Leveraging Loyalty Programs Using Competitor Based Targeting

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Abstract

Loyalty programs are widely used by firms but their effectiveness is subject to debate. These programs provide discounts and perks to loyal customers and are costly to administer, and with uncertain effectiveness at increasing spending or stealing business from rivals. We use a large new dataset on retail purchases before and after joining a loyalty program (LP) at the customer level to evaluate what determines LP effectiveness. We exploit detailed spatial data on customer and store locations, including locations of competing firms. A simple analysis shows that location relative to competitors is the strongest predictor of LP effectiveness, suggesting that LPs work primarily through business stealing and not through other demand expansion. We next estimate what variables best predict LP effectiveness using high-dimensional data on spatial relationships between customers, the focal firm's stores, and competing stores as well as customers' historical spending patterns. We use LASSO regularization to show that spatial relationships are more predictive of LP effects than are past sales data. Finally, we show how firms can use this type of predictive analytics model to leverage customer and competitor location data to substantially increase the performance of their LP through spatially driven targeting rules.

Keywords: Loyalty programs, predictive analytics, spatial models, retail competition, machine learning

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1 Introduction

Loyalty programs are now prevalent in many industries. The loyalty programs as marketers know them today originated in the airlines in the 1980s and have since permeated industries such as hotels, casinos, retailers, grocery stores, and restaurants, among others. The pervasiveness of loyalty programs is partly due to their flexibility in how they can be structured (e.g., earning rates and rewards) and managed for strategic decisions (e.g., targeting to increase customer engagement).

In spite of the popularity of loyalty programs with firms, their effectiveness at increasing profits has long been subject to debate. This debate has centered on the costs of giving discounts and perks to the most loyal customers, as well as the costs of administering the program itself, and whether these costs are justified by increases in spending by those customers. Loyalty programs have the potential to increase profits by increasing switching costs for existing customers, stealing business from rivals, or through second degree price discrimination. They may also indirectly increase profits by increasing customers psychological perceptions of the firm, by generating customer data that can be used for targeted promotions or CRM, or by exploiting agency issues such as flights booked by business travelers and paid for by their employers (Dreze and Nunes (2008), Roehm et al. (2002), Verhoef (2003), and Shugan (2005)).[1]

Empirical studies of whether loyalty programs actually do increase profits have found mixed results. Verhoef (2003) finds that the effects are positive but very small, DeWulf et al. (2001) finds no support for positive effects of direct mail, Shugan (2005) finds that firms gain short term revenue at the expense of longer term reward payments, and Hartmann and Viard (2008) found no evidence that loyalty programs create switching costs.

In this paper, we consider whether and when loyalty programs are profitable and to what extent this profitability results from stealing business from rivals or increasing overall demand via one of the mechanisms described above. We approach this problem in a novel way using a large and detailed dataset on retail spending. We observe spending before and after customers join a loyalty program and exploit variation across markets with different levels of competition and types of competitors. This comparison can be made at a granular level using detailed information on customer and competitor location. By measuring how total spending changes at the customer level for customers facing different local competitive structures we can observe, for instance, if customers

[1]For a more complete review, please see Bijmolt et al. (2011), Liu and Yang (2009), and McCall and Voorhees (2010)

in more isolated markets change their spending or if they merely start receiving discounts on their purchases and how this differs in highly competitive markets. This type of variation can help resolve the question of when LPs are profitable and to what extent do they work through business stealing versus other demand expansion.

We use a large and detailed dataset that results from merging credit card spending data with customer data from a leading retailer to show that the local competitive structure is more predictive of how customers respond to joining an LP then are their historical spending patterns. In particular, an individual's spatial relationship with competitor stores is the main determinant of LP effectiveness in simple comparisons. This suggests that the loyalty program is working through business stealing and does not otherwise raise demand. To our knowledge, this is the first paper to explicitly link the competitive structure of a market with the performance of a loyalty program.

While model-free comparisons suggest spatial competitive structure is the crucial determinant of LP effectiveness, the full relationship is likely to be highly complex. To capture the complex spatial relationship between the customer, focal firm, and competition, we estimate the relationship between the change in spending (conditional a customer on joining the LP) and a very large number of variables on purchase data and spatial relationships with competitors at the individual level. This estimation is essentially a prediction problem with a very large number of potential predictive relationships. Our estimation procedure therefore combines LASSO regularization with a selection correction approach to allow for many potential variables and to infer the true impact of spatial structure and other variables on loyalty program performance.

This estimation serves two purposes. First, it validates the descriptive result that spatial competitive structure is a stronger predictor of LP effectiveness than are past spending patterns or other RFM variables. Second, we then use the output to show how firms can take advantage of this insight and leverage customer and competitor location data to increase the performance of their LP through spatially driven targeting rules. Because location and travel costs form an important part of preferences over retailers, this can be thought of as a strategy for targeting price discounts on observable preference heterogeneity. The variation across customers in the profitability of their joining the LP is large, with 49.1% of joiners resulting in a net loss to the firm, suggesting the gains from improving targeting can be quite high. We find that, consistent with the spirit of recent work in targeting (e.g., Ascarza (2018)), firms should focus on the customers who are more "spatially vulnerable" relative to the competition and avoid promoting the LP to customers who, for example, have limited access to their competitors.

The field of economics, and then later marketing, has a long history of incorporating location effects, dating back to the study of how location with respect to competitors determines market power (e.g., Hotelling (1929)), including empirical studies of how firms strategically employ and respond to spatial differentiation (Seim (2006), Davis (2006), Thomadsen (2007)). This includes research studying how market characteristics influence a firm's price and promotion activity (Hoch et al. (1995) and Bronnenberg and Mahajan (2001)).

Recent work has explored the benefits of geotargeting, where promotion or other marketing activity is a function of a customer's real-time location using mobile data (Luo et al. (2014), Chen et al. (2016)). Fong et al. (2015) and Dube et al. (2017) have also considered "geoconquesting", where the marketing activity focuses on instances when the customer is located near a competitor as opposed to near the focal firm. This literature is limited, but potential gains from geoconquesting are especially likely when the marketing activity is based in part on business stealing, as it is for loyalty programs. One contribution of this paper is to point out the potential gains from orienting promotional activity towards geoconquesting, even in a non-mobile setting.

While the previous literature therefore incorporates select spatial components, mostly it does not fully account for the complex customer-store-competitor spatial relationship. In prior work, competitor information is often integrated into models through simple customer-store or store-competitor distance metrics, thereby eliminating the possibility of complex spatial analyses. Beyond complex spatial analysis alone, the interplay between the competitive structure and loyalty program effectiveness has not yet been explored.

We also contribute to the study of competitive promotions and competitive price discrimination. Price discrimination strategies such as loyalty rewards should never lower profits by a monopolist but in oligopoly settings this is no longer true as firms may face a prisoner's dilemma (Shaffer and Zhang (1995)). Chen et al. (2001) shows that when individual targeting is possible but imperfect, it can soften price competition among competing firms, but as targeting precision increases the prisoner's dilemma reasserts itself. Ultimately then, it is an empirical question whether and when targeted price discrimination can increase profits. Previous work has shown that in practice the benefits of using targeted pricing can be quite high (Rossi et al. (1996), Besanko et al. (2003)). Li et al. (2018) specifically consider competitive price discrimination across markets and show that the profitability of tailoring prices to local markets depends on both the local market structure and competitive intensity across markets. Our analysis also considers local market structure but with price discounts in the form of a loyalty program that can be targeted at the individual level.

