j, 0, \sqrt{\sum_{r=1}^{R_c} \frac{\sigma^2_{Q_r}}{\sigma^2_r} B_{ji-1}}) \) is the p.d.f. of the normal distribution in Equation (13), and the last term is the conditional likelihood of the observed number of backers across the various reward levels of the project.

One issue with the above likelihood function is that, relative to the number of backers for a project, the potential market size \( M \), tends to be a large number for most projects. This can result in very small standard errors of the parameter estimates in the maximum likelihood procedure. Hence, we adjust the likelihood function in order that the standard errors are not influenced by the size of the potential market size. A similar idea of adjusting the likelihood function was also used in prior research (Song and Chintagunta, 2003). Consequently, we minimize the following ‘scaled’ negative log-likelihood function in the estimation:

### 3.6 Correct Endogeneity Issues

As our interests lie in analyzing the impact of changing the reward structure on backers’ behaviors, one potential issue is that the data we observe is already a reflection of project creators’ strategic behaviors. In other words, creators’ behaviors are endogenously generated and it is not fair to just model the backer-side’s behaviors. To resolve this concern, we endogenize creators’ decisions in our model. Specifically, we correct endogeneity for creators’ decision to adjust the number of reward options in the reward menu.
We model creators’ decision \( y_{jt} \) as changing the number of reward options at a given day \( t \) for project \( j \). \( y_{jt} \) is a discrete ordinal decision variable. If \( y_{jt} \) is a negative integer, it means removing the corresponding number of reward options. If \( y_{jt} \) is 0, it means the creator does not make any change to the number of reward options. If \( y_{jt} \) is a positive integer, it means adding the corresponding number of reward options.

We use ordered probit model to model creators’ decisions. The assumption is that there is a continuous latent metric \( y_{jt}^* \) underlying the ordinal response \( y_{jt} \).

\[
y_{jt} = \begin{cases} 
-1, & y_{jt}^* \leq \nu_0 \\
0, \nu_0 < y_{jt}^* \leq \nu_1 \\
1, \nu_1 < y_{jt}^* \leq \nu_2 \\
2, & y_{jt}^* > \nu_2
\end{cases}
\tag{22}
\]

where, \( \nu_k (k = \{0, 1, 2\}) \) are thresholds that partition the latent utility into a series of regions corresponding to the various ordinal categories. In our data, we labeled removing number of rewards as \( y_{jt} = -1 \), making no changes as \( y_{jt} = 0 \), adding one reward as \( y_{jt} = 1 \) and adding more than one reward as \( y_{jt} = 2 \).

We allow for endogeneity in the latent metric. In order to do this, we specify the latent utility of creators of project \( j \) at time \( t \) as:

\[
y_{jt}^* = \tau_0 + \tau_1 Y_{jt} + \xi_{jt}
\tag{23}
\]
where $Y_\mu$ are observable project-level characteristics that are observed by the researcher as well as the creator and affect the latent utility of the creator. $\xi_\mu$ are mean-zero random shock that are unobserved (to the researcher) and affect creators’ latent utility, where

$$\xi_\mu \sim N(0, \sigma_{\xi_\mu}^2)$$  \hspace{1cm} (24)

$Y_\mu$ serves as instruments that are uncorrelated with $\xi_\mu$. We model there is a correlation $\omega$ between $\xi_\mu$ and $\eta_\mu$ in equation 12.

$$\omega = corr(\xi_\mu, \eta_\mu)$$ \hspace{1cm} (25)

Therefore, given $\hat{\eta}_\mu$, the conditional probability of $\xi_\mu | \hat{\eta}_\mu$ is a normally distributed random variable which has the following distribution.

$$\xi_\mu | \hat{\eta}_\mu \sim N\left(\frac{\sigma_{\xi_\mu}}{\sigma_{\eta_\mu}}\hat{\eta}_\mu, \sigma_{\xi_\mu}^2 (1 - \omega^2)\right)$$ \hspace{1cm} (26)

The method we model endogeneity is known as the “limited information” approach, which has been used in prior literature (Villas-Boas and Winer 1999; Nair 2007). There are three reasons why we need to model creators’ behaviors in this way: (a) in the crowdfunding context, we are not sure about the objective function of the project creator. Therefore, we could not simply assume that they are to maximize the total pledged amount or total number of backers for the project; (b) even if we are aware of the objective function of the project creator, imposing function forms would bias our estimation; (c) our primary goal is to make recommendations for the reward structure change, which would not be possible if restrictions from the optimal structure design is imposed in the estimation process.
Therefore, the probability of each ordinal outcome is specified as:

\[
\begin{align*}
\Pr(y_{jt} = -1 | \hat{\eta}_{jt}) &= \phi(v_0 - \tau_0 - \tau_1 Y_{jt}) \\
\Pr(y_{jt} = 0 | \hat{\eta}_{jt}) &= \phi(v_1 - \tau_0 - \tau_1 Y_{jt}) - \phi(v_0 - \tau_0 - \tau_1 Y_{jt}) \\
\Pr(y_{jt} = 1 | \hat{\eta}_{jt}) &= \phi(v_2 - \tau_0 - \tau_1 Y_{jt}) - \phi(v_1 - \tau_0 - \tau_1 Y_{jt}) \\
\Pr(y_{jt} = 2 | \hat{\eta}_{jt}) &= 1 - \phi(v_2 - \tau_0 - \tau_1 Y_{jt})
\end{align*}
\] (27)

Where, \( \phi \) is the p.d.f of \( \xi_j | \hat{\eta}_{jt} \) in equation 26.

Estimation of models involving ordered probit model will not result in a unique solution. For identification purpose, we impose some identification constraints. We normalized the variance of \( \xi_j \) as 1, which implies \( \sigma^2_{\xi_j} = 1 \). And we normalize one of the threshold as 0, \( \nu_0 = 0 \). Therefore, in addition to the parameters that need to be estimated

\[ \Theta = \{ \alpha, \beta, (\rho_0, \rho_1), (\gamma_0, \gamma_1), (\mu_C, \sigma_C) \} \],

we also need to estimate the parameters in the latent utility function (\( \tau_0, \tau_1 \) in equation 23), the correlation parameter (\( \omega \) in equation 25), and the thresholds in the ordered probit model (\( \nu_1, \nu_2 \) in equation 27). Thus, all parameters that need to be estimated are

\[ \Theta = \{ \alpha, \beta, (\rho_0, \rho_1), (\gamma_0, \gamma_1), (\mu_C, \sigma_C), (\tau_0, \tau_1), (\nu_1, \nu_2), \omega \} \).

