

COMPETITIVE STORE CLOSING DURING AN ECONOMIC DOWNTURN: A
MATHEMATICAL PROGRAMMING APPROACH

by

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ABSTRACT

SANJAYA MAYADUNNE. Competitive store closing during an economic downturn: a mathematical programming approach (Under direction of DR. CEM SAYDAM and DR. MONICA JOHAR)

A game theoretic mixed integer program model is introduced to determine optimal store closing decisions in a competitive market. The model considers the case of two rival firms seeking to downsize operations in a region. Both firms are looking to reduce operating costs by closing a number of stores while minimizing demand lost to its rival. We assume a competitive game and apply the model to find the equilibrium store closing decisions. The model is first applied to a competitive environment for a single period and then incorporated into a solution procedure for a multi period game. The model facilitates the analysis of different strategies that can be used by a retail chain to maximize revenue in depressed market conditions. We find that the profitability is not always the most important factor to consider when determining the number and locations of stores to be closed and that an increase in demand variance will increase the likelihood that an unprofitable store will be kept open for an extended period of time. Our results further indicate that, depending on individual store characteristics it may be optimal to close a profitable store. Our results provide guidelines for developing effective strategies to systematically reduce the number of stores so that net revenue is maximized while competitive pressure is exerted on rival stores.

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CHAPTER 1: INTRODUCTION

1.1. Problem Domain

Over the last decade the retail industry has experienced a spate of downsizing. Major players such as Sears, K-Mart and Albertsons closed a significant number of stores during this period. In 2011 alone Sears holdings announced the closing of 79 K-Mart and Sears stores across the United States [1]. The current economic downturn has meant that this trend is expected to continue in the immediate future. In 2010 Cardona [2] reported the imminent closure of stores among ten big retailers including Saks and Winn Dixie. Even retail firms that are generally immune to recessionary effects are feeling pressured. Cardona quotes Walmart CEO Mike Duke as saying "The slow economic recovery will continue to affect our customers, and we expect they will remain cautious about spending". Further, Kahn and McAllister [3] explain that the increasingly competitive nature of the retail Industry has placed increasing pressure on profit margins and as a result "retailers have undertaken a rash of mergers and acquisitions" which also results in the closure of select outlets. This phenomenon is not restricted to the United States. Europe has seen a similar wave of retrenching. For example in the Netherlands 2000 out of 5500 grocery stores are expected to close over a 10 year period [4].

1.2. Popular Downsizing Strategies

Once the decision to downsize has been made the focus then shifts to the following question: Which and how many stores to close? Hernandez and Bennison [5] attempt to

determine popular strategies related to optimal store location. They used a survey based method to examine the criteria used by firms to determine optimal store location. They describe techniques used by management when determining the location of a new store, a relocation of a store and a store closure. 220 retail firms with portfolios of over 50 stores were surveyed. The following techniques were identified as being widely used, (1) Experience where decisions are based on rules of thumb, (2) Checklists where locations are analyzed based on a formalized set of checklists, (3) Multiple regression/discriminant analysis where future sales of a store are predicted based on current conditions at a location, (4) Cluster analysis where the portfolio is segmented before closing decisions are made, (5) Spatial interaction where the relationship between the store location and retail demand by product category is analyzed and (6) Expert systems where a neural network is trained with information on the profitability of existing stores. Hernandez and Bennison found that the majority of the firms used a combination of the above techniques when deciding on store locations. Almost all the firms relied on experience in conjunction with an analytical technique. Among the analytical tools used multiple regression, cluster analysis and spatial interaction were the most popular. They go on to find that firms are increasingly using Geographical Information Systems in the decision making process. The use of GIS to operationalize and support the techniques used has “enabled the organization to move away from ‘gut feel’ to having factual information relating to a location, and had improved the quality analytical capabilities of these techniques.

Boufounou [6] used econometric methods when planning new locations for bank branches. The study was aimed at the banking sector in Greece where retail banking is in

an increasing state of flux. Hence “The optimum number of branches, their optimum location and the optimum mix of services each of them should provide are three key interrelated issues.” Boufounou characterized location features, trade area characteristics and competitive situation features as some of the external factors that should be taken into account when determining optimal branch location. An analysis was conducted on a representative sample of 62 branches of all sizes of the Commercial Bank of Greece network. These branches belong to 3 different regional administrations. Results indicate that factors such as total rentier’s income, number of own bank branches in the region and the number of competitor branches in the region have a significant impact on the size of deposits at a branch. Subsequently the attractiveness of a new site can be evaluated using these measures.

1.3. Estimating Demand Captured

Prior research has examined the effect of store locating decisions and the resulting redistribution of demand. Drezner [7] developed a model based on Huff’s method of estimating market share. The model calculates the total market share captured by a retail chain before and after a new store is added. The assumption is made that the probability of a customer patronizing a given store is function of factors such as the floor area of the store which was suggested by Huff or the MCI product proposed by Nakanishi and Cooper [8]. Similar to most studies in location based demand the competition space is broken down into a number of smaller zones and the demand originating from each zone is aggregated into a point at the center of the zone. The objective is to find the best possible location for a new outlet. The solution procedure is based on a iterative algorithm first introduced by Weiszfeld. Experiments were conducted to find the optimal

location using the algorithm and show that it provides a significantly higher market share to the firm when compared to locating a new store at a random location. Serra and Colome [9] use Revelle's [10] MaxCap model to determine demand captured by a store. A key difference here is that the demand capture is not always treated as binary (Where the store closest to a zone will capture the entire demand originating from that zone). Instead a number of different methods are used to calculate the demand allocation. Based on the allocation method a number of different models are introduced. The model results are then compared to each other to determine if there is a significant difference in optimal store location based on the method of demand allocation. The variable ρ_{ij} denotes the proportion of demand from zone i that is captured by a store located at j . In model 1 it is assumed to be binary and is 1 if the store located at j is the closest to i . In models 2 and 3 it is assumed that the probability that a customer at location i will shop at a store at j is a relative function of the distances from i to j and i to all other stores. In model 2 this probability is a function of distance and various other consumer preferences that are independent of location. In model 3 it is based on the proportional distance to each store regardless of ownership. Results indicate that there are significant variations in optimal store location given by each model. This suggests that it is important to carefully analyze the behavior of the type of consumer in the region under study. However there have been few studies that specifically examine the problem of determining optimal store closing strategies.

1.4. The Effect of Retained Sales and Consumer Behavior on Store Closings

Haans and Gijsbrechts [11] describe the increasingly dynamic and competitive nature of the retail industry and the resulting effect of shrinking margins. Retailers have

therefore been forced to look at ways to increase the efficiency of their operations. Mergers and acquisitions and downsizing are oft used strategies and generally result in store closures. K-Mart and Albertsons are two recent examples. Store closing involves two types of decisions, how many outlets to close and which outlets to close. Haans and Glibrechts then explain that individual outlet closing decisions should be based on both the outlet's revenue and the resulting loss in revenue to the organization.

Here the concept of "*retained sales*" is introduced. Retained sales occur when an organization closes an outlet but continues to operate multiple other outlets in the vicinity. It can be assumed that the organization will retain a fraction of customers who frequented the closed store since they will now continue shopping at one of the stores operating nearby. The amount of sales retained is dependent on a number of factors. First if all replacement stores are beyond a distance threshold the consumer might drop the purchase altogether. If the most convenient replacement store is of a rival chain the sale will be lost. Second if the chain has a series of stores of the same format with similar offerings then the consumer's shopping list will remain unaltered. However if the format or size of stores differ then it is possible that the consumer's planned list of items will be altered. Finally even if the replacement stores in the chain are identical the extra distance the consumer has to travel will cause him/her to adjust the quantities purchased. Their findings confirm that a substantial portion of sales of a closed store can be recovered by adjacent stores.

Other studies have presented insights that can be used to determine the effect of store closures. Rhee and Bell [12] examine the determinants of consumer mobility. They assume that while consumers patronize a number of different stores they have a primary

affiliation to a main store. They find that nearly three quarter of consumers do have a primary store. The strength of this affiliation depends on a number of factors. For example they are less likely to switch based on temporary price reductions and the majority of transitions occur across competing stores of the same format. Also the longer customers stay with a preferred store the less likely to switch. These factors can be used to determine the redistribution of demand in the event of that stores are closed. They further describe strategies that retailers can use to limit mobility and encourage the consumer to stay with a particular store format. These can be used by a firm to minimize demand lost as a result of store closures. Campo, Gijsbrechts and Nisol [13] discuss consumer behavior when choosing a store. They examine the effect of store complementarity on the frequency and distance a customer will travel to a given store. They find that (i) Consumers “alternate visits to high and low fixed cost stores to balance transportation and holding costs against acquisition costs” and (ii) when different stores offer the best value for different product categories, it may induce consumers to visit these stores together on combined shopping trips. Based on these findings, when closing stores in a region, retail firms can better estimate the redistribution of demand. Mccurley et al. [14] analyze the impact of different variables that influence the consumer’s store patronage behavior. They conduct the study across three segmentation alternatives and compare the segmentation approach to a single aggregate model. One of their findings confirmed that consumer transaction costs increase with distance.

1.5. Study Motivation and Expected Contribution

While substantial work has been done in the area of spatial retail competition the effects of a retail chain’s store closures on a competitor’s revenue and store closing

decisions has not yet been examined. Since retail stores operate in a competitive environment chain-level effects are not simply a function of a retailer's existing store locations but are also contingent on the location of stores operated by rival firms. A fraction of the sales that were captured by a closed store will be redistributed not only among other stores in the chain but also among rival stores in the vicinity. Thus, a firm's decision on whether to close or keep a store open is influenced by its' competitor's actions and vice versa. The decision to close a store should not only consider recoverable revenue but also the resulting effect on stores operated by a competitor. In other words, every decision by a firm to keep a store open potentially puts additional pressure on the rival firm to close its non-profit making stores. The problem can then be viewed as a sequential game. The store closing decisions are optimal for the first mover (leader) when the post decision net revenue is maximized after the second mover (follower) has made its store closing decisions. We develop a mixed integer model to determine optimal store closing decisions for a retail firm in order to maximize revenue, over a period of time. The model considers re-distribution of demand between rival stores based on location and consumer characteristics. We are then able to provide a solution to the retail chain that will be applicable in a real world competitive market. By applying the model to series of simulated scenarios we gain insights into optimal strategies that should be adopted by each firm under different market and spatial conditions. These can be used by management to better understand how the change in factors such as demand and operating costs will affect the optimal store closing decision of the rival firm.

The rest of the paper is organized as follows. In Section 2 we review relevant spatial retail competition literature and in Section 3 we present the mixed integer programming model that finds the equilibrium store closing decisions for both firms for a one period problem. In Section 4 we propose a heuristic that utilizes the MIP model to provide a high quality solution to the problem extended over multiple time periods. In Section 5 we conduct a series of numerical experiments on a set of simulated data. The results are used to determine best store closing strategies (for each store and the firm as whole) over a period of time. In Section 6 we conduct two case studies where the heuristic is applied to find optimal solutions for the competition between (1) Lowes v Home Depot and (2) CVS v Walgreens in the urban region of Mecklenburg NC.

CHAPTER 2: LITERATURE REVIEW

This section consists of three parts. First, we discuss prior literature on redistribution of demand as a result of store closings or openings. Second, we position our work relative to existing research on store closures in the context of retail chains. Third, we contrast our work with existing research on market capture. Third, we contrast our work with existing research on market capture.

2.1. Market Capture and Redistribution of Demand

The phenomenon of locating stores has been studied extensively. An important aspect of a store opening or a closing decision is to understand the resulting redistribution of demand. Redistribution is determined by both spatial and non-spatial factors. Ingene and Yu [15] conducted a study across nine retail trade sectors in order to develop a develop theoretical model to explain “consumer behavior in the context of spatially extensive retail markets.” Several socio-economic factors that influence retail sales were identified. These include demographics such as household make-up and size, income, travel costs and spatial competition. Mejia and Benjamin [16] examine non spatial factors that influence shopping center patronage. They review prior research in the fields of real estate, marketing and urban economics to determine which non spatial factors play the greatest role in driving a store’s retail sales. They explain that recognizing these are especially important in the current economic context due to increased retail competition and increasingly higher real estate costs. Some of the

factors identified include (i) differentiation where a shopping center adds unique anchor retailers and offers a complementary mix of non anchor stores. (ii) store image which is based on attributes such as available merchandise, service and convenience. (iii) quality of facilities described here as the design of a store/shopping center which allows for the easy flow of shoppers and (iv) the attributes of building in which the store is located. A newer larger facility is likely to generate more sales per square foot.

Huff [17] developed the model of retail gravitation which can be used to determine when consumers will choose one shopping center over another. He postulates that the consumer's preference for one shopping center over another is determined by the utility that can be gained by visiting each one. This utility is a function of two variables- (i) the number of items of the kind that a consumer desires that are made available in the shopping center and (ii) the travel time to the shopping center. The assumption made is that the consumer knows apriori the range of the good he is interested in that is also available in the shopping center. The larger the range the greater the probability that his shopping trip will be successful. Therefore he will be willing to travel a greater distance if in doing so he increases the probability of being able to purchase the right goods. However as the distance traveled increases the increased travel costs cuts into the total utility of the trip. Okoruwa et al. [18] further develop Huff's model by adding retail center specific variables and consumers' socio economic characteristics such as employment, education and length of time residing at the current location. They consider three categories of data- "socioeconomic and demographic characteristics of shoppers, shopping center specific variables and the friction factor". The friction or impedance factor is determined by the time taken for the customer to drive to the store. Customer

visits to fifteen different retail centers in the Atlanta metropolitan area were studied to determine the significance of each of these variables. The following socio economic variables were found to have a significant impact on the number of sales- per capita buying income, average household size, population density and total population. General merchandise sales for each shopping center are estimated as follows- First using the variables described above total sales arising from the region is estimated. The total is then allocated to each store by using the “Poisson gravity model”.

Nakanishi and Cooper [8] propose the “multiplicative competitive interaction” (MCI) model which allows for including other store characteristics such as “quality of service, atmospherics, cleanliness and product quality” in addition to distance and size when determining customer decisions. An advantage of the MCI model over Huff’s model is that, when examining competition between firms that employ different strategies it captures the interactions of these strategies.

We consider Huff’s model of demand allocation to be most relevant for this research since we examine competition between similar stores. Hence consumers maximize their utility by minimizing travel costs resulting in store choice made primarily based on travel time. We further incorporate factors such as population, household size, and income when determining the demand arising from the region under study.

2.2. Existing Research on Store Closures in the Context of Retail Chains

To the best of our knowledge there appears to be a few papers related to optimal store closure strategies. Shields and Kures [19] introduce the case of the closing of a substantial number of K-Mart corporation's stores. In 2002 and 2003 K-Mart announced the pending closure of 607 stores in 40 states and Puerto Rico. This resulted in a 30% reduction of the company's store count. Shields and Kures examine both the economic and spatial factors that influenced these decisions. Among these factors are the degree and proximity of the competition in the local market and the local demographic characteristics. Shields and Kures adopt the simplifying assumptions of Ingene and Yu [15] and make the following assumptions, (1) demand is known, (2) all households have the same demand schedule, (3) households are equally spaced, (4) transportation costs are equal in all directions, (5) customers pay transportation costs, (6) firms maximize profits, and (7) there is easy entry and exit into the market. They then develop an empirical model that seeks to explain the factors that influence a store closing decision. The explanatory variables are market size which represents the number of households located within a 15 minute drive from the store, Income which is the percent of the aforementioned households with an annual income greater than 20,000, Spatial Competition which is the distance from a K-Mart store to the nearest rival store, Transportation Costs from a K-Mart to the nearest distribution center and Demographics which represents the average household size within a 15 minute drive from the store. They find that "market size", "spatial competition", "distance to distributor" and "Income" had a statistically significant impact on store closing decisions.

Haans and Glibrechts [11] explain that individual outlet closing decisions should be based on both the outlet's revenue and the resulting loss in revenue to the organization. Their findings confirm that a substantial portion of sales of a closed store can be recovered (retained) by adjacent stores. In this research, we specifically use the concept of retained sales since one of the objectives is to maximize the demand that is redistributed to stores of the same chain.

ReVelle et al. [20] present an Integer Program model to determine the optimal manner in which a firm can reduce facilities within a region. They look at a scenario where competing firms operate stores in a given regions. The stores are similar in size and layout and offer a homogenous product. Thus consumers will choose to shop at the store closest to them. In a situation where a decline in demand occurs and one of the firms (firm A) is forced to close a number of stores then individual store closing decisions are based on (1) Consumer population in a region (2) Distance from the region to the store (3) Distance from the region to the nearest store of a rival firm. A store located closest to a region will capture the demand in that region. The model developed can be regarded as the inverse of Revelle's Maximum Capture Model described previously. The model is applied to a scenario where 2 firms compete in a market divided in to 55 nodes. Each firm has 4 stores. Initially firm A has 35% of the demand in the market. When firm A closes 1 store it is still able to retain almost 30% of the market share. If 2 outlets are closed then market share drops to 24% and if only 1 store is kept open market share is 13%.

Our research differs from the ones discussed above. The above research, evaluate reasons for store closures and factors that should be considered when selecting stores for

closure. However, they do not consider the effect of closing an individual store on the other stores in the same chain or on the stores of a rival chain. Nor do they consider the effects of a possible shift in demand in future periods. We take into account both the competitive aspect of the decision making process and the impact of the variance in demand from one period to the next when developing our model.

2.3. Prior work on market capture

Hotelling [21] first took into consideration that a market is in fact an extended region where the cost to the buyer is the price of the good purchased plus the transportation cost to the seller. Thus given identical product offerings the consumer will choose to shop at the business where the total cost of purchase is lowest. Hotelling illustrated this by presenting two businesses (A and B) located at two points on a line. If the buyers are uniformly distributed along the line, then each business will be best served by moving toward each other. If the prices at both businesses are the same then the equilibrium solution is reached when both A and B are located next to each other at the center of the line. Each business captures 50% of the market.