The remainder of the paper proceeds as follows. Section 2 describes the data on retail sales histories and competitor and customer locations. Section 3 provides model free evidence that the spatial competitive structure surrounding a customer is the key determinant of LP effectiveness. Section 4 describes a LASSO estimation of the complex interaction between competitive structure and LP effectiveness and then uses this result to form a potential targeting strategy. Section 5 discusses managerial implications and avenues for future research.

2 Data

In this section we describe the customer transaction data, competitive location data, and provide an overview of the spatial metrics used to characterize the competitive structure.

2.1 Transaction Data

The transaction data comes from a Fortune 500 specialty retailer, one of the 10 largest retailers in the U.S. This data is highly detailed: we observe the full basket of purchases from 10,029 customers between March 2012 and March 2014. These sum to over 2.4 million SKU level purchases across 897,819 store trips. On average, each customer has about 90 trips across nearly five different store locations through the two year observation period, spending about $110 per store visit, and traveling about 5.7 miles.

Customers	10,029
Date range	March 2012 to 2014
Avg. trips/customer	90
Spend/trip (net, after discounts)	$110.18
Average # of locations visited	4.7

Table 1: Summary Statistics

Crucially for this analysis, individuals are identified through their credit card rather than a loyalty program card. This allows us to observe transaction activity both before and after the customer joins the loyalty program. We also observe all marketing activity for these customers through the firm's email campaigns: over 900,000 emails were sent to about 39% of the customers and 11% of the customers received promotions specifically encouraging enrollment in the loyalty program.

Importantly, the data also contains the customer's location and the latitude/longitude of each of the firm's store locations, which provides us with a complete picture of all customer interactions with the firm across different store locations as well as the specific products purchased at each store location over time.

We further take advantage of a unique feature of this loyalty program in that the program discounts are earned and applied on only a single large category of the firm's goods. We label this a *limited* loyalty program to emphasize the distinct structure. As requested by the firm providing the data, we cannot disclose the type of goods subject to discounts. However, because this firm competes with both generalists, who also sell a large variety of categories, and specialists, who only sell the products in the specific category the LP applies to, this feature provides an additional lever with which to study the interaction between competitive structure and LP effectiveness. It also allows us to study whether and when the loyalty program causes spillovers into other category purchases.

2.2 Competitor Data

The competitor data contains the locations of four primary competitors of interest, who were selected based on discussions with the focal firm. The four competitors (see Table 2) vary in both size and product breadth. Competitor #1 is a big box store with a wide product variety (BB). The remaining three competitors are small-box stores. Competitor #2 and competitor #3 offer a wide assortment of products (SB1 and SB2), whereas competitor #4 specializes in the product category for which the limited loyalty program applies (SS).

Competitor	Reference	Footprint	Product Breadth
#1	BB	Big-Box	Wide
#2	SB1	Small-Box	Wide
#3	SB2	Small-Box	Wide
#4	SS	Small-Box	Specialized

Table 2: Competitor Types

The variety in the size and product breadth allows us to compare how the impact of the competitive structure might be competitor or type specific. More importantly, it allows us to gain insight into the extent of category-level versus store-level business stealing.

The latitude and longitude locations of each competitor are collected from the Google Maps API. We first pulled all competitors within a 30 mile radius of each of the focal stores, and then pulled all competitors within 30 miles of each customer located within a 30 mile radius of each focal store. This expanded footprint ensures that our definition of the competitive structure is customer centric rather than limited to the perspective of the focal store.

2.3 Quantifying the Competitive Structure

Our analysis measures and highlights the impact of the complex spatial relationship between the customer, the focal store, and the competitors on customer behavior and ultimately firm profits. Quantifying this relationship in such a way to accurately reflect the tradeoffs that an individual likely encounters when deciding which store to visit requires several complex considerations.

A common approach in quantifying competitive structure is to simply use the distance between a focal store and the customer along with the distance between the competitor and the focal store (or more commonly still, an indicator variable if they are both within, say, a 5 mile radius of the focal store). The drawback of this approach is that it does not jointly consider the customer-store-competitor location, resulting in a potential homogenization of very distinct competitive structures.

This limitation is illustrated in Figure 1: two competitors, C_1 and C_2, and a customer, I, are positioned near the focal store S. Both competitors are nearly the same distance to the store, but their respective relationships to the customer and the focal store are considerably different. The customer has to pass by the focal store in order to visit the first competitor, C_1, which suggests some spatial advantage for the focal store. However, the second competitor, C_2 is positioned right next to the customer, acting as a convenient alternative to the focal store. One goal of this analysis is to incorporate these complex spatial structures into the manager decision process, a strategy that has heretofore been ignored in the analyses of loyalty program effectiveness.

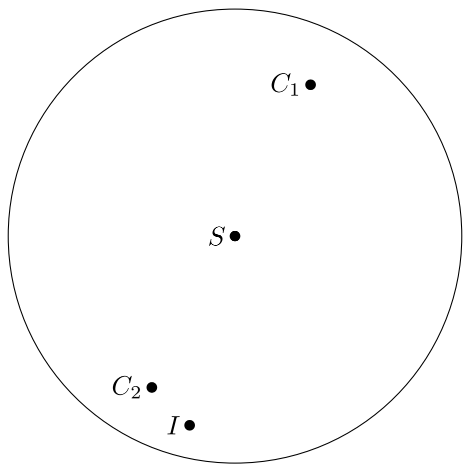


Figure 1: Limitation of Radii Approach

We recognize that it is unreasonable to expect a single metric to capture the complex nature of the spatial relationship between the customer, focal store, and competitor in its entirety. Instead, we approach the problem by proposing a large number of distance metrics, each of which captures at least some of the complex spatial relationship on its own, and then in our empirical analysis uncover which metrics or which interactions between metrics best characterize customer behavior. By honing in on the right combination of distance metrics we can determine which *specific* features of the spatial relationship influence customer behavior the most.

We therefore consider standard distance metrics between each customer and competitor with the the focal firm in addition to the following:

- How much closer is the focal store to the customer, relative to the competitor?
- How *sparse* is the focal store and competitor, relative to the customer?
- Are the focal store and competitor *in the same direction* from the customer, and to what

extent?

We also allow for interactions between population density and distance metrics to incorporate the difference in transportation costs between urban and rural areas. For brevity, the complete description of the distance metrics considered are contained in the appendix.

3 Spatial Competitive Structure and LP Performance

We first provide model free evidence that the spatial competitive structure, and hence business stealing, are key determinants of LP performance. Our analysis focuses on two metrics of LP effectiveness: the probability that a customer joins the program, and the change in average monthly spend for customers who decide to join. Here and throughout the paper, we use the change in spending net of the LP discounts. For customers who join the LP but do not change shopping patterns, this change is negative by default because of the discounts and a positive change for this metric can therefore be taken as strictly beneficial for the retailer. In this section we look at how these metrics relate to the the distance between the customer and the focal store and the four competitor types.

One challenge in analyzing LP effectiveness is that the customer's decision to join the loyalty program may be related to unobserved heterogeneity. While we observe purchases both before and after each customer joins the LP, which allows us to condition on individual-level fixed effects, it is still true that if customers join due to anticipated changes in their level of spending, the estimated change in behavior attributed to the loyalty program may be over-estimated. We accommodate this possibility in three ways. First, we assume that the location of each customer is essentially exogenous prior to joining the LP, in which case the difference in spending across customers with respect to the spatial relationship between the customer, the focal store, and the competition still provide valid comparisons. Second, when we estimate a full model of the LP in the following section, we use exclusion restrictions combined with a control function approach to account for this unobserved heterogeneity. Finally, we replicate our results using only spending that does not qualify for the LP discounts and is thus not potentially biased by selection on unobservables.