We also use the MLE approach to estimate the parameters. The likelihood function – equation 21a become as follows:

\[
L = \prod_{j=1}^{J} \left[ \phi(Q_j, \mu_C, \sigma_C) \prod_{t=2}^{T_j} \phi(\eta_{jt}, 0, \sum_{r=1}^{R_j} \frac{\sigma_{Q_{jt}}^2}{\sigma_r^2} B_{rjt-1}) \right] \times \prod_{r,j} \left( \Pr_{rjt} \left( Q_j, \eta_{jt} \right)^{B_{rjt}} \right) \times \prod_{t=2}^{T_j} \prod_{m=-1}^{2} \Pr(y_{jt} = m | \hat{\eta}_{jt})^{r_m} \] (28a)
where $I_{jt}^m$ is an indicator variable that denotes the decision $m (m=-1, 0, 1, 2)$ the creator of project $j$ made at time $t$.

The scaled log-likelihood function – equation 21b will become as follows:

$$-\ln(L(\Theta)) = -\sum_{j=1}^{J} \left\{ \ln\left[ \phi\left(Q_j, \mu_c, \sigma_c\right) \right] + \sum_{t=2}^{T_j} \ln\left[ \phi\left(\eta_{jt}, 0, \sqrt{\sum_{r=1}^{R_j} \frac{\sigma_{Q_{jr}}^4}{\sigma_r^4}} B_{jt-1}\right) \right] \right\} \frac{\sum B_{jt}}{M_c} (28b)$$

$$-\sum_{j=1}^{J} \sum_{t=2}^{T_j} \sum_{m=-1}^{2} I_{jt}^m \ln(\Pr(y_{jt} = m | \eta_{jt}))$$

### 3.7 Estimation Results

In this section, we first present the estimation results after we correct the endogeneity issues, and then discuss the major differences of results before and after we account for the endogeneity issues.

#### 3.7.1 Results after Correcting Endogeneity Issues

Based on the AIC/BIC criterion, we reported estimation results of the following structural model, which are shown in Table 3.3. First, we look at the results for the backers’ behaviors. Among the project level variables, we find that most backers prefer to not donate in projects in the Game and Film categories when compared with the outside option. This is inferred from the large negative means of project qualities in these categories ($\mu_{Game}, \mu_{Film}$) and the fairly low variances of the project qualities ($\sigma_{Game}^2, \sigma_{Film}^2$). Note that these estimates correspond to a fairly large market size of potential
backers \((M = 10,000)\). Hence, given the large market size, vast majority of the backers prefer not to donate in an individual project.

From the estimates of the parameters corresponding to the variance of quality signals from reward levels, we can infer that, controlling for the number of backers in the reward levels, the precision of the signal is greater for the reward levels with lower dollar value \((\gamma = 0.5465)\). In other words, when backers donate into lower dollar value rewards it gives a more precise signal of the project quality. One possible explanation is that the content of reward levels with lower dollar value is typically more generic tastes while that of reward levels with higher ones is more unique tastes. Therefore, backers would perceive a higher precision signal from reward levels with lower dollar value.

From the estimates of the parameters corresponding to the level of risk aversion of backers of particular projects, we see that backers are generally risk averse \((\rho = 2.2222)\). However, project creators that have larger social networks on Facebook are able to attract backers to their projects that are less risk averse \((\rho = -0.4054)\). One explanation could be that many of those backer may be friends of the creator who are less risk averse to donating in his or her project despite the uncertainty of the project quality.

Next, among the coefficients for the project and reward level variables, we find that more popular projects that have managed to garner large amounts of donations till date continue to attract more backers (coefficient value of 0.7394). However, the percentage of the Goal reached till date acts oppositely (coefficient value of -0.1036).

Next, we focus on the PRS to see how the project reward structure influences backers. First, of course, we get the intuitive result that, all else equal, backers are less
likely to donate in higher dollar value reward levels (coefficient of $P_r = 1.4052$). Next, we see that controlling for everything else, backers are less likely to donate in a project with more reward level options (coefficient value of -2.1025). To the extent that higher dollar value reward levels tend to be lower down in the menu of rewards options, we also find that the reward levels that are further down the menu tend to be less popular (coefficient of $r_{loxn} = -0.2667$). But interestingly, reward levels that have been popular options till date (i.e., high $B_{ij-1}$) are perceived to be even more favorable if they are pushed lower down the menu of options (coefficient of $B_{ij-1} \times r_{loxn} = 0.0763$), presumably by introducing weaker or less attractive options ahead of them in the menu.

Hence, while the early preliminary analysis suggested that a change in the PRS over the course of the project duration increases the odds of success for a project, here we see that project creators need to be strategic about changing the PRS. In particular, the attractiveness of popular reward levels can be further improved by introducing new reward level options above them. This finding is one of our most important contributions to the existing literature on sharing economy. Different from Burtch et al. (2013), we find creators could strategically design their incentives to attract backers at the reward level.

This change in the attractiveness of certain reward options due to a change in the PRS may be explained by the Contrast Principle or the theory of Context-dependent preferences in the Consumer Behavior Theory literature (Tversky and Simonson, 1993). According to these theories, consumers are more comfortable comparing and contrasting between more similar alternatives, and the relative attractiveness of an alternative can be increased by strategically introducing new alternatives. This result may also be explained
by the behavioral theory. As reward levels that are further down the menu tend to be less popular, it is reasonable that the placement of a new incentive alternative should be above an already popular reward level rather than below. Further investigation can reveal whether cognitive theories of consumer choice behavior such as the Contrast Principle or Construal Level Theory (Trope et al., 2007) can indeed play a crucial role in the successful dynamic design of the PRS.

Besides, creators also need to pay attention to the content of the reward. We find that rewards that include Product Samples such as, say, a game DVD, are most attractive for backers (Coefficient value of 0.8336). Other reward types such as Decorative Items (e.g., posters and stickers) Unique or special reward types, and Backers’ Engagement in Product Creation (e.g., participating in designing the product), Contributor Acknowledgement (e.g., name shown on the contributor list) are also fairly valuable propositions for backers (positive coefficients of 0.2404, 0.1915, and 0.1263, respectively). Rewards that include tickets for a one-time event or simple expressions of gratitude, such as “Thank you” messages, are the least attractive among all reward types, presumably because they elicit very low engagement with the project and therefore the backers are not attracted by those reward options.

In this part, we look at results of the creator side after we correct the endogeneity issue. There exists endogeneity between creators’ decision to change the number of reward options and backers’ behaviors (positive significant correlation estimate, 0.1159).

Among the project level variables that affect creators’ latent utility, we find that the higher number of barren rewards in the reward menu, the less likely the creator is to remove reward options (the positive coefficient of 0.0406). Meanwhile, the higher
proportion of barren rewards in the reward menu, the less likely the creator is to add reward options (the negative coefficient of -0.6084).