ReVelle [10] presents the MAXCAP model that evaluates optimal store locations for a firm that is entering a market region. It is an extension of the Hotelling problem to incorporate multiple new outlets. Given a region divided into nodes with known demand and existing facilities (outlets) a firm wishes to maximize captured demand by introducing a number of new facilities into the region. The assumption that the stores are homogenous which is often made when developing models to evaluate spatial competition is relevant in this case as well. A region is captured if the new facility is closer to it than any existing facility. If the new store is located adjacent to an existing

store then the region closest to is considered to be doubly served. The demand originating from that region is divided equally among both facilities. An integer program model is formulated to solve the problem. ReVelle goes on to extend the model by allowing for multiple objectives. A weighting method is used so that the firm can achieve a secondary objective concurrently. For example while primarily looking to capture a region a firm might also be interested in maximizing the capture of a certain demographic of the population (i.e. customers over the age of 50).

Wang et.al. [22] evaluated the situation where customer demand distributions change. The problem then becomes one of simultaneously opening and closing stores. Change in customer demand in a particular region can render unprofitable a store located in that region. The firm is then better served by closing that store and opening one located so that a total weighted travel distance for customers is minimized. Since there are costs involved in both store openings and closings this has to be achieved while meeting a budget constraint. They take an example from the banking industry. Changes in population distribution has meant that a significant number of customers are now located beyond a threshold distance from all bank branches. Due to high operating costs the total number of branches cannot exceed a given threshold. Therefore the bank will not simply open new branches to meet customer demand but will instead close and relocate existing branches. Wang et.al adopt solution techniques from the p-median literature in order to formulate an integer programming model for this problem. They then test a Greedy-Interchange heuristic and a Tabu Search algorithm on the problem and compare solution quality and time to results given by CPLEX. One of the weaknesses of the model is the simplifying assumption that a branch is able to serve all

customers within a threshold distance. This does not allow for the fact that each branch has limited capacity.

Kolli and Evans [23] introduce a multi objective linear program model in order to select the optimal sites for new franchises. The objective of the franchisee and the franchisor which may conflict with each other are taken into account. In a region populated by a number of franchise outlets the introduction of any new franchises will change the market share of the existing ones. Given that the outlets are similar customers who patronized existing outlets will switch to the new one/s if they are closer to them. Here a conflict of interest between the franchisor and the franchisees arises. Any new additions will decrease market share of the franchise's existing outlets but will also increase the total number of sales at all the outlets (existing and new) thus increasing the franchisor's revenue. The objective function includes the following- (i) Maximize the number of customers that visit the franchisor's outlets. This can be achieved by maximizing the number of customers attracted from competing outlets and (ii) Minimizing the number of customers lost from each of the existing franchises.

Marianov et al. [24] introduced a model to determine market capture where consumers rank facilities by both shorter travel time and shorter waiting time. They examine a scenario where a firm wants to enter a market where a rival firm already operates facilities. Based on Kohlberg [25] and Brandeau and Chiu [26] the assumption is made that a customer's choice of a facility depends on the distance to the facility and the waiting time at the facility. Waiting time at a facility is based on a queue with Poisson arrivals, a mean arrival rate λ , exponentially distributed service time with mean μ and m servers. It is assumed that there is finite capacity where a maximum of K

customers can be serviced in a facility. They use combination of Feo and Resende's [27] Greedy randomized adaptive search procedure (GRASP) and Tabu search to solve the problem. The results were compared to solutions given by ReVelle's Maxcap model where customer store choice is based solely on travel costs. Somewhat surprisingly MAXCAP provides solutions that are very close to the solutions obtained by the heuristic.

Benati and Hansen [28] look at the problem of locating facilities under the assumption that customer store choice is not deterministic in nature. For each customer the decision to choose a store is based on a probability distribution. The probability that customer chooses a store is a function of the distance to the store. Keeping in line with the other studies in this area they assume that generally, the closer the distance, the higher the probability. This approach allows for the fact that certain customers will value other factors over distance when choosing and that a firm cannot forecast the choice of every customer. They present three different solution methods including two mixed integer programming models to solve the problem. Random test problems were devised based on the spatial characteristic of the Italian city of Torino. They show that the introduction of probabilistic behavior does affect the optimal location of activities.

Murray [29] examines retail site selection under conditions of uncertainty. It is assumed that due to factors such as land suitability, access, costs etc a store may have to be located some distance away from the recommended site. Therefore, while there are numerous models which provide exact location sites it is useful to understand the change in demand captured if the site has to be moved. In this analysis the planar multi-facility location-allocation problem first developed by Cooper [30] is utilized to initially find the

optimal location for new facilities. Then the coordinates of these locations are perturbed on a random basis to simulate the condition where the selected site is not suitable for building a facility. An analysis was carried out for three different problem sets. Results indicate that, as the number of facilities located increases, siting uncertainty is more susceptible to significant errors.

The research approaches described above do not fully capture the competitive aspect of the game between rival chains. The assumption is that a firm makes optimal location decisions for new stores while its rival's store locations are fixed. However it is realistic to expect the rival firm to counter these moves by possibly introducing new stores of its own. The following studies acknowledge the game theoretic aspect of new facility location.

Serra and ReVelle [31] examine a situation where rival firms (A and B) are preparing to enter a region. When determining the location of a new store a firm is influenced by the possible location choice of its competitor. The scenario is similar to the one discussed in ReVelle's "Maximum Capture" problem. The method introduced here uses the "MaxCap" model as a starting point. The "MaxCap" model is incorporated in a heuristic algorithm to find the optimal locations for firm A's new stores taking into account firm B's optimal responses. The algorithm first locates firm A's stores in the region using any method. It then uses the "MaxCap" model to determine the optimal store locations for firm B. Firm A's market capture is calculated and stored. One of firm A's stores is now relocated to a different node and the process is repeated. If firm A's market capture improves the new location is kept and the entire loop repeated. An interesting observation is that the first mover (firm A) can at most capture 50% of the

market since the worst case for firm B is to simply locate its stores adjacent to firm A's stores.

Ghosh and Craig [32] use a similar approach to determine the best locations for a firm entering market given that its competitor will follow soon after. They acknowledge the importance of recognizing that the market is constantly undergoing competitive and demographic changes. First the MCI model is used to determine the potential market share gained by locating a store at a given site. Similar to Serra and ReVelle the firm's objective is to maximize market given that its competitor will follow suit. An iterative algorithm is developed where, for each strategy employed by the first mover (A) the second mover (B)'s best response is found. A's strategy is then reviewed to see if any changes can bring about an improvement in performance. This is repeated until the equilibrium strategies are found. Initially the number of stores to be opened is set as a predetermined constant. Ghosh and Craig then modify the model by specifying a cost for each additional store that is opened in order to find the optimal number of new stores for each firm. Relocation can be profitable when there is a shift in demand but comes with an inherent cost.

Labbe and Hakimi [33] describe a game where two competitors first select a facility location each and then determine the quantities to be released to the market. They account for the transportation cost involved when moving goods to the market. This cost is a function of the facility's location. The final selling price of goods will then depend on the distance from the facility to the market. Therefore when locating a new facility its proximity to the market has to be considered. The problem is solved in two stages. The first stage two competing firms select a site or sites for their new

facilities. Then the unit transportation cost between the facility and each potential market is estimated. This is assumed to be concave and increasing with distance. The transportation cost is added to marginal production cost to determine the total marginal cost of bringing the product to each market. Given this cost the second stage is a non zero sum non cooperative two person game where each firm tries to maximize profits by controlling the quantity of goods released to each market. Labbe and Hakimi show that a subgame perfect equilibrium exists for this game.

Chawla et al. [34] consider a sequential two player location game where the objective is to maximize market share. Two firm's choose sites to locate new stores in stages (in each stage the leader chooses a site and the follower responds with his choice of location). The competition is modeled as a zero sum game where minimizing Leader's payoff is equivalent to maximizing Follower's payoff. Therefore the objective function is the min-max payoff for the leader. They show that while there is a first-mover disadvantage, there is also an upper bound to the extent of this disadvantage. For example for a game played in a two dimensional Euclidean space the leader can guarantee at east $1/3$ of the total payoff. Similar to results given by Hotelling's model in a multi-step location game played on a unit line, where the number of moves is known the Nash equilibrium results in a payoff of $1/2$ to both players. They then devise a strategy for the leader in a unit line game where the number of moves is not known that will net no less than half of the total share. This is done by the leader first locating at the single-stage equilibrium location and then replicating each move of the follower.

Dasci and Laporte [35] examine a similar situation but where both firms have a profit maximization strategy. Due to the introduction of fixed operating costs the number

of firms to be located is made endogenous. The solution methodology is a continuous model where each firm's location strategies are based on location densities rather than a specific point. By treating location points as such it becomes possible to solve the model analytically. The assumption is that the leader clearly signals the location strategies chose at which point the follower devises the best response. They show that by doing so the leader gains the first mover advantage which can be used to prevent the follower from entering a given market. This enables the leader to make positive profits even if she is at a cost disadvantage. They show that the leader's fixed costs could be more than twice those of the follower, yet she could stay as a monopoly in a market. This is due to the fact that the follower will not enter parts of the market where it cannot recover its fixed costs. However they also provide instances where the leader better off by allowing the follower to enter the market.

In this study we examine a scenario which is the inverse of the market capture problem studied by Serra and ReVelle [31]. Here, the two rival firms are looking to reduce the number of existing stores in a given region, due to a decrease in expected demand during a recession. There are a number of differences between this scenario and the one analyzed by them. First, in this case the initial store locations are fixed. As a result, both competitors have complete information about demand redistribution in a region, as a result of potential store closings. Second, as Hans and Gijsbrechts [11] point out “consumer reactions to store closures are not simply the mirror image of their response to store openings”. In the case of store closings, one can assume that demand previously captured by a closed store can be redistributed to other open equidistant stores in the region. However, a similar phenomenon may not hold for a store entering a

new region. Third, when optimizing over multiple time periods, it may be necessary to keep a loss making store open to take advantage of a future rise in demand, a concept which does not apply to store openings. Finally, in the case of store closings it is possible to keep a loss making store open, for a few time periods, with the primary objective of driving an adjacent rival store out of business. Such a strategy would not make sense when making a store opening decision since the related cost would require a long term commitment.

CHAPTER 3: MODEL DEVELOPMENT

3.1. Preliminaries

We develop a mathematical programming model to study optimal store closing decisions between two rival firms. We consider a scenario of two rival chains operating in a large metropolitan region. The stores are generally homogenous in nature with similar offerings and at a similar price range. Based on Huff's model of retail gravitation we assume that the stores compete for customers primarily on a spatial basis. Prior research has found that, consumers usually report spatial convenience as the most important criterion when choosing a store. Arnold et al. [36] conducted a study across six major markets in North America and Europe, to determine the attributes that consumers consider when choosing a retail food store. They find that locational convenience and low prices are considered the most important attributes across markets and cultures. Fox, Montgomery and Lodish [37] find that, travel time has a significant and substantial negative effect on store patronage. Their results indicate that travel time has a consistent negative effect across formats. This is particularly significant for retail stores (grocers, drug stores) but is less sensitive to mass merchandisers if there are significant price differences at different stores. Leclerc et al. [38] find that consumers place a high value on time due to the fact that "outcomes of time (losses or savings) cannot as easily be transferred (i.e., recouped or applied) to new situations.

When a firm closes a store, the demand lost can be captured by stores of either firm within a distance threshold. Hence in our model we reallocate demand to the closest open stores in a given geographical region when one or more stores are closed. This reallocation of demand is a function of the maximum distance the consumers in a particular region are willing to travel for a good sold at a particular type of store, referred to as the maximum *range of a good* [39]. For example, the range for pharmaceutical goods might be much lower than that for home improvement goods.

Examples of such retail chains include CVS-Walgreens, Lowes-Home Depot, etc. In a typical large urban region in the southeast Home Depot operates 13 stores while Lowes operates 23 stores within 25 miles of the city center. The retail hardware industry still generates the majority of sales via in store visits. In 2012 Lowes estimated that online sales accounted for 1.5% of total sales. Similarly Home Depot's online sales portion was less than 1% for the same year. The competition between Lowes and Home Depot in the United States is clearly duopolistic in nature. They dominate smaller chains and independent stores by offering a vast range of products offered at lower prices [40]. It is therefore likely that customers of a closed store will seek out the closest open store of the same or rival firm within the range of the goods. During the period from 2008-2011, in the midst of the housing slump, Home Depot closed 22 of its flagship stores in 12 states with the stated goal of "reducing cannibalization and driving higher returns" [41]. In 2011 alone Lowes closed 27 underperforming stores in 15 states in an effort to increase profitability [42]. The process to determine optimal store closing decisions is non-trivial and has an impact across multiple dimensions. First, spatially each decision to close a store will directly affect the revenue of all adjacent stores due to demand being

redistributed. Second, this can have an impact on the closing decisions of the aforementioned stores, which in turn will affect the revenue of all other stores which are adjacent to them. Thus, one can observe a ripple effect that could be felt across a geographical region. Third, a decision to close or keep a store open will have an impact across time. Next, we discuss these effects in detail with two small scale hence manually tractable scenarios shown in Figures. 1 and 2.

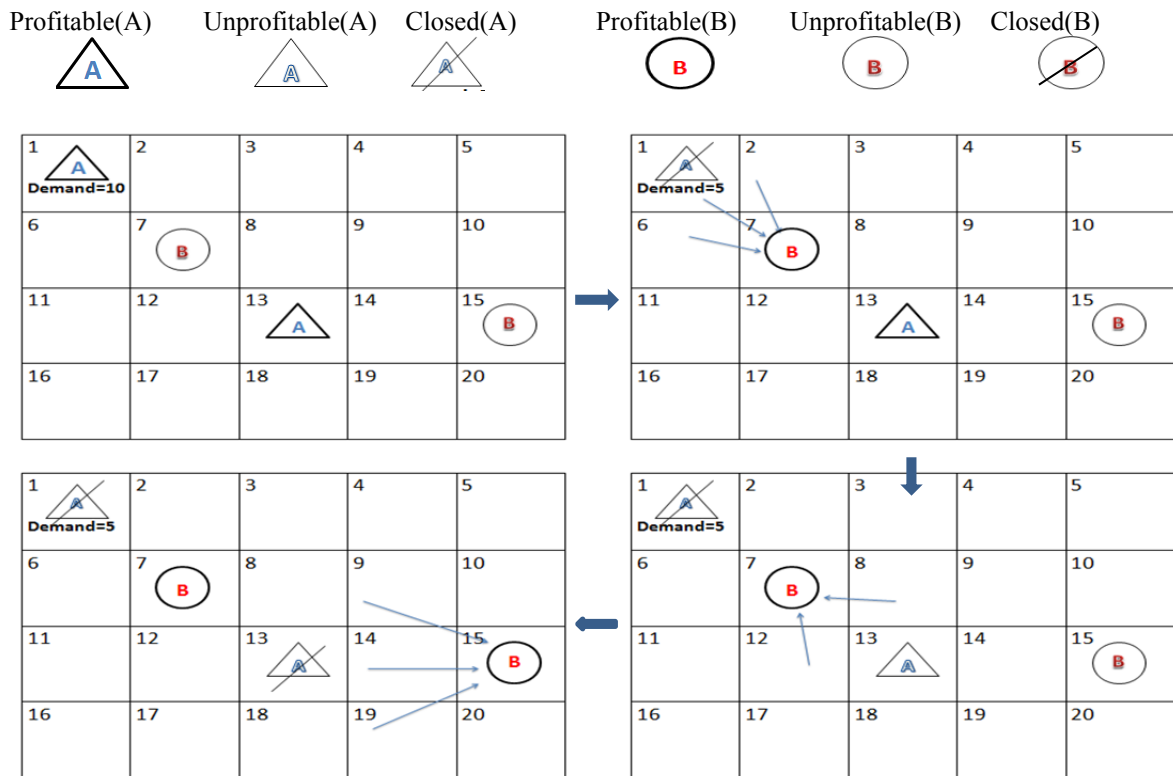


FIGURE 1: The spatial impact of a store closing decision

Figure 1 illustrates the impact a single store closing decision can have across a region. The region is divided into 20 zones where Firm A has stores in zones 1 (A1) and 13 (A13) and Firm B has stores located in zones 7 (B7) and 15 (B15). A store can potentially capture demand from any zone adjacent to it. Initially, both Firm A stores are profitable, while both Firm B stores are unprofitable and are scheduled to be closed. However, suppose that a decrease in demand originating from zone 1 forces A1 to close.

This causes patrons of *A1* from zones 1, 2 and 6 to shift to *B7*, making *B7* profitable. If *B7* stays open, it will continue to capture a portion of the demand from zones 8 and 12 from *A-13*. This results in the closure of store *A-13*, which further benefits Firm B.

