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ESSAYS ON SPATIAL PRICE COMPETITION

PRIYANKA GUPTA

NANYANG BUSINESS SCHOOL

2020

ESSAYS ON SPATIAL PRICE COMPETITION

PRIYANKA GUPTA

Nanyang Business School

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2020

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Summary

Demand system estimation of differentiated goods is one of the core areas of research in marketing. A fundamental assumption in demand estimation has been that markets are independent of each other. This may be plausible at the market level when consumers do not consider the options available across markets. However, I consider demand system estimation at the store level as opposed to the market level that is standard in the literature. The challenge for store-level estimation is that within any geographic boundary, such as a city or township, the assumption that the stores are independent of each other is not tenable. In this thesis, I establish the importance of spatial interaction among retail outlets in demand system estimation in the differentiated goods market.

The empirical literature on the effect of spatial distance among geographically connected retailers is thin. Extant literature on spatial-temporal models examines phenomena such as social influence among spatially connected consumers and strategic interaction among firms that affects their location choices, entry/exit decisions, pricing strategy, and product assortment choices. Little is known about whether spatial distances matter in store-level demand estimates. In the existing literature, the spatial map can be based on product characteristic distance or psychometric/demographic similarity. To the best of my knowledge, this is the first study to use the actual physical distance between stores to create a spatial weights matrix. This matrix is used to obtain the spatially weighted price for each store that is used as another explanatory variable in the demand estimation.

The thesis consists of two main chapters on empirical analysis. The first chapter is a prelude to these two main chapters. In the first chapter, I discuss why and how a spatial linear demand system model can be examined. The focus of this chapter is primarily to illustrate the manner in which the various parameters of a linear demand system model developed for a store-level demand analysis should be

interpreted. In addition, I discuss how the aggregate market-level analysis is different from the store-level analysis.

The second chapter builds on the discussions in the first chapter to empirically demonstrate the spatial interaction phenomenon. This study uses a spatial linear system of equations model that incorporates spatial connectivity among the stores for the demand estimation of differentiated goods. I obtained store-level scanner panel data and the geographic coordinates of 981 stores in the Singapore market. I then estimate the cross-price and cross-store elasticities for the two major brands in the cola-flavored carbonated soft drinks category. The findings show that spatial price coefficients are significant and positive, which means that a price increase (decrease) in nearby stores leads to an increase (decrease) in demand in the focal store. Additional results demonstrate that intra- and inter-channel store substitution effects are asymmetric and depend on the market power of the brand (leader vs. follower and gap in market share).

The third chapter moves from brand space to a reduced form spatial econometric model on characteristic space for the demand system equation. The linear demand system model of Chapter 2 is useful when there are only a few brands. However, when the market consists of many brands, which is often the case, an estimation model in the characteristic space is useful. I extend the characteristic space model to incorporate spatial distance among the retailers. Then I examine the top five SKUs based on their store-wise market share in the carbonated soft drinks category. This analysis reveals that, for certain brands, there is evidence of cross-store substitution. The significance of spatial coefficients in the final results lends support to the importance of spatial price in demand estimation and the existence of spatial spillover effects in elasticity estimates. This chapter empirically demonstrates the feasibility of extending this model to multiple brands and can be used to determine whether category characteristics or country characteristics moderate our findings.

Introduction

“Locations are not independent observations in a cross-sectional regression but rather are systematically linked to one another through trade, transportation and migration flows.” – Redding and Hansberg (2017)

Pricing and related decisions (e.g., price promotion) are of fundamental importance to manufacturers and retailers. Typically, the effects of various factors (including price) on demand are measured in terms of elasticities. Own and cross-price elasticities are important parameters that influence optimal pricing or price promotion decisions by brand managers. Demand system estimation is used for estimating these elasticities. The existing methods in the demand system estimation literature allow for the estimation of these elasticities at the market level. However, several retail outlets (especially in urban centers) constitute these markets. Two pertinent questions that arise are: Should the brand manager make decisions at the market level or at the store level? And if retail store managers have discretion over pricing decisions, should they consider the inter-store competition at the brand level or at the category level?

Broadly, this research uses two strands of the modeling approach. In one strand, researchers adopt the price space approach and, typically, use a vector-auto regression-type model for estimating price elasticities (e.g., Fok et al., 2006; Horvath and Fok, 2013). In the second strand, researchers use the characteristic space approach and typically use the random coefficient logit model (e.g., Berry et al., 1995; Nevo, 2001; Petrin, 2002). A fundamental assumption in both approaches is that the markets are independent of each other. This means that the sales and price at the respective outlet is considered to be independent of sales and price at other stores. It is assumed that price changes in other stores do not affect the sales or price in the focal store.

In this thesis, I consider demand system estimation at the store level. The ability to estimate demand parameters at the store level should, in principle, lead to more optimal pricing or discount decisions. The challenge for store-level estimation is that within any geographic boundary, such as a city or township, the assumption that the stores are independent of each other is not tenable. Consumers can buy from multiple outlets during a single shopping trip or multiple trips in a certain span of time due to the close proximity between the outlets and to lower switching costs (Keng and Ehrenberg, 1984; Kumar and Leone, 1988). Thus, the demand for a product in an outlet is possibly influenced by the price of the product in both the focal and neighboring outlets. Therefore, the analysis should include an additional dimension of competition, which is inter-brand inter-store.

The analyses in this thesis benefit both brand managers and store managers. For brand managers, estimated price elasticities will have a spatial component. The inclusion of spatial interdependence corrects own-brand price elasticity estimates. Hence, managers can optimize their price promotion expenditure, which, in principle, can free up funds for other types of marketing expenditures. In addition, brand managers can optimally design price promotions at the store level rather than at the market level. The ability to estimate price elasticity at the store level would also help store managers. Suppose that only market-level price elasticities can be estimated. If a store manager optimizes on the basis of these market-level aggregate price-elasticity estimates, all store managers will make the same decision, thereby reducing the effectiveness of the outcome. With the store-level elasticity estimates, which include spatial interdependence, each store manager has access to information at a more granular level.

Due to the potential interdependence among stores, a few questions arise: (a) How can we estimate the demand parameters at the store level in the absence of non-iid assumption, and (b) How are the

aggregate demand parameters associated with the store-level demand parameters? These are the central questions that I examine in this thesis.

The structure of the thesis is as follows. Chapter 1 is the prelude to the two main chapters (2 and 3) on empirical analysis. In this chapter, I discuss the various parameters, particularly those related to spatial spillover effects, in a linear demand system model that allows for not only cross-brand substitution but also cross-store substitution. This discussion is useful for the interpretation of the effects estimated in the subsequent chapters. In addition, I examine how the aggregate market-level demand parameters are associated with the store-level demand parameters.

In Chapter 2, I develop a linear system of equations model that would maintain the principles used in the time series models of demand systems but that incorporates spatial connectivity among the stores. I obtained store-level scanner panel data and the geographic coordinates of the stores. I then estimate the cross-price and cross-store elasticities for the two major brands in the cola-flavored carbonated soft drinks category.

In Chapter 3, I develop a reduced form spatial econometric model on the characteristics space for the demand system equation. This model allows for the inclusion of a large number of brands in the estimation model by mapping the brands to a low-dimension characteristics space. Then I estimate the demand system for the top five brands in the carbonated soft drink category.

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Chapter 1

Spatial effects and inter store price competition among
geographically connected retailers

1.1. Introduction

Location choice is a critical strategic decision in retailing because it is fixed in nature. Once the firm chooses a location, it is an expensive decision to reverse that choice. Consumers' choice to shop at a particular store is greatly influenced by the distance to the store from their location (Bell et al., 1998; Huff, 1962). While the general notion of product differentiation has received much attention in academic research using the location-choice models, as in Hotelling (1929) and Salop (1979), we know little about the effects of physical distances among the outlets on the market dynamics in the differentiated goods sector. In this chapter, I discuss a linear demand system model at the store level that incorporates spatial price competition among geographically connected stores.

The objectives of this discussion are twofold. First, I wish to illustrate how the parameters of the store-level demand functions can be interpreted. This would facilitate an understanding of the empirical analyses in the subsequent chapters, in which I develop empirical models for store-level demand estimation. Second, I wish to examine how the market-level aggregate demand function parameters are associated with the store-level demand function parameters. A novelty in my spatial price competition model is the incorporation of a measure of physical distance among the stores. The marketing literature contains some discussion of location choice by retailers. However, to our knowledge, there is no discussion in the literature on the effect of physical distance among stores on cross-store substitution. By including a physical distance component in the model, we are able to examine how the spatial spillover effect due to any price change can propagate through a network of geographically connected stores.

At the outset, I wish to highlight that the objective is not to derive the equilibrium conditions and their characterization. The empirical models in the subsequent chapters are, by nature, reduced forms. Therefore, it is not necessary to derive the equilibrium conditions to interpret the reduced form

parameters. My focus is, rather, to generate insights into the various types of elasticities that manifest themselves in a demand system model when spatial price competition is incorporated into the model. Hence, I examine a bare-bones scenario that would be helpful for this purpose.

For ease of exposition, I consider a differentiated goods market with two competing brands. We start our discussion with a scenario in which these two brands are marketed through two unconnected stores. We then incorporate spatial connectedness between these two stores. Finally, we incorporate two channels with two stores per channel in the model. This is without any loss of generality, as the intuition easily carries to a more complex scenario with multiple channels and stores.

The structure of this chapter is as follows. I begin with a short literature review of spatial price competition models in section 1.2. In section 1.3, I present a linear demand system model suitable for spatially connected stores. In section 1.4, I discuss the various types of spatial spillover effects that can be examined using the model. In section 1.5, I attempt to reconcile the parameters in the aggregated market-level model with the parameters in the store-level model. In section 1.6, I discuss the managerial implications of my research. In section 1.7, I conclude.