Descriptive Analysis:

We first examine the role of competitive structure on LP effectiveness in a transparent model-free comparison. We calculate the average probability of customer joining and the average change in monthly spending under four possible competitive structures (as illustrated in Figure 2): (1) when the focal store is within five miles of the customer and the competition is not, (2) when both the focal store and the competition are within five miles of the customer, (3) when the competition is within five miles of the customer and the focal store is not, and (4) when neither the focal store or the competition are within five miles of the customer.[2]

Table 3 shows average outcomes in each competitive structure. For customers relatively close to the focal store (regions 1 and 2), the change in spending after joining the LP is significantly higher than for those who are not located near the focal store (regions 3 and 4). Customers in regions 1 and 2 increase their spending by $22 per month compared to essentially no change in spending for customers in regions 3 and 4.

Interestingly, for customers in region 1 (that is, when the focal store is relatively isolated), the probability of joining the LP is the highest, but the change in spend at these stores for customer that join the LP is negligible. This is intuitive: if there are no relevant competitors nearby it is likely that the focal store already has the majority of this customer's share of wallet.

However, in the second region when the customer has access to both the focal store and the competition, the change in spend is very high at $80 per month. These customers may have been splitting their purchases across stores and consolidate activity to the focal store upon joining the loyalty program. Customers in this region are driving the entire result that customers near the focal store significantly increase their spending. This is true despite the fact that they represent under one quarter of the customers near the focal store. A naive analysis of spatial effects that compared customers in region $1 + 2$ to those outside it would miss this distinction.

Region 3 stands out as an outlier in the opposite direction. This region has the smallest share of customers, and those customers have the lowest sales pre LP, the lowest join rate, and display a large negative change in spending after joining. This change is almost entirely in non-qualified spending and this group also exhibits a large decrease in trip frequency after joining. One interpretation is that customers located near a competitor likely join the LP after the decision has been made to shift non-qualified spending to the competition, and use the LP solely for the qualified spending discounts. They then shop at the focal store much less often and only for the qualified category.

[2]To be clear, a single focal store can be in multiple categories, since it depends on the relationship with respect to the individual.

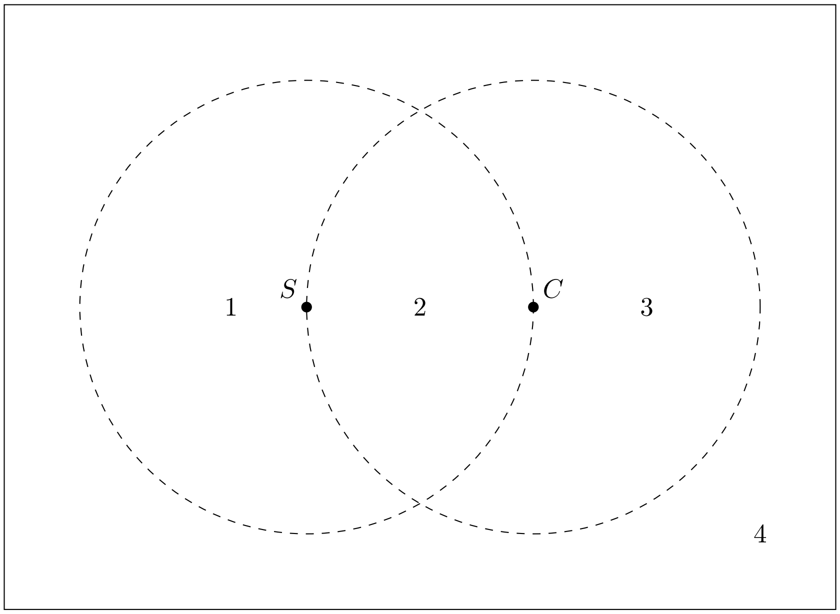


Figure 2: Competitive Structure Illustration

Region	**Pr(Join)**	**Δ Sales|Join**	**Δ Non-Qual Sales|Join**	***n* Join**	**Δ Trip Freq**
1+2	4.2%	$22	$13	429	-0.05
3+4	4.0%	-$2	-$24	487	-0.01
1	4.2%	$4	-$7	328	-0.13
2	4.1%	$80	$79	101	0.22
3	3.6%	-$85	-$82	87	-0.67
4	4.0%	$16	-$11	400	0.13

Table 3: Region Effects

To understand what is driving these findings we break down the results by competitor type. Figure 3 shows the average change in monthly spending, and how it varies by both competitive structure and type of competitor. As shown previously, the largest gains are when both the competitor and focal store are near the customer, which presents the most likely scenario for business stealing opportunities. This change is also largest when the competitor is the big-box generalist, suggesting this is the most profitable firm to steal business from.

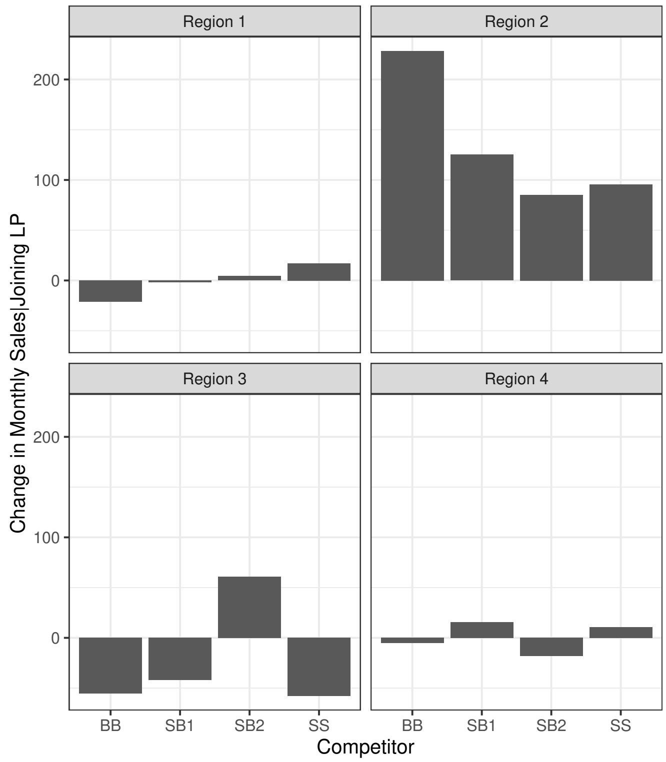


Figure 3: Change in Monthly Spend by Competitor Type

To better understand this mechanism, recall that the LP only applies to a specific large category and not all products, and that one of the competitors (SS) specializes in selling only that category. We thus highlight the portion of change in spend that occurs in the LP category of interest. Figure 4 shows how spending changes across competitor types within each region for this category. Interestingly, the changes are driven in large part by purchases outside of the category for which the loyalty program applies. If there was no spillover effects of the loyalty program, we would expect zero change in purchases that will not impact the LP rewards. Upon joining the LP, customers may decide to consolidate purchase behavior with one store rather than cherry picking rewards from the focal store (in the qualifying category) and continuing with the same purchase patterns at other stores in the non-qualifying categories.