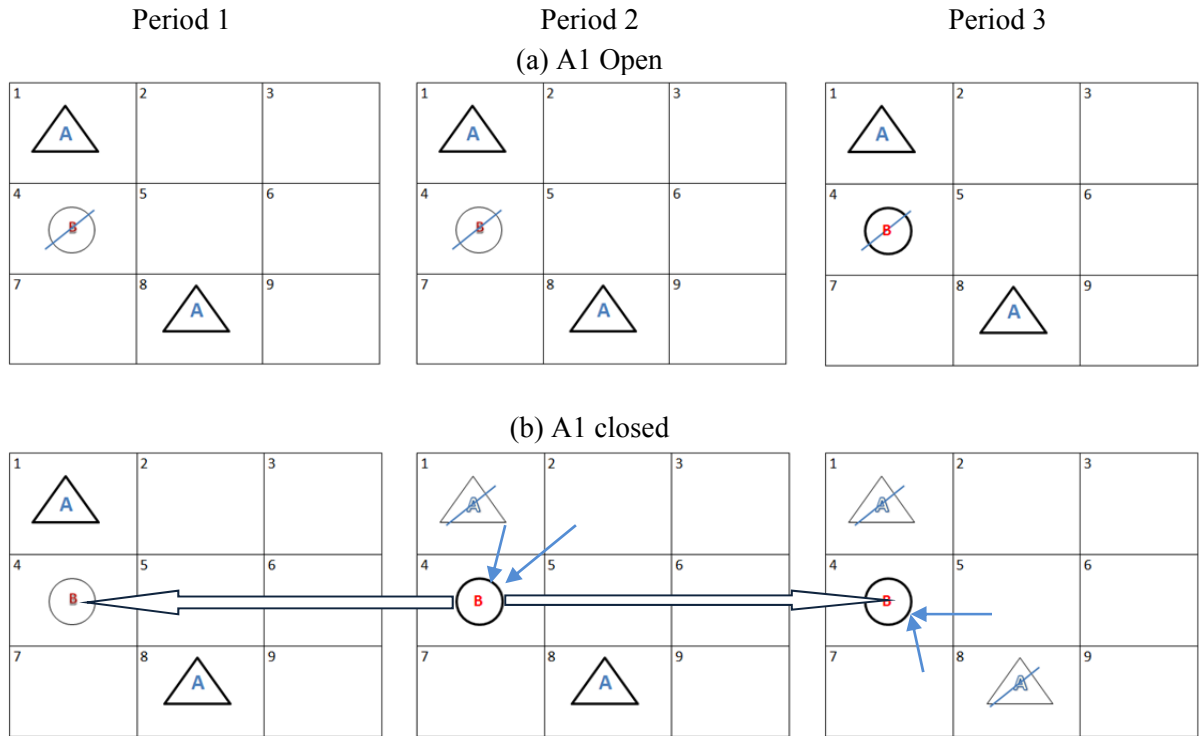


FIGURE 2: The impact over time of a store closing decision

Figure 2 illustrates the impact of a store closing decision on both past and future time periods. In Figure 3(a) we assume that demand originating from zones 1 and 2 will be high enough in all 3 period for *A1* to be kept open. Initially, store *B4* is unprofitable in period 1 and 2 and will thus be closed in period 1. Figure 3(b) shows the effect of a change in forecasted demand in period 2. If demand in zone 1 is expected to decrease from period 2 onwards then, *A1* becomes unprofitable in periods 2 and 3 and will be closed in period 2 transferring demand from zones 1 and 2 to *B4*. Since *B4* is now expected to be profitable in periods 2 and 3 it will stay open in all 3 periods. In periods 2 and 3 *B4* will capture demand from zones 5 and 7 decreasing revenue for store *A8*.

The objective of both firms is to maximize net revenue by optimizing store closing decisions over a period of time. We formulate the problem as a competitive game and find the equilibrium store closing decisions for both firms over multiple periods. We assume each firm has a total of n stores and geographical region is divided into zones. We consider a multi-period game with Firm A moving in the first period (closing a set of stores first) and Firm B reacting in the second period, and so on. Exact size of the zones could be context specific (e.g., 2X2 miles). The demand in each can be a function of various factors such as population, average income level and shopping season. The demand is dynamic and can vary from one time period to the next. Demand from a zone is allocated as follows:

- If the zone is within the distance threshold of one or more of Firm A 's stores, then
- If Firm A has at least one store that is closer than any one of Firm B 's stores then the entire demand from that zone is captured by Firm A
- If the closest Firm A and Firm B stores are of equal distance away from the zone then the demand is shared

3.2. Illustrative Example

We start with a 25 zone, one period problem with 5 firm A and 5 firm B stores open in the initial iteration. In order to demonstrate the advantage of taking a game theoretic approach to the problem we also solve the problem using a non strategic approach where the first mover's (firm A 's) store closing decisions are not influenced by firm B 's possible responses. We assume that the stores are homogenous and each requires a minimum of 8 units of demand to break even.

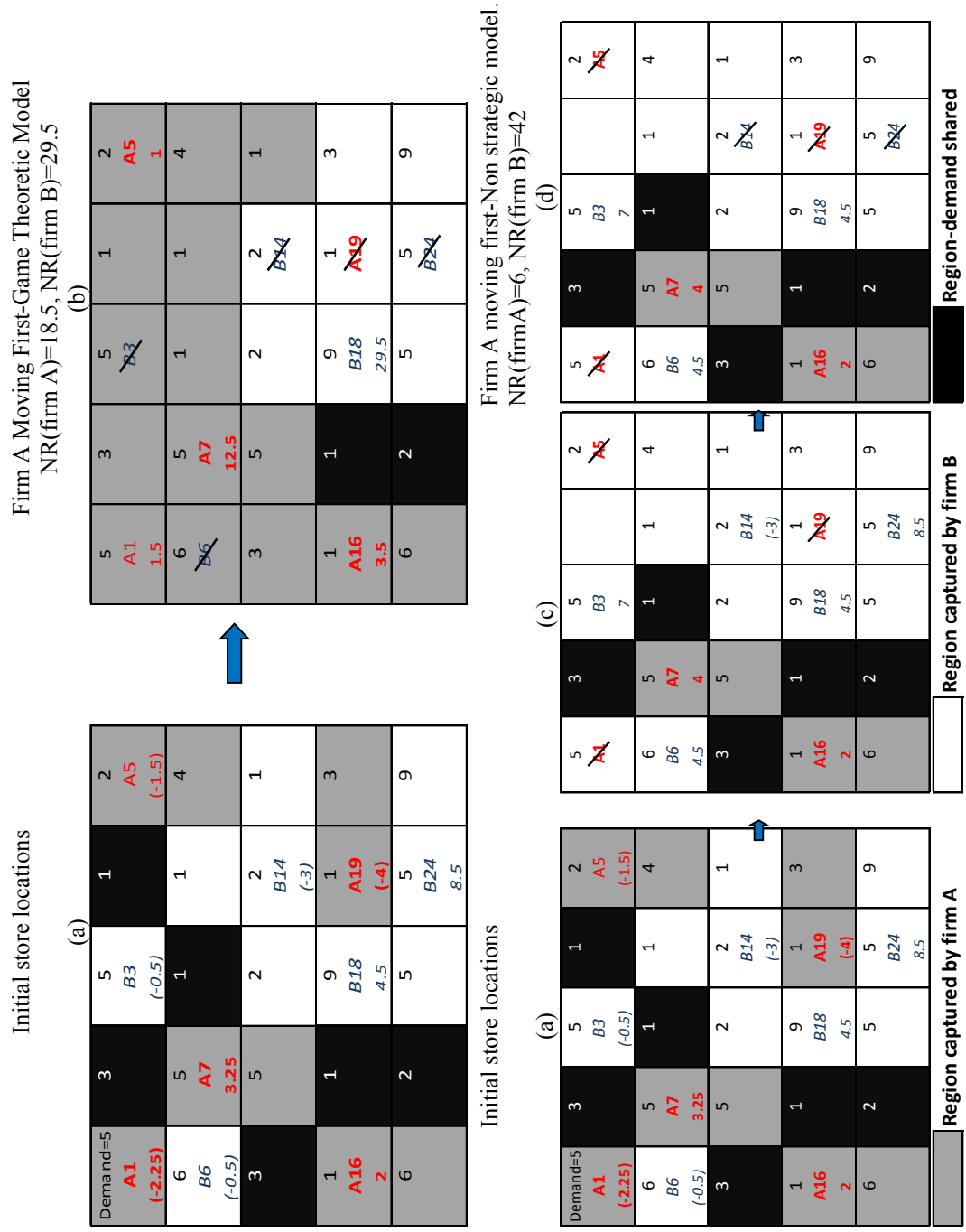


FIGURE 3: Illustrated example

In Figure 3 grid (A) shows the initial store locations. The game theoretic solution is shown in Grid (B). In Figure 4 we show the decisions that firm A takes as the first mover with Grid (C) followed by the store closure decisions made by firm B in response to A 's moves which is shown with grid (D). Figure 4 shows firm A 's store closing decisions when firm B 's possible response is not accounted for and firm B 's subsequent response respectively. Net revenue is given below the store ID. As shown in grid (C) if firm A does not account for firm B 's potential moves then it will first close all stores with current net revenue < 0 ($A1$, $A5$ and $A19$). The model results in Grid (B) however demonstrates that keeping $A1$ and $A5$ open can force $B3$ and $B6$ to close thereby increasing total net revenue from 6 to 18.5 units.

3.3. Model Formulation

The model parameters and variables are given in Table 1.

TABLE 1: Model variable definition

Symbol	Definition	Type
Decision Variables		
X_j^{ft}	= 1 if a store of firm f located in sector j is kept open in time period t , 0 otherwise.	Decision variable
Store revenue related		
R_j^{ft}	Revenue earned by a store of firm f located in sector j in time period t .	Derived variable
$R_{c_k}^b$	Revenue earned by the set of firm b stores	Derived variable
r^t	Average demand per one unit of population in time period t	Exogenous variable

TABLE 1: (Continued)

d_0^{fj}	Minimum demand needed to cover operating costs for firm f store j	Exogenous variable
Demand capture related- single store		
Q_{ij}^{ft}	= 1 if in time period t firm f store located at zone j is one of the closest open stores to zone i , 0 otherwise.	Derived variable
V_{ij}^{ft}	$V_{ij}^a = 1$ if in time period t , the distance from zone i to the firm A store located in zone j is equal to the distance from i to any open firm B store. Similarly $V_{ij}^b = 1$ if in time period t , the distance from zone i to the firm B store located in zone j is equal to the distance from i to any open firm A store.	Derived variable
\bar{U}_{ij}	Set of stores at time period 0 that are closer to zone i than a store located in sector j	Exogenous variable
M_j	Set of zones that are within coverage distance of the store located in sector j	Exogenous variable
Demand capture related- set of stores		
$Y_{ic_k^b}$	=1 if there are no open firm A stores that are closer to zone i than all firm B stores in combination $c_k^b \forall k = \{1 \dots n\}$, 0 otherwise	Derived variable
$W_{ic_k^b}$	=1 if there is at least 1 open store of firm A which is equidistant to zone i as any firm B store in combination $c_k^b \forall k = \{1 \dots n\}$, 0 otherwise	Derived variable
$L_{c_k^b}$	Number of stores in combination $c_k^b, k=\{1..n\}$	Exogenous variable
n	Number of all possible store opening combinations for firm B.	Exogenous variable

TABLE 1: (Continued)

C_b	Set of all possible store opening combinations for firm B. $C_b = \{c_1^b, c_2^b, \dots, c_n^b\}$	Exogenous variable
$\bar{U}_{ic_k^b}$	Set of firm A stores that are closer to zone i than all firm B stores in combination $c_k^b \forall k = \{1 \dots n\}$	Exogenous variable
$\hat{U}_{ic_k^b}$	Set of stores at time period 0 that are equidistant to zone i as any firm B store in combination $c_k^b \forall k = \{1 \dots n\}$	Exogenous variable
$M_{c_k^b}$	Set of zones that are within coverage distance of at least 1 store in the set c_k^b	Exogenous variable
Initial Problem state		
S^f	Set of stores of firm f that are open at time period 0. (f=a,b)	Exogenous variable
P_i	Population in sector i	Exogenous variable
N	Number of stores open at time period 0	Exogenous variable

The mathematical formulation of the problem is as follows,

3.3.1. Objective Function

Maximize,

$$\sum_{j \in S^a} R_j^{at} \quad (1)$$

Where,

$$R_j^{at} = \sum_{i \in M_j} (P_i r^t (Q_{ij}^{at} - \frac{1}{2} V_{ij}^{at}) - rd_0) X_j^{at} \quad (2)$$

The firm's objective is to maximize the total net revenue for Firm A in time period t . Here we assume that the minimum demand required for a store to cover operating costs (d_0) is known by both firms. The revenue for each individual store is a function of the demand it attracts from the set of zones (M_j) within the distance threshold. Since we assume competition on a spatial basis, if firm A 's store at zone j is one of the closest to zone i then that store captures at least half of the demand ($P_i r$) originating from that zone ($Q_{ij}^{at} = 1$). If there is at least one of firm B 's stores located at a zone (j) as close to zone i , then firm A loses half of the demand originating from zone i to the firm B store. ($V_{ij}^{at} = 1$ and $Q_{ij}^{at} - \frac{1}{2} V_{ij}^{at} = 0.5$). Net revenue for a store located at j is the sum of revenue gained from all zones within coverage distance less the operating costs (d_0). If firm A decides to close the store at j then $X_j^{at} = 0$ resulting in $R_j^{at} = 0$. Equation (2) is linearized as follows,

$$R_j^{at} \leq \sum_{i \in M_j} P_i r^t \left(Q_{ij}^{at} - \frac{1}{2} V_{ij}^{at} \right) - d_0 \quad \forall j, t$$

$$R_j^{at} \leq \sum_{i \in M_j} P_i X_j^{at} \quad \forall j, t$$

Firm A 's net revenue is dependent on both its own store closing decisions and firm B 's subsequent reaction. As we have shown in figure 1 since firm A decisions will influence firm B 's reaction it might be optimal to keep a store (j) open even in instances when $R_j^{at} \leq 0$.

3.3.2. Constraints Related to Demand Redistribution

Here we introduce the set of constraints that allocate demand from a zone to a store. The set \bar{U}_{ij} contains all stores (firm A and B) that are closer to zone i than the store in zone j . A store located at zone j captures at least a portion of demand from zone i if there are no other stores closer to zone i . If all stores in the set are closed then in constraint (3) below Q_{ij}^{ft} is allowed to take a value of 1.

$$Q_{ij}^{ft} \leq 1 - (\sum_f \sum_{h \in \bar{U}_{ij}} X_h^{ft} / N) \quad \forall i, j, t \quad (3)$$

Constraint (4) describes the instance when demand from a zone is shared by both firms. The set \hat{U}_{ij} contains the stores located at an equal distance from i as the store at j . If there are one or more firm b stores in the set that are kept open we assume that the demand originating in zone i is split evenly among both firms ($V_{ij}^{at} = 1$). If all firm b stores in the set are closed then V_{ij}^{at} is allowed to take a value of 0.

$$V_{ij}^{at} \geq (\sum_{h \in \hat{U}_{ij}} X_h^{bt} / N) - (1 - Q_{ij}^{at}) \quad \forall j, i, t \quad (4)$$

Since there can be instances when neither A 's store at zone j nor B 's stores in the set \hat{U}_{ij} are the closest to zone i ($Q_{ij}^a = 0$), the constraint ensures that V_{ij}^a cannot be forced to take a value of 1 if $Q_{ij}^a = 0$ since the store cannot lose 50 percent of zero demand.

Finally we consider the allocation of demand when a zone is shared by multiple stores of the same firm or firms. Here we have to ensure that this demand is counted only once in the revenue calculation of the firms. Constraint (5) ensures that the demand is allocated to one store. For example if there are 3 firm A stores and 2 firm B stores

closest to zone i , then 50% of the demand originating from i is allocated to one of the 3 firm A stores and 50% to one of the 2 firm B stores.

$$\sum_{j \in S^f} Q_{ij}^{ft} \leq 1 \quad \forall i, t \quad (5)$$

3.3.3. Constraints Related to the Rival Firm's Optimal Response

In order to determine the equilibrium store closing decisions we now have to ensure that firm B 's response is the one that maximizes its' net revenue given firm A 's initial moves. We note that B 's closing decisions are denoted by X_j^{bt} . Given that the net revenue for firm A ($\sum_{j \in S^f} R_j^{at}$) is a function of X_j^{bt} , we introduce a series of constraints that constrain X_j^{bt} so that B 's response is optimal. We first determine the set (C_b) of all possible responses for firm B . These are the different combinations (c_k^b) of stores that B can opt to close or keep open. Constraint (6) ensures that the values of X_j^{bt} are allocated so that the resulting net revenue for B is the highest net revenue possible.

$$\sum_{j \in S^b} R_j^{bt} \geq R_{c_k^b} \quad \forall c_k^b \in C_b, j, t \quad (6)$$

Where R_j^{bt} is computed as follows:

$$R_j^{bt} = \sum_{i \in M_j} (P_i r^t (Q_{ij}^{ft} - \frac{1}{2} V_{ij}^b) - rd_0) X_j^b \quad \forall j, t \quad (7)$$

$$V_{ij}^{bt} \geq (\sum_{j \in \mathcal{O}_{ij}} X_j^{bt} / N) - (1 - Q_{ij}^{bt}) \quad \forall j, i, t \quad (8)$$

We now introduce a set of constraints that calculate net revenue given by any possible combination of store closings. The net revenue for each combination is

dependent on firm A 's decisions. We first determine the set of zones ($M_{c_k^b}$) that are within distance threshold (e.g., distance thresholds) of all B stores in the set c_k^b . If any one of the stores in the set c_k^b is at least as close to zone i as any open firm A store then this combination will give B at least 50% of the demand from i ($Y_{ic_k^b} = 1$). If any one of B stores in the combination is closer to zone i than any open firm A stores then $W_{ic_k^b} = 0$ giving the entire demand from zone i to B . If the closest store to zone i in the set c_k^b and the closest open a store to zone i are equidistant from zone i then both $Y_{ic_k^b}$ and $W_{ic_k^b}$ will take a value of 1, essentially sharing the demand. The net revenue for any combination is calculated by subtracting the total demand required to cover the total operating cost ($rd_0L_{c_k^b}$) of the stores in set c_k^b .

$$R_{c_k^b}^t = \sum_{i \in M_{c_k^b}} P_i r^t (Y_{ic_k^b} - 0.5W_{ic_k^b}) - rd_0L_{c_k^b} \quad \forall c_k^b, t \quad (9)$$

Constraint (10) ensures that $Y_{ic_k^b}=1$ if in time period t there are no firm A stores closer to zone i than any of the firm B stores in the set c_k^b . The set $\bar{U}_{ic_k^b}$ denotes the firm A stores that are closer to zone i than any of the b stores in the set c_k^b and is exogenous to the model. $Y_{ic_k^b}$ can take a value of 1 iff all firm A stores in $\bar{U}_{ic_k^b}$ are closed.

$$Y_{ic_k^b} \geq 1 - \sum_{j \in \bar{U}_{ic_k^b}} X_j^{at} \quad \forall i, c_k^b \quad (10)$$

Similarly the set $\hat{U}_{ic_k^b}$ denotes the firm A stores that are as close to zone i as the closest b stores in the set c_k^b and is also exogenous to the model. If any of the firm A stores in the set $\hat{U}_{ic_k^b}$ are kept open then B shares that demand with A and $W_{ic_k^b}$ is allowed to take a value of 1.

$$W_{ic_k^b} \leq \sum_{j \in \hat{U}_{ic_k^b}} X_j^{at} \quad \forall i, c_k^b \quad (11)$$

As described in constraint (4) a set of open b stores can share demand originating from a zone with an open firm A store iff there are no other open a stores closer to that zone.

$$W_{ic_k^b} \leq Y_{ic_k^b} \quad \forall i, c_k^b \quad (12)$$

CHAPTER 4: SOLUTION PROCEDURE

Smith et al. [43] formulate a similar problem where a firm (leader) decides to introduce a selected set of products to the market. The rival (follower) will counter by introducing its own set of products with the goal of minimizing the leader's revenue. They describe the complexity of the problem by stating that, "The follower's problem is NP-hard in the strong sense, and thus so is the leader's problem. Indeed, the leader's problem is not known to belong to NP, because evaluating the objective function value of a proposed solution to the leader's problem requires the optimization of the follower's problem". They further describe the need for alternate solution methods- "Difficulties in solving the problem by mathematical programming techniques arise due to the facts that the leader variables appear in constraints of the follower's problem, and that the follower's problem contains integer variables". Given the complexity of the optimization problem even a scenario related to a single time period which is of realistic size and scope cannot be solved in a reasonable amount of time. Further an integer programming approach cannot be used to solve a problem extending over multiple time periods due to the fact that optimal decisions in each period are based on store closures in the preceding period. The problem is dynamic in nature and the solution changes as information is updated. We therefore employ a dynamic programming approach where backward induction is used to find the optimal solution. We propose a multi – step heuristic that

combines optimization and simulation to find the optimal store closing decisions for both firms over a multi period planning horizon. This heuristic is shown in Figure 4.