1.2. Literature review

The analysis of spatial price competition can be traced back to Hotelling (1929), who examined equilibrium in a duopoly using the linear city model. The model illustrates how duopoly firms would behave in terms of choice of location along a line and in terms of their pricing decisions. However, the location along the line, in the linear city model, is primarily an abstraction of the broad notion of horizontal product differentiation. Salop (1979) extended the concept to a circular city model, which allows for unrestricted entry and exit, while the location along the circular line also represents horizontal

product differentiation. The industrial organization and quantitative marketing literature contains many analytical and empirical papers based on these models, which examine price competition in the differentiated goods markets.

In marketing literature, ‘location’ affects the choices of firms as much as the choices of consumers. The first stream of literature examines the strategic interaction among firms located in a geographic space (Seim, 2006; Jia, 2008; Ellickson and Misra, 2008; Orhun, 2013). Researchers study substantive, econometric, and theoretical questions of interest pertaining to retailer entry (Bresnahan and Reiss, 1991; Mazzeo, 2002; Ciliberto and Tamer, 2009; Zhu et al., 2011) and location choice (Seim, 2006; Zhu and Singh, 2009; Orhun, 2013; Datta and Sudhir, 2013). The second stream of literature studies the effect of location on consumer store choices and falls under the purview of retailing within marketing. Researchers and retail managers in this area have traditionally used gravitational types of models to predict retail trade areas and consumer patronage patterns (Converse, 1949; Reilly, 1953; Huff, 1962).

Within the firm strategy literature, Zhu et al. (2011) modeled spatial competition among retailers subject to entry by a discount store. They studied the multi-product pricing strategy employed by an incumbent store and the effect of the location of the discount store. In this model, stores and consumers are all aligned along a straight line similar to Hotelling’s (1929) set-up. The incumbent retailers are located at two extremes on the line and consumers are heterogeneous in their location along the line, yielding different transportation costs and shopping preferences due to differences in reference prices. Orhun’s (2013) paper unravels the factors leading to the geographical location decisions of retailers in light of researcher uncertainty pertaining to location characteristics and a firm’s uncertainty about a competitor’s actions. The approach in this paper is to examine differentiation decisions conditional on entry, very similar to Einav (2010) and Ellickson and Misra (2008), who determined the basis for the pricing strategy of retail firms conditional on market entry. Datta and Sudhir (2013) furthered the

understanding of a firm's entry, location, and format choice in a large number of U.S. markets working within spatial zoning restrictions on business entry through a static, structural simultaneous move game theory model. Zhu and Singh (2009) analyzed the factors underlying the entry and location choices of firms in the retail discount industry to infer competitive interaction parameters based on their revealed preferences using a dataset containing store locations (street address and ZIP codes).

In the second stream of literature, among the various gravitational models that predict retail trade areas and consumer patronage patterns, Huff's probabilistic model of retail gravitation is probably the most well-known and used (Huff, 1962, 1963, 1964). The Huff model is a spatial interaction model that calculates the gravity-based probabilities of consumers at each origin location patronizing each store in the store dataset. In essence, the model states that the probability of any shopper choosing a particular retail center is equal to the ratio of the utility of that center to the sum of the utilities of all potential competing centers in the system (Huff, 1964). Specifically, the utility or attractiveness of a center is directly related to the size of that center and inversely related to the distance separating consumers from the center. Huff's model assumes that consumers with comparable socioeconomic characteristics will depict similar retail center patronage and that there are no internal differences of significance within the area of analysis.

Huff's model is probably the most parsimonious specification of modern theory-based approaches to the study of consumer spatial behavior and has survived much empirical testing since its formulation (Huff 1962; Lakshmanan and Hansen 1965; Turner and Cole 1980; Gautschi 1981). Huff's competitive system includes all potential retail centers in that system (Huff, 1964). While this approach may be appealing when there are only a few recognizable shopping centers within a city, the situation becomes less defensible when there are many shopping centers with varying degrees of consumer patronization.

Consumers may patronize different subsets of shopping areas within the basic set or they may patronize shopping areas that have not been included in the set.

None of the research mentioned above analyzes the impact of location coordinates or actual physical distances among outlets on demand and the subsequent impact on price elasticity estimates. The models discussed in this chapter establish the linkage between spatial and product differentiation by using both attribute distances in the characteristic space as product differentiators and actual distances between stores in the physical space as spatial differentiators.

1.3. Linear demand system model with spatial interaction

A manufacturer serves the end consumer through wholesalers and outlets or various distribution channels as we know them and the channel often makes crucial decisions determining the final price, promotional effort, and so forth. In the extant literature, the outlets operate independently of each other and there is no cross-outlet influence on outlet-wise demand. However, similar to strategic interaction among firms and social interaction among consumers, outlets may exert spatial influence on each other through store switching or multiple store shopping by consumers (Keng and Ehrenberg, 1984; Kumar and Leone, 1988). This spatial interaction among outlets impacts price elasticity calculations. To understand price-elasticity estimations incorporating spatial interaction, we consider different scenarios starting with the current prevalent framework and progressively incorporating physical distances among the stores.

1.3.1 Demand system with two brands and two independent outlets

First, we consider a linear demand system in the absence of any spatial dependence among the outlets. We assume that the prices can vary across outlets for each brand. Essentially, this suggests that the store

managers are able to adjust prices to some degree. Suppose that there are two brands (A and B) in a differentiated goods category. These brands are sold through two outlets: Outlet 1 and Outlet 2. Throughout, I use Q_{ij} and P_{ij} to denote the quantity demanded for brand ‘ i ’ in outlet ‘ j ’, where both variables are log-transformed. This is illustrated in Figure 1.1 below.

Figure 1.1: Two brands and two independent outlets

The two outlets are not spatially connected. This implies that there is no spatial price competition, i.e., the demand for a product in an outlet is influenced only by the price of the product in that outlet. The price of the neighboring (adjacent) outlet does not affect the demand in the focal outlet. This means that the customers do not cross-shop and that there is no cross-store substitution—an assumption in the market-level demand estimation. Because the two outlets are not spatially connected, following Kadiyali et al. (2001), we can write the demand for the two brands in the two stores as follows¹:

$$Q_{Ai} = D_{Ai}(P_{Ai}, P_{Bi}) = \mu_{Ai} + \beta_{AAi}P_{Ai} + \beta_{ABi}P_{Bi},$$

$$Q_{Bi} = D_{Bi}(P_{Ai}, P_{Bi}) = \mu_{Bi} + \beta_{BAi}P_{Ai} + \beta_{BBi}P_{Bi}, \quad \dots\dots\dots(1.1)$$

¹ Singh and Vives (1984) show that the quadratic utility function can lead to linear demand functions for a differentiated goods duopoly.

There is no spatial interaction between the outlets implying that two different set of customers shop at each of the outlets. Since the variables are log transformed, it follows from the system of Equations in (1.1) that the elasticities for outlet 1 and outlet 2 may be different. These elasticity matrices (for outlet 1 and outlet 2) are as follows:

$$\epsilon_i = \begin{bmatrix} \frac{\partial Q_{Ai}}{\partial P_{Ai}} & \frac{\partial Q_{Ai}}{\partial P_{Bi}} \\ \frac{\partial Q_{Bi}}{\partial P_{Ai}} & \frac{\partial Q_{Bi}}{\partial P_{Bi}} \end{bmatrix} = \begin{bmatrix} \beta_{AAi} & \beta_{ABi} \\ \beta_{BAi} & \beta_{BBi} \end{bmatrix}, \text{ where } i=1,2.$$

1.3.2 Two brands and two outlets with spatial interaction

Now we examine how the demand functions need to be modified if the outlets are spatially connected. If the outlets are spatially connected, then that same set of customers are able to buy from both the outlets. In Figure 1.2, I illustrate this scenario.

Figure 1.2: Two brands and two outlets with spatial interaction

Following from Singh and Vives (1984) linear model of demand, consider the case of an economy with a monopolistic sector and two firms each producing a differentiated good, and a competitive numeraire

sector. There is a continuum of consumers of the same type with a utility function separable and linear in the numeraire good. The representative consumer maximizes $(Q_A, Q_B) - \sum_{i=A,B} P_i Q_i$, where Q_i is the amount of good i and P_i its price. U is assumed to be quadratic and strictly concave $U(Q_A, Q_B) = \alpha_A Q_A + \alpha_B Q_B - \frac{\beta_A Q_A^2 + 2\gamma Q_A Q_B + \beta_B Q_B^2}{2}$ where α_i and β_i are positive, $i = A, B$, $\beta_A \beta_B - \gamma^2 > 0$, and $\alpha_i \beta_j - \alpha_j \gamma > 0$ for $i \neq j, i = A, B$. This utility function gives rise to a linear demand structure. Inverse demands are given by $P_A = \alpha_A - \beta_A Q_A - \gamma Q_B$ and $P_B = \alpha_B - \gamma Q_A - \beta_B Q_B$ in the region of quantity space where prices are positive. Letting $\delta = \beta_A \beta_B - \gamma^2$, $a_i = (\alpha_i \beta_j - \alpha_j \gamma)/\delta$, $b_i = \beta_j/\delta$ for $i \neq j, i = A, B$ and $c = \gamma/\delta$, we can write demand as,

$$Q_A = a_A - b_A P_A + c P_B$$

$$Q_B = a_B + c P_A - b_B P_B$$

Now consider that there are two outlets (1 & 2) selling the products produced by the two firms. The customer has option of buying each of the product from any of the two outlets or both the outlets such that $Q_A = Q_{A1} + Q_{B1}$ & $Q_B = Q_{B1} + Q_{B2}$. The representative consumer maximizes $(Q_{A1}, Q_{B1}, Q_{A2}, Q_{B2}) - \sum_{i=A,B} \sum_{j=1}^2 P_{ij} Q_{ij}$, where Q_{ij} is the amount of good ' i ' bought from outlet ' j ' and P_{ij} its price. U is assumed to be quadratic and strictly concave $U(Q_{A1}, Q_{B1}, Q_{A2}, Q_{B2}) =$