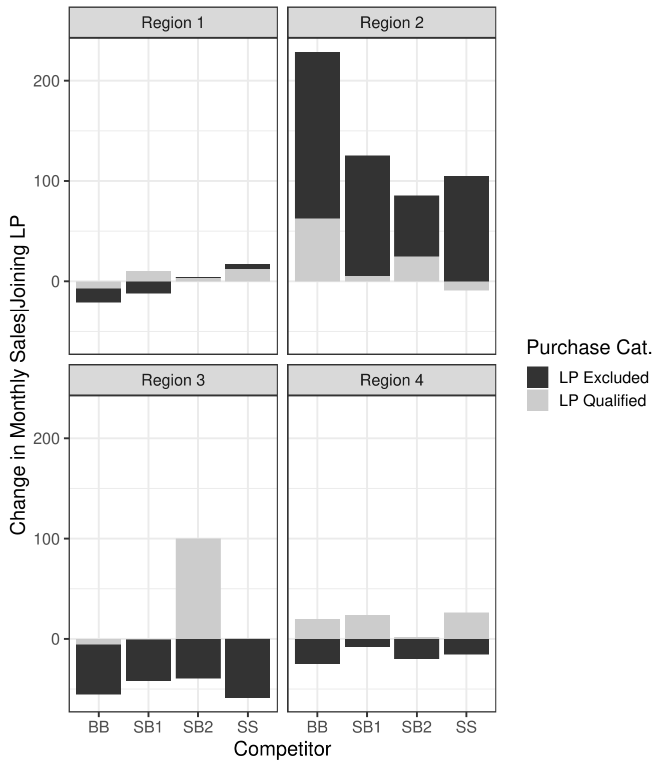


Figure 4: Change in Monthly Spend by Competitor Type and Purchase Category

4 LASSO Regularization and Competitive Targeting

In this section we propose an approach that accounts for the complex spatial interaction of competitive structure on LP effectiveness. This serves two purposes. First, we can analyze the estimation results directly to evaluate the relative importance of competitive structure and traditional predictors of LP effectiveness like sales histories as well as simple measures of customer location. Second, the estimation provides a ready-made targeting strategy for a firm seeking to improve LP effectiveness by providing predictions of which customers are the most profitable to target based on their spending histories, precise locations, and unique competitive structures. The wide variation across customers in profitability suggests the gains from targeting the program can be quite large.

We combine two stages of estimation to estimate the impact of the competitive structure on customer behavior. First we model the probability that a customer joins the firm's limited loyalty program, conditional on the competitive structure. Then, we model the change in spending conditional on participating in the LP in addition to the competitive structure. We estimate in two stages to allow the competitive structure to influence the join probabilities and changes in spend differently, and to control for self-selection into the LP.

The goal of the estimation is to predict which customers are likely to be profitable as members of the LP based on their past sales and spatial characteristics. Because the goal is prediction and the data are high-dimensional, the problem is well-suited to statistical methods built around dimension reduction or "regularization." We ultimately use a LASSO approach because this will allow us to test inclusion of a large number of possible spatial measures and let the model select the most predictive variables. The output also provides a clearer interpretation than other methods and one goal of the analysis is to assess which individual factors best predict LP effectiveness.

4.1 First Stage: Probability of Joining and Selection Bias

Let the indirect utility of joining the firm's loyalty program for customer i at focal store s be

$$u_{is} = \beta' X_{is} + \delta' Z_{is} + \varepsilon_{is} \tag{1}$$

Here X contains all the distance metrics (specific to each customer-store combination) and Z contains firm-level marketing and store-specific customer purchase behavior. X_{is} contains the competitive structure parameters between customer i at focal store location s. These metrics are intended to jointly capture the complex spatial relationships between the customer, focal store, and competitors. Since there can be more than one focal store in the vicinity of an individual, these metrics vary across each store s for a given individual i. Likewise, since each customer's location is unique, the spatial metrics also vary across each individual i from all observations for store s.

β reflects the impact of the competitive structure on an individual's likelihood of joining the program. We avoid specific interpretations within this vector of coefficients (e.g. representing the cost of transportation) and instead interpret the coefficients as holistically capturing the many spatial factors that a customer considers before committing to the firm's loyalty program (e.g., convenience of the focal store relative to the competition, isolation of the focal store, distance to the store versus other competitors, etc.).

Z_{is} includes traditional RFM variables along with basket specific metrics: monthly trip frequency, overall sales, distinct number of items, number of product categories, basket size, discounts received, sales in the category of interest, and sales in the category of interest for those products that are included in the limited LP. In preparation for our second stage model on the change in monthly spend, we also include variables in Z_{is} that will be used to control for selection bias, discussed in further detail below. Z_{is} therefore contains proportion of sales in the category of interest, an indicator for whether the customer received marketing activity specifically encouraging joining the LP, and an indicator for whether the customer received any marketing promotion.

To satisfy the exclusion restriction, these variables need to influence the probability of joining the loyalty program but not influence the change in spending upon joining the program. We argue that these variables satisfy the exclusion restriction, primarily because our dependent variable is the *change* in spend with the focal store, rather than spend alone. While these variables could be correlated with spending levels, it is unlikely there is a relationship between these Z variables and change in spend upon joining the LP other than through the direct effects of the LP.

δ captures the effects of the marketing and past purchase behavior on the utility received from joining the loyalty program. For instance, if a large proportion of spend is already dedicated to the category for which the LP benefits, it seems natural that the customer would be more inclined to join the LP.

The error term ε_{is} captures the idiosyncratic variation in utility across customers and stores. Assuming the $\{\varepsilon_{is}\}$ are independent and identically distributed Type I extreme value, we can derive the join probabilities as follows:

$$\Pr\left(j_i = 1 | X_{is}, Z_{is}, \beta, \delta\right) = \frac{\exp\left(\beta' X_{is} + \delta' Z_{is}\right)}{1 + \exp\left(\beta' X_{is} + \delta' Z_{is}\right)} \tag{2}$$

where $j_i = 1$ if customer i joins the limited loyalty program at some point during the observed data.

4.2 Second Stage: Change in Spend

In the second stage we model the change in monthly store-level spend, conditional on joining the loyalty program. Let y_{is} be the *change* in monthly sales for customer i at store s. We model this relationship as:

$$y_{is} = \gamma' X_{is} + \kappa' Z^*_{is} + \phi\left(\hat{p}_{is}\right) + \eta_{is} \tag{3}$$

where η_{is} is an unobserved, normally distributed random error centered at zero. Here X_{is} is defined in the same way as in the first stage model and Z^*_{is} is the same as Z_{is} but with the three selection variables removed. We predict changes in store-level spend (rather than changes in firm-level spend) to recognize that changes may be dependent on the spatial relationship a customer has with an individual store's location. In other words, the change in spend for an individual customer may depend on which specific competitors are located in the vicinity of a given store location.

A common issue in analyzing the effectiveness of loyalty programs is that of self-selection. Individuals are not randomly assigned to participate in loyalty programs, rather they choose to be in the loyalty program for a variety of reasons. Because of this self-selection, estimates of LP effectiveness may be upward biased. For example, those who join are more likely to spend more, regardless of whether they are in the LP or not, so comparing the spending amounts of those who join with those that do not capture differences in spending patterns, not the effectiveness of the LP.

We are able to mostly eliminate this concern using data containing spending both before and after the customer joins the program. While this captures most unobserved heterogeneity, there is still potentially the issue that the customer may have joined because of anticipated increases in spending over time. As with before, this may lead the analyst to incorrectly believe that the loyalty program is causing a large increase in spend when the change may have been due to this unobserved heterogeneity.