The thresholds for the latent utility of the creator are estimated to be 5.6277 and 6.1012, which are both statistically significant.

Table 3.3 Estimation Results of Structural Model Using Daily Aggregate Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate*</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Distribution of Project Quality</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \mu_{Game} )</td>
<td>-7.5286</td>
<td>0.976</td>
</tr>
<tr>
<td>( \mu_{Film} )</td>
<td>-8.2498</td>
<td>1.0283</td>
</tr>
<tr>
<td>( \sigma^2_{Game} )</td>
<td>0.7664</td>
<td>0.1034</td>
</tr>
<tr>
<td>( \sigma^2_{Film} )</td>
<td>0.8959</td>
<td>0.127</td>
</tr>
<tr>
<td><strong>Risk Aversion</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho_0 )</td>
<td>2.2222</td>
<td>0.2542</td>
</tr>
<tr>
<td>( \rho_1 ) (Coeff. of ( \ln(1 + #FB ) friends) )</td>
<td>-0.4054</td>
<td>0.0393</td>
</tr>
<tr>
<td><strong>Variance of Quality Signal from Reward Levels</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \gamma_0 )</td>
<td>-1.8693</td>
<td>0.4046</td>
</tr>
<tr>
<td>( \gamma_1 ) (Coeff. of ( P_r ) )</td>
<td>0.5465</td>
<td>0.12</td>
</tr>
<tr>
<td><strong>Project and Reward Level Variables (X_{rjt})</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(1+ # Projects backed by creator)</td>
<td>0.0708</td>
<td>0.1302</td>
</tr>
<tr>
<td>Log(1+Donation till date in $)</td>
<td><strong>0.7394</strong></td>
<td>0.041</td>
</tr>
<tr>
<td>%Goal Reached till date</td>
<td>-0.1036</td>
<td>0.0111</td>
</tr>
<tr>
<td>Time period ( (t) )</td>
<td><strong>0.0305</strong></td>
<td>0.0106</td>
</tr>
</tbody>
</table>
Table 3.3 continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_{\text{ squared}}$</td>
<td>-0.0195</td>
<td>0.022</td>
</tr>
<tr>
<td>$I(t = \text{Day1, Day2, Day3})$</td>
<td>-0.1747</td>
<td>0.1089</td>
</tr>
<tr>
<td>$I(t = \text{Day Tj-2, Day Tj-1, Day Tj})$</td>
<td>0.1738</td>
<td>0.0938</td>
</tr>
<tr>
<td>Log(1+ $#$ Options in Rewards Menu)</td>
<td>-2.1025</td>
<td>0.242</td>
</tr>
<tr>
<td># Total backers (in 100s) till previous period in reward level $r \left(B_{rjt-1}\right)$</td>
<td>-0.0014</td>
<td>0.0024</td>
</tr>
<tr>
<td>Location of reward level $r$ in Rewards Menu ($r_{\text{loxn}}$)</td>
<td>-0.2667</td>
<td>0.003</td>
</tr>
<tr>
<td>$B_{rjt-1} * r_{\text{loxn}}$</td>
<td>0.0763</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Project and Reward Level Variables ($X_{rjt}$)

<table>
<thead>
<tr>
<th>Indicators for Reward Categories (a reward level can be combinatio n of multiple categories)</th>
<th>Parameter Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I$ (Decorative Item = Poster, Sticker, Painting, etc.)</td>
<td>0.2515</td>
<td>0.0149</td>
</tr>
<tr>
<td>$I$ (In-Kind Item = Shirt, Mug, Bag, etc.)</td>
<td>0.0258</td>
<td>0.0201</td>
</tr>
<tr>
<td>$I$ (Tickets for early access to product)</td>
<td>-0.2052</td>
<td>0.03</td>
</tr>
<tr>
<td>$I$ (Contributor Acknowledgement)</td>
<td>-0.0398</td>
<td>0.0166</td>
</tr>
<tr>
<td>$I$ (Gratitude = Signed / Thank You message)</td>
<td>-0.4154</td>
<td>0.0142</td>
</tr>
<tr>
<td>$I$ (Product Samples like DVD)</td>
<td>0.8606</td>
<td>0.0165</td>
</tr>
<tr>
<td>$I$ (Backer Engagement in Product creation)</td>
<td>0.1326</td>
<td>0.0276</td>
</tr>
<tr>
<td>$I$ (Other or Unique Reward Types)</td>
<td>0.2195</td>
<td>0.0174</td>
</tr>
<tr>
<td>$S$ Value of reward level $r(P_r)$</td>
<td>1.4052</td>
<td>0.085</td>
</tr>
</tbody>
</table>
Table 3.3 continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate*</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Creator side Variables (Yjt)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation parameter</td>
<td>0.1159</td>
<td>0.0038</td>
</tr>
<tr>
<td>Constant parameter ($\tau_0$)</td>
<td>3.5697</td>
<td>0.1469</td>
</tr>
<tr>
<td>Number of barren rewards</td>
<td>0.0406</td>
<td>0.0139</td>
</tr>
<tr>
<td>Proportion of number of barren rewards</td>
<td>-0.6084</td>
<td>0.2304</td>
</tr>
<tr>
<td>Threshold 1 in ordered probit model ($\nu_1$)</td>
<td>5.6277</td>
<td>0.1348</td>
</tr>
<tr>
<td>Threshold 2 in ordered probit model ($\nu_2$)</td>
<td>6.1012</td>
<td>0.5801</td>
</tr>
</tbody>
</table>

* Parameter estimates in bold letters are significant at least at the 95% confidence level.

3.7.2 Comparison of Results Before and After Correcting Endogeneity

For most of the parameter estimates, the estimates do not change much under models before and after correcting endogeneity. However, there is a huge change for the variable we correct endogeneity, namely, the number of reward options (-0.9111 and -2.1025, before and after). We found that the impact of the number of reward options would be underestimated if we do not consider endogeneity. This implies that if there is endogeneity, as there are more backers contributing to the project, the creator will strategically be more likely to add reward options. The negative impact of the number of reward options would be even larger.

The other difference in the estimation is that the sign of the variance of quality signal is reversed before and after correcting endogeneity (-0.6437 and 0.5465, before and after). Before correcting the endogeneity, the negative sign of $\gamma_1$ indicates that when backers donate into higher dollar value rewards it gives a more precise signal of the
project quality. After correcting the endogeneity, the positive sign indicates that when backers donate into lower dollar value rewards, it gives a more precise signal of the project quality. As we explained earlier, lower dollar value rewards are more likely to be more generic reward types while higher dollar value rewards are more unique. The possible explanation is that if creators could strategically change the reward structure, the backers will not value the high dollar value rewards to get signals as much as getting signals from lower dollar value rewards.