$$\sum_{j=1}^2 \sum_{i=A,B} \alpha_{ij} Q_{ij} - \frac{\sum_{j=1, i=[A,B]}^2 \beta_{ij} Q_{ij}^2 + \sum_{k=1}^2 2\gamma_k Q_{A1} Q_{Bk} + \sum_{k=3, j=1}^2 2\gamma_k Q_{A2} Q_{Bj} + \sum_{k=5, i=A}^2 2\gamma_k Q_{i1} Q_{i2} + \sum_{k=4, j=2}^2 2\gamma_k Q_{A1} Q_{Bj} + \sum_{k=6, i=B}^2 2\gamma_k Q_{i1} Q_{i2}}{2}. \text{ Solving the utility}$$

function by imposing conditions of non-negative price and quantity as above, gives linear demand functions (following Singh and Vives (1984)):

$$Q_{Ai} = \alpha_{Ai} - b_{AAi} P_{Ai} + b_{ABi} P_{Bi} + \theta_{AAi} P_{Aj} + \theta_{ABi} P_{Bj}$$

$$Q_{Bi} = \alpha_{Bi} + b_{BAi} P_{Ai} - b_{BBi} P_{Bi} + \theta_{BAi} P_{Aj} + \theta_{BBi} P_{Bj}$$

where ‘ i ’ is the focal outlet= $\{1,2\}$ and ‘ j ’ is the spatially connected outlet to the focal outlet, $j=2$ for $i=1$ and $j=1$ for $i=2$.

The above system of equations can be adapted to incorporate spatial distances from the focal store to the competing stores. As the number of stores increases, prices of all competing stores can be included in the above equations. Inclusion of prices of competing stores in the above equation leads to exponential increase in the number of parameters to be estimated. This makes it infeasible to include all spatially connected stores in the above systems of equations if there are large number of stores. To solve this, instead of incorporating all other spatially connected stores individually, one can generate spatially weighted indices of prices for brand A and B ($\sum_j w_{ij}P_{Aj}$ and $\sum_j w_{ij}P_{Bj}$, where ‘ j ’ denotes stores connected to ‘ i ’) and use these indices in the system of equations to incorporate the potential spatial price competition.

The spatial weights w_{ij} can be calculated in a manner similar to estimation of probability of retail center patronization by a consumer in Huff model (1964). The Huff model of retail gravitation states that the probability of any shopper choosing a particular retail center is equal to the ratio of the utility of that center to the sum of utilities of all potential competing centers in the system (Huff, 1964). Specifically, the utility or attractiveness of a center is directly related to the size of the center and inversely related to the distance separating consumers from the center. The mathematical formulation of Huff's model is expressed as follows:

$$P_{ij} = \frac{\frac{S_j}{T_{ij}^\lambda}}{\sum_{j=1}^n \frac{S_j}{T_{ij}^\lambda}}$$

P_{ij} = the probability of a consumer at a given point of origin i travelling to a shopping center j

S_j = the square footage of selling space devoted to the sale of a class of goods by shopping center j ;

T_{ij} = the travel time/ distance involved in getting from a consumer's origin i to shopping center j ; and

λ = a parameter that reflect the effect of travel time or distance on various kinds of shopping trips.

n = total number of shopping centers

Following from above, the weights w_{ij} can be plausibly assumed to be some inverse function of the distance between focal store, ‘ i ’ and the spatially connected stores, i.e., we can write $w(d_{ij})$. This means, that as the distance from the focal store to the spatially connected stores increases the degree of competition (and therefore the extent of substitution to the competing store) reduces. Thus the following system of equations can be considered to be demand functions for each store which incorporates potential spatial substitution.

$$\begin{aligned} Q_{Ai} &= D_{Ai}(P_{Ai}, P_{Bi}, P_{Aj}, P_{Bj}) = \mu_{Ai} + \beta_{AAi}P_{Ai} + \beta_{ABi}P_{Bi} + \theta_{AAi}w(d_{ij})P_{Aj} + \theta_{ABi}w(d_{ij})P_{Bj}, \\ Q_{Bi} &= D_{Bi}(P_{Ai}, P_{Bi}, P_{Aj}, P_{Bj}) = \mu_{Bi} + \beta_{BAi}P_{Ai} + \beta_{BBi}P_{Bi} + \theta_{BAi}w(d_{ij})P_{Aj} + \theta_{BBi}w(d_{ij})P_{Bj} \quad \dots\dots (1.2) \end{aligned}$$

Here θ represents the spatial coefficient weighted by spatial weights $w(d)$ defined as function of distance d between the outlets. Differentiating above demand functions w.r.t. each of the prices gives elasticity measures for Outlet 1 and Outlet 2. Each of the outlet has two types of effects – direct effects within store and spatial effects across stores due to cross-store substitution (*cf.* Elhorst, 2010).

$$\epsilon_i|direct = \begin{bmatrix} \frac{\partial Q_{Ai}}{\partial P_{Ai}} & \frac{\partial Q_{Ai}}{\partial P_{Bi}} \\ \frac{\partial Q_{Bi}}{\partial P_{Ai}} & \frac{\partial Q_{Bi}}{\partial P_{Bi}} \end{bmatrix} = \begin{bmatrix} \beta_{AAi} & \beta_{ABi} \\ \beta_{BAi} & \beta_{BBi} \end{bmatrix}, \epsilon_i|spatial = \begin{bmatrix} \frac{\partial Q_{Ai}}{\partial P_{Aj}} & \frac{\partial Q_{Ai}}{\partial P_{Bj}} \\ \frac{\partial Q_{Bi}}{\partial P_{Aj}} & \frac{\partial Q_{Bi}}{\partial P_{Bj}} \end{bmatrix} = \begin{bmatrix} \theta_{AAi}w(d_{ij}) & \theta_{ABi}w(d_{ij}) \\ \theta_{BAi}w(d_{ij}) & \theta_{BBi}w(d_{ij}) \end{bmatrix}$$

With spatial interaction between outlets, there are dual effects at play when price of a brand goes up- same-store price elasticity and cross-store price elasticity. Hence, due to spatial influence, the demand for any given outlet is not only affected by its own price but also by the price of the brand in spatially connected outlets weighted by some functions of the distances, $w(d_{12})$ and $w(d_{21})$. As seen here, there

is a new component to price elasticity in addition to own price elasticity and cross brand price elasticity is cross store price elasticity. A change in price of Brand A in Outlet 1 not only changes the demand of Brand A & Brand B in Outlet 1 $\left(\frac{\partial Q_{A1}}{\partial P_{A1}}, \frac{\partial Q_{B1}}{\partial P_{A1}}\right)$ but also influences the demand of Brand A & Brand B in Outlet 2 $\left(\frac{\partial Q_{A2}}{\partial P_{A1}} \& \frac{\partial Q_{B2}}{\partial P_{A1}}\right)$. Now, the consumer has a choice to walk to nearest other store with a different price of Brand A and buy from there in addition to the earlier options of buying Brand A or Brand B from the same store when the price of Brand A changes in that store. Hence, there is both a brand preference and an outlet preference component to price elasticity.

1.3.3 Multiple channel outlets in a market

In the packaged and durable goods industries, manufacturers sell to channel partners (wholesalers, retailers) who sell to consumers. Multiple channels/retail formats exist in a market. These channels differ in terms of outlet size (small vs. large), location (inside shopping malls vs. residential neighborhoods), product assortment (limited vs. full range), operating margins (high vs. low), volume (low vs. high), and number of staff numbers (few vs. many). Differences in the mentioned features impact service levels, running costs, and the shopping benefits offered to consumers. While one channel may offer a wide selection of products and brands, as well as high inventory levels, thereby allowing consumers to shop for the goods that their households need for a significant period of time, other channels may sell a limited range of products for customers who are on the go and who need to pick up just a few items (Kotler and Armstrong, 2010).

The difference in running costs combined with the different kinds of shoppers to whom an outlet caters will result in a price difference among channels for the same product. For example, convenience channel prices are almost always higher than prices in the supermarket channel. The premium pricing reflects

the added value of being able to buy something quickly, although supermarkets command more loyalty from repeat and large-volume customers due to their more competitive price points. In a typical market set-up, each channel contains multiple channels and multiple outlets. In the next section, we consider a more general market scenario with two brands, two channels, and two outlets within each channel. All the outlets spatially interact with each other and consumers can shop from either or any combination of the outlets in the same shopping trip or multiple shopping trips.

1.3.4 Two brands, two channels and two outlets within each channel with spatial interaction among all outlets

One can further extend the model discussed in 1.3.2 to incorporate different types of retail channels. This is illustrated in Figure 1.3.

Figure 1.3: Two brands, two channels and four outlets with spatial interaction

In this case, the demand functions can be written as follows:

$$Q_{Ai}^{C_j} = \mu_A^{C_j} + \beta_{AA}^{C_j} P_{Ai} + \beta_{AB}^{C_j} P_{Bi} + \sum_{l=C_1}^{C_j} \theta_{l,AA}^{C_j} \left(\sum_{\substack{k=1 \\ k \in l \\ k \neq i}}^N w(d_{ik}) P_{Ak} \right) + \sum_{l=C_1}^{C_j} \theta_{l,AB}^{C_j} \left(\sum_{\substack{k=1 \\ k \in l \\ k \neq i}}^N w(d_{ik}) P_{Bk} \right) \dots (1.3)$$

$$Q_{Bi}^{C_j} = \mu_B^{C_j} + \beta_{BA}^{C_j} P_{Ai} + \beta_{BB}^{C_j} P_{Bi} + \sum_{l=C_1}^{C_j} \theta_{l,BA}^{C_j} \left(\sum_{\substack{k=1 \\ k \in l \\ k \neq i}}^N w(d_{ik}) P_{Ak} \right) + \sum_{l=C_1}^{C_j} \theta_{l,BB}^{C_j} \left(\sum_{\substack{k=1 \\ k \in l \\ k \neq i}}^N w(d_{ik}) P_{Bk} \right) \dots (1.4)$$

where ‘ C_j ’ stands for Channel ‘ j ’, $j \in \{1, 2, 3, \dots, J\}$, $i \in C_j = \{\text{all } C_j \text{ outlets}\}$ for each value of j , N = total number of outlets.