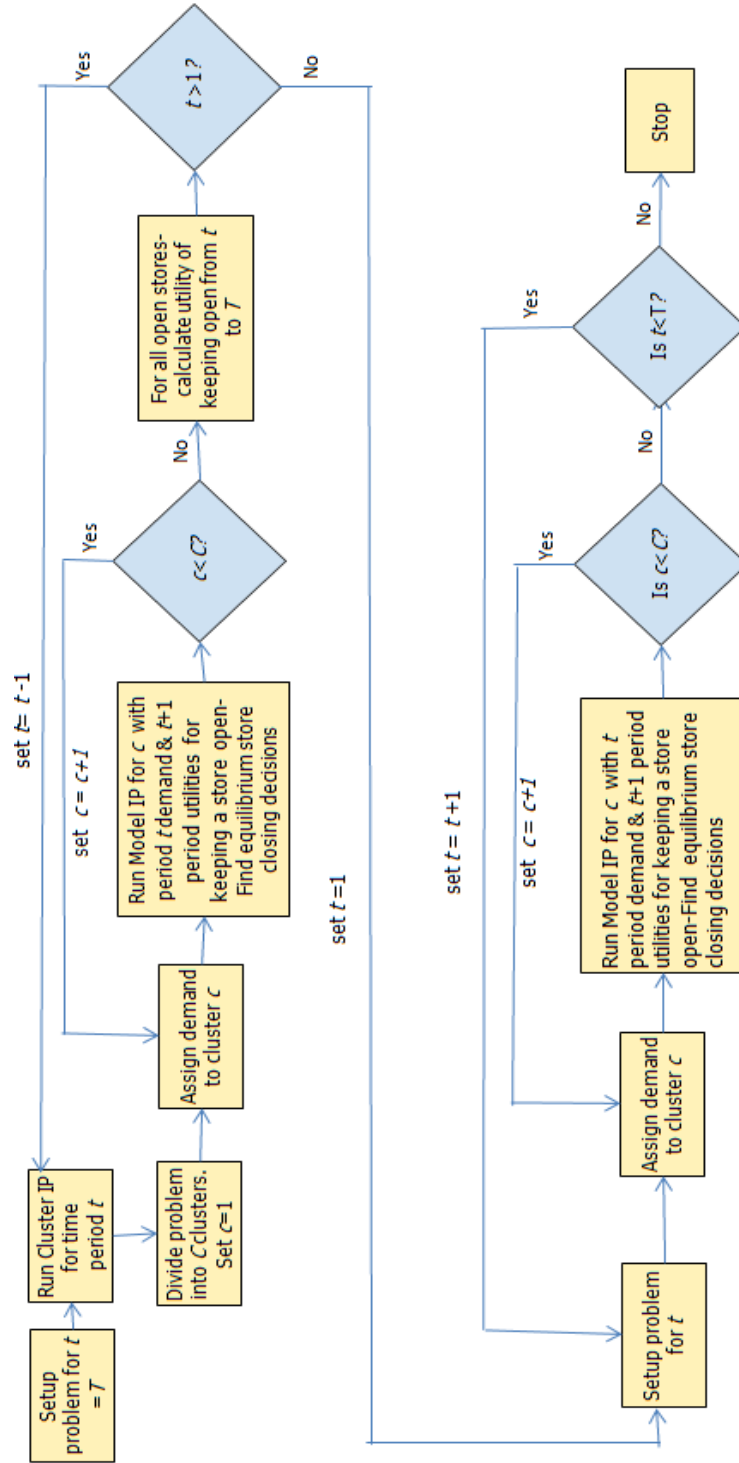


FIGURE 4: Heuristic for Solving a Multi Period Problem

4.1. Clustering Algorithm

In order to break the problem into smaller, tractable components we first employ a clustering algorithm that in each time period assigns groups of stores into smaller clusters. These are then solved as standalone problems. Stores are assigned to a cluster using an integer programming model. The demand from each zone is assigned to a cluster based on a series of properties.

4.1.1. Clustering IP

When grouping sets of stores into separate clusters it may be necessary to separate stores which are within coverage distance of one or more common zones. We call these stores “directly connected stores”. A decision to close any given store has the potential to impact the revenue of all other stores that it is directly connected to (i.e. the revenue of a store is a function of the store closing decisions of the stores that are directly connected to it). If two directly connected stores are put into different clusters then this relationship is not captured. Therefore when grouping stores the objective should be to minimize the number of directly connected stores that are assigned to separate clusters (Minimize the number of direct connections that are broken). In the example given below the maximum number of stores in a cluster is set at 5. Figure 5 demonstrates two ways in which this can be achieved.

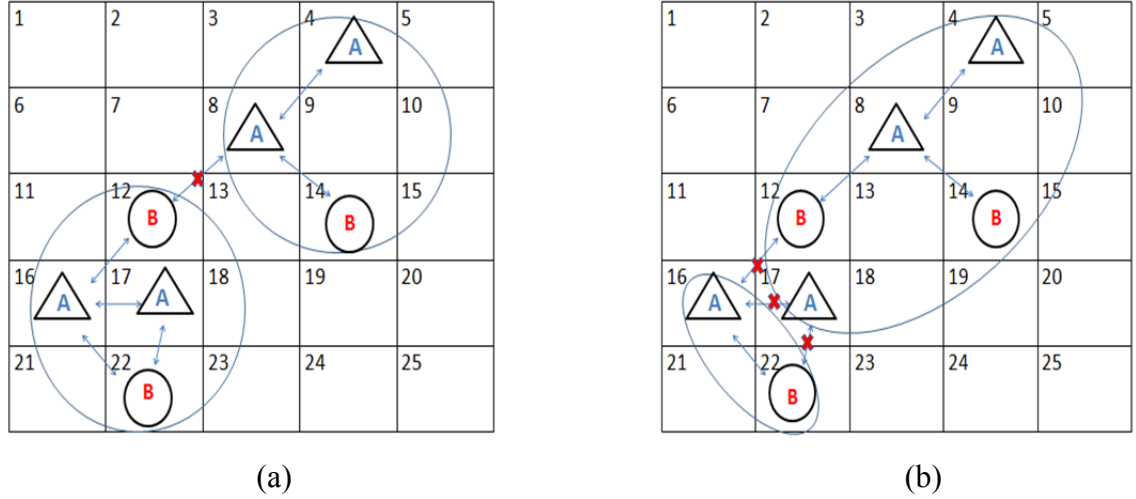


FIGURE 5: Clustering examples

Figure 5 (b) shows that the 7 stores can be separated into two clusters of 5 and 2 stores by severing connections between stores located in zone 12 and 16, stores located in zones 16 and 18 and stores located in zones 18 and 22. Figure 5 (a) shows that the separation can be done in a more efficient manner. Severing the connection between stores located in zones 8 and 12 creates two clusters of 4 and 3 stores. The model parameters and variables are given in Table 2.

TABLE 2: Cluster IP variable definition

Symbol	Definition	Type
Y_{ij}	1 if a store located at zone i and a store located at zone j are in the same cluster, 0 if not	Decision variable
m_{ij}	1 if a store located at zone i and a store located at zone j are directly connected, 0 if not	Exogenous variable
K	Maximum number of stores that can be included in the same cluster	Exogenous variable

TABLE 2: (Continued)

S	Set of stores in the region	Exogenous variable
n	number of stores in set S	Exogenous variable

The formulation of the model is as follows,

Max

$$\sum_{i \in \{S\}} \sum_{j > i, j \in \{S\}} m_{ij} Y_{ij}$$

The objective function is to maximize the number of directly connected stores that are assigned to the same cluster (Minimizes the number of direct connections that are broken).

ST

$$\sum_{j \neq i, i \in \{S\}} Y_{ij} \leq K - 1 \quad \forall i \quad (2)$$

$$Y_{ij} = Y_{ji} \quad \forall i, j \quad (3)$$

$$Y_{i,i+1} = Y_{ij} + Y_{i+1,j} \quad \forall j \neq i, i+1 \quad i = \{1 \dots n-1\} \quad (4)$$

$$Y_{i,i+2} = Y_{i,j} + Y_{i+2,j} \quad \forall j \neq i, i+2 \quad i = \{1 \dots n-2\}$$

$$\vdots \quad \quad \quad \vdots \quad \quad \quad \vdots$$

$$Y_{i,i+n-1} = Y_{i,j} + Y_{i+n-1,j} \quad \forall j \neq i, i+n-1 \quad i = \{1 \dots n-(n-1)\}$$

Constraint (2) restricts the number of stores allocated to a cluster to a pre-determined maximum. Constraint (3) ensures that a direct connection between store i and store j is equivalent to the connection between j and i . Finally constraint (4) places any two stores that have an unbroken direct connection to a common third store in the same cluster.

4.1.2. Demand Allocation

In order to solve clusters as independent problems, demand originating from each zone has to be allocated to a cluster. The allocation is determined by the number and the ownership of stores that are within coverage distance of each zone. We introduce a set of rules that can be used in this process. We denote the distance from zone i to the closest open firm f store in cluster g as D_{ifg} and the net revenue in the current period for the aforementioned firm f store in cluster g as R_{fg} . It is important to note that when we form clusters we have to carefully distribute the shared demand between clusters so that the conditions of the full problem are approximated to the greatest possible degree. We perform this demand distribution on an iterative basis. First demand is allocated for cluster 1. The IP model is then run for cluster 1 and information regarding the stores that are closed and kept open is noted. This information is used when allocating demand to the next cluster and so on. Specifically, we use the following rules when allocating the shared demand between clusters.

One of the closest stores in cluster 1 to zone i belongs to firm A and one of the closest stores in cluster 2 to zone i belongs to firm B . ($D_{iA_1} \leq D_{iB_1}$ and $D_{iA_2} \geq D_{iB_2}$)

- i. If $D_{iA_1} = D_{iB_2}$ then 50 percent of demand from zone i is assigned to each cluster.
- ii. If $D_{iA_1} > D_{iB_2}$ then demand from zone i is assigned to cluster 2.
- iii. If $D_{iA_1} < D_{iB_2}$ then demand from zone i is assigned to cluster 1.

Consider the scenarios shown in Figure 6.

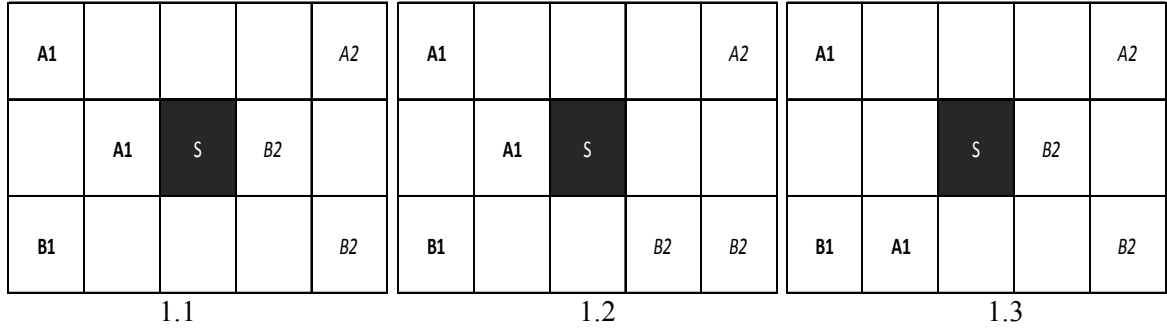


FIGURE 6: Demand allocation scenarios 1.1-1.3

When solving the full problem in scenario 1.1 the benefit to firm A of keeping store A1 open should include 50% of the demand originating from the shared zone. In scenario 1.2 it should include the entire demand from the zone and in scenario 1.3 A1 is not in a position to capture any of the demand from the shared zone.

The closest store in cluster 1 to zone i belongs to firm A and The closest store in cluster 2 to zone i belongs to firm A . ($D_{iA_1} < D_{iB_1}$ and $D_{iA_2} < D_{iB_2}$)

- i. If $D_{iA_1} > D_{iB_2}$ then assign demand to cluster 2.
- ii. If $D_{iA_1} = D_{iB_2}$ then,

If $R^{A_2} > 0$ then assign 0% of the demand to cluster 1. Else if $R^{A_2} \leq 0$ then assign 50% of demand to cluster 1

Then run Model IP for cluster 1 and if $X^{A_1} = 1$ then assign 50 percent of the demand to cluster 2. Else if $X^{A_1} = 0$ then assign 100% of the demand to cluster 2

- iii. If $D_{iA_1} < D_{iB_2}$ then ,
- If $R^{A_2} > 0$ then assign 0% of the demand to cluster 1. Else if $R^{A_2} \leq 0$ then assign 100% of demand to cluster 1

Then run Model IP for cluster 1 and if $X^{A_1} = 1$ then assign 50 percent of the demand to cluster 2. Else if $X^{A_1} = 0$ then assign 100% of the demand to cluster 2

A1				A2	A1				A2	A1				A2
	B1-C			B2		B1-C		A2-C	B2	B1	A1-C			B2
	A1-C	S		A2-C		A1-C	S					S	A2-C	
2.1					2.2					2.3				

FIGURE 7: Demand allocation scenarios 2.1-2.3

In scenario 2.1 the loss to firm A when A1 is closed should include the demand from zone S since B1 is in a position to capture that demand. Therefore in the full problem when making the decision to close A1 the entire demand from zone S must be considered. To approximate this, the demand from S is assigned to cluster 1.

In the full problem for scenario 2.2 the loss to firm A if A1-C is closed should include 50% of zone S, if we know apriori that A2-C will be kept open. This is due to the fact that A2-C is in a position to retain 50% of the demand if A1-C is closed, while the remaining demand will be captured by B1-C. If we know that A2-C will be closed then the loss to the firm if A1-C is also closed, includes the entire demand from zone S. We predict the decision to open or close A2-C by calculating its net revenue (R^{A_2}) at the beginning of the time period (before store closures for the period have been made). Therefore the appropriate allocation to cluster 1 is 50% of the demand from zone S if $R^{A_2} > 0$ and 100% of the demand from zone S if $R^{A_2} < 0$

In scenario 2.3 the loss to firm A if A1-C is closed should not include the demand from zone S if we know apriori that A2-C is kept open and vice versa. Therefore, similar to the steps given above, if $R^{A_2} > 0$, we allocate 0% of the demand from zone S to cluster 1 and, if $R^{A_2} < 0$ we allocated 100% of the demand to cluster 1.

A similar allocation will be done if the closest store in cluster 1 to zone i belongs to firm A and The closest store in cluster 2 to zone i belongs to firm A. ($D_{iA_1} > D_{iB_1}$ and $D_{iA_2} > D_{iB_2}$)

4.1.3. Clustering Algorithm Performance

In order to determine the accuracy and efficiency of our algorithm we created a hypothetical 400 sq. mile region (20x20 miles) organized into 100 zones of 4 sq. miles (2x2) each. We first generated 16 problem instances by randomly locating 10 stores for firm A and 10 stores for firm B. The zone in which each store is located is drawn randomly from a uniform (1-100) distribution). For each instance the demand originating from each zone is also generated randomly from a normal distribution with a mean of 6 and a standard deviation of 2. We then vary the distance threshold (6, 7, and 8 miles) for each of the 16 problem instance creating a total of 48 problems. For each of the 48 problem configurations the average and standard deviation of solution quality (QOS) and time to best solution (TBS) are recorded. We limited the solution time of CPLEX to 10 hours and recorded the best solution found by CPLEX or the upper bound after CPLEX has run for 10 hours and time to the best solution. The solution quality for the CPLEX solution is 1 (100%) if it solves to optimality within 10 hours or else is the percentage of the upper bound. We computed the solution quality of our algorithm as a percentage of the best solution found by CPLEX or the upper bound. Table 3 displays the mean and standard deviation for solution quality (QS) and time to best solution (TBS), respectively.

TABLE 3: Computational statistics for the clustering algorithm

Dist Threshold	QOS		TBS	
	Mean, Std Dev. (%)		Mean, Std Dev. (min)	
	CPLEX	Cluster Algorithm	CPLEX	Cluster Algorithm
6	1.00, 0.00	0.95, 0.03	25.07, 15.91	0.15, 0.03
7	0.99, 0.03	0.92, 0.04	197.86, 234.52	0.17, 0.02
8	0.95, 0.07	0.95, 0.05	330.5, 302.43	0.19, 0.04

Overall the results show that the clustering algorithm produces very good results. The average of solution quality across all problem configurations is nearly 94% of the CPLEX solution with a standard deviation of 4.3%. The usefulness of the algorithm is particularly evident when the distance threshold is set to 8 miles. The algorithm on average nearly matches the CPLEX results while taking a fraction of the time to find the best solution.