We employ a Heckman-style two-stage correction method in an attempt to correct any remaining selection bias. First we estimate the join probabilities using the first stage specification above, including variables that serve as plausible exclusion restrictions. Then, we take the estimated join probabilities for each observation and include them in the second stage model of change in spend as a control function. Our approach is to place a flexible function ϕ over $\hat{p}$ using high-order polynomials to control for unobserved heterogeneity.[3]

[3] See Heckman (1979) for an introduction to the two-stage estimator and Ahn and Powell (1993) for extensions to more flexible selection correction functions. For a recent application, see Ellickson and Misra (2012).

4.3 LASSO Estimation

Our proposed model contains a large number of spatial variables defined to capture the competitive structure. On the one hand, capturing the spatial relationship between the customer, focal store, and competitors is complex and may require many variables. However, all else being equal a concise model is preferable from a managerial standpoint. In addition, many of the spatial metrics we devised may be redundant or highly correlated with each other. To systematically remove variables that are either unnecessary or redundant we employ the Least Absolute Shrinkage and Selection Operator (LASSO) estimator, introduced by Frank and Friedman (1993) and Tibshirani (1996).

In general, for a model with a k-dimensional parameter vector θ the LASSO method performs the following:

$$(\theta^*) = \arg\min \left\{ -\log L(\theta) + \lambda \sum_k |\theta_k| \right\} \tag{4}$$

Where L is the likelihood of data given the model specified, and λ is a tuning parameter that represents the penalty incurred if we choose a nonzero value for any parameter θ_k. This approach regulates the trade-off between an accurate model with more predictive power and a concise model that is more readily interpretable by managers.[4] We select the tuning parameter λ through ten fold cross-validation, which is perhaps the simpliest and most widely used method for this task.[5]

4.4 Estimation Results

The results from the LASSO estimation are presented in Table 4. For model validation purposes, we split the original data into a 75% training set and 25% test set. The results presented below were estimated using the training set alone. For brevity, the table only displays variables that are significant in at least one of the two models (with the exception of the coefficients on the control function polynomials). First we discuss how the competitive structure influences the join probabilities before discussing the estimated impact on the change in monthly spending, as both are

[4] An alternative approach would be a ridge regression or similar method. In this case the penalty is applied more smoothly, shrinking coefficients on highly correlated variables towards each other. We prefer the LASSO approach because the penalty structure removes coefficients entirely, resulting in clearer model interpretation. Specifically, we can see that many non-spatial variables will drop out altogether. This direct interpretation of the model's results is a key output of interest. A ridge regression would lack this clean interpretation but would result in similar quantitative predictions and can be provided upon request.

[5] See James et al. (2013) for more information.

influenced differently. From a statistical standpoint, it is relatively easy to interpret the marginal effects of each the variables. However, we must emphasize that many of the spatial impacts are codependent and interpreting the marginal effect of one coefficient while holding another spatial variable constant is sometimes impossible. Later, we present stylized heatmaps to better understand the impact of the spatial relationships on change in spend.

4.4.1 Join Probabilities

The logistic regression results are shown in Table 4, and the full list of spatial variable definitions is provided in Table 7. In this first model many of the traditional distance metrics drop out of the model (e.g., direct distance between the focal store and the customer) in favor of secondary spatial metrics.

For instance, as the angle between the big box competitor (BB) increases, the probability of joining the LP at the focal store also increases. This indicates that the probability of joining increases if the competitor is in the opposite direction relative to the customer, rather than in the same direction. This effect also holds for the small box specialist (SS).

The last two sets of spatial components (ccbar and icbar) are designed to account for differences in markets with the presence of multiple competitors of the same type. The first of these variables, ccbar, is the average distance between each competitor and its competitive center (defined as the average latitude and longitude across competitors of the same type). A relatively high value indicates that the competitors are relatively spread out in a market. The negative coefficient on the big box generalist (ccbar_1) indicates that the more dispersed these stores are in a market, the less likely the customer is to join the LP. The second variable, icbar, measures the average distance between each customer and each of the competitors. While a customer may be close to the competitive center, a high value of icbar indicates that each individual competitor (of a given type) is still relatively far away. This coefficient is positive for the two small-box generalists (SB1 and SB2), suggesting that a relatively sparse distribution of these competitors may be beneficial to the focal firm.

Finally, we consider the variables used to correct for potential selection bias. First, we see a strong positive effect on the proportion of sales in the category of interest: customers who dedicate a greater portion of store spend to the LP category are more likely to benefit from the LP discounts. There is also a positive impact of whether or not they received a marketing promotion, both general emails and those specifically designed to enroll them in the LP.

4.4.2 Change in Monthly Spend

In this section we now review the influence of the competitive structure on the estimated LP effectiveness, as measured by change in monthly spending at the focal store, conditional on joining the firm's loyalty program. Before discussing the spatial effects, we first review the results from the selection correction. To correct for selection bias, we include up to the sixth order polynomials on the predicted join probabilities from the previous stage. In our original LASSO regularization none of these variables were significant, suggesting that selection resulting from unobserved heterogeneity is not a substantial driver of the change in spending. However, in the results presented we explicitly incorporate these variables at the cost of out-of-sample performance in order to properly control for potential selection on unobservables.

Recall the dependent variable in this estimation is the change in monthly spend after joining the loyalty program, net of any LP discounts. For this table, we only included customers who had at least some spending both before and after joining. Since we are interested in how spending *changes* after joining, rather than *whether* spending occurs or not, this seems to be a reasonable filter.

First, there is a positive impact on the squared distance between the customer and the focal store, suggesting that the greater gains come from those located further away from the focal store. This aligns with our previous intuition: customers located near the focal store are more likely to already dedicate the majority of their spend with the focal store, so the potential for increases in spend are limited, relative to those who are further away and thus more likely to be sharing spend with the competition.

Importantly, the distance between the customer and the competition also influences changes in spend at the focal store. Customers who exhibit the largest changes in spend are those who are relatively far from the the big-box generalist (ic1sq) and the second small-box generalist (ic3sq) and close to from the other competitors, holding all other variables constant.

Many of the radius band coefficients drop out of this model. However, we see that the intercept angle is retained. The difference in the estimated change in spend for a customer where a big-box (BB) competitor is in the same line of travel as the focal store (intercept angle of zero) versus in the opposite direction (intercept angle of 180 degrees) is about $125, holding all other variables constant. This is a non-trivial amount that cannot be captured using traditional spatial measures. However, it is important to again point out that many of these distance metrics cannot vary independently of others. The heatmaps presented later will illustrate the degree to which the intercept angle influences the change in spend while simultaneously accounting for other changes.

Finally, population density along with its interactions with the direct distance measures has a significant impact on the change in monthly spend. On its own, the effect is positive: more densely populated areas are associated with a greater change in spend. This is intuitive as more densely populated areas tend to have a greater level of competition and higher incomes. There are also numerous interactions with our simple distance metrics. For instance, increases in the distance between the store and the customer influence customers in dense areas more negatively, relative to customers in less dense areas. This appears to be capturing the challenges of traveling in more densely populated areas (e.g., traveling a given distance in a city versus a rural setting).

As an important robustness check, we also include a column where the estimation proceeds as before but only using the change in spending on products that do not qualify for the LP discounts. Recall that the specific concern regarding unobserved heterogeneity was a correlation between decision to join the LP and planned changes in spending over time related to the LP discounts. Because these discounts do not apply to the non-qualified categories, the concern about unobserved heterogeneity does not apply here either. Comparing this column and the column for all spending shoes a very high correlation in the LASSO coefficients and perfect correlation in which variables are retained. This adds further evidence that selection on unobserved heterogeneity does not have a meaningful effect on our results.