### 3.8 Counterfactual Analysis

According to the findings in Section 6, we find that project creators could strategically manipulate the reward structure. In this section, we conduct several sets of counterfactuals to investigate: (1) the impact of adding a new reward option to the reward structure; (2) the impact of changing the timing to make changes to the reward structure.

We simulate the above scenarios using the following project setting. The project category we choose is film category. The starting reward dollar structure for the project is $10, $10, $10, $10, $50, $50, $50, $50, from top to bottom. We fix the reward type for each reward to be the same so that the only difference across reward options is the location on the reward menu for this project. We set the project quality to be the sum of the quality mean and quality standard deviation in the film category. The project duration is set 30 days.

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5 In the simulation, the reward type for each reward is a combination of decorative item, in-kind item, contributor acknowledgement, backer engagement, and unique reward.
6 Given the project setting, this quality value could give us reasonably good simulation results.
3.8.1 Adding a Reward Option to the Reward Structure

In this part, we investigate the impact of adding a reward option to the reward structure. Here we fix the timing of making such changes, such as toward the end of the project duration. We simulate two different cases: (1) adding a reward, such as $5, above the focal $10 reward options; (2) adding a reward, such as $30, below the focal $10 reward options.

The main findings are as below: (1) in Figure 3.1, we find that adding a reward on top of a popular reward could make the popular one even more popular; however, the total number of backers actually decreases compared to the original reward structure. (2) In Figure 3.2, we could see that adding a reward below the popular reward distracts attention from other rewards and make existing rewards less popular.

![Figure 3.1](image-url)
3.8.2 Changing the Timing of Making Changes to the Reward Structure

In this section, we conduct experiments to study the impact of different timing in changing the reward structure. In other words, we make the structure change either (1) in an early stage or (2) in a relatively later stage.

The main findings are as follows: (1) in Figure 3.3, we could see that adding a reward above a reward in an early stage distracts attention from other reward options. Therefore, it actually slows down escalation of rewards becoming popular ones and not make the other reward options even more popular; (2) however, adding a reward above a reward in a later stage could help make the already popular reward even more popular (Figure 3.1).
3.9 Conclusions and Implications

A crucial aspect to the functioning of these collaborative economies is the incentive structure that encourages participation. In this paper, we have used the structural modeling approach to study how providers or project backers respond to dynamic changes in non-monetary incentives in reward-based crowdfunding, one type of the collaborative economy. First, our reduced-form analysis showed that a change in the project reward structure over the course of the project duration increases the odds of success for a project. The findings from the structural model further indicate that reward
levels that have been popular options till date or that have gained recent popularity are perceived to be more favorable if they are pushed lower down the menu of options, presumably by introducing weaker or less attractive options ahead of them in the menu. This implies that project creators could strategically and dynamically design the reward structures during the funding period to attract more backers. This finding suggests that cognitive theories of consumer choice behavior such as Contrast Principle or the theory of Context-dependent preferences may have a crucial role in the successful dynamic design of non-monetary incentive structures. According to the counterfactual analysis, we find that adding a reward above reward options in a later stage could help escalate the popular rewards become even more popular compared to making changes in an earlier stage. Furthermore, when adding reward above the popular rewards, adding above the popular ones could make the popular ones even more popular while making the total number of backers decrease.

Our research is of significant importance to both academic research and industry practice. On one hand, we could provide some guidelines to the project creators regarding how to strategically manipulate the reward structures to incentivize users to participate. On the other hand, our research extends and contributes to incentive design in crowdfunding and collaborative economy in general. To our best knowledge, this is the first paper to investigate the non-monetary incentive design in crowdfunding. This pioneer work can easily prompt the investigation of other interesting research questions in this area.

The current research has some limitations that could be addressed in future research. Firstly, our analysis only uses two categories. It would be interesting to look at
how the results are contingent on different categories. We are working on generalizing
the findings to more categories. Secondly, when we categorize the reward descriptions,
we focus more on characterizing rewards into different categories. If the quantity
differences could be considered as well, the results would be more interesting. Those
issues would be addressed in our future research.
CHAPTER 4. EFFECTS OF INFORMATION AND COUPONS ON CUSTOMERS’ PURCHASE BEHAVIORS: A FIELD EXPERIMENT

4.1 Introduction

In Chapter 2, we develop a SVM based approach to identify customers to be nudged when dealing with products faced with supply constraints. Also we investigate how well the identified customers could be converted by nudging strategies, such as sending out information and/or coupons using emails. In this chapter, we further explore the effects of the nudging strategies on customers’ purchase behaviors. Specifically, we explore the short-term and long-term role information and coupons play in shaping customers’ behaviors and also the effects of information and coupons on influencing different types of customers.

Email targeting has emerged as an important digital channel to offer personalized promotions to customers. Email coupons are similar to traditional offline coupons in the sense that they are targeted to individual customers. Coupons often act as a marketing tool to charge a lower price to customers who have a lower willingness-to-pay. This view is supported by a set of empirical work studying the characteristics of customers who take advantage and redeem the traditional offline coupons (Swaminathan and Bawa 2005; Chiou-Wei and Inman 2008). However, surprisingly, given the popularity of email targeting in the industry, there has not been much work that focused on studying email
targeting specifically probably because of limited access to such marketing data. Interestingly, in one of recent papers on email targeted promotions, Sahni et al. (2014) analyzed data from a set of field experiments on an online platform and found that email promotions could serve as a role to inform customers. Although their work expands the role of coupons from just attracting lower willingness-to-pay customers to informing customers as well, they do not differentiate impacts of email targeting of different promotion depths. In another stream of marketing literature, characteristics of coupons, such as promotion depths (10%, or 20% off discount), have also been broadly studied and shown that they have significant different impacts on customers’ price expectations (Kalwani and Yim 1992).

To our best knowledge, there is no work investigating how email promotions of different depths plays different in informing customers or acting as a price discrimination tool. Also, if coupons could serve as a form of “advertising”, why not just send out information or “advertisements” instead of digital coupons? Does the high discount coupon play the same role in informing customers as the low discount one does? Also, in our context where there is limited product availability, strategies other than just sending coupons may be more desirable. For some customers, it is sufficient that we provide information alone but no coupons. Also, when a coupon is provided, customers may perceive the product unpopular and therefore may anchor their valuations for the product lower (Dodson et al. 1978). The anchoring effects have to be considered when sending coupons. Little has been formally studied about the different impacts of information versus coupons, and coupons of different promotion depths, on nudging new customers to purchase.
In this paper, we explore the aforementioned research questions using data from a field experiment run in an online grocery store. Analysis of the experimental data revealed some interesting managerial insights. We find that low coupons are more effective in performing as an information role in the long term than pure information strategies. However, high coupons serve more as a role in attracting price sensitive customers in the short term and do not perform well in the long run in informing the customers. We find that customers who are new to the store are more likely to be nudged by high discount coupons; whereas customers who have engaged with the store over a longer duration are converted using information. However, we did not find coupons with a low discount value to be as effective. We also provide a possible explanation for our observations.