4.2. Estimating the net benefit of keeping a store open

The value of keeping a store (located in zone j) open in a given period is the difference in the optimal store closing solution in the period and the optimal solution when the store in question is forced to close. An open store provides value to the firm in two ways

- i. Capture demand from adjacent zones thus increasing revenue
- ii. Increase pressure on a rival store by denying demand from flowing towards it

Therefore the net benefit of the open store is not simply its net revenue in the period. It can be greater than the net revenue in cases where the decision to keep it open forces one or more rival stores to close. It can be less than the net revenue if there are one or more of stores of the same firm in position to retain demand if it is closed. The net benefit of keeping a store open in period t is given as

$$B_j^{ft} = \max \sum_{j \in S^f} R_j^{ft} |_{X_j^f=1} - \max \sum_{j \in S^f} R_j^{ft} |_{X_j^f=0}$$

When running the model for period t the future benefit is incorporated into the revenue calculation as follows,

$$R_j^{ft} \leq \sum_{i \in M_j} P_i r^t \left(Q_{ij}^{ft} - \frac{1}{2} V_{ij}^{ft} \right) - d_0 + \sum_{\theta=t+1}^T B_j^{f\theta} X_j^{ft}$$

CHAPTER 5: EXPERIMENTS

5.1. Experimental Parameters

Table 4 describes the numerical values and justifications for parameters used in our experiments. These parameters can be divided into five categories: Problem environment parameters, distance threshold, variance in demand and store operating costs. Where possible, we have attempted to base the parameter values on ranges that are encountered in practice.

TABLE 4: Experiment parameters

Type	Value	Comments
Problem Environment	400 sq.miles, 20 Stores	Approximate parameters for a typical mid-size city and its suburbs in the east of the United States
Distance Threshold	6,7,8,9m	The average distance traveled per shopping trip is 7 miles in 2001 and 6.5 miles in 2009 with a 95% confidence interval of +/- .2miles. [44]
Percent change in Demand	Uniformly distributed +/- 20%,30%,40%	In 2008 and 2009 quarterly percent changes in consumption of durable goods ranged from -38.5% to 50.5% in different categories.[45]
Initial Conditions	Demand	A combination of initial demand and operating cost that results in an average of approximately 1/3 of the stores have a net rev <0

5.1.1. Problem Environment Parameters

Our intention is to study approximate competitive conditions for two retail chains operating in a midsize urban region. A typical midsize city and its suburbs in the eastern United States appears to have on average 10 stores each belonging to Lowes and Home Depot in a 350-550 sq. mile area. Some examples are

- Charlotte, NC has 12 Lowes and 11 Home Depot outlets in a 546 sq. mile area
- Columbia, SC has 8 Lowes and 5 Home Depot stores in a 540 sq. mile region
- Orlando, FL has 10 Lowes and 10 Home Depot stores in a 380 sq. mile area.

Based on these observations, we created a hypothetical 400 sq.mile region divided into 100 zones each 2x2 miles in size. A total of 20 stores (10 stores belonging to each firm) are randomly placed in one of the zones.

5.1.2. Distance Threshold

According to the 2009 National Household Travel Survey [44] the average distance traveled per shopping trip is 7 miles in 2001 and 6.5 miles in 2009 with a 95% confidence interval of ± 0.2 miles. For our experiments we choose four values ranging from 6 miles to 9 miles.

5.1.3. Variance in Demand

The percent change in demand from one period to the next (e.g. quarter to quarter) is largely influenced by the prevailing economic conditions. In a thriving economy it is expected that demand will generally show a steady increase but is less likely to display sharp fluctuations. During and immediately after a recession demand is much more volatile especially in the case of durable goods. For example in 2008 and

2009 the U.S. bureau of Economic Analysis [45] reported quarterly percent changes in consumption of durable goods that ranged from -25.8% to 20.6%. Percent changes in certain categories of durable goods had an even wider range. For example the percent change in the consumption of motor vehicles and parts ranged from -38.5% to 50.5%. We attempt to recreate both types of economic conditions by varying the percent change in demand from +/- 20% to +/- 40% per time period (quarter)

5.1.4. Zone demand and store operating cost

Our intention is to create a scenario where due to a decrease in demand it is no longer feasible for a firm to continue to operate all stores located in a given region. However demand does not decrease to the point where the firm has to completely exit the market. We selected a combination of demand and operating cost values that reflect these conditions. When operating costs are set at 15 units/store, in the 32 scenarios generated, an average of 36.25% of stores is unprofitable at the beginning of the planning period with a range of 20-70%.

5.2. Experiment Results

5.2.1. Effect of increasing Distance Threshold

Karimifar et al. [46] describe how a customer is attracted to a retail facility. As discussed previously it is always assumed that distance between the customer and the facility plays a crucial role in this attraction. The customer will travel to a store if the price of the goods s/he intends to purchase plus the travel cost is less than the utility obtained from these goods. A retail firm can employ several strategies that will increase the distance that the consumer is willing to travel to its store. First, a reduction in price of goods sold will allow the customer to spend more on travel (increase distance) and

still obtain a positive net utility from making the shopping trip. Second, numerous measures can be taken to increase convenience in the store which in turn will reduce the time the consumer has to spend shopping. The trip cost includes the cost of getting to the store and the cost of time spent on travel and in store. Saving time spent in store will encourage the shopper to spend more time travelling to it. Convenience can be increased by increasing the number of checkout lanes, increasing floor size etc. Third any measures taken that will increase the utility that the consumer gains from the trip will have a similar effect. An example would be to increase the product mix offered at the store. Karimifar et al. summarize all these aforementioned measures as increasing the quality of a retail facility which in turn increases its attractiveness to the consumer. Further Grewal et al. [47] find that consumers view travel time more adversely when they are uncertain about the availability of certain products in the store. Therefore they suggest that an alternate method of encouraging customers to travel greater distances to a store is to provide a “high level of certainty that the merchandise will be available”. We examine the effect on net revenue of both rival firms undertaking measures to increase the distance threshold.

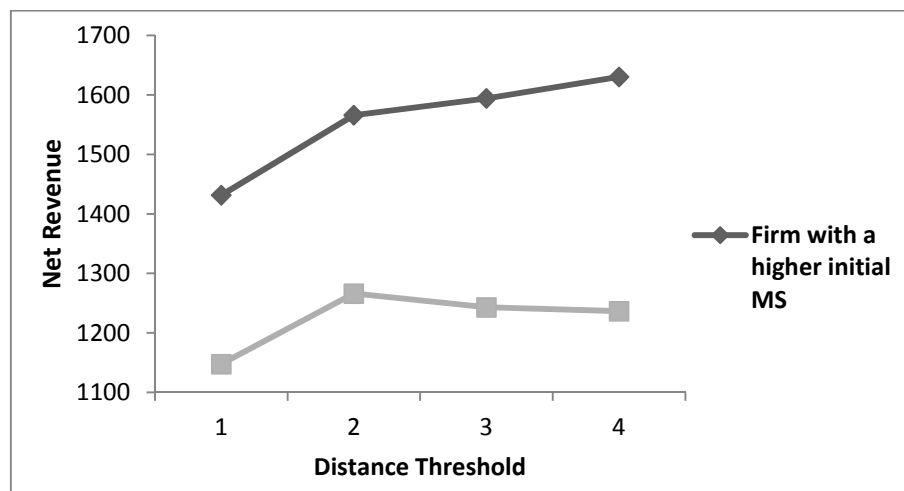


FIGURE 8: Effect of increasing distance threshold on net revenue

Initially an increase in the distance threshold will allow each firm to increase the efficiency in which demand is distributed among its stores. For example a firm can capture demand from a region using 2 stores where previously 3 stores were required thus significantly reducing operating costs. However further increases will allow the rival firm to encroach on zones it had previously captured. As each individual store is capable of attracting demand from a larger number of zones it becomes increasingly more difficult for a firm to force a rival store out of a region that it intends to capture. Therefore on average implementing steps that increase the distance threshold will result in diminishing and ultimately possible negative marginal returns unless a firm initially has a clear advantage in captured market share.

The firm that initially captures the majority of the total market region can continue to increase net revenue by increasing the distance threshold. A firm with a higher market share generally has

- i. Sections of the total region captured exclusively (few or no rival stores in these sections)
- ii. Multiple stores that are located in sections dominated by its rival.

Increasing the distance threshold will therefore enable this firm to close stores and thus reduce cannibalization in regions it captures exclusively while continuing to operate stores in regions dominated by its rival. It is therefore possible for a firm that has captured the majority of the market to continue enjoying positive marginal returns as the distance threshold is increased. However, the assumption that its rival will do the same means that these are diminishing in nature.

We now attempt to determine scenarios where an increase in distance threshold would be most beneficial for a firm. As discussed previously this strategy is ideal for a firm which well placed to make inroads into regions currently captured by its rival. If all or most of a firm's stores are concentrated in a particular region then an increase in distance threshold can be used to reduce cannibalization without losing demand and thus capture that region with a fewer number of stores. Here the increase in net revenue is achieved primarily via cost reduction. However it may be possible to achieve a similar cost reduction without the need for an increase in the distance threshold. Therefore the benefit of this strategy is not as pronounced. We look at the resulting increase in net revenue as distance threshold is increased for different geographical distributions of stores.

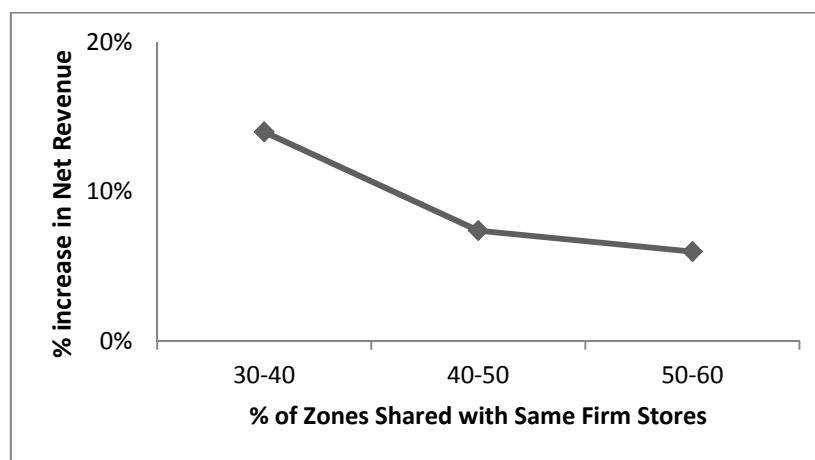


FIGURE 9: Effect of increasing distance threshold under different spatial conditions

A distribution where a majority of a firm's stores are in a position to exert pressure on rival stores, force them to close and thus secure new avenues of revenue will generally enjoy the highest percentage increase in net revenue if the distance threshold is increased. This is due to the fact that the aforementioned stores are located among a number of rival firm stores and are thus more vulnerable to a drop in demand. Any

measures taken to increase the distance threshold will strengthen their position by potentially opening up new streams of revenue which increases the likelihood that they are kept open. In figure 9 the percentage of zones shared with same firm stores is, the ratio of the number of zones that are within the threshold distance of two or more stores of the same firm to the total number of zones that are within the threshold distance of at least one store belonging to that firm. For example the 30-40% (50-60%) grouping shows a distribution where firms have stores in place so that of all zones it can potentially capture, at least 60-70 percent (40-50 percent) are also within the threshold distance of rival stores. The effect of an increase in the distance threshold in each of these scenarios is illustrated below.

1 A-1	2	3	4	5
6	7	8 <i>B-13</i>	9 <i>B-9</i>	10
11 A-11	12	13	14	15
16	17	18	19	20 <i>B-20</i>
21	22 A-22	23	24	25

a

1 <i>B-1</i>	2	3 A-3	4	5
6	7	8	9	10
11	12	13	14	15 <i>B-15</i>
16 <i>B-16</i>	17	18	19	20 A-20
21 A-21	22	23	24	25

b

FIGURE 10: Examples of spatial distributions

Assume an initial 3 mile distance threshold. In Figure 10(a) firm A has 3 zones (6, 16, 17) that are within coverage distance of two or more of its stores and 1 zone (12) that it shares with firm B. In Figure 10(b) there are no zones that are within coverage distance of any two firm A stores and 10 zones (2, 7, 14, 15, 19, 20, 16, 17, 21, 22) that are within coverage distance of firm A and firm B stores and. In the first scenario firm A captures demand from 11 zones (1, 2, 6, 11, 12, 16, 17, 18, 21, 22, 23) while incurring a cost of operating 3 stores for a net revenue of 61 units. Increasing the distance threshold to 4 miles puts A-11 in a position to capture demand from zone 1. Therefore firm A can close

A-1 and still retain demand from zone 1. There are no new zones captures and the benefit arises purely as a result of the cost savings. However in scenario 2 where A has stores in position to exert pressure on B increasing the distance

5.2.2. Impact of Applying Store Closing Strategies

A decision to close any individual store comes with an underlying cost. In 2008 Starbucks announced the closing of 600 stores across the United States. [48] The cost related to the closings was estimated to be \$348 million including costs tied to lease terminations and severance payments. Therefore it is usefully for the firm to understand the different scenarios in which there is the greatest benefit to closing stores. We examine the increase in net revenue after closing stores for different distributions of store locations in a given region.

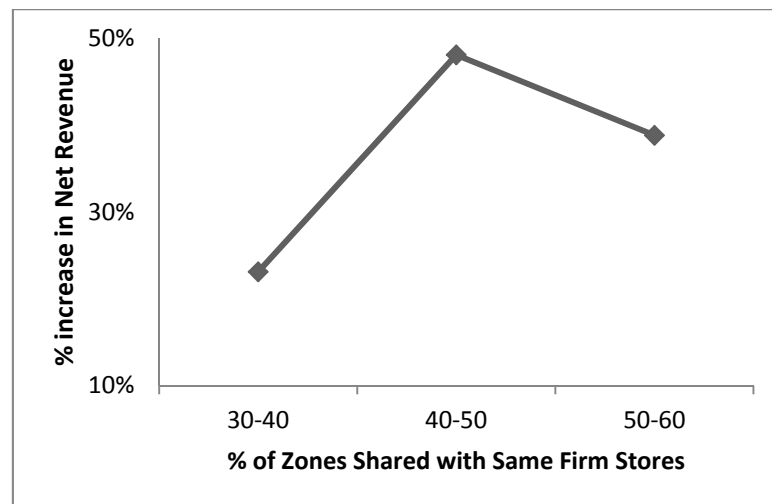


FIGURE 11: Impact of store closing strategies under different spatial conditions

Our results indicate that a firm is in the best position to increase net revenue when initially it has an even mix of its stores placed close to each other and close to rival stores. An example of this type of distribution is given below.

1 <i>B-1</i>	2 <i>A-2</i>	3 <i>A-3</i>	4	5
6	7 <i>B-7</i>	8	9	10 <i>B-10</i>
11	12	13	14 <i>A-14</i>	15 <i>B-15</i>
16 <i>B-16</i>	17 <i>A-17</i>	18	19	20 <i>A-20</i>
21 <i>A-21</i>	22	23	24	25

FIGURE 12: Spatial distribution that provides a high increase in net revenue

If the majority of a firm's stores are located away from each other and among rival stores (30-40% grouping) then as discussed above they are especially vulnerable to a decrease in demand and have a greater likelihood of being closed. If the majority of a firm's stores are clustered together (50-60% grouping) then as mentioned previously the opportunity to capture zones from rival stores is limited. Therefore the ideal distribution is to be in a position to capture new zones with groups of stores located in a rival's territory.

5.2.3. Individual Store Closing Decisions

The experiment results presented above provides insights that help the firm develop an overall downsizing strategy which will be applicable to all stores in the region. It is also useful to gain an understanding about the factors that affect the feasibility of keeping an individual store open. The profitability of the store in question is just one of several factors that will influence its possible future closure. We look at variables such as the variance in demand in future periods and the number of zones captured by exclusively by a store to determine the potential benefit of keeping it open.

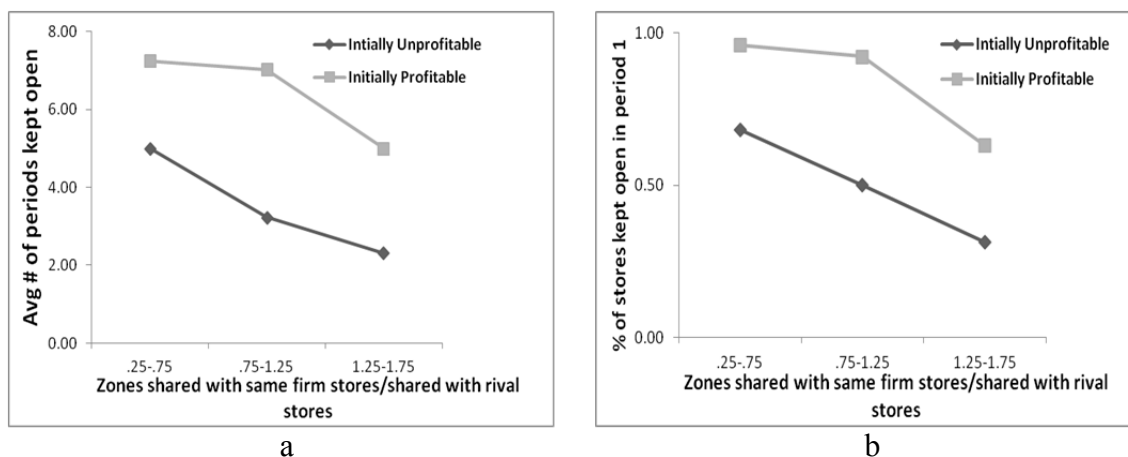


FIGURE 13: Effect of the mix of adjacent stores on a given store's profitability

We first determine the competitive environment in the area that the store is located and examine its influence on the decision to close or keep the store open. As expected under most conditions if the store captures enough demand to cover operating costs (initially profitable) then it (i) is more likely to be kept open for at least one more period and (ii) will on average be kept open longer than a store which is initially unprofitable. However this is not always the case. The number and type of stores located adjacent to the store in question also plays a role in determining its value to the firm. It is very likely that an unprofitable store that is located among a number of other stores belonging to the same firm will close immediately. Here the cost savings will outweigh any demand lost. Similarly it is less likely that a profitable store in the same location will be kept open for an extended period of time. In this case it is possible to close the store and use the adjacent stores to retain most of the demand. However if the store is surrounded by a number of rival stores then it is more likely to be kept open in period 1 and in average will be kept open for longer. This is the case even if the store is initially unprofitable. Two possible reasons for this are,

- i. The majority of the demand lost by closing the store will be captured by rival stores. Even if the store is currently unprofitable if there is a possibility that demand will increase in future periods it is advisable to keep it open.
- ii. The store can be kept open so that it can be used as a tool to pressurize rival stores into closing.