4.4.3 Summary

The LASSO results suggest that the customer behavior appears to be influenced by the competitive structure of the local market. The regularization tends to keep quite a few of the spatial metrics, suggesting that relatively simple distance metrics are, on their own, unable to fully characterize the predicted behavior. This is not very surprising: there are many intuitive reasons why a customer may change their spending patterns after joining a loyalty program with respect to their location.

4.5 Visual Representation of Results

Even after variable reduction via LASSO, it is still difficult to interpret the spatial forces at play strictly from coefficients due to their codependency. We therefore visually illustrate some of the

Table 4: Lasso Pr(Join) and Change in Sales|Join

	Coefficient	Pr(Join)	Change in Sales|Join	Change in Non-Qualified Sales|Join
1	(Intercept)	-3.5018	-19.3914	-44.8786
2	sisq		0.0042	0.0149
3	ic2	0.001		
4	ic3	0.0054		
5	ic1sq		0.2113	0.2076
6	ic2sq		-0.1402	-0.1407
7	ic3sq		0.146	0.135
8	ic4sq	-1e-04	-0.1257	-0.0991
9	sc1	0.0026		
10	sc1sq	1e-04	-0.0207	-0.0237
11	sc2sq		-0.0453	-0.0284
12	sc3sq		-0.1096	-0.1168
13	sc4sq	-1e-04	0.1089	0.0917
14	s4	-0.302		
15	nAll_1	0.0225		
16	n1_1	0.683		
17	n3_1	0.1946		
18	n5_1	0.1593		
19	n10_1	-0.0474		
20	n15_1	0.0514		
21	nAll_2	-0.0014	0.4925	0.4141
22	n1_2	-0.2532		
23	n10_2	0.0332		
24	n15_2	-0.0158		
25	nAll_3	-0.0141		
26	n1_3	0.2901		
27	n3_3	-0.0033		
28	n5_3	-0.069		
29	n10_3	0.0579		
30	nAll_4	-0.0077		
31	n3_4	0.1371		
32	n15_4	-0.0044		
33	cInt1: BB intercept angle	0.0013	0.692	0.752
34	cInt2: SB1 intercept angle		-0.2691	-0.2939
35	cInt3: SB2 intercept angle	5e-04	0.53	0.5497
36	ccbar_1 (avg. BB-BB comp. center km)	-0.0126		
37	ccbar_2 (avg. SB1-SB1 comp. center km)	0.0097	1.2723	0.8758
38	icbar_2 (avg. customer-SB1 km)	0.0036		
39	icbar_3 (avg. customer-SB2 km)	0.0039		
40	icbar_4 (avg. customer-SS km)	-1e-04		
41	Prop. of sales in LP category (pre LP)	5.7842		
42	Received promotional email	0.0762		
43	Received promotional email for LP	1.3227		
44	Trips/month	0.0106	-27.3642	-25.6736
45	Total sales (pre LP)	2e-04	0.0066	0.0017
46	Total sales in LP category (pre LP)		0.0353	0.0136
47	Total qualified sales in LP category (pre LP)		-0.1075	-0.0428
48	Number of focal stores w/i 60km	0.0035	1.059	1.0569
49	Population Density (in sq miles)		0.0279	0.0251
50	Population Density x si		-0.0019	-0.0017
51	Population Density x ic1		-0.0019	-0.0018
52	Population Density x ic2		-6e-04	-9e-04
53	Population Density x ic4		0.0036	0.0036
54	Population Density x sc1		-2e-04	-3e-04
55	Population Density x sc2		0.0014	0.001
56	Population Density x sc3		-7e-04	
57	Population Density x sc4		-0.002	-0.0021
58	distinctSKU	-0.0055	-0.8616	
59	numItems	0.0019	-4.3895	-3.9053
60	distinctCategories	-0.0989		
61	poly(phat,1)		-617.5849	-382.4511
62	poly(phat,2)		4871.7517	4215.9458
63	poly(phat,3)		-4705.8528	-4272.9904
64	poly(phat,4)		-3849.4443	-3371.5503
65	poly(phat,5)		432.9157	467.4562
66	poly(phat,6)		4049.8262	3559.0346

LASSO's results on how the competitive structure influences LP effectiveness. To do so, we show the predicted change in spending for hypothetical customers and represent the results in a series of heatmaps showing different competitive structures. These maps show how there is large heterogeneity across different customers with different competitive structures in the potential gains from having them join the LP.

Six heatmaps are presented in Figure 5. The color on the heatmap reflects the estimated change in spend from a customer in that position if they were to join the focal store's loyalty program. Heatmaps (a), (b), (c), and (d) illustrate the differences between the four competitor types, keeping the relative position between the focal store and competitor the same. The fifth heatmap (e), plots all four competitors on a single map, each an equal distance from the focal store. Finally, the last heatmap (f) draws a random observation from the data to illustrate the predicted effects from an actual competitive structure. Since these maps are mostly stylized representations of the actual data we focus on comparing the magnitudes across maps rather than specific prediction levels.

In the first heatmap (a), the greatest change in sales is from customers who are located in between the big-box generalist (BB) and the focal store, suggesting that changes in spend are primarily driven by shifting store spend away from the competition. The second heatmap shows a slightly different pattern. First, we notice that the overall magnitude in predicted changes is reduced, suggesting that any potential gains from the first small-box generalist (SB1) are relatively limited. Here again most of the gains are coming from those directly between the focal store and competitor, but unlike the big-box store there is not as stark of a dropoff in spend once customers move outside of the direct path between the focal store and this competitor.

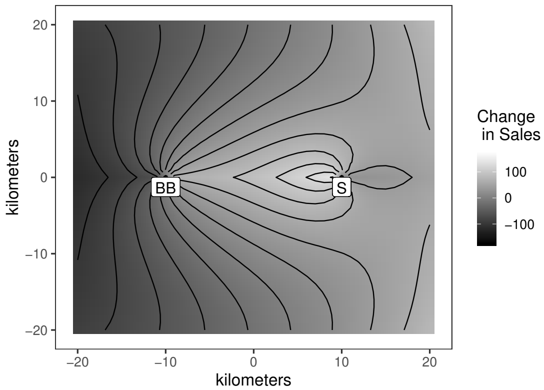
For the second small-box generalist (SB2), the effect appears to mimic the first competitor (BB) at a slightly reduced magnitude. Again we see the strongest gains from those located directly between the focal store and competition, but this slowly drops off as customer move further outside of the direct line of travel.

In the fourth heatmap (d), the small-box specialist (SS) displays a pattern unique to the other three competitors. Recall that this competitor specializes in selling the same products that qualify for the focal store's loyalty program. In this map customers located near the competitor exhibit the lowest changes in spend. This suggests that taking business from this competitor may be difficult if the focal customer are located nearby.