In this chapter, Section 4.2 presents the relevant prior literature on coupons and email targeting. The experiment design will be described subsequently. Section 4.4 analyzes the data from the experiment. Conclusions and implications will be discussed in Section 4.5.

### 4.2 Literature Review

In this part, we review prior work that is related to our study: (1) effects of coupons on customers’ expectation and purchase behaviors; (2) effects of characteristics of coupons on effectiveness of promotions.
4.2.1 Effects of Coupons on Customers’ Expectation and Purchase Behaviors

There has been a lot of research that study the impact of traditional offline coupons on customers’ expectation and purchase behaviors. Prior literature has found conflicting effects of coupons on consumers’ choices and brand evaluations. Neslin and Shoemaker (1989) found that promotions negatively influence brand evaluations. However, Davis et al. (1992) provided disconfirming evidence regarding this aspect. In addition, research shows that consumers’ choices are positively impacted by the discount rate (Leone and Srinivasan 1996). However, price promotions could also reduce postpromotion choices because the brand quality could be reduced (Dodson et al 1978), or customers’ price expectations could be lowered (Monroe 1971).

Although email targeting becomes widespread in industry, we found there is only limited amount of work studying the impact of targeted emails on those behaviors, probably because of limited access to the marketing data. Wattal et al. (2011) study implications of personalization of email contents. Kumar et al. (2014) study the impact of marketing activities on the propensity of a consumer getting in and out of email marketing lists. Sahni et al. (2014) analyzed 70 randomized experiments and found that targeted promotions can serve as a form of “advertisement”.

4.2.2 Effects of Characteristics of Coupons on Effectiveness of Promotions

Characteristics of coupons include promotion frequency (how frequent a coupon is targeted to customers), promotion depth (to what extent the price is discounted, such as 10% or 20%), and promotion frame (percentage off versus cents off). Research shows that both frequency and depth of promotion have significant impacts on consumers’ price
expectations (Kalwani and Yim 1992). There is also work that study how promotion frame moderates the effect of promotion depth on postpromotion price expectations and choice (DelVecchio et al. 2007).

Although Sahni et al. (2014) concluded that targeted promotions can serve as a form of “advertising”, its findings are quite general regardless of the characteristics of the promotions. Actually in their data, email promotion offers consist of different promotion depths and promotion frames. To our best knowledge, there has been no research so far that studied if different promotion depths play different roles in informing customers. Also no prior work has compared the role of coupons versus pure information. In other words, if coupons could serve as a form of “advertising”, why not just send out information or “advertisements” instead of digital coupons? Specifically, in our context where there is limited product availability, strategies like sending out pure information about the product, other than just sending coupons, may be more desirable in certain circumstances. Therefore, we conduct a field experiment to evaluate the effectiveness and effects of information and/or couponing in influencing customers’ behaviors.

4.3 Experiment Design

We conduct a field experiment in an online grocery store to investigate different roles of promotion depths in informing customers and the impacts of information and coupons on different types of customers. The research context is the same as used in Section 2.6.1. The experiment design has been shown in Table 2.3. The experiment procedures have been described in Section 2.6.1 and Section 2.6.2. We will not repeat those contents in this chapter.
4.4 Analysis and Discussion

We conduct two sets of analysis in this section. First, we analyze the experiment data and investigate the information carryover effect of information and coupons in nudging customers to purchase. Second, we further understand the effects of information and coupons in converting different types of customers.

4.4.1 Information Carryover Effects of Information and Coupons

In this section, we analyze the role of coupons of different promotion depths in influencing customers’ behaviors. Given our research focus, we only consider subjects who opened the promotion emails in our experiment, and track their behaviors one season following the experiment.

First, we calculate the conditional conversion rate under different treatments. The conditional conversion rate is defined as the proportion of customers who purchased the product conditional on their opening the emails. Given the availability of the data we access, two types of conditional conversion rates are calculated: (1) the short term one, which is directly influenced by the treatments they receive during the campaign period, when customers could redeem the coupon they received; (2) the long term one, which is purely influenced by the information they receive in the campaign period but there is no such coupons available during the subsequent one season following the campaign period.

Table 4.1 shows that the number of subjects opening the emails is consistent across the treatments but that the conversion rates are not. The table segregates customers based on when they purchased the product – either during the campaign period or outside.

7 The period following the experiment is not strictly one season give the restrained access to the data from the company we work with.
Note that, even if customers had purchased during the campaign period, we do not have access to information about whether they actually redeemed the coupon or not. For the rest of the analysis, we assume that any purchase during the campaign involves the redemption of the coupon. Observe that during the one week campaign, the high coupon appears to produce the best outcome. A large number of customers took advantage of the offer to evaluate the product. Amongst the low coupon treatment, the conversion rate is perhaps the worst. We will evaluate that aspect of the result later. Surprisingly, we find that the extent to which discounts are offered do not have a monotonic variation with respect to conversion rates. Following the campaign period, the conversion rates are the lowest for the high coupon treatment. The total conversion for the entire season is similar across the information only and low coupon treatments. The main summary is that high coupons are quite effective during the campaign period. However, the low-coupon may play a role similar to the information only treatment. Perhaps, it may be the reason why customers did not buy as much during the campaign period but bought it later.

In other words, in the short term, intuitively, we can see that high coupons are statistically more effective in converting customers to purchase the product compared to the other two (one-side t test, p<0.01). Interestingly, the effectiveness of low coupon is statistically even worse than just sending out information (one side t test, p<0.01). However, in the long term, surprisingly, low coupon treatment has the highest impact to convert customers to purchase while high coupon treatment is statistically the worst. In other words, we found that low coupons are more effective in performing as an information role in the long term than pure information treatments. However, high coupons serve more as a role in attracting price sensitive customers in the short term.
Table 4.1 Performance of Treatments in the Experiment

<table>
<thead>
<tr>
<th></th>
<th># of Subjects opening the emails</th>
<th>Conditional conversion rate during the campaign</th>
<th>Conditional conversion rate in 1 season (excluding conversions during the campaign)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Coupon</td>
<td>70</td>
<td>20.00%</td>
<td>4.29%</td>
</tr>
<tr>
<td>Low Coupon</td>
<td>63</td>
<td>4.76%</td>
<td>7.94%</td>
</tr>
<tr>
<td>Information</td>
<td>70</td>
<td>7.14%</td>
<td>5.71%</td>
</tr>
</tbody>
</table>

Secondly, we convert the summary data from Table 4.1 into an influence proportion matrix\textsuperscript{8}, which is shown in Table 4.2. The rows in the table represent the treatments while the columns are the condition under which the converted customers are influenced to purchase. For example, in the “Low Coupon” row, 4.76% of customers who opened the email in the campaign period bought the product during the campaign period while 7.94% eventually purchased the product within a season after the campaign period. Those 7.94% customers purchased because of the information received but not the low coupon treatment. As seen in Table 4.2, there are some N/A values, which means there is no such data for this cell. In the previous example, there is no such data for the high coupon column under low coupon treatment (row).