Substituting $J=2$ and $N=4$ in Equations (1.3) and (1.4), $j \in \{1, 2\}$, the brand and channel-wise demand equations become,

For $j=1$, $i \in C_1 = \{\text{all } C_1 \text{ outlets}\} = \{1, 2\}$

$$Q_{Ai}^{C_1} = \mu_A^{C_1} + \beta_{AA}^{C_1} P_{Ai} + \beta_{AB}^{C_1} P_{Bi} + \theta_{C_1,AA}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) + \theta_{C_2,AA}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) \\ + \theta_{C_1,AB}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) + \theta_{C_2,AB}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) \dots \dots (1.5)$$

$$Q_{Bi}^{C_1} = \mu_B^{C_1} + \beta_{BA}^{C_1} P_{Ai} + \beta_{BB}^{C_1} P_{Bi} + \theta_{C_1,BA}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) + \theta_{C_2,BA}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) \\ + \theta_{C_1,BB}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) + \theta_{C_2,BB}^{C_1} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) \dots \dots (1.6)$$

For $j=2$, $i \in C_2 = \{\text{all } C_2 \text{ outlets}\} = \{3, 4\}$

$$\begin{aligned}
Q_{Ai}^{C_2} = & \mu_A^{C_2} + \beta_{AA}^{C_2} P_{Ai} + \beta_{AB}^{C_2} P_{Bi} + \theta_{C_1,AA}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) + \theta_{C_2,AA}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) \\
& + \theta_{C_1,AB}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) + \theta_{C_2,AB}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) \quad \dots \dots (1.7)
\end{aligned}$$

$$\begin{aligned}
Q_{Bi}^{C_2} = & \mu_B^{C_2} + \beta_{BA}^{C_2} P_{Ai} + \beta_{BB}^{C_2} P_{Bi} + \theta_{C_1,BA}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) + \theta_{C_2,BA}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Ak} \right) \\
& + \theta_{C_1,BB}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_1 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) + \theta_{C_2,BB}^{C_2} \left(\sum_{\substack{k=1 \\ k \in C_2 \\ k \neq i}}^4 w(d_{ik}) P_{Bk} \right) \quad \dots \dots (1.8)
\end{aligned}$$

1.4. Spatial spillover effects

1.4.1 Outlet-wise direct and spatial spillover (indirect) effects

The approach outlined in LeSage and Pace (2009) gives the matrix of partial derivatives of sales of each brand with respect to price of brand in outlet 1 up to outlet 4. I illustrate this by expanding the matrix of Brand A price elasticity for the four outlets with spatial weights as per ‘ W ’.

$$W = \begin{bmatrix} 0 & w(d_{12}) & w(d_{13}) & w(d_{14}) \\ w(d_{21}) & 0 & w(d_{23}) & w(d_{24}) \\ w(d_{31}) & w(d_{32}) & 0 & w(d_{34}) \\ w(d_{41}) & w(d_{42}) & w(d_{43}) & 0 \end{bmatrix} = \begin{bmatrix} 0 & w_{12} & w_{13} & w_{14} \\ w_{21} & 0 & w_{23} & w_{24} \\ w_{31} & w_{32} & 0 & w_{34} \\ w_{41} & w_{42} & w_{43} & 0 \end{bmatrix}$$

$$\frac{\partial Q_A}{\partial P_A} = \begin{bmatrix} \frac{\partial Q_{A1}}{\partial P_{A1}} & \frac{\partial Q_{A1}}{\partial P_{A2}} & \frac{\partial Q_{A1}}{\partial P_{A3}} & \frac{\partial Q_{A1}}{\partial P_{A4}} \\ \frac{\partial Q_{A2}}{\partial P_{A1}} & \frac{\partial Q_{A2}}{\partial P_{A2}} & \frac{\partial Q_{A2}}{\partial P_{A3}} & \frac{\partial Q_{A2}}{\partial P_{A4}} \\ \frac{\partial Q_{A3}}{\partial P_{A1}} & \frac{\partial Q_{A3}}{\partial P_{A2}} & \frac{\partial Q_{A3}}{\partial P_{A3}} & \frac{\partial Q_{A3}}{\partial P_{A4}} \\ \frac{\partial Q_{A4}}{\partial P_{A1}} & \frac{\partial Q_{A4}}{\partial P_{A2}} & \frac{\partial Q_{A4}}{\partial P_{A3}} & \frac{\partial Q_{A4}}{\partial P_{A4}} \end{bmatrix} = \begin{bmatrix} \beta_{AA}^{C_1} & \theta_{C_1,AA}^{C_1} w_{12} & \theta_{C_2,AA}^{C_1} w_{13} & \theta_{C_2,AA}^{C_1} w_{14} \\ \theta_{C_1,AA}^{C_1} w_{21} & \beta_{AA}^{C_1} & \theta_{C_2,AA}^{C_1} w_{23} & \theta_{C_2,AA}^{C_1} w_{24} \\ \theta_{C_1,AA}^{C_2} w_{31} & \theta_{C_1,AA}^{C_2} w_{32} & \beta_{AA}^{C_2} & \theta_{C_2,AA}^{C_2} w_{34} \\ \theta_{C_1,AA}^{C_2} w_{41} & \theta_{C_1,AA}^{C_2} w_{42} & \theta_{C_2,AA}^{C_2} w_{43} & \beta_{AA}^{C_2} \end{bmatrix}$$

$$\frac{\partial Q_A}{\partial P_B} = \begin{bmatrix} \frac{\partial Q_{A1}}{\partial P_{B1}} & \frac{\partial Q_{A1}}{\partial P_{B2}} & \frac{\partial Q_{A1}}{\partial P_{B3}} & \frac{\partial Q_{A1}}{\partial P_{B4}} \\ \frac{\partial Q_{A2}}{\partial P_{B1}} & \frac{\partial Q_{A2}}{\partial P_{B2}} & \frac{\partial Q_{A2}}{\partial P_{B3}} & \frac{\partial Q_{A2}}{\partial P_{B4}} \\ \frac{\partial Q_{A3}}{\partial P_{B1}} & \frac{\partial Q_{A3}}{\partial P_{B2}} & \frac{\partial Q_{A3}}{\partial P_{B3}} & \frac{\partial Q_{A3}}{\partial P_{B4}} \\ \frac{\partial Q_{A4}}{\partial P_{B1}} & \frac{\partial Q_{A4}}{\partial P_{B2}} & \frac{\partial Q_{A4}}{\partial P_{B3}} & \frac{\partial Q_{A4}}{\partial P_{B4}} \end{bmatrix} = \begin{bmatrix} \beta_{AB}^{C_1} & \theta_{C_1,AB}^{C_1} w_{12} & \theta_{C_2,AB}^{C_1} w_{13} & \theta_{C_2,AB}^{C_1} w_{14} \\ \theta_{C_1,AB}^{C_1} w_{21} & \beta_{AB}^{C_1} & \theta_{C_2,AB}^{C_1} w_{23} & \theta_{C_2,AB}^{C_1} w_{24} \\ \theta_{C_1,AB}^{C_2} w_{31} & \theta_{C_1,AB}^{C_2} w_{32} & \beta_{AB}^{C_2} & \theta_{C_2,AB}^{C_2} w_{34} \\ \theta_{C_1,AB}^{C_2} w_{41} & \theta_{C_1,AB}^{C_2} w_{42} & \theta_{C_2,AB}^{C_2} w_{43} & \beta_{AB}^{C_2} \end{bmatrix}$$

$$\frac{\partial Q_B}{\partial P_A} = \begin{bmatrix} \frac{\partial Q_{B1}}{\partial P_{A1}} & \frac{\partial Q_{B1}}{\partial P_{A2}} & \frac{\partial Q_{B1}}{\partial P_{A3}} & \frac{\partial Q_{B1}}{\partial P_{A4}} \\ \frac{\partial Q_{B2}}{\partial P_{A1}} & \frac{\partial Q_{B2}}{\partial P_{A2}} & \frac{\partial Q_{B2}}{\partial P_{A3}} & \frac{\partial Q_{B2}}{\partial P_{A4}} \\ \frac{\partial Q_{B3}}{\partial P_{A1}} & \frac{\partial Q_{B3}}{\partial P_{A2}} & \frac{\partial Q_{B3}}{\partial P_{A3}} & \frac{\partial Q_{B3}}{\partial P_{A4}} \\ \frac{\partial Q_{B4}}{\partial P_{A1}} & \frac{\partial Q_{B4}}{\partial P_{A2}} & \frac{\partial Q_{B4}}{\partial P_{A3}} & \frac{\partial Q_{B4}}{\partial P_{A4}} \end{bmatrix} = \begin{bmatrix} \beta_{BA}^{C_1} & \theta_{C_1,BA}^{C_1} w_{12} & \theta_{C_2,BA}^{C_1} w_{13} & \theta_{C_2,BA}^{C_1} w_{14} \\ \theta_{C_1,BA}^{C_1} w_{21} & \beta_{BA}^{C_1} & \theta_{C_2,BA}^{C_1} w_{23} & \theta_{C_2,BA}^{C_1} w_{24} \\ \theta_{C_1,BA}^{C_2} w_{31} & \theta_{C_1,BA}^{C_2} w_{32} & \beta_{BA}^{C_2} & \theta_{C_2,BA}^{C_2} w_{34} \\ \theta_{C_1,BA}^{C_2} w_{41} & \theta_{C_1,BA}^{C_2} w_{42} & \theta_{C_2,BA}^{C_2} w_{43} & \beta_{BA}^{C_2} \end{bmatrix}$$