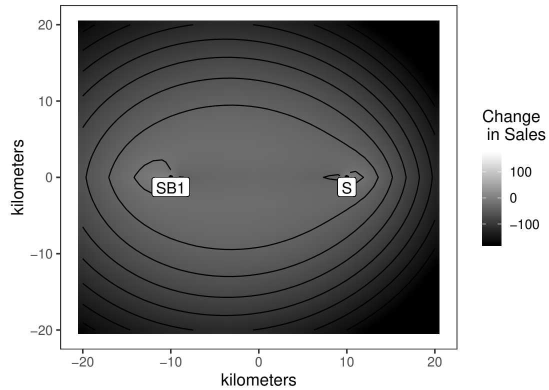
The fifth heatmap, (e), combines all of the competitors to illustrate the relative influence simultaneously. This shows that most of the gains are from customers near the big-box generalist, and less so from the small-box specialist. This map highlights that the value of a potential customer is heavily dependent on the extent to which the focal store can steal business from the competition.

Finally, the last heatmap presents the predicted change in spend from an actual market structure in the data. Customers located on the far side of the second small-box specialist (SB2), and the big-box generalist (BB), have the lowest predicted change in spend. These customers are relatively far away from the focal store with a competitor directly in their path of travel, resulting in limited predicted gains. On the other hand, the other two competitors (SB1 and SS) are relatively close and the line of travel is not as critical with these competitors. The customers that show the most promise are those that are relatively close to the focal store but in the direction of the second small box generalist (SB2) and the big-box generalist (BB). To be clear, this will not necessarily always be true: the positioning of the competitors relative to the focal store (or their absence from the market) dictates which customers are likely to contribute to the greatest changes in spend once they join the loyalty program.

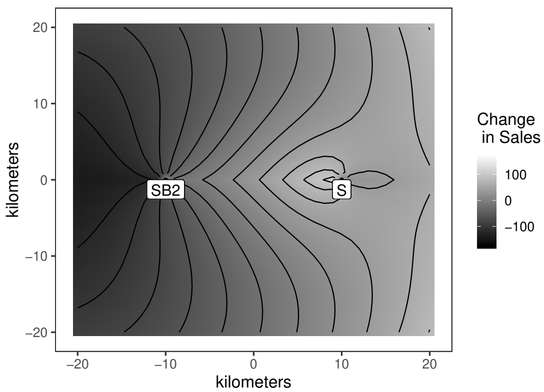
The heatmaps presented highlight two key advantages of this analysis. First, the geographic influence of a competitor is relatively complex. Simple radii surrounding either the competitor or the focal store may not sufficiently capture the influence of the competitive structure on customer behavior. Second, these complex relationships are not fixed and can vary by the type of competitor in an area. This is an important consideration for the firm in the formation of targeting strategies: the combined relationship between the location of each competitor, customer, and focal store strongly influences the customer's interaction with the focal firm.



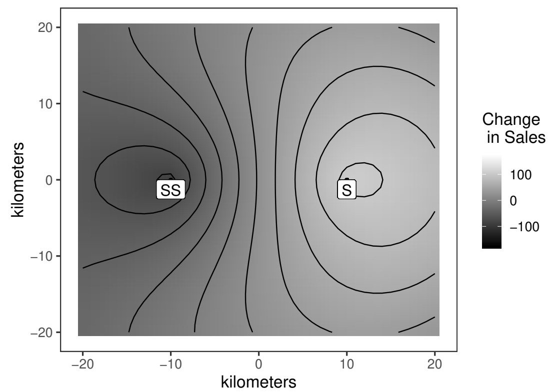
(a) Big Box (BB)



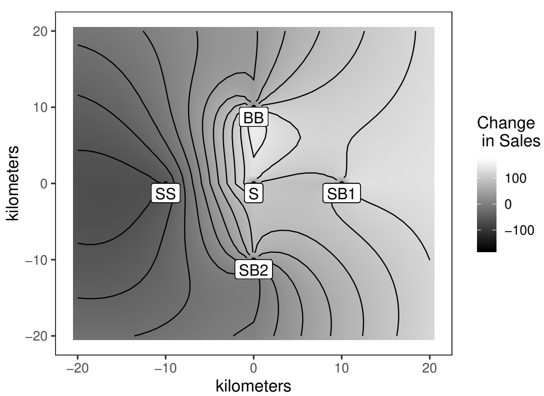
(b) Small Box #1 (SB1)



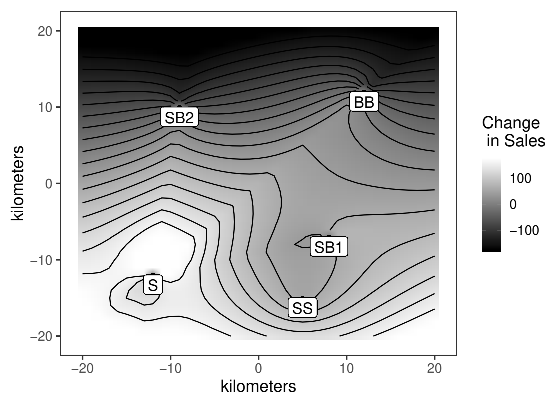
(c) Small Box #2 (SB2)



(d) Small Box Specialist (SS)



(e) All Competitors



(f) Random Selection From Data

Figure 5: Change in Monthly Spend by Competitive Structure

4.6 Competitive Targeting: Out of Sample Validation

In this section we use the LASSO results to form a targeting strategy designed to improve LP profitability. The goal is for the firm to take advantage of detailed data on customer and competitor locations to precisely target customers who are likely to be most profitable to join the LP. The estimation in the previous sections allows us to predict change in spending for each potential customer as a function of their location and proximity to each store type.

To evaluate the potential increase in profits from this type of targeting, we use a validation or holdout sample of customers who joined the LP but were not used in estimation. For each we predict their change in spending using the estimates.

For simplicity, we allow the firm to target at the customer-store level. Our dependent variable of interest is the expected change in monthly spending. We then target all the customers at stores whose predicted incremental profits from joining the LP is positive. Finally, we measure the success of each targeting approach by calculating the actual change in spending from these customers. Importantly, none of these observations were used to estimate the LASSO regression presented earlier.

Rule-of-Thumb Targeting Strategies:

The performance of the spatial LASSO strategy is compared to numerous other potential targeting strategies and the results are shown in Table 5. We first describe a series of simple targeting strategies that are not based on the full competitive structure but instead rely on simpler spatial information or more traditional RFM metrics. The mass marketing strategy simply targets all customers. In aggregate, they show a positive change in monthly spending after joining.

We also consider targeting only those that exhibit relatively high spending amounts (prior to joining the LP) at a few reasonable cutoff points (based on the empirical distribution of monthly spend). We consider three levels as a cutoff: \$80 (the median level of monthly spend), \$100, and \$200 (about the 75th quantile of monthly spend). In each of these the change in monthly spend actually declines substantially. Targeting high-spending customers to join the LP is therefore a highly unprofitable strategy.

We also consider a naive location-based targeting strategy that targets all customers within a few kilometers of the focal store. If we limit the targeting to only those customers within 5 kilometers of the target store we get a small positive boost, but even this is not as strong as a mass marketing approach.

A second type of naive location-based targeting would be to take advantage of the business stealing aspect of loyalty programs by targeting all customers located near a competitor. We test this strategy and find that targeting all customers within 5 km of a competitor would result in a substantial decrease in profits.

Model-Based Targeting Strategies:

Next, we consider a series of targeting strategies based on models designed to predict changes in spending. We compare a series of models distinguished by how they are estimated and which data we use as inputs to estimate them. First is a naive spatial model that only considers the distances between the focal store and customer, and each of the four competitors. As with the LASSO model, this naive model is estimated on the training observations and validated on the holdout set. We see that the actual change in spend is only slightly positive, and worse than a mass marketing approach.