Table 4.2 . Influence Proportion Matrix

<table>
<thead>
<tr>
<th></th>
<th>Information</th>
<th>Low coupon</th>
<th>High coupon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>12.86%</td>
<td>N/A*</td>
<td>N/A</td>
</tr>
<tr>
<td>Low coupon</td>
<td>7.94%</td>
<td>4.76%</td>
<td>N/A</td>
</tr>
<tr>
<td>High coupon</td>
<td>4.29%</td>
<td>N/A</td>
<td>20%</td>
</tr>
</tbody>
</table>

\*N/A denotes that there is no such data for this cell as explained in the main text.

\textsuperscript{8} This table is useful in the sense that it could help our understanding for Figure 4.2 and Figure 4.3.
Based on the t test statistics⁹, we found that promotions do cause a significant carryover effect even to the season after the promotion ended, not only to the week after the promotion expires (Sahni et al. 2014). More specifically, we found that low discount promotions could cause a higher carryover effect than information only treatments while high discount promotions could not. That said, in the long run, it makes sense that low discount promotions are sent out to certain customers than just sending out information only emails. Even though low coupons may make customers perceive the product on promotion as low quality, it does provide a long term effect in informing customers and nudge them to purchase it.

### 4.4.2 Effects of Treatments on Customer Types

Next we study how well the treatments affect different customer types. For this analysis, we again restrict the analysis to subjects who opened the emails. The number of subjects who opened the email was 203, of which 34 converted. Among the converts and non-converts, we are interested in retracting the characteristics of those customers. We used a logit regression model to evaluate how well the feature set of the individual customer predicted their conversion (1 as converts and 0 as non-converts). The feature set in this logit model also includes the treatment the subject was assigned to. Interestingly, we find that only the “purchase” variable (i.e. the number of previous purchases) to be a significant factor. As a next step, we estimated a different logit model where we interacted “purchase” with treatments. Even though the interaction terms are not significant, it appears to indicate that high coupons are more effective when

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⁹ The differences across groups are all statistically significant at least 99% confidence level.
customers has little prior purchasing experience (Refer to Appendix C for details about the two logit models we run.). This motivates our analysis in Figure 4.1.

![Bar chart showing average number of previous purchases](image)

Figure 4.1 Average Number of Previous Purchases

Following our previous analysis, we analyzed the number of previous purchases made by the customer segments. Figure 4.1 captures both the average number of purchases made by top 1000 customers identified by SVM (bars with inclined lines) and the average by the converts (bars with horizontal straight lines). This figure shows that customers with relatively fewer purchase experience react positively to the high coupon treatment compared with other treatments.

In the previous analysis, we only focused on the aggregate level analysis with respect to treatments. Because we would like to analyze the reaction of individual customers, we also consider the survival analysis. The survival analysis also gives insights into when the customer would purchase the product without interventions and how interventions affect the purchasing behaviors. Details about the survival analysis are
provided in Appendix D. The hazard function is estimated based on customer data at the end of 2013 using non-parametric methods. They are shown as the blue curves in Figures 4.2 and Figure 4.3, where the horizontal axis “lenfol” represents the number of previous orders customers have placed. Note that the hazard rate function is right censored because we do not observe the customer population for duration beyond 2013.

Figure 4.2 Hazard function and customers identified by treatments
Figure 4.3 Hazard function and customers identified by how they were influenced to purchase the focal product

Figure 4.2 identifies the purchasing customers based on the treatments that they were subjected to. Because the coupon had a validity period and not all customers purchased within the period, we identified customers who purchased subsequent to the coupon validity as having been affected only because of information. Figure 4.3 simply accounts for whether information played a role or not. Notice between the figures that a large number of customers in the low-coupon treatment purchased the product subsequent to the window. It appears that the figures are consistent with findings in Figure 4.1 in that high coupons are effective with relatively newer customers. One possible explanation is that new customers may have significant distractions and
providing emails with health related messages possibly does not attract attention. Offering high coupons may gain their attention. On the other hand, for experienced customers, their purchasing habits are relatively set routines. So, information is sufficient as a nudge.

4.5 Conclusions and Implications

In this chapter, we analyzed data from a field experiment and investigate if promotions of different depths play a different role in informing customers in a short term and long term. We found that promotions do cause a carryover effect even to the season after the promotion ended, not only to the week after the promotion expires (Sahni et al. 2014). More specifically, we found that low discount promotions could cause a higher carryover effect than information only treatments while high discount promotions could not. Furthermore, we find additional managerial insights. We find that customers who are new to the store are more likely to benefit from high coupons, while relatively older customers are converted using information. Coupons with a low discount value, however, are not found as effective as the other two strategies.

Our work has both significant theoretical contributions and industrial implications. First, our paper enriches the promotion literature on email targeting. Second, the work extends findings from prior literature on the information role that coupons play both in the short term and long term. From the perspective of the marketing managers, they could strategically leverage coupons of different promotion depths and/or information depending on their objective. For example, high coupons could attract attention of customers who have a lower willingness-to-pay in the short term but might lower
customers’ price expectation. Low coupons actually could play an important role in informing customers in a relatively long term, which is even higher than purely sending out information. Additionally, we offer insights regarding how to actively nudge using different strategies for different types of customers.

Although our work convey interesting findings, we admit there are some limitations. Firstly, our results are only based on one field experiment. It would be interesting to test our results on more experiments in which different promotion frames could be used as well. Second, only one product is involved in the experiment. It would be more insightful to validate this result using different product categories. Besides, given the limited access to the individual level data in the experiment, we could not conduct more sophisticated analysis, such as difference in difference approach. If individual level purchase data is available in future field experiments, it would be interesting to conduct such analysis and gain more insightful results.
CHAPTER 5. CONCLUSIONS

With the increasing availability of information technologies, shaping customers’ behaviors is more easily accomplished given the company’s ability to adapt their offerings according to customers’ demand as well as track customers’ online behaviors. In this dissertation, predictive analytics, structural model and field experiments are employed to analyze vast amount of data to understand customers’ online purchase and contribution behaviors. Our work makes significant contributions to the information systems, supply chain, recommender systems, predictive analytics, email marketing and crowdfunding literatures. The interdisciplinary nature of our research highlights the role of big data analytics in understanding and nudging customers’ behaviors. Therefore, our work also generates meaningful insights to business managers.