$$\frac{\partial Q_B}{\partial P_B} = \begin{bmatrix} \frac{\partial Q_{B1}}{\partial P_{B1}} & \frac{\partial Q_{B1}}{\partial P_{B2}} & \frac{\partial Q_{B1}}{\partial P_{B3}} & \frac{\partial Q_{B1}}{\partial P_{B4}} \\ \frac{\partial Q_{B2}}{\partial P_{B1}} & \frac{\partial Q_{B2}}{\partial P_{B2}} & \frac{\partial Q_{B2}}{\partial P_{B3}} & \frac{\partial Q_{B2}}{\partial P_{B4}} \\ \frac{\partial Q_{B3}}{\partial P_{B1}} & \frac{\partial Q_{B3}}{\partial P_{B2}} & \frac{\partial Q_{B3}}{\partial P_{B3}} & \frac{\partial Q_{B3}}{\partial P_{B4}} \\ \frac{\partial Q_{B4}}{\partial P_{B1}} & \frac{\partial Q_{B4}}{\partial P_{B2}} & \frac{\partial Q_{B4}}{\partial P_{B3}} & \frac{\partial Q_{B4}}{\partial P_{B4}} \end{bmatrix} = \begin{bmatrix} \beta_{BB}^{C_1} & \theta_{C_1,BB}^{C_1} w_{12} & \theta_{C_2,BB}^{C_1} w_{13} & \theta_{C_2,BB}^{C_1} w_{14} \\ \theta_{C_1,BB}^{C_1} w_{21} & \beta_{BB}^{C_1} & \theta_{C_2,BB}^{C_1} w_{23} & \theta_{C_2,BB}^{C_1} w_{24} \\ \theta_{C_1,BB}^{C_2} w_{31} & \theta_{C_1,BB}^{C_2} w_{32} & \beta_{BB}^{C_2} & \theta_{C_2,BB}^{C_2} w_{34} \\ \theta_{C_1,BB}^{C_2} w_{41} & \theta_{C_1,BB}^{C_2} w_{42} & \theta_{C_2,BB}^{C_2} w_{43} & \beta_{BB}^{C_2} \end{bmatrix}$$

From the above matrices, it is obvious that the model parameters are able to capture the effect of price change in one store on the demand in other spatially connected stores. The diagonal elements of the partial derivative matrices represent the effect of price change on own sales in the same store and can be termed as direct effects. All the non-diagonal row elements are caused due to price changes in adjoining stores and are termed as indirect effects or spatial spillover effects.

Table 1.1: Direct and spatial price elasticity estimates for Outlet 1

Outlet 1	Direct effect	Spatial spillover effect
$\frac{\partial Q_A}{\partial P_A}$	$\beta_{AA}^{C_1}$	$\theta_{C_1,AA}^{C_1}w_{12} + \theta_{C_2,AA}^{C_1}w_{13} + \theta_{C_2,AA}^{C_1}w_{14}$
$\frac{\partial Q_A}{\partial P_B}$	$\beta_{AB}^{C_1}$	$\theta_{C_1,AB}^{C_1}w_{12} + \theta_{C_2,AB}^{C_1}w_{13} + \theta_{C_2,AB}^{C_1}w_{14}$
$\frac{\partial Q_B}{\partial P_A}$	$\beta_{BA}^{C_1}$	$\theta_{C_1,BA}^{C_1}w_{12} + \theta_{C_2,BA}^{C_1}w_{13} + \theta_{C_2,BA}^{C_1}w_{14}$
$\frac{\partial Q_B}{\partial P_B}$	$\beta_{BB}^{C_1}$	$\theta_{C_1,BB}^{C_1}w_{12} + \theta_{C_2,BB}^{C_1}w_{13} + \theta_{C_2,BB}^{C_1}w_{14}$

The direct and spatial elasticity matrices are therefore:

$$\epsilon_1|_{direct} = \begin{bmatrix} \beta_{AA}^{C_1} & \beta_{AB}^{C_1} \\ \beta_{BA}^{C_1} & \beta_{BB}^{C_1} \end{bmatrix},$$

$$\epsilon_1|_{spatial} = \begin{bmatrix} \theta_{C_1,AA}^{C_1}w_{12} + \theta_{C_2,AA}^{C_1}w_{13} + \theta_{C_2,AA}^{C_1}w_{14} & \theta_{C_1,AB}^{C_1}w_{12} + \theta_{C_2,AB}^{C_1}w_{13} + \theta_{C_2,AB}^{C_1}w_{14} \\ \theta_{C_1,BA}^{C_1}w_{12} + \theta_{C_2,BA}^{C_1}w_{13} + \theta_{C_2,BA}^{C_1}w_{14} & \theta_{C_1,BB}^{C_1}w_{12} + \theta_{C_2,BB}^{C_1}w_{13} + \theta_{C_2,BB}^{C_1}w_{14} \end{bmatrix}$$

Similarly, ϵ_2, ϵ_3 and ϵ_4 can be calculated for the other 3 outlets.

1.4.2 Channel-wise price elasticity estimates with spatial spillover

The direct effects represented by diagonal elements in the above matrix are equal whereas indirect effects vary due to different spatial weights ‘w’. The price elasticity matrices for Brand A and Brand B for respective channel in the presence of spatial inter-dependence or store substitution effect are listed in Table 1.2 below.

Table 1.2: Channel-wise price elasticity estimates with spatial spillover

Type of effect	Channel type of connected outlets	Channel type of focal outlet	
		Channel 1	Channel 2
Direct effect – own store own and cross price elasticities	NA	$\begin{bmatrix} \beta_{AA}^{C_1} & \beta_{AB}^{C_1} \\ \beta_{BA}^{C_1} & \beta_{BB}^{C_1} \end{bmatrix}$	$\begin{bmatrix} \beta_{AA}^{C_2} & \beta_{AB}^{C_2} \\ \beta_{BA}^{C_2} & \beta_{BB}^{C_2} \end{bmatrix}$
Indirect effect – spatial spillover effect due to a change in own brand price in all connected outlets	Channel 1	$\begin{bmatrix} \theta_{C_1,AA}^{C_1} & \theta_{C_1,AB}^{C_1} \\ \theta_{C_1,BA}^{C_1} & \theta_{C_1,BB}^{C_1} \end{bmatrix}$	$\begin{bmatrix} \theta_{C_1,AA}^{C_2} & \theta_{C_1,AB}^{C_2} \\ \theta_{C_1,BA}^{C_2} & \theta_{C_1,BB}^{C_2} \end{bmatrix}$
	Channel 2	$\begin{bmatrix} \theta_{C_2,AA}^{C_1} & \theta_{C_2,AB}^{C_1} \\ \theta_{C_2,BA}^{C_1} & \theta_{C_2,BB}^{C_1} \end{bmatrix}$	$\begin{bmatrix} \theta_{C_2,AA}^{C_2} & \theta_{C_2,AB}^{C_2} \\ \theta_{C_2,BA}^{C_2} & \theta_{C_2,BB}^{C_2} \end{bmatrix}$

1.5. Reconciling market-level and store-level demand function parameters

It is useful to examine how the market level demand function parameters are connected to the store level demand function parameters. Consider the aggregate model (market-level aggregate data) for Brand A and B

$$Q_A = \delta_A + \alpha_{AA}P_A + \alpha_{AB}P_B \quad \text{.....(1.9)}$$

$$Q_B = \delta_B + \alpha_{BA}P_A + \alpha_{BB}P_B \quad \text{.....(1.10)}$$

where $P_A = f(P_{A1}, P_{A2}, \dots, P_{AN})$ and $P_B = f(P_{B1}, P_{B2}, \dots, P_{BN})$. Typically, $f(\cdot)$ is a weighted average of the prices.

On the other hand, the store level demand functions for Brand A and B are:

$$Q_{Ai} = \mu_A + \beta_{AA}P_{Ai} + \beta_{AB}P_{Bi} + \theta_{AA}W_{-i}P_{A(-i)} + \theta_{AB}W_{-i}P_{B(-i)} \quad \text{.....(1.11)}$$

$$Q_{Bi} = \mu_B + \beta_{BA}P_{Ai} + \beta_{BB}P_{Bi} + \theta_{BA}W_{-i}P_{A(-i)} + \theta_{BB}W_{-i}P_{B(-i)} \quad \text{.....(1.12)}$$

($i=1, 2, 3 \dots N$ where N =total number of outlets)

Adding up the outlet-level demand equations over all outlets gives:

$$\begin{aligned} \sum_{i=1}^N Q_{Ai} &= N\mu_A + \beta_{AA}(P_{A1} + P_{A2} + \dots P_{AN}) + \beta_{AB}(P_{B1} + P_{B2} + \dots P_{BN}) + \theta_{AA} \left(\sum_{i=1}^N W_{-i} P_{A(-i)} \right) \cdot \mathbf{1} \\ &\quad + \theta_{AB} \left(\sum_{i=1}^N W_{-i} P_{B(-i)} \right) \cdot \mathbf{1} \end{aligned} \quad \dots \dots (1.13)$$

$$\begin{aligned} \sum_{i=1}^N Q_{Bi} &= N\mu_B + \beta_{BA}(P_{A1} + P_{A2} + \dots P_{AN}) + \beta_{BB}(P_{B1} + P_{B2} + \dots P_{BN}) \\ &\quad + \theta_{BA} \left(\sum_{i=1}^N W_{-i} P_{A(-i)} \right) \cdot \mathbf{1} + \theta_{BB} \left(\sum_{i=1}^N W_{-i} P_{B(-i)} \right) \cdot \mathbf{1} \end{aligned} \quad \dots \dots (1.14)$$