The second model considers only historical sales information: proportion of sales in the category of interest, overall sales, category level sales, and category level sales that specifically qualify for the LP. This model also underperforms a mass targeting strategy and actually results in negative profits from targeting.

Finally, we show results for our spatial LASSO approach. It outperforms all other targeting strategies in the validation sample, with the predicted actual change in sales roughly 9 times higher than that of a mass marketing targeting scheme. These results are generally consistent with the predictions from all observations, not only the ones from customers who end up joining the LP.

One argument might be that since marketing is done via email and is relatively inexpensive, why not simply send marketing campaigns to everyone? The key here is that in some cases it might be preferable to limit LP enrollment to certain individuals. While the firm cannot prevent interested customers from joining its loyalty program, it can choose to whom it promotes the program. Carefully targeting the right type of customer for this type of promotion can substantially increase its profitability. While this has generally been known, we show two distinct contributions. First, targeting based on location substantially outperforms targeting based on historical sales patterns. Second, simply incorporating traditional spatial metrics like distance between customer and store does not capture the complexity of competitive structure. Instead, we show how firms can take advantage of rich spatial data on both customers and competitors locations using a machine learning approach. This is particularly true for loyalty programs, which rely at least partially on business stealing to be effective.

	Avg. Δ Sales		Avg. Δ Non-Qualified Sales	
Targeting Strategy	in-sample	out-of-sample	in-sample	out-of-sample
Mass Marketing	-$18.69	$6.91	$-24.32	$2.59
Top spender (>$80)	-$83.07	-$38.10	-$88.18	-$33.29
Top spender (>$100)	-$95.38	-$45.16	-$99.92	-$40.19
Top spender (>$200)	-$181.13	-$103.67	-$178.76	-$95.73
Within 5 kilometers of focal store	$46.60	$12.60	$38.86	$13.23
Within 5 kilometers of any competitor	-$47.57	-$54.54	-$53.00	-$41.93
Naive spatial	$40.72	$3.97	$55.13	$11.21
Historical sales only	$29.06	-$23.06	$28.96	$15.58
Spatial LASSO	$84.03	$65.69	$77.61	$51.31

Table 5: Targeting Validation Performance

4.7 Spatial Variable Contribution

In the previous section, we accentuated the value of integrating spatial information into the predictive targeting process. In this section we provide an additional measure of the contribution of spatial variables to the model fit relative to other types of variables. Specifically, we highlight that our spatial metrics contribute substantially more towards R^2 relative to traditional variables.

Table 6 presents the model fit using our two dependent variables of interest, where each row represents a single subset of the available variables. The first column displays the pseudo-R^2 from a logistic regression and the second column the standard R^2 from a linear regression. The variables are separated into one of five labels: our proposed spatial metrics, RFM (trip frequency and sales information), basket composition (number of items per basket, distinct items, distinct categories, and discounts received), selection variables (proportion of sales in the category of interest and the two marketing indicators), and finally the control function polynomials from the predicted LASSO join probabilities.

The spatial metrics explain considerably more than any of the alternative variable types. The sum of the R^2 values across the partial models is similar to the fit from the aggregate model in the final row. This suggests that the variable types tend to be relatively orthogonal to each other. In other words, the spatial information appears to be adding a non-trivial amount of unique information to the model that would otherwise be absorbed into the residuals.

A natural rebuttal to this table is that the results are driven simply by the sheer number of spatial variables relative to the other variable types. This is only partially true: recall that all of the spatial metrics are derived solely from the latitude and longitude of the focal store, competition, and the customer. From a managerial perspective it is very easy to recreate the diverse set of spatial metrics once these few location points are obtained. In this sense, it is more the variety among the spatial variables we designed, rather than simply the number of variables, that contributes a substantial amount of information to each model.

Variable Type	**Pr(Join)**	**Δ Sales|Join**
Spatial	3.4%	14.9%
RFM	0.6%	9.8%
Basket composition	0.0%	3.7%
Selection	1.4%	
Control function polynomials		0.8%
All variable types	5.2%	27.1%

Table 6: Pseudo-R^2 and R^2 by variable type

5 Discussion and Conclusion

Both academics and managers have been interested in measuring the factors contributing to a successful loyalty program. We argue that a significant but largely overlooked driver of a loyalty program's success is the joint relationship among the focal firm's stores, the competition, and the customer, or what we collectively label the *competitive structure*.

We find strong model-free evidence that this is the case, and then proceed to model the full relationship. Doing so faces two challenges. First, we recognize that customers may self-select into loyalty programs (e.g., an individual joins in anticipation of a large change in spend). We mitigate this issue by utilizing flexible control function approach, a common strategy for this situation. The second, and more substantive, obstacle is that of incorporating complex spatial information into a parsimonious modeling approach. Rather than focus on specifying the "correct" functional form we adopt a LASSO approach to determine which, of many, spatial components are most strongly related to changes in spending patterns.

Our results indicate that the competitive structure plays a substantial role in predicting 1) whether or not a customer joins the loyalty program and 2) the extent to which spending changes after joining the LP. Since the location of any individual customer is effectively exogenous with respect to the focal store and the competition, the combined variation in the customer, focal store, and competitor locations across observations allows us to infer precisely how the spatial information influences spending patterns at the individual level. While we cannot prove with our data, we posit that many of the patterns observed can be attributed to business stealing. For example, most of the large increases in spend come from customers located directly between the focal store and a competitor, suggesting that customers consolidate purchase activity across stores once enrolled in the loyalty program.

We then illustrate how the model can be used to improve targeting decisions. Because the profitability of a customer joining the LP varies widely across the population the gains to improving targeting are substantial. We show that targeting on spatial variables outperforms traditional targeting strategies that rely on past spending patterns. An additional benefit of spatial targeting is that it requires only readily available location data. We also show that the LASSO model outperforms many other targeting strategies out of sample, thus providing reassurance to practitioners interested in implementing this method.

Still, our analysis is not without limitations. First, we cannot guarantee that self-selection issues have been completely eliminated. However, since most firms are unlikely to randomly enroll customers in their loyalty programs, self-selection will likely remain a challenge in future analyses of LP effectiveness. Second, due to the nature of the data we cannot make very strong statements on the extent of business stealing that may be occurring. In the absence of data from multiple competitors or direct responses from the customers themselves, we can only infer the degree of business stealing based on changes in shopping behavior as a function of competitive structure.

We hope that our research provides the foundation for future work that integrates the complex spatial information into models of customer behavior, especially in their relationship to making more strategic targeting decisions.

6 Appendix 1: Distance Metrics

In the table below, x denotes the competitor type. In our empirical application this is either the big box generalist (BB), the small box generalists (SB1 or SB2), or the small box specialist (SS).

Distance Metric	**Description**
si	Distance between the focal store s and individual i (in km)
ic$x$	Distance between the individual and competitor x (in km)
sc$x$	Distance between the focal store and competitor x (in km)
sx	Sparsity metric for competitor x, defined as sc$x$/(ic$x$ + si)
nAll_x	Total number of x competitors within the region
nd_x	Total number of x competitors within d km of the individual
cInt$x$	Angle formed between focal store and competitor with individual at apex (0 means s and x are in same direction relative to c 180 means s in opposite direction of x)
icbar_x	Average km between the individual and each individual competitor x (if only one competitor of type x in an area, this equals ic$x$)
ccbar_x	Average km distance between each competitor and the competitive center (if only one competitor of type x in an area, this equals 0)

Table 7: Distance Metric Descriptions

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