In Chapter 2, we develop a SVM based approach to identify limited number of customers to be nudged to purchase products with supply constraints. We evaluate and compare the proposed approach with other existing techniques via a randomized field experiment. We find that, in terms of the successful nudges, our SVM-based approach performed better than other approaches. Our findings generate insights to business managers on what techniques they can use to identify potential customers to be nudged and how different nudging strategies could be used to shape customers’ behaviors.
We are not only focusing on nudging customers to purchase. In Chapter 3, we pay attention to nudging customers to contribute, specifically, in a reward-based crowdfunding platform. We develop a structural model to understand backers’ learning and pledging behaviors. We use it to test a variety of behavioral theories of how PRS and intertemporal changes in the PRS influence backers’ pledging decisions over the course of a project’s funding period. Interestingly, estimation results show that reward levels that have been popular options till date or that have gained recent popularity are perceived to be more favorable if they are pushed lower down the menu of options, presumably by introducing weaker or less attractive options ahead of them in the menu. From the counterfactual analysis, we further show that project creators could strategically add a reward option above popular rewards in a relatively later time period to make the popular options even more popular.

In Chapter 4, we further investigate the impact of different nudging strategies, such as information only, low discount, high discount, on customers’ purchase behaviors. We evaluate the effectiveness of those different nudging strategies via a randomized field experiment. Consistently with prior literature, we found coupons could serve as a form of “advertisement”. Furthermore, our findings provide evidence that coupons with a low discount value could have a longer information carryover effect than those with a higher discount one. We also evaluate how well the identified customers are nudged through information and/or couponing. The experiment shows that customers who are new to the store are more likely to benefit from high coupons, while relatively older customers are converted using information. Coupons with a low discount value, however, are not found as effective as the other two strategies.
In conclusion, this dissertation leverages state-of-the-art methodologies, such as predictive analytics and structural modeling, and analyze enormous amount of data to understand and nudge customers’ purchase and contribution behaviors in two types of online engagement platforms. We propose methods to identify customers to be nudged, study impacts of different nudging strategies, and also model customers’ behaviors so that effective nudging strategies could be provided to business managers. Our work makes significant contributions to both the theoretical literature and business practice. As big data analytics become more and more popular, there will be more groundbreaking studies in this area in the near future.
REFERENCES
REFERENCES


APPENDICES
Appendix A  Support Vector Machine

In this section, we briefly discuss the main idea of SVM. For details, refer to Vapnik (2000) and Cui and Curry (2005). SVM classification is also known as “maximum margin classifier”. The main idea of SVM is to find a separating hyperplane which “lies midway between the convex hulls of the two groups and be orthogonal to the shortest line connecting these hulls” (Vapnik 2000).

There are two forms of the objective function: a primal and a dual form:

\[
f(x) = w^* \cdot x + w_0^* = \sum_{i=1}^{n} a_i^* y_i (x \cdot x_i) + w_0^*,\]

where \( w \) denotes a weight vector, \( x \) represents an input feature vector and \( w_0 \) is a constant.

The kernel function is specified as \( \emptyset(x \cdot z) = \emptyset(x) \cdot \emptyset(z) \). Given this feature of the kernel transformation, we can conclude that the solution to the optimization problem is the same no matter if the problem is solved in the original attribute space using or in the transformed feature dimension.

\[
Max \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_i a_j y_i y_j \emptyset(x_i \cdot x_j)
\]

s.t. \( \sum_{i=1}^{n} y_i a_i = 0, a_i \geq 0 \)

where \( a_i \) are Lagrange multipliers in the original optimization problem.

The kernel function we use in our capacity constrained supply chain context is Gaussian (radial basis) kernel.
Appendix B  Examples of Analysis in Section 2.5

Take training period 10 (April, 2011 to June, 2011) as an example. We use customers’ purchase data in period 11 to period 20 to evaluate the number of successful predictions from period 10. Figure B.1 shows the cumulative number of success over the multiple subsequent time periods. We could see that if we use longer time window to observe the targeted customers, some of them do convert to purchase in later time periods in a self-discovery manner. 15% of the predictions convert to purchase among the top 1000 ranked customers from period 10.

![Figure B.1 Accumulative Number of Success in Lifetime Prediction (Period 10)](image)

Again take the training period 10 as an example. We use the subsequent 10 periods as the test window, and track the purchase patterns of those top 1000 customers. Figure B.2 conveys that if we extend the time window to lifetime and
track the repeat purchases behaviors of those converted customers, we could find that those converted customers do purchase this product repeatedly. On average every converted customers come back to purchase 4.2 times.

Figure B.2 Number of Repeat Purchases of Converted Customers in Lifetime (Period 10)
Appendix C  Analysis Using the Experiment Data

Conditional on customers opening the emails, we investigate how customers behave to convert to purchase or not purchase. We use converts/non-converts (1/0) as response variable in the logit regression model. We use features of those customers and treatments (dummy variables) as predictor variables. We conducted several additional analysis to understand what types of customers are more prone to convert under different treatments. We have the following findings.

First, as shown in Table C.1, we put all the predictor variables in the logit regression and found only the purchase experience i.e. the number of previous orders has a significant impact on the conversion odd (p<0.01).

Table C.1 Analysis of Maximum Likelihood Estimates of Model 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>-3.9352</td>
<td>0.7549</td>
<td>27.1747</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>highDummy</td>
<td>1</td>
<td>0.6704</td>
<td>0.5109</td>
<td>1.7216</td>
<td>0.1895</td>
</tr>
<tr>
<td>lowDummy</td>
<td>1</td>
<td>-0.0903</td>
<td>0.5743</td>
<td>0.0248</td>
<td>0.8750</td>
</tr>
<tr>
<td>Beef</td>
<td>1</td>
<td>0.6444</td>
<td>0.6655</td>
<td>0.9377</td>
<td>0.3329</td>
</tr>
<tr>
<td>Pork</td>
<td>1</td>
<td>0.7777</td>
<td>0.6435</td>
<td>1.4607</td>
<td>0.2268</td>
</tr>
<tr>
<td>otherRedMeat</td>
<td>1</td>
<td>0.7288</td>
<td>0.7384</td>
<td>0.9743</td>
<td>0.3236</td>
</tr>
<tr>
<td>poultry</td>
<td>1</td>
<td>0.6667</td>
<td>0.6363</td>
<td>1.0978</td>
<td>0.2948</td>
</tr>
<tr>
<td>seafood</td>
<td>1</td>
<td>0.5952</td>
<td>0.6508</td>
<td>0.8364</td>
<td>0.3604</td>
</tr>
<tr>
<td>otherMeat</td>
<td>1</td>
<td>1.0460</td>
<td>1.2875</td>
<td>0.6601</td>
<td>0.4165</td>
</tr>
</tbody>
</table>
Table C.1 continued