Here, $(\sum_{i=1}^N W_{-i} P_{A(-i)}) \cdot \mathbf{1}$ is the dot product of $(\sum_{i=1}^N W_{-i} P_{A(-i)})$ and an $N \times 1$ vector of ones ($\mathbf{1}$). Comparing the parameters in Equations (1.9) and (1.13) gives:

$$\delta_A = N\mu_A$$

$$\alpha_{AA} f(P_{A1}, P_{A2}, \dots, P_{AN}) = \beta_{AA}(P_{A1} + P_{A2} + \dots P_{AN}) + \theta_{AA}(\sum_{i=1}^N W_{-i} P_{A(-i)}) \cdot \mathbf{1}$$

$$\alpha_{AB} f(P_{B1}, P_{B2}, \dots, P_{BN}) = \beta_{AB}(P_{B1} + P_{B2} + \dots P_{BN}) + \theta_{AB}(\sum_{i=1}^N W_{-i} P_{B(-i)}) \cdot \mathbf{1}$$

Similarly for Brand B, comparing Equations (1.10) and (1.14) gives:

$$\delta_B = N\mu_B$$

$$\alpha_{BA} f(P_{A1}, P_{A2}, \dots, P_{AN}) = \beta_{BA}(P_{A1} + P_{A2} + \dots P_{AN}) + \theta_{BA}(\sum_{i=1}^N W_{-i} P_{A(-i)}) \cdot \mathbf{1}$$

$$\alpha_{BB} f(P_{B1}, P_{B2}, \dots, P_{BN}) = \beta_{BB}(P_{B1} + P_{B2} + \dots P_{BN}) + \theta_{BB}(\sum_{i=1}^N W_{-i} P_{B(-i)}) \cdot \mathbf{1}$$

Based on above equations, we obtain price elasticity estimates as:-

$$\text{From Equations (1.9) and (1.10), } \frac{\partial Q_A}{\partial P_A} = \alpha_{AA} \text{ and } \frac{\partial Q_B}{\partial P_B} = \alpha_{BB}$$

$$\text{From Equations (1.11) and (1.12), } \frac{\partial Q_{Ai}}{\partial P_{Ai}} = \beta_{AA} + \theta_{AA} W_{-i} \text{ and } \frac{\partial Q_{Bi}}{\partial P_{Bi}} = \beta_{BB} + \theta_{BB} W_{-i}$$

It is evident from the above, that the outlet-level elasticity for any brand is likely to vary across stores and is likely to be different from the aggregate elasticity. Only under the assumptions that, (a) the outlets are independent from each other, and (b) all outlets have the same elasticity, we get $\frac{\partial Q_A}{\partial P_A} = \frac{\partial Q_{Ai}}{\partial P_{Ai}}$. Otherwise, typically we expect $\frac{\partial Q_A}{\partial P_A} \neq \frac{\partial Q_{Ai}}{\partial P_{Ai}}$.

1.6. Managerial implications

For brand managers, as per the above analysis, price elasticities have a spatial component. This means that each channel will respond differently to a 1% increase in the brand's price. There will be both intra- and inter-channel spillover of demand. Any change in demand in the convenience channel will be the sum total of own-brand price elasticity and spatial spillover from/to connected convenience stores and supermarkets. Similarly, any change in demand in the supermarket channel will be the combined effect of own-brand price elasticity and spatial spillover from/to connected supermarkets and convenience stores. The inclusion of spatial interdependence corrects own-brand and cross-brand price elasticity estimates. It makes the demand for the brand less elastic to own-brand price changes. Hence, managers can either spend less on promotion, thereby freeing up money for alternative media to boost sales, or increase the price with a lesser impact on demand.

The above price elasticity estimates also imply that if the store manager optimizes on the basis of aggregate price-elasticity estimates $\left(\frac{\partial Q_A}{\partial P_A}, \frac{\partial Q_A}{\partial P_B}\right)$, all the store managers will make the same decision, thereby reducing the effectiveness of the outcome. With store-level demand estimates $\left(\frac{\partial Q_{Ai}}{\partial P_{Ai}}, \frac{\partial Q_{Ai}}{\partial P_{Bi}}\right)$ and the inclusion of spatial interdependence, each store manager has access to information at a more granular level. For example, a convenience store manager can now evaluate the impact of a price change in connected convenience stores and supermarkets on its demand store-wise. The same is true for a

supermarket store manager. This helps the store managers filter out stores that are key shifters of demand and watch their actions more closely for timely reactions.

1.7. Summary and discussion

The extant literature on spatial interaction in marketing has considered strategic interaction among firms and impacts on certain marketing-mix elements such as product assortment (Horsky and Nelson, 1992; Draganska et al., 2009), pricing strategy (Greenhut and Greenhut, 1975; Ellickson and Misra, 2008; Singh and Zhu, 2008), entry and location choice (Zhu and Singh, 2009; Zhu et al., 2011; Orhun 2013) and location choice under zoning constraints (Datta and Sudhir, 2013). Yet another stream of marketing literature within the retailing area uses gravitation models to investigate consumer store choice (Converse, 1949; Reilly, 1953; Huff, 1962). The Huff model states that the probability of any shopper choosing a particular retail center depends on the attractiveness of that center as defined by its size and distance from the consumer as compared to other centers. The literature has largely ignored the potential effect of inter-store distances on store substitution. However, in densely populated cities or townships, where the stores are often located in close proximity to each other, consumers have the option to not only choose alternative brands within a store but also across stores.

Whether such cross-store substitution occurs and the extent of such a substitution are the primary empirical questions discussed in the subsequent chapters. Prior to delving into the empirical analysis, it is useful to discuss the various types of elasticities, particularly the elasticity of substitution across stores and its relationship to physical distance, which could be examined using a linear demand system. In this chapter, I consider these issues. The discussions in this chapter highlight three important points. First, I illustrate that a linear demand system can be easily extended to incorporate the potential physical distance effects in the model. Second, I elaborate on how the parameters of the linear model can allow

us to examine direct and spatial spillover effects due to potential cross-store substitution. Third, it is improbable that the aggregate-level elasticities would be useful for store-level optimal pricing or discounting decisions.

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Chapter 2

A spatial econometric analysis of price competition in the carbonated soft drinks category among geographically connected retailers

2.1. Introduction

Keng and Ehrenberg (1984) showed that consumer cross-shopping within a market is high. The purchase of products in one store, perhaps as the result of price promotions, may lead to a decrease in sales of similar products in another store. Cunningham (1961) noted long ago that consumers' store loyalty was often not exclusive or undivided. Most buyers of a product at a particular chain or store group buy it there relatively infrequently. They often also buy the product elsewhere. The fact that promotions on specific brands can generate cross-store competitive effects raises an interesting issue. Do significant numbers of consumers alter their shopping plans simply to take advantage of price reductions offered on a specific brand? If not, what might account for brand-specific, cross-store competitive effects?

While there is some research in the marketing literature on store-level demand estimation (e.g., Kumar and Leone, 1988), an important aspect that has been ignored is the interdependence among geographically connected stores due to potential cross-store substitution. This research examines store-level demand system estimation for differentiated goods when, in a geographical area, the stores cannot be assumed to be independent of each other. The ability to estimate the demand at the store level should, in principle, give greater flexibility to the store managers in terms of optimizing the marketing mix. Insofar as there is a need to generate consistent estimates of the demand system parameters at the store level, the assumption that observations are independently distributed has severe implications. Potential cross-store substitution necessarily leads to endogeneity bias, which must be carefully dealt with for statistical inference. In this chapter, I discuss how a widely used time series model for the demand system estimation of differentiated goods can be extended to allow for cross-store dependence.

Two broad types of empirical models have been used in the marketing literature for demand system estimation for differentiated goods. One type of model is based on the random coefficient logit model proposed by Berry et al. (1995); the demand for any brand is considered to be a function of its own price and characteristics. The other type of model is the application of vector auto-regression models for time-series data (Dekimpe and Hanssens, 1995; Dekimpe and Hanssens, 1999; Pauwels et al., 2004). In such models, the demand for any brand is modeled as a function of the prices of all other brands and own-brand characteristics.

Researchers typically use retail-level scanner panel data to estimate various types of elasticities of demand in order to examine hypotheses related to the demand functions. While retail scanner panel data are the main type of data used for such purposes, researchers typically aggregate the observations to a market level and then assume that the markets in the data are independent. In this research, I also use scanner panel data but, instead of aggregating the store-level observations to the market level, I examine how demand functions at the store level can be estimated if the stores are assumed to not be independent of each other.

Kumar and Leone (1988) examine the phenomenon of store substitution for the disposable diaper category when retailers offer promotions. Other papers using store-level data to examine demand include Fok et al. (2006), Nijs et al. (2001), and Horvath and Fok (2013). However, in their estimation, the observations are assumed to be independent. Conventional wisdom in retailing argues that consumers frequently switch stores to take advantage of promotions. Consumers are opportunistic, leading to low store loyalty behavior as a result of frequent price promotions (Keng and Ehrenberg, 1984). This explains a retailer's emphasis on price promotions, including loss leaders to maintain or build store traffic (Walters and MacKenzie, 1988).

In this chapter, I conduct an empirical examination of the spatial price competition effects in the carbonated soft drinks category in Singapore. Multiple stores are located within walking distance of each other. A suitable empirical framework must take into account the spatial connectedness among these retailers. For this purpose, we obtain geo-location coordinates of the retail stores and examine the following: (a) whether there is any cross-store substitution with changes in price, and (b) how this substitution propagates with inter-store physical distance. To our knowledge, this is the first study that incorporates inter-store physical distance in the demand system estimation for differentiated goods.