Figure13(b) shows indicate that a store which is currently unprofitable but located among rival stores provides a greater benefit to the firm than one that is profitable but located adjacent to other stores also belonging to it. Figure13(a) shows that this benefit extends to future periods.

5.2.4. Variance in Demand

We further considered other factors that might increase the value of keeping an unprofitable store open. Variance in demand from period to period can result in a change in a store's ability to generate revenue. In a recessionary climate demand shifts of this nature can be pronounced. Petev et al. 's [49] study of consumption during the recent recession confirmed the well-known fact that, spending on durable goods will see wide upward and downward swings at the onset of booms and recessions, respectively. They further state that during the most recent recessionary period a similar trend was observed for non-durable goods as well.

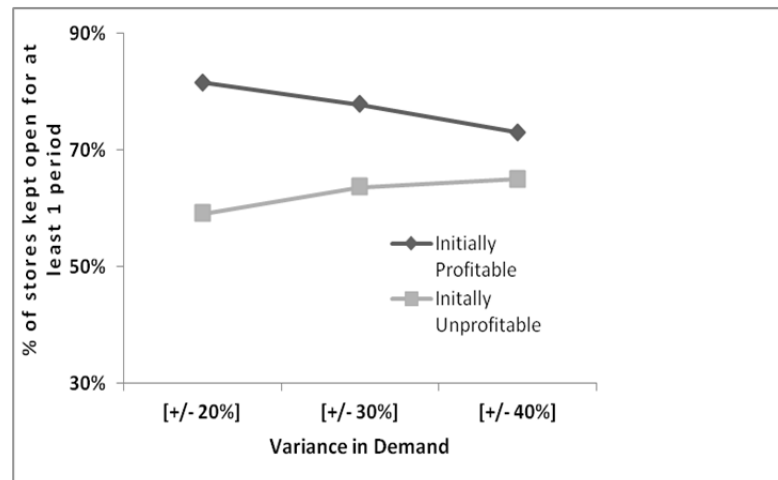


FIGURE 14: Impact of variance in demand on store closing decisions

If a high variance in demand is expected from one period to the next then there is a greater likelihood that

- i. A store that is currently unprofitable will yield a positive net revenue in the future
- ii. A store that is currently enjoying positive net revenue will be unprofitable in the future.

Therefore when making store closing decisions in a volatile environment it is advisable for the firm to place a lower emphasis on net revenue figures and to strongly consider some of the other factors discussed. Often it may be optimal to keep an unprofitable store open for a few extra periods in anticipation of an increase demand. In such a scenario the initial market captured by can be used to evaluate the value of keeping it open. Next we examine how initial market capture affects a store's future profitability under varying levels of demand variance.

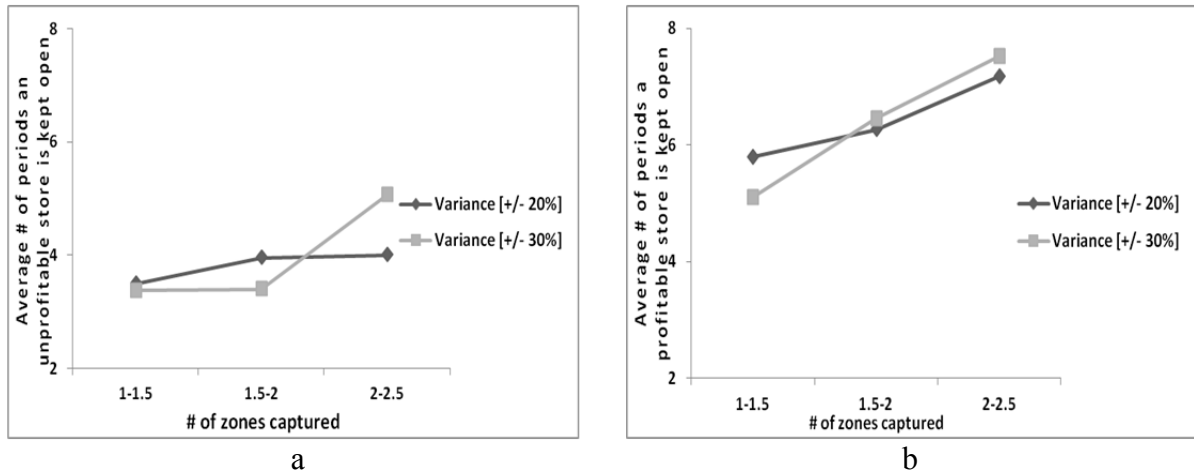


FIGURE 15: Impact of variance in demand on individual store closing decisions

Figure 15(a) and Figure 13(b) show that, (i) stores that initially capture a higher market area will on average be kept open for longer than one that captures fewer zones and (ii) this result is pronounced under conditions of higher demand variance. Closing a store that currently captures larger number of zones will result in the firm giving up a portion of the market share in the region. In the case of a store that is profitable these zones currently yield relatively high demand and thus by keeping it open for longer the firm can enjoy the related revenue stream for multiple periods. In the case of an unprofitable store losing these zones will result in the firm less prepared to take advantage of an increase in demand in the future. Figure 13(a) shows that a store that is initially unprofitable and captures a larger number of zones (2-2.5 category) will see a considerable increase in the time it is kept open when the variance in demand is high. We can conclude that under volatile demand conditions a firm should focus on maintaining its market share.

CHAPTER 6: CASE STUDIES

In this chapter we apply our model and the solution algorithm to two case studies. The first case study corresponds to two leading home improvement chains, namely Lowes and Home Depot. The second case study examines the competition between the two largest retail pharmacy chains- CVS and Walgreens. Our intention is to determine if experimental results obtained previously hold in a real world scenario.

6.1. Case Study 1: Lowes and Home Depot

We first examine the spatial competition between Lowes and Home Depot stores in Mecklenburg County and its immediate surroundings. We did not restrict our study to Charlotte or Mecklenburg County since there are several stores belonging to both firms that are located in its immediate surroundings. These stores will have an impact on the decision to close or keep store(s) open located within Mecklenburg County. Therefore, we expanded the region of study so that it includes the areas where these stores are located. The total area considered for our study is approximately 1435 sq mi (35 x 41 miles) in size. Since census tracts are non-uniform in shape and size we impose a grid on the region to simplify the assignment of demand to each store. We divide the region into 378 4 sq mi (2 x 2 miles) zones. There are a total of 19 stores operated by Lowes and 13 operated by Home Depot in the selected region under study. Figure16 shows the locations of these stores.

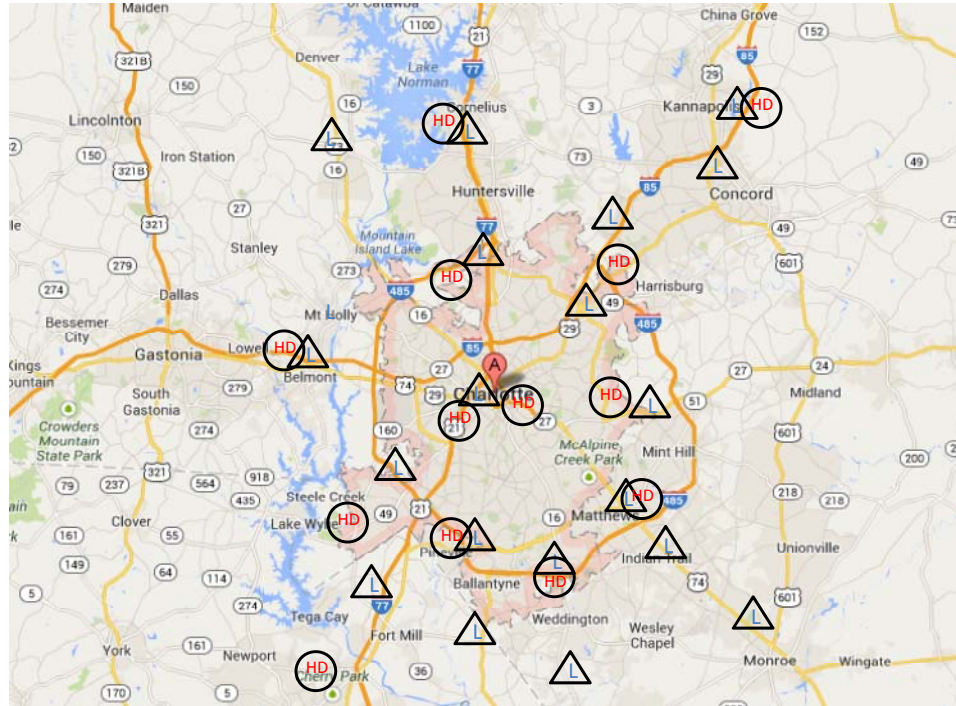


FIGURE 16: Geographical area of Interest-Lowes v HD

The U.S. home improvement business is considered a duopoly with “the only players of any account being Lowes and its larger rival Home Depot” [50]. Stores owned by each firm are very similar in nature when it comes to product selection and pricing. A recent price comparison of a variety of goods found at both stores found that prices for both large and small goods are very similar. A selection of 39 general items cost \$1,924.08 at Lowes and \$1,925.35 at Home Depot. A comparison of costs to purchase products when building a new home deck was also done. It was found that difference was less than 2%. Materials and supplies cost \$1,507.32 at Lowes and \$1,541.56 at Home Depot [51]. Further both firms will price match identical items [52]. When rating stores on product selection, the consumer reports website *cheapism.com* concluded that while each store had an advantage in a few categories, overall the score for selection was a tie [51]. As a

result we can conclude that the majority of consumers will choose to shop at Home Depot or Lowes based on proximity of the nearest store.

In recent times the home improvement sector had experienced a sharp decline in sales due to a number of factors such as “a weak housing market, stubbornly high unemployment and consumers saddled with debt” [50]. Our goal is to examine how significant drops or fluctuations in demand during a recessionary period will influence the optimal store closing strategies for Home Depot and Lowes stores located in a metropolitan region.

6.1.1. Demand Distribution across the Region

We first determine the demand for hardware goods sold at Lowes and Home Depot arising from each of the aforementioned zones. Here we assume that, in (a) the number of households in each zone and (b) the incomes for these households largely influence the change in demand from one zone to the next. Demographic information regarding households at the census tract level was obtained from the U.S. Census Bureau [53] The region is divided into 378 zones. Each zone is 4 sq mi in size (2 x2 miles). Since the census tracts are in various shapes and sizes, we approximated the number of households and the average household income for each zone as illustrated in Figure 17.

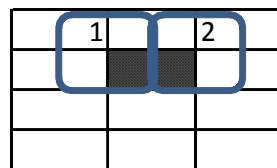


FIGURE 17: Estimating demand for a zone from census tracks 1 and 2

In Figure17 above we estimate the number of households for the shaded zone. We assume that 25% of the households in census tract (CT) 1 and 25% of the households in

CT 2 are located in the zone. The total household income (THI) for the zone(i) is given as,

$$THI_i = 0.25 * \text{Number of households in CT1} * \text{average household income in CT1} + 0.25 * \text{Number of households in CT2} * \text{average household income in CT2}$$

We approximate the total sales for all Lowes and Home Depot stores in the region by making the assumption that,

$$\text{Total Sales} = \text{Average sales per Lowes store} * \text{Number of Lowes stores in the region} + \text{Average sales per HD store} * \text{Number of HD stores in the region}$$

$$\text{Sales originating from each zone } i = \text{Total Sales} * THI_i / \sum_i THI_i$$

The demand volume for each zone and the location of stores in the grid is depicted in Figure 18 below.

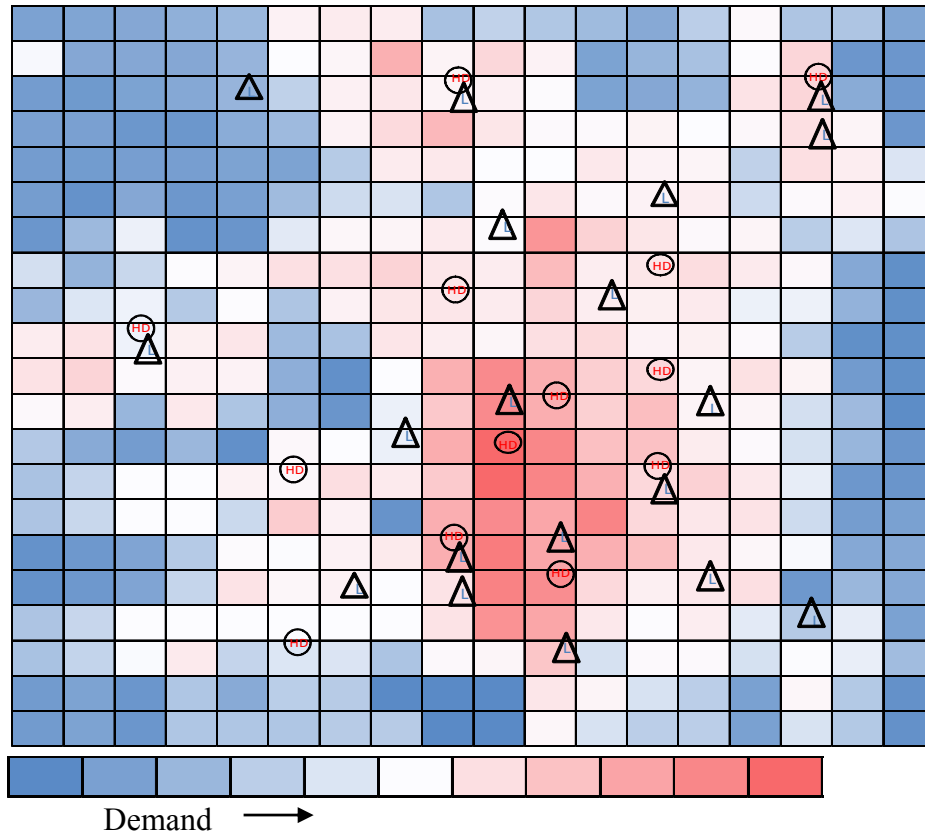


FIGURE 18: Representation of the demand in the region in a grid format

Values for average sales, number of stores, gross margins and operating costs for each type of store in 2012 were obtained from annual reports for Lowes [54] and Home Depot [55] Data for 2013 was obtained from quarterly reports found on the investor relations website for each firm. The parameters that we varied are demand variability and distance threshold. The complete list of parameter settings are shown in Table 5.

TABLE 5: Case study parameters-Lowes vs. Home Depot

Type	Value	Comments
Problem Environment	1435sq.miles, 32stores	Parameters for the region described above
Distance Threshold	6,7,8 mi	The average distance traveled per shopping trip is 7 miles in 2001 and 6.5 miles in 2009 with a 95% confidence interval of +/- .2miles. [44]
Percent change in Demand	Uniformly distributed +/-20%,30%,40%	In 2008 and 2009 quarterly percent changes in consumption of durable goods ranged from -38.5% to 50.5% in different categories.[45]
Initial Conditions	Total Demand	In order to recreate recessionary conditions total demand for the region was calculated as 75% of the estimated total sales in 2013.
Ratio of Sales HD : Lowes	1.16:1, 1.08:1	Sales per store were 16% higher for HD over Lowes in 2013 and 8% higher in 2011.
Gross Margin	34% [54, 55]	
Operating Costs	HD=12.25 million Lowes=15.84 million	

We evaluated a 2 year planning horizon divided into 8 time periods (quarters). We considered two scenarios based on ratio of sales of HD to Lowes: First, based on revenue reports for 2013 we estimate that, on average each store belonging to Home Depot generates revenue that is 16% higher than the average revenue generated by a store belonging to Lowes. Second, based on revenue reports for 2011 we estimate that, on average each store belonging to Home Depot generates revenue that is 8% higher than the average revenue generated by a store belonging to Lowes.

6.1.2. Impact of Variance in Demand

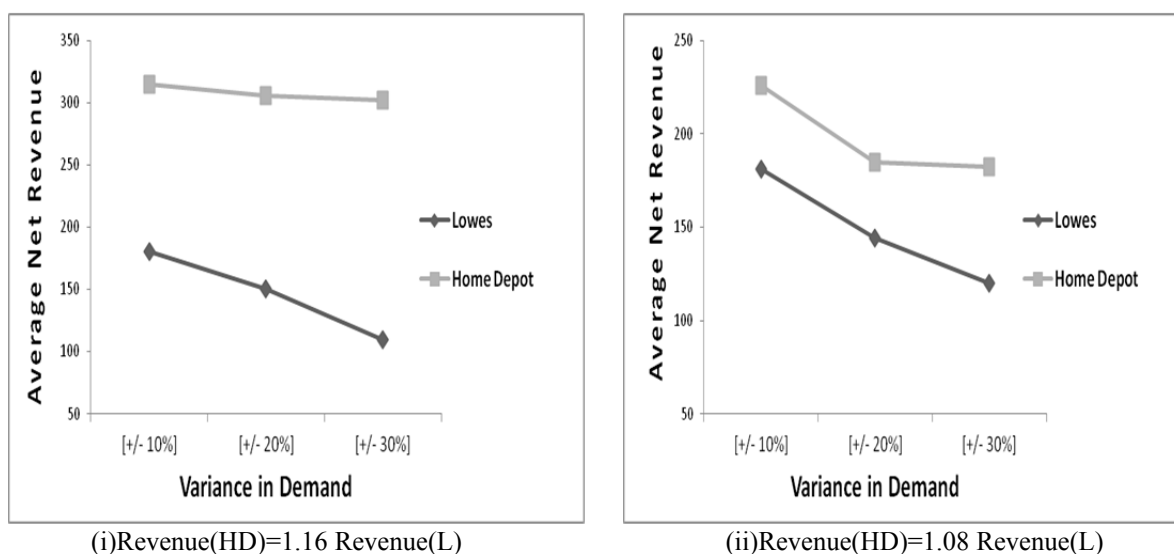


FIGURE 19: Impact of variance in demand on revenue-Lowes vs HD

Our experimental results indicated that in periods where variance in demand is high it is difficult for a firm to sustain or increase profits. It is often necessary to keep unprofitable stores open when riding out periods of low demand. However, when the difference in revenue per store for is high for Home Depot(16%)it can be seen that while Lowes experiences a decrease in profitability as variance in demand increases Home Depot is able to maintain the same level of profitability. The ability to generate significantly larger amounts of revenue than its rival is invaluable during a recession where demand

can fluctuate considerably from one time period to the next. This remains the case even when it is necessary to expend a greater amount of resources to do so since, as described above, we estimate the operating costs for Home Depot to be higher than the operating costs for Lowes. In the case where Home depot generates 8% more revenue than Lowes while the difference in operating costs stays the same, the advantage Home Depot has is not as pronounced. Initially both firms experience a decline in profitability as demand variance increases from 10% to 20%. However, when variance increases further Home Depot is able to maintain the same level of profits. This shows that especially in periods where a high degree of variability in demand is expected it is optimal for a firm to expend more resources in order to outsell its rival.