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>diary</strong></td>
<td>1</td>
<td>0.5287</td>
<td>0.6278</td>
<td>0.7090</td>
<td>0.3998</td>
</tr>
<tr>
<td><strong>notMeat</strong></td>
<td>1</td>
<td>0.3334</td>
<td>0.6173</td>
<td>0.2918</td>
<td>0.5891</td>
</tr>
<tr>
<td><strong>organic</strong></td>
<td>1</td>
<td>-0.1363</td>
<td>0.2126</td>
<td>0.4109</td>
<td>0.5215</td>
</tr>
<tr>
<td><strong>nonOrg</strong></td>
<td>1</td>
<td>-0.0809</td>
<td>0.2235</td>
<td>0.1311</td>
<td>0.7173</td>
</tr>
<tr>
<td><strong>grassfed</strong></td>
<td>1</td>
<td>-0.4590</td>
<td>0.6769</td>
<td>0.4599</td>
<td>0.4977</td>
</tr>
<tr>
<td><strong>nonGrass</strong></td>
<td>1</td>
<td>0.6273</td>
<td>1.3108</td>
<td>0.2290</td>
<td>0.6323</td>
</tr>
<tr>
<td><strong>price</strong></td>
<td>1</td>
<td>0.00811</td>
<td>0.00439</td>
<td>3.4158</td>
<td>0.0646</td>
</tr>
<tr>
<td><strong>purchase</strong></td>
<td>1</td>
<td>0.6170*</td>
<td>0.1922</td>
<td>10.3071</td>
<td>0.0013</td>
</tr>
</tbody>
</table>

*parameter significant at at least 99% confidence level

Secondly, another logit regression model with interaction term between number of previous orders, which is significant, and treatments is analyzed to study how this effect would change with respect to different treatments. Results are shown in Table C.2. Even though the interaction effects are not significant, the model with interaction terms does provide a better goodness of fit and indicate customers’ different responses to the treatments. (The direction of impact of high coupon/low coupon is also consistent with our findings in Figure 4.2). This in fact motivates us to analyze the hazard ratio along the number of previous purchases and plot Figure 4.2 and Figure 4.3.
Table C.2 Analysis of Maximum Likelihood Estimates of Model 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>-2.8870</td>
<td>0.7183</td>
<td>16.1527</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>highDummy</td>
<td>1</td>
<td>1.3611</td>
<td>0.8748</td>
<td>2.4210</td>
<td>0.1197</td>
</tr>
<tr>
<td>lowDummy</td>
<td>1</td>
<td>-0.9704</td>
<td>1.1627</td>
<td>0.6966</td>
<td>0.4039</td>
</tr>
<tr>
<td>purchase</td>
<td>1</td>
<td>0.1710*</td>
<td>0.0941</td>
<td>3.3005</td>
<td>0.0693</td>
</tr>
<tr>
<td>highDummy*purchase</td>
<td>1</td>
<td>-0.0946</td>
<td>0.1220</td>
<td>0.6013</td>
<td>0.4381</td>
</tr>
<tr>
<td>lowDummy*purchase</td>
<td>1</td>
<td>0.1748</td>
<td>0.1532</td>
<td>1.3028</td>
<td>0.2537</td>
</tr>
</tbody>
</table>

*parameter significant at at least 90% confidence level
Appendix D  Survival Analysis

The primary focus of survival analysis is to model the hazard rate, \( h(t) \), which describes the instantaneous rate of an event occurring at time \( t \). The event in our context is defined as customers’ discovering and purchasing the focal product, which is grass-fed beef. The mortality of a customer is assumed to occur as soon as the customer purchases the grass-fed beef. The number of purchases between a customer’s first purchase in this store and his first purchase of the grass-fed beef product is the longevity of the customer in our dataset. Note that the longevity in our dataset is right-censored, because we have purchase history information only until 2013.

The “hazard” function, \( h(t) \), which describes the probability of the event occurring at time \( t \) \( f(t) \), conditional on the subject's survival up to that time \( t \) \( (S(t)) \), is \( h(t) = \frac{f(t)}{S(t)}. \) Kernel-smoothed estimators of the hazard function \( h(t) \) are based on the Nelson-Aalen estimator of the cumulative hazard function \( \hat{H}(t) \). Details on using individual level data for estimating \( h(t) \) could be found at SAS (2010). The Nelson-Aalen estimator of the cumulative hazard function is a non-parametric estimator and is given by \( \hat{H}(t) = \sum_{t_i \leq t} \frac{d_i}{n_i} \), where \( d_i \) is the number of customers who discover and purchase the product out of \( n_i \) potential customers in interval \( t_i \). The estimator is calculated, then, by summing the proportion of those potential customers who discovered and purchased the product in each interval up to time \( t \). The estimated hazard function is shown as the solid line in Figure 4.2 and Figure 4.3.
Appendix E  A Sample of Reward Description Categorization

Table E.1  A Sample of Reward Description Categorization

<table>
<thead>
<tr>
<th>Reward level</th>
<th>Reward description</th>
<th>Decorative Item</th>
<th>In-Kind Item</th>
<th>Tickets for early access to product</th>
<th>Contributor Acknowledgement</th>
<th>Gratitude</th>
<th>Product Samples</th>
<th>Backer Engagement in Product creation</th>
<th>Other or Unique Reward Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>The Appreciator: A &quot;Special Thanks&quot; shout out on our Facebook Page for being a valued supporter of these great men and what they are doing.</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>The Good Deed: A Special Thanks on the official &quot;Cycle of Life&quot; Facebook Page and 2 &quot;Cycle of Life&quot; custom engraved &quot;Livestrong&quot; style bracelets.</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>100</td>
<td>The Supporter: Everything listed in the above donation categories plus an Official &quot;Cycle of Life&quot; T-Shirt and an additional 2 &quot;Cycle of Life&quot; bracelets. A special thanks in the credits and a DVD copy of the completed</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Level</td>
<td>Reward Description</td>
<td>250</td>
<td>500</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
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<td>250</td>
<td>The Activist: A Total of 10 &quot;Cycle of Life&quot; Bracelets, 2 T-Shirts, 1 Dry-fit custom Designed exercise shirt, a &quot;special thanks&quot; in the credits, as well as a digital copy of the project upon completion.</td>
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<td>500</td>
<td>The Producer: You will receive all of the above listed rewards as well as a co-producer credit in the completed documentary.</td>
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<td>The Executive: All of the rewards listed above except you will be acknowledged as a Producer in the credits of the documentary.</td>
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