This study makes two key contributions. First, I show how a linear system of equations model can be extended to incorporate spatial distances among stores in order to estimate store-level demand. My model addresses the endogeneity bias that arises from spatial dependence. Second, I find evidence of a few substantive results regarding spatial effects in the cola-flavored carbonated soft drinks category. Specifically, my study shows that the spatial spillover effect for own-brand is significant and positive. This indicates that a price increase in a store leads some consumers to switch stores to purchase the same brand. I also examine whether this spatial spillover effect differs by channel (supermarkets and convenience stores). The results indicate that intra- and inter-channel store substitution effects are asymmetric and depend on the brand's relative market share.

The chapter is structured as follows. In section 2.2, I discuss the papers in the extant literature; in section 2.3, I discuss the empirical model that includes both temporal and spatial responses to price changes along with the necessary identification restrictions; in section 2.4, I describe the data and report summary statistics; in section 2.5, I discuss the results using the spatio-temporal model; in section 2.6, I discuss the managerial implications of the findings; and in section 2.7, I conclude.

2.2. Literature review

Many researchers have applied time series models to empirically examine the demand for differentiated goods. In Table 2.1, I list a number of papers in this area. There is extensive literature on the dynamic effects of price promotions on demand (Paap and Franses, 2000; Van Heerde, Leeflang, and Wittink, 2000). Promotions represent a significant proportion of a marketing budget. In many industries, more money is spent on promotions than on advertising, as promotions have proven to be more effective for customer acquisition, generating incremental traffic and inducing product trials. The literature has found that sales promotions lead to significant sales spikes (Woodside and Waddle, 1975; Moriarty, 1985; Blattberg and Wisniewski, 1989). This finding is fundamental to virtually all research done in this field.

Mace and Neslin (2004) examined pre- and post-promotion dip. Lim, Currim, and Andrews (2005) studied the period of adjustment of price promotions due to stockpiling. Pauwels et al. (2002) applied a VARX model to examine store-level demand, assuming the stores to be independent. Other papers using store-level data to examine demand include those by Fok et al. (2006) and Nijs et al. (2001). In their study, Fok et al. (2006) captured the immediate and dynamic effects for multiple brands and categories. Nijs et al. (2001) explained short- and long-run category-level, price-promotion elasticities with promotion frequency and depth, competitive reactivity, and other covariates.

Studies have investigated differences in consumer responses to promotions by product, category, market, and type of consumer. One of the explanations that the literature offers for an asymmetric consumer response to sales promotions is higher brand equity (Bolton, 1989; Vilcassim and Jain, 1991). Brand equity refers to the value of a product with a brand name in comparison to that product's value if it did not have a brand name (e.g., Aaker, 1991; Ailawadi, Lehmann, and Neslin, 2003; Keller, 2003). In general, consumers are purported to react differently to marketing-mix efforts for a branded product

in comparison to marketing efforts for an unbranded product yielding incremental volume, price premiums, and profit (Ailawadi, Lehmann, and Neslin, 2003; Slotegraaf, Moorman, and Inman, 2003). Slotegraaf and Pauwels (2008) empirically measured the degree of brand equity and found that it has a significant, positive effect on the extent to which a brand is affected by promotional efforts in the long run. Steenkamp et al. (2005) offered empirical confirmation that powerful brands have greater price promotion reaction elasticity.

Research comparing differences between national brands and private labels and asymmetric price effect supports the above findings. Price promotions offered for private labels typically yield a lower immediate category incidence elasticity than do those for national brands (Srinivasan et al., 2004). Price promotions on national brands offer better switching incentives than do those of private labels (Horvath and Fok, 2013). Promotion-based share gains for private labels are rather insignificant (Aggarwal and Cha, 1998; Blattberg and Neslin, 1989). Horvath et al. (2005) estimated brand-specific effects using a VARX model for pooled store data. They showed that the tuna category is much more dependent on competitive reactions and feedback effects than the shampoo category, in which distinct brand positioning limits the effect of competitive reactions.

As per Horváth and Fok (2013), higher-priced brands are believed to offer better quality. The authors estimated the cross-price promotional effects for brands in 33 product categories across five stores in the first stage, while in the second stage they related these cross-price elasticities to various brand, category, and store characteristics. Price promotion by a higher-priced brand affects the share of a lower-priced brand more so than the reverse (Allenby and Rossi, 1991; Blattberg and Wisniewski, 1989; Sethuraman et al., 1999). Blattberg and Wisniewski (1989) empirically demonstrated that when a high-priced (high-quality) brand promotes, consumers of a low-priced (low-quality) brand will upgrade, though the reverse is not true. The authors explained it in terms of a U-shaped heterogeneity distribution

in preferences for the higher-priced brand over the lower-priced brand. Sethuraman et al. (1999) meta-analyzed 1060 cross-price effects from 280 brands and found that the asymmetry holds with cross-price elasticities. These studies employed time-series methods that used aggregate data. None of these studies allowed for inter-store dependence. A possible reason for this could be that the stores in their dataset were located far apart, making inter-store substitution implausible.

However, there is evidence that consumer cross-shopping within a market is high (Keng and Ehrenberg, 1984). Kumar and Leone (1988) found that geographic proximity between stores dictates inter-store sales displacement between them triggered by retail promotions. This clearly indicates that price promotions in one store have the potential to decrease the sales of a similar product in another store due to the fact that consumers purchase more of that product from the promoting store (Walters Rockney, 1991). An empirical study by Gijsbrechts, Campo, and Nisol (2008) showed that consumers are opportunistic and switch between multiple stores to capitalize on fixed-cost and category complementarities even in the absence of specific price promotions. As such, the spatial distribution of retailers also affects the market response of marketing variables in addition to other factors (Bronnenberg and Mahajan, 2001). Ignoring the spatial dynamics may lead to under or overestimation of price elasticities and temporal effects, in turn leading to inefficient market decisions and suboptimal marketing resource allocation.

It might be useful to briefly describe the applications of spatial models that appear in the marketing literature. In Table 2.2, I list a few important papers examining spatial effects on marketing strategies. Researchers have examined location effect from the points of view of both consumer store choice and firm strategy choice. The consumer behavior for store selection has been found to be very similar to the consumer behavior for brand choice. Store choice is estimated as a two-stage process in which consumers first select a region or suburb and then select a store within that region. Store location plays

an important role in store choice specifically due to traveling cost (Brown, 1989; Craig, Ghosh, and Mc Lafferty, 1984; Huff, 1964). Consumers make tradeoffs when choosing a store. Baumol and Ide (1956) and Brown (1978) observed that shoppers may be willing to travel farther to stores offering more product assortments.

Chan, Ma, Narasimhan, and Singh (2004) investigated the drivers of consumers' store choice decisions using AC Nielsen scanner panel data from 642 Denver-area consumers in 37 product categories during a 119-week period spanning January 1993-April 1995. The results showed that the availability of private labels, larger product assortment, and distance to the store are important determinants of store choice. Bell and Lattin (1998) modeled households' store choice outcomes using an MNL model, with two types of explanatory variables at the store level: (i) expected basket attractiveness (i.e., composite attractiveness of a basket of product categories at the store) and (ii) geographic distance between the consumer and the store. The authors demonstrated that large basket shoppers preferred hyper-store formats, while small basket shoppers preferred small, traditional stores. All these studies employed individual-level data to reveal valuable information about the effects of location/distance on individual store choice behavior.

In firm strategy models, firms make strategic choices/decisions such as pricing (Ellickson and Misra, 2008), entry-exit decisions (Seim, 2006), location choices (Orhun, 2013), spatial competition (Cleeren et al., 2010; Zhu et al., 2011), and expansion decisions (Nishida, 2014) based on competitor action/reaction. These models follow the static/dynamic discrete games theoretical approach and use structural modeling techniques for estimation. Ellickson and Misra (2008) examined the choice of pricing strategies (EDLP vs. high and low vs. hybrid) by supermarkets (Walmart, K-Mart, and Target). Seim (2006) studied entry and store location in the video rental industry using nested logit to distinguish entry from location choice.

Orhun (2013) used the static discrete games approach to study the trade-offs that firms face when deciding whether to locate their stores closer to high-population-density areas. In the same issue, Datta and Sudhir (2013), removed one common unobservable from the above model by using data on spatial zoning restrictions, which is an important factor, as there are government regulations in many areas for strict residential and commercial zones. A study by Zhu et al. (2011) answered the question of what happens to incumbent multi-product retailers when they face an entry from a discount chain. The researchers showed that the distance between the location of the new entrant and the incumbent plays an important role. Cleeren et al. (2010) modeled inter- and intra-format competition between discounters and supermarkets in the German market. Jia (2008) studied the effect of the entry of Walmart on other stores in different markets in the U.S. and how the chain economies benefit retailers. On the other hand, Nishida (2014) studied the impact of the opening of multiple stores of the same chain in the vicinity, trade-off between store sales cannibalization and cost savings in logistics due to clustering.

Yet another stream of spatial regression models uses a set of explanatory variables and map locations to predict the dependent variable or outcome variable of choice. Examples of such models are Bronnenberg and Sismeiro (2002), Yang and Allenby (2003), Bell and Song (2007), Bronnenberg and Mahajan (2001), Bronnenberg et al. (2007), and Mittal et al. (2004). Bronnenberg and Mahajan (2001) used spatial dependence in promotional policies among retailers in contiguous market areas to deal with endogeneity or reverse causation problems between local market shares and promotion intensity. Bronnenberg et al. (2007) showed the existence of spatial variations in the market shares of so-called national brands depending on the order of entry into the market for a large number of product categories in U.S. markets. Using data from an Internet retailer called Netgrocer.com, Bell and Song (2007) demonstrated that when non-adopters socially interact with existing customers in spatially proximate

areas, the chances of adoption increase. Consumers of a service or product are dispersed geographically. Understanding the spatial variation in the preference weights that consumers assign to evaluate overall service quality and responsiveness to change in service quality can help managers efficiently plan quality improvement programs aimed at different consumer groups in space, as studied by Mittal et al. (2004).