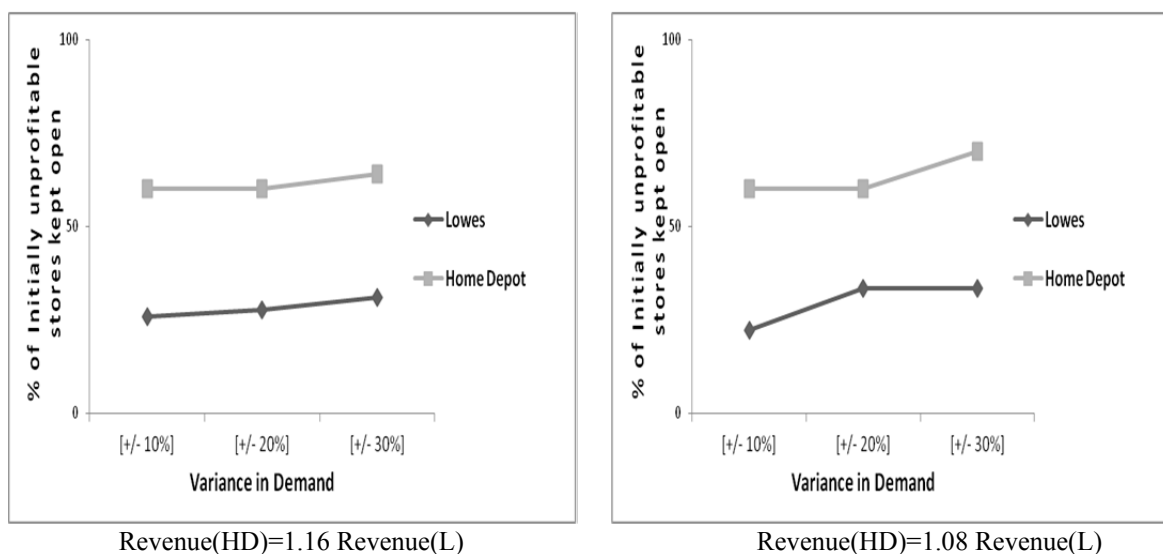
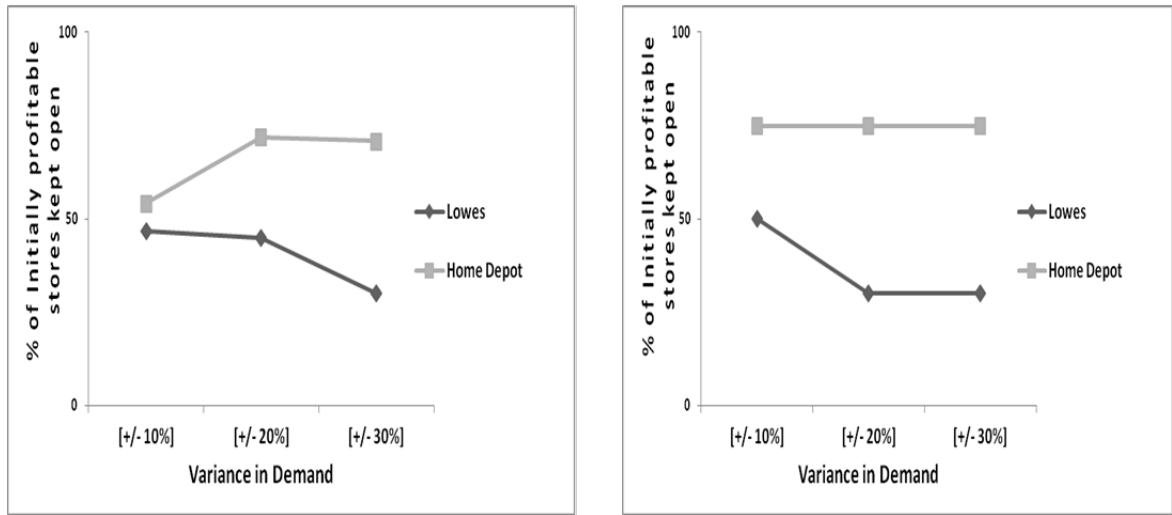


FIGURE 20: Impact of variance in demand on initially unprofitable stores

In our experimental results (figure 14, section 6.4) we found that both firms need to carefully evaluate the decision to close an *unprofitable* store in periods of greater demand volatility. In many cases it is optimal to absorb losses from keeping an unprofitable store open in anticipation of an increase in demand in the future or to drive a rival firm store out of business. By preserving market share the firm is better

positioned to take advantage of demand fluctuations. Figure 20 shows that the result described above holds for instances where difference in revenue is 16% and when difference in revenue is 8%.



(i) Revenue(HD)=1.16 Revenue(L)

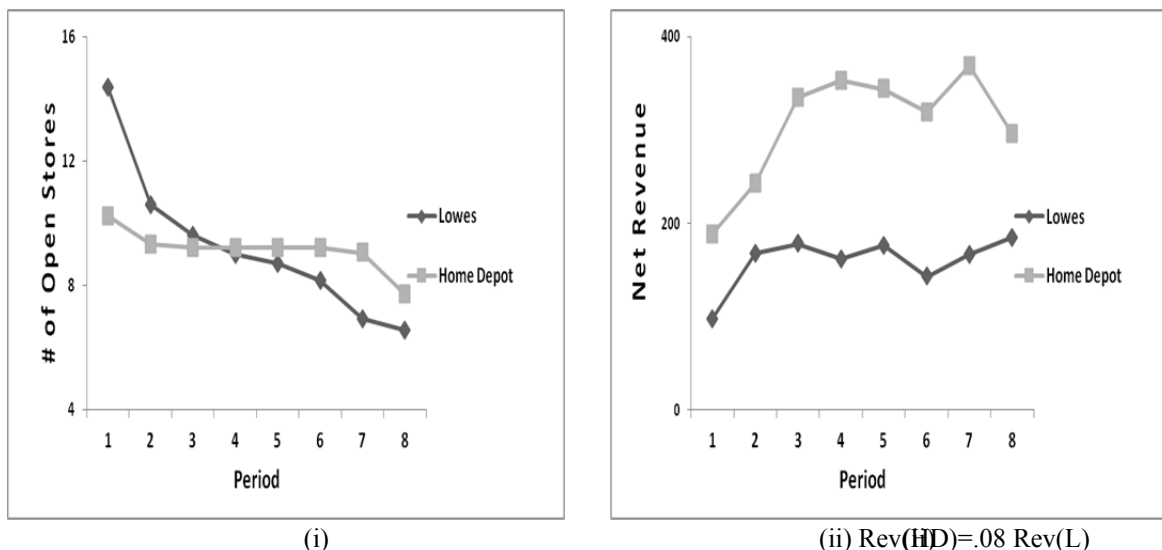
(ii) Revenue(HD)=1.08 Revenue(L)

FIGURE 21: Impact of variance in demand on initially profitable stores

Our experimental results (figure 14, section 6.4) indicated that as volatility in demand increases it is more likely that stores which are *initially profitable* are forced to close. In Figure 21 we see that, as variance in demand increases, Lowe's is forced to close additional stores that are initially profitable while Home Depot can continue to keep these stores open. The ability to generate higher revenue enables Home depot stores to remain profitable in periods when there is a drop in demand.

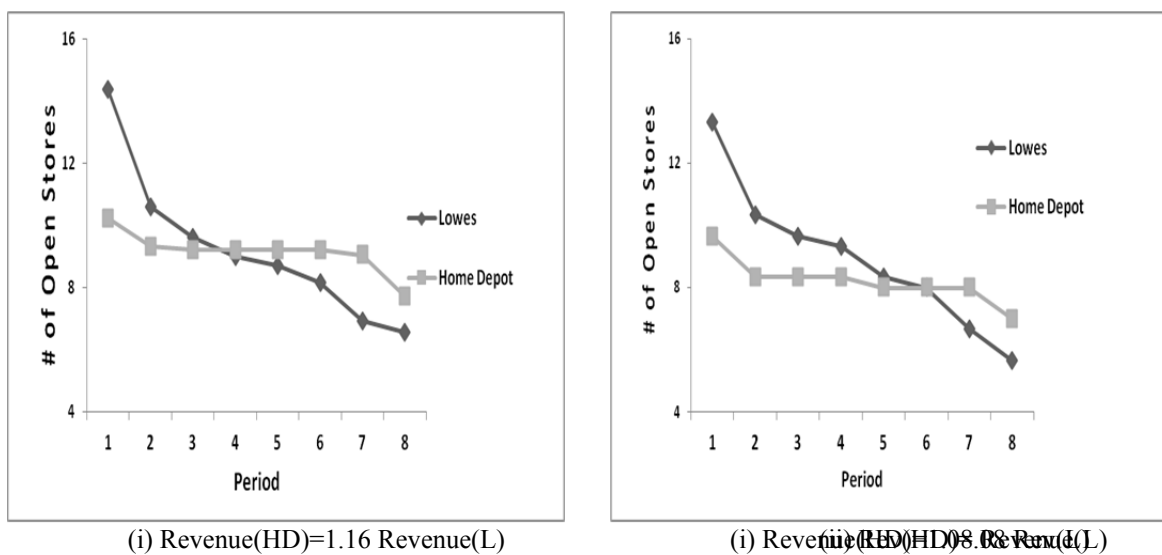
6.1.3. Optimal Store Closing Decisions for Each Period

The results shown in figures 22 (i) and 22 (ii) indicate how Home Depot, by generating higher revenue is better positioned to ride out periods of low demand. In periods 2-7 Home Depot is able to keep a set number of stores open even as demand fluctuates. Thus it is able to force a significant number of Lowe's' stores to close.



(i) (ii) $\text{Rev}(\text{HD}) = .08 \text{ Rev}(\text{L})$
 FIGURE 22: Store closing decisions and the resulting impact on revenue

In periods 4-6 it can be seen that by choosing to keep some unprofitable stores open Home Depot experiences a decrease in profits. However since this done with the intention of forcing Lowes stores to close the loss is compensated by a sharp increase in profitability in period 7 once Lowes closes 3 additional stores.



(i) $\text{Revenue}(\text{HD}) = 1.16 \text{ Revenue}(\text{L})$ (i) $\text{Revenue}(\text{HD}) = .08 \text{ Revenue}(\text{L})$
 FIGURE 23: Store closing decisions by period

We next compare the total number of stores closed in each period when Home Depot's revenue is 16% greater than Lowes and when its revenue is 8% greater than Lowes. In each case Home Depot is able to maintain a relatively consistent number of stores from one period to the next. When $\text{Revenue}(\text{HD}) = 1.16 \text{ Revenue}(\text{L})$, Home Depot leaves 9 stores open in periods 2-7 and when $\text{Revenue}(\text{HD}) = 1.08 \text{ Revenue}(\text{L})$, it is able to keep 8 stores open in periods 2-4 and 7 stores open in periods 5-7. The ability to maintain stability when it comes to keeping stores open enables Home Depot to gain a competitive advantage in the region resulting in higher profits even in periods of high demand volatility as discussed in section 7.1.2.

The results given above indicate that Home Depot is at a competitive advantage in the region especially in times where there is a drop in sales and demand is volatile from one period to the next. We now attempt to determine if Lowes has characteristics which allow it to remain competitive and maintain a presence in the region. We observe that in zones where both firms have a store trying to capture demand it is more likely that the Lowes store will close if there is a drop in sales. However since Lowes has 19 stores to Home Depot's 13 in the region there are several Home Depot stores that are surrounded by two or more Lowes stores. By keeping these stores open Lowes can pressurize the Home Depot stores into closing, in these regions. Figure 24 indicates that when a Home Depot store competes against a single Lowes store then, given the advantage in revenue generation, Home Depot will likely stay open and force Lowes store to close. However, when a Home Depot store is surrounded by 3 or more Lowes stores it will close more than 50% of the time on average (Figure 24)

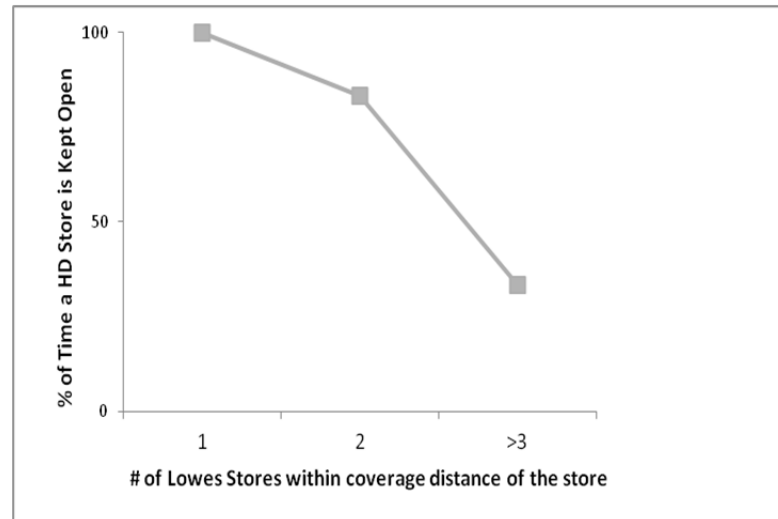


FIGURE 24: Impact of having more than one Lowes store surrounding HD stores

6.1.4. Impact of distance threshold on revenue

Our experimental results discussed in section 6.1 indicated that increasing the distance threshold will result in diminishing and ultimately possible negative marginal returns (Figure 8). This will be true unless a firm initially has a clear advantage in captured market share. We observe a similar result here. Figure 25 shows how Home Depot which has a clear advantage in revenue generation will enjoy an increase in net revenue as distance threshold is increased but at a diminishing rate.

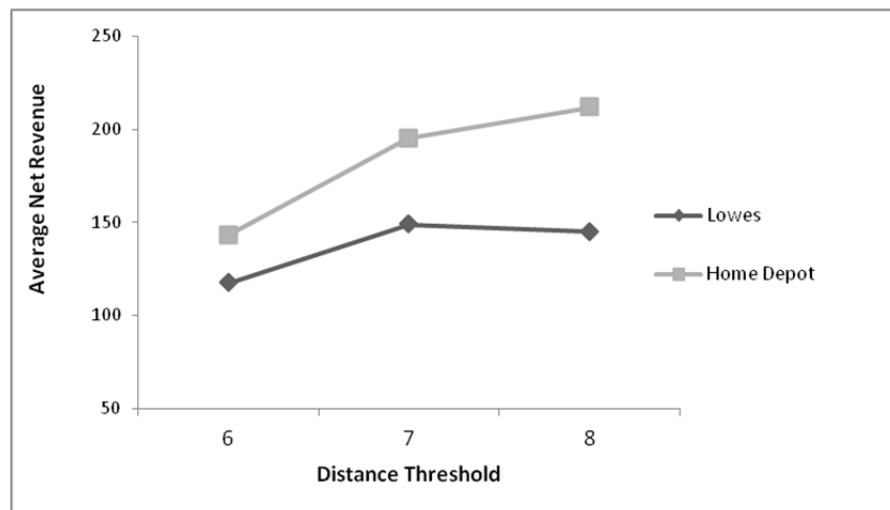


FIGURE 25: Effect of increasing distance threshold on revenue-Lowes v HD

6.2. Case Study 2: CVS and Walgreens

Next we consider the spatial competition between CVS and Walgreen stores in the city of Charlotte and its immediate surroundings. The total area considered for our study is approximately 306 sq mi.(17 x 18 miles) in size. We divide the region into 306 1 sq.mi. zones. We chose to increase granularity of the problem since consumers are more sensitive to changes in distance when deciding to frequent a drugstore when compared to their decision process in selecting a hardware store [37]. There are a total of 24 stores operated by CVS and 16 operated by Walgreens in the selected region under study. Figure26 shows the locations of these stores.

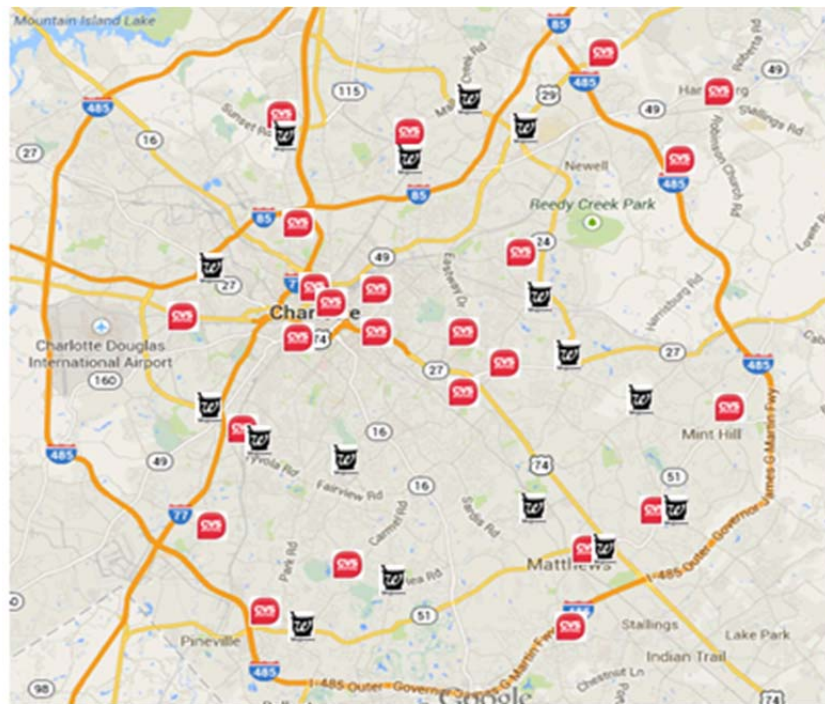


FIGURE 26: Geographical area of interest-CVS v Walgreens

The industry is primarily an evolving duopoly, with major players Walgreens and CVS dominating the industry. This trend is expected to continue, and these two companies are the primary beneficiaries of ongoing consolidation [56]. A comparison of prices and of

non prescription items done at each store done by Angela Coley for “MoneyTalksNews”

[57] yielded the following information-

- i. Over-the-counter drugs: an 80-count package of Advil Liqui-Gels costs \$10.99 at both CVS and Walgreen
- ii. Personal Care: a 24-ounce bottle of Dove Go Fresh body wash costs \$7.49 at Walgreens and \$7.19 at CVS
- iii. Paper products: a 12-pack of Charmin Basic is priced at \$7.99 at Walgreens and \$8.39 at CVS
- iv. Cleaning supplies: 35-count package of Clorox Cleaning Wipes- \$3.59 at Walgreens, \$3.69 at CVS
- v. Snacks: SlimFast snack bars- \$4.49 Walgreens, \$4.99 CVS.

When comparing prescription drugs consumerreports.org found that the average price gap for a series of brand name drugs sold at CVS and Walgreens is less than 1% [58].

Given the similarity in price and the emphasis placed on travel time by consumers when selecting a drugstore [37] we can assume that one of the primary ways that these chains compete is on a spatial basis.

The demand volume for each zone and the location of stores in the grid is depicted in Figure 27 below.

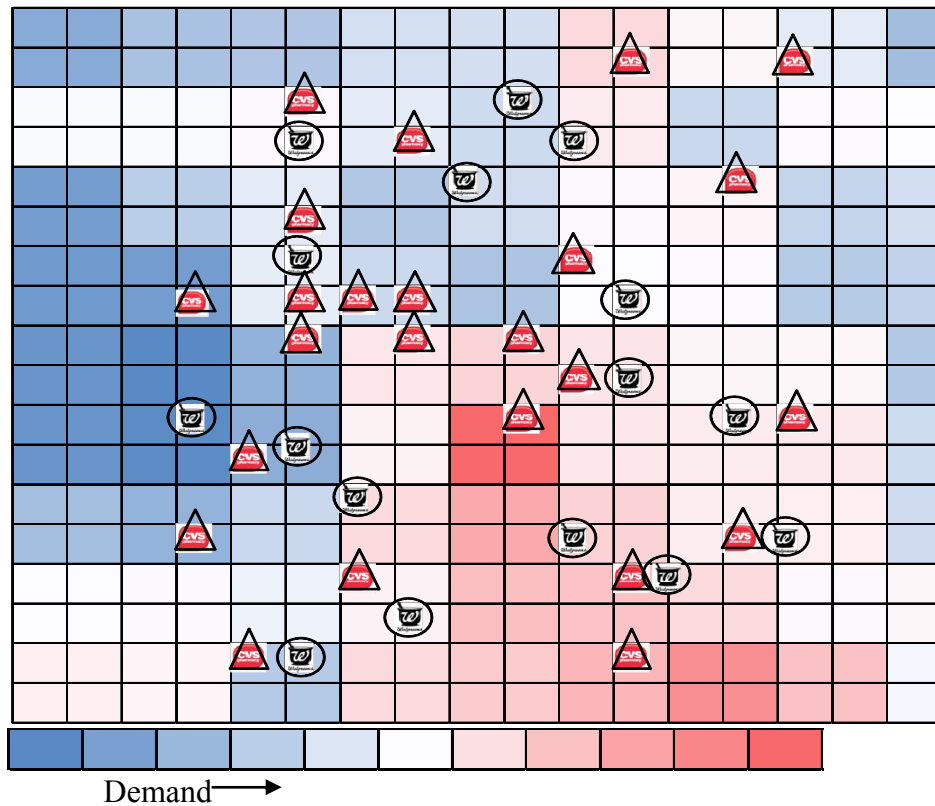


FIGURE 27: Representation of the demand in the region in a grid format

Figure 27 shows that CVS has concentration of stores in the center of the region and looks to locate multiple stores in regions where high demand is expected. Walgreen on the other hand locates stores on the outskirts in areas where demand is lower but where there is less competition from its rival. Our results indicate that this strategy helps Walgreens stay competitive in the region even though its operating costs are higher. Values for average sales, number of stores, gross margins and operating costs for each type of store in 2012 were obtained from annual reports for CVS [59] and Walgreens [60].

TABLE 6: Case Study Parameters- CVS vs Walgreens

Type	Value	Comments
Problem Environment	306 sq.miles, 40 stores	Parameters for the region described above
Distance Threshold	3,4,5 miles	The average distance traveled per shopping trip is 7 miles in 2001 and 6.5 miles in 2009 with a 95% confidence interval of +/- .2miles [44]. Consumers spend less time travelling to shop at a drugstore [56]
Percent change in Demand	Uniformly distributed +/-10%,20%,30%	In 2008 and 2009 quarterly percent changes in consumption of durable goods ranged from -38.5% to 50.5% in different categories.[45]
Initial Conditions	Total Demand	In order to recreate recessionary conditions total demand for the region was calculated as 75% of the estimated total sales in 2013.
Gross Margin	28%	
Operating Costs	CVS=2.13 million Wal=1.94 million	

6.2.1. Impact of Variance in Demand

As described in section 7.1.2 based on our experimental results we expect that an increase in demand volatility will be unfavorable to both players. This can be seen in Figure 28.

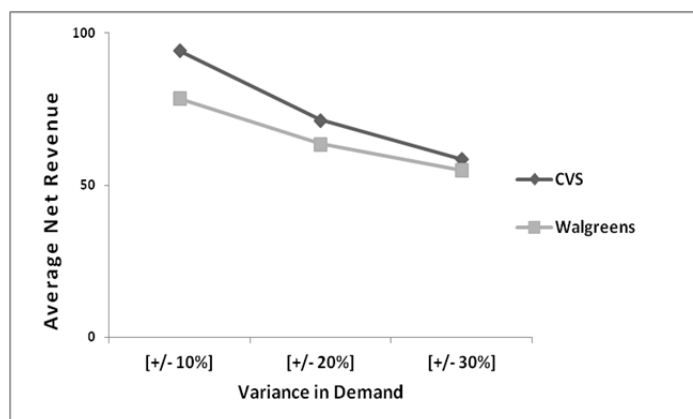


FIGURE 28: Impact of variance in demand on revenue- CVS vs. Walgreens

Initially CVS enjoys higher net revenue due to the following reasons: (i) it has lower store operating costs and (ii) it enjoys a competitive advantage by having a larger number of stores in the region. Both firms will see their net revenue decrease as the variance in demand from period to period increases. However, the decrease is lower for Walgreens. We can attribute this to the fact that it has a number of stores located in regions where competition from rival stores is minimal and where there is no cannibalization of demand from any of its other stores. As a result Walgreens can afford to keep these stores open in periods where there is a sharp decrease in demand as long as a similar increase is expected in future periods. Any losses suffered initially can be recouped since there is no danger of cannibalization of revenue or losing revenue to a rival store. On the other hand if an increase in demand in future periods is not expected the store can be closed at the beginning of the planning horizon. This leads to a more stable solution as seen in Figure29.

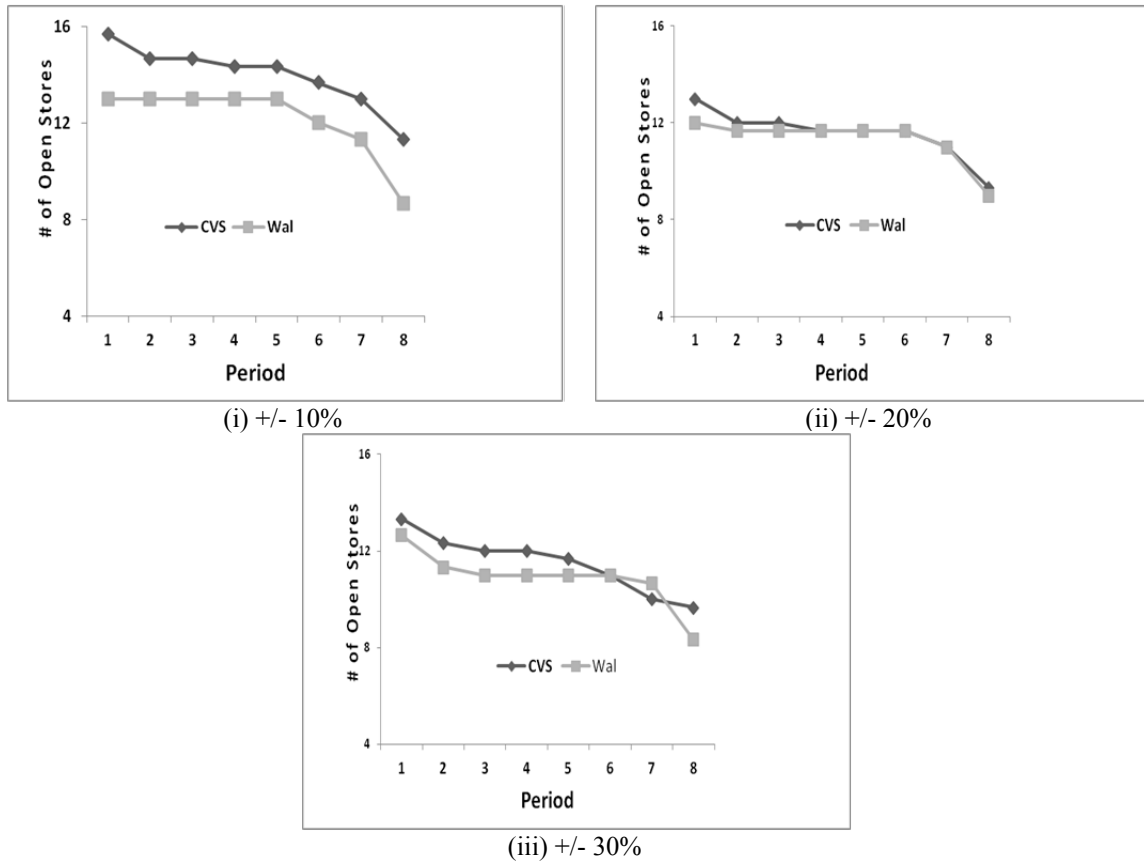


FIGURE 29: Store Closing Decisions by period for different demand scenarios

Figure 29 (i) shows that when variance in demand is low the pattern of store closing from one period to the next is similar for both players. When variance increases it has a negative effect on CVS as it results in larger number of stores being closed over the eight time periods. On the other hand the number of Walgreens stores closed in periods 2-7 is very similar in each of the 3 demand scenarios. We can conclude that Walgreens is spatially better positioned to ride out periods of high demand volatility.

6.2.2. Impact of Increasing Distance Threshold

As seen in our experimental results and in case study 1 taking measures to encourage consumers to travel longer to patronize a store will result in increasing profits but at a decreasing rate. A similar result can be seen here.

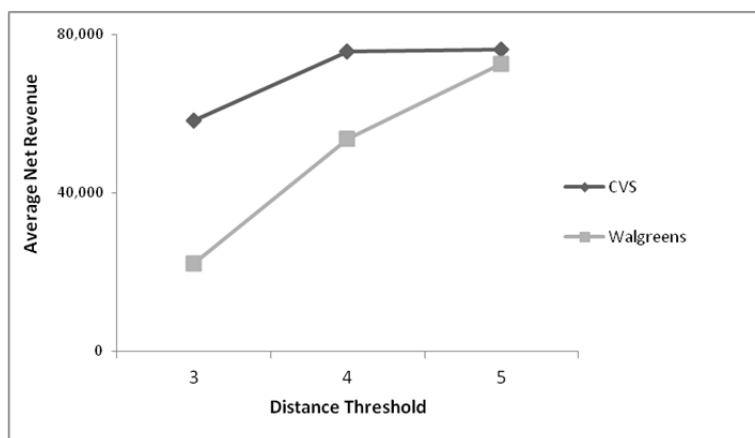


FIGURE 30: Effect of increasing distance threshold on revenue-CVS v Walgreens

Figure 8 (section 6.1) shows that the firm which has stores in regions where there is little to no competition from rival stores stands to benefit the most by an increase in distance threshold. As the distance threshold increase profits will continue to go up. On the other hand if a firm's stores are located in clustered together among one or more rival stores a continued increase in distance threshold will result in a decrease in profit. Based on the locations of stores in this area it can be assumed that CVS has adopted a strategy of concentrating its stores in high demand areas while Walgreens focuses on capturing as many zones as possible by spreading out its stores across the region. Therefore in this case increasing the distance threshold will have a greater positive impact on the net revenue of Walgreens.

CHAPTER 7: CONCLUDING REMARKS

The recent economic recession and the subsequent slow recovery have resulted in a substantial decrease in consumer spending. This has adversely affected a number of retail chains. Stores which were previously profitable are now making losses. As a result these chains have been forced to downsize operations and close a large number of its stores. The purpose of this work is to provide the firm with a solution strategy such that the profit over the planning horizon is maximized. This strategy details the number and location of stores that should be closed or kept open in a given time period. The problem of location analysis in the area of competitive store closing- while relevant in the current business environment is one that is highly under researched.

This dissertation presents a mixed integer programming model which finds the equilibrium solution to the game between two rival chains looking to close stores in a given region. The model introduced in Section 3 captures the redistribution of demand capture that occurs when one or more stores are closed. The model provides the optimal store closing decisions for two rival firms, so as to maximize individual profits. Since a problem of practical size and scope cannot be solved using the model within a reasonable time frame, a clustering algorithm is introduced. The purpose of the algorithm is to divide the problem into smaller more tractable problems

Experimental results show that it is possible to solve large problems using the clustering algorithm in a fraction of the time that would otherwise be needed. Further,

our tests showed that the quality of the solutions was on average within 94% of the optimal solutions. The dissertation next introduces a solution method for a problem spanning multiple time periods. An integer programming approach cannot be used to in this instance due to the dynamic nature of the problem when extended over multiple time periods. Optimal decisions in each period are based on store closures in the preceding period and the problem parameters change as information is updated. Consequently, a heuristic based on dynamic programming is developed where backward induction is used to find the optimal solution.

The heuristic is then applied to a series of simulated problems. A scenario that approximates spatial competition between two retail chains in a mid size urban region is generated. Results of the experimental runs provide insights into various strategies that firms can adopt when choosing to close stores. Taking steps to increase the distance that a customer will travel to a store results initially has a positive effect on the firm's overall net revenue. However, continuing to employ this strategy will not always increase net revenue and will in some instances result in a decrease in profits. In periods where there is a high variance in demand a decision to close a store will depend more on the location of the store than on its profitability. In this case it is optimal for the firm to prioritize capturing market share over maximizing profit.

The dissertation then looks at two case study problems. First the competition between Lowes and Home Depot is considered followed by the one between CVS and Walgreens. Mecklenburg County, NC and its immediate surrounding were selected as the geographical area of study.

It is noticeable that the observations from the competition between Lowes and Home Depot are very similar to our experimental results especially when one chain does not have a significant advantage over the other. As expected an increase in demand variance has an adverse effect on both firms. Further it results in a greater likelihood that initially unprofitable stores will be kept open. The impact of increasing distance threshold on both chains also falls in line with our experimental results where it initially results in an increase in profitability but at a decreasing rate and continued increases in distance threshold can result in a decrease in profits. In the scenario where Home Depot enjoys a significant (16%) advantage in revenue generation we notice some deviations from our previous experimental results which featured two chains that generate approximately equal revenue. Here Home Depot's net revenue is not affected by an increase in demand variance. We also do not see an increase in the percentage of Home Depot's initially profitable stores being closed. Overall when generating 16% higher revenue Home Depot is able to minimize the number of stores it closes in each period and thus is relatively immune to marked fluctuations in demand. In the scenario where the difference in revenue is not as high (8%) Home Depot loses its advantage and the results are similar to the ones given in the simulated competition. Here Lowes is able to compete on equal terms with Home Depot due to a spatial advantage where it has a larger number of stores spread across the region.

The results obtained from the Walgreens vs. CVS case study also for the most part matched the experimental results. Under initial conditions CVS enjoys higher average per store profitability than Walgreens due to the fact that it's operating costs are lower. However an increase in distance threshold benefits Walgreens more than it does

CVS. This is due to the spatial distribution of stores in the region where Walgreens has stores spread out and CVS locates its stores in clusters. As a result Walgreens is also better positioned to ride out an increase in demand variance even though its average store operating cost is higher than CVS.

There are certain factors related to the competition under study that this research does not consider. First a scenario where a firm looks to open and close stores over a given planning horizon is not examined. In a situation where a recovering economy causes considerable shifts in demand across a region and across time closing a store for a few time periods and/or relocating existing stores may be an applicable strategy. Further the competition examined here does not account for a third player in the game. While the competition between Lowes and Home Depot is clearly duopolistic in nature in the case of a CVS vs. Walgreens the proximity of a store such as Walmart could have an impact on the distribution of demand. Finally when determining optimal store closing decisions the cost of closing a store is not accounted for. In cases where there is a significant financial and reputation costs of closing a store the firm may decide to keep it open even when it is not optimal to do so.

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