Bronnenberg and Mela (2004) studied the roll-out distribution strategy for a new product. This paper used a descriptive model to study the spatio-temporal diffusion of two new brands launched in the frozen pizza category in the U.S. market. It understood the processes of spatial evolution, market selection, competitive contagion, and trade area coverage. Choi et al. (2010) studied the spatio-temporal diffusion of an online grocery retailer using both spatial proximity in physical space and demographic similarity between prior and potential adopters to explain market penetration. Similar to the above study, Katona et al. (2011) explained the diffusion process in an online social platform using the similarity between characteristics of existing adopters and potential adopters as a powerful indicator of the likelihood of becoming a member.

Du and Kamakura (2011), showed that even for low-involvement consumer packaged goods, the rate of adoption is influenced by the number of consumers who have already adopted the product. All the above studies either use spatial dependence to infer co-dependent consumer preferences and, hence, choice decisions or use spatial competition to assess the strategic impact of firms' own decisions and competitor actions on profitability, sales, location choices, or entry/exit in a game-theoretic set-up. None of these studies examines the market response models (price elasticities) in the presence of spatial interdependence between store locations. This is the first study to examine the effect of spatial interconnectedness among stores on own-brand elasticity estimates using actual distances between stores as spatial weights.

Extending the Fok et al. (2006) model, I estimate the own-brand price elasticity with spatial store inter-dependence. The spatial inter-dependence makes it interesting to study the spatial dynamics of the sales response and to estimate the direct and indirect own-brand effects of price movements. In this study, I investigate how the elasticity estimates propagate in a dynamic and spatial context jointly. The innovation in my research is that I investigate both dynamic and spatial effects by allowing the stores to be spatially correlated. This consists of studying how a change in the price of a brand in one store affects own- and cross-brand demand across stores within the same and different channels.

Table 2.1: Selected papers applying time series models for demand estimation

Author	Year	Journal	Key question examined	Empirical model	Data type	Remark	Temporal dependence	Spatial dependence
Van Heerde Leeflang and Wittink	2000	JMR	The authors propose models that account for factors that cause pre and post-promotion dips	Three alternative distributed lead and lag structures	Store-level scanner data for tuna and toilet tissue	Estimated dip between 4 and 25% of the current sales effect	yes	no
Pauwels et al.	2002	JMR	Long-term effect of price promotions on brand sales	VEC and VAR model	HH scanner panel data for canned soup and yogurt category	Permanent promotion effects are virtually absent for each sales component	yes	no
Mace and Neslin	2004	JMR	Empirically study the relationship between pre- and postpromotion dips	Promotion lags and leads in a regression model	Weekly store data for ten product categories in 83 stores	The 24 characteristics explain significant variation in the elasticities	yes	no
Lim Currim and Andrews	2005	IJRM	Usage rates and customer loyalty effect on adjustment period, permanent, and total effects of price promotions	VARX model	Scanner data on yogurt, margarine, paper towels, and detergent categories	Find substantial differences between consumer segments	yes	no
Horvath et al.	2005	IJRM	Apply a model that accommodates dynamic effect in demand and reaction functions.	Fixed effects VARX model	104 weeks data for 28 stores for tuna fish and shampoo category	Cross-brand feedback effect is greater than traditional competitive reaction effects	yes	no
Fok et al.	2006	JMR	Sales response model to explain the differences in immediate and dynamic effects of price on sales	VECM	7 years weekly sales data of 100 brands and 25 categories	Immediate effect is zero but long-term effect of a regular price change is not zero	yes	no
Horvath and Fok	2013	Mktg Sci	Studies relative importance of moderating factors across three different scenarios	HB-VEC-VARX model	5 years sales data on brands in 33 categories in 5 stores	Competitive reactions accumulate rather than diminish cross-price elasticities.	yes	no
Current study	2019						yes	yes

Table 2.2: Selected papers examining spatial effect on firm strategies

Author	Year	Journal	Key question examined	Empirical model	Data type	Remark	Temporal dependen	Spatial matrix
Bronnenberg and Sismeiro	2002	JMR	Using multimarket data to make brand performance predictions for markets for which no data exists	Hierarchical Bayes model	Data for 3000 stores in 64 US mkts + trade dimension data + location zip codes for all IRI mkts + census data	More efficient estimates of the price elasticities are obtained if spatial dependence is taken into account	yes	At market level
Bronnenberg and Mela	2004	Mktg Sci	A descriptive model of the spatial and temporal evolution of retail distribution for new packaged goods.	Conditional discrete time hazard model	Store level sales data for frozen Pizza category for a national sample of 1900 supermarkets	Neighboring markets are more likely entered. Retailers adopt more likely if other retailers in that area adopt.	yes	Neighbor contiguity matrix
Bell and Song	2007	QME	Examines customer trials at Netgrocer.com	Discrete time hazard model	Data spans 29701 residential zip codes, 45 months and zip code contiguity relationships	NA	yes	Zip-code contiguity matrix
Choi et al.	2010	JMR	Analyzing space– time diffusion process as a function of both proximity and similarity	Bayesian spatio-temporal model	New buyers at Netgrocer. com over 45 months and spanning 1459 zip codes	Proximity effect is strong in the early phases of demand evolution	yes	Zip-code contiguity and demographic similarity
Du and Kamakura	2011	JMR	Measures the degree of contagion in the diffusion of new consumer packaged goods (CPGs).	Discrete-time proportional hazard model	Data for 5912 households and 67 new CPGs across a 124-week observation window	Find statistically significant contagion effects	yes	Nearest neighbor
Ellickson and Misra	2008	Mktg Sci	This paper analyzes pricing strategies of Supermarkets as a discrete game	Simultaneous discrete choice models	Trade Dimension's 1998 Supermarket data combined with US census data	Firms cluster by strategy rather than isolating themselves in product space	no	K-means clustering
Cleeren et al	2010	Mktg Sci	Study the degree of intra- and interformat competition between discounters and supermarkets	“multiple-agent qualitative-response” models	Addresses of all supermarkets and discounters in Germany	Competition between supermarkets is found to be more severe than within the discounter channel	no	Town or market level
Zhu et al	2011	QME	Analyzes competition between two spatially differentiated multiproduct retailers	Game-theory models	Grocery stores sales data	The store closer to the entrant is better off compared to the incumbent located further away	no	NA
Datta and Sudhir	2013	QME	Investigates the impact of spatial zoning restrictions on location	Static, simultaneous move game model with incomplete information	Set of 100 markets in US	Zoning reduces entry	no	NA
Nishida	2014	Mktg Sci	Investigates the trade-off between business stealing vs cost saving from clustering own stores	Static entry game of complete information with post-entry outcome data	Convenience store industry on the island of Okinawa in Japan	Evidence of retailer's trade-off is positive across markets and negative within a market	no	NA
Current study	2019						yes	Euclidean distances among stores

2.3. Empirical model

As evident from literature, customers are opportunistic and switch between stores to capitalize on promotions. Ignoring the spatial dynamics may lead to under or overestimation of price elasticities thereby leading to inefficient market decisions and suboptimal marketing resource allocation. In order to develop a linear systems of equations model with spatial dependence for demand estimation, I borrow heavily from the spatial econometrics literature. Anselin (1988), Anselin and Florax (1995) and Fischer and Getis (1997) are some of the earlier studies that deal with space-time data. Most of the earlier studies consider only spatial cross-section analysis. Few studies that consider spatio-temporal models (Bronars and Jansen, 1987; Pace et al., 2000) take a very restrictive approach to spatial representation of the agents or entities involved. A regressand lagged either in time and space appears in earlier textbooks on spatial econometrics but both time and space lags are not taken together in estimation. I develop a linear system of equations model by putting restrictions on the VARX model and include spatial interdependence among outlets in the model.

2.3.1 Spatial linear system of equations model for demand estimation

Consider a demand system model for two brands A and B. A VARX model for sales volume for these two brands, with price as the exogenous variable can be written as:

$$\begin{bmatrix} 1 & \rho_{AB} \\ \rho_{BA} & 1 \end{bmatrix} \begin{bmatrix} Q_{At} \\ Q_{Bt} \end{bmatrix} = \begin{bmatrix} \mu_A \\ \mu_B \end{bmatrix} + \begin{bmatrix} \delta_{AA} & \delta_{AB} \\ \delta_{BA} & \delta_{BB} \end{bmatrix} \begin{bmatrix} Q_{A,t-1} \\ Q_{B,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{AA} & \beta_{AB} \\ \beta_{BA} & \beta_{BB} \end{bmatrix} \begin{bmatrix} P_{At} \\ P_{Bt} \end{bmatrix} + \begin{bmatrix} \gamma_{AA} & \gamma_{AB} \\ \gamma_{BA} & \gamma_{BB} \end{bmatrix} \begin{bmatrix} P_{A,t-1} \\ P_{B,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{At} \\ \epsilon_{Bt} \end{bmatrix} \dots\dots(2.1)$$

Q_{At} and Q_{Bt} are sales volume of brands A and B at time t , P_{At} and P_{Bt} are net price per litre of brand A and B at time t . This is a general VARX model, which allows Q_{At} and Q_{Bt} to affect each other. I impose the restriction $\rho_{AB} = \rho_{BA} = 0$. This restriction is plausible under the assumption that a consumer considers price and other characteristics to make a purchase decision. Therefore,

the quantities are affected due to any change in price or any other characteristics. A direct effect of the quantity of a competing brand is actually not quite interpretable. By putting these restrictions, (2.1) reduces to a linear system of equations similar to the one discussed in Chapter 1, difference being that since it is panel data, we have lagged price and quantity.

$$\begin{bmatrix} Q_{At} \\ Q_{Bt} \end{bmatrix} = \begin{bmatrix} \mu_A \\ \mu_B \end{bmatrix} + \begin{bmatrix} \delta_{AA} & \delta_{AB} \\ \delta_{BA} & \delta_{BB} \end{bmatrix} \begin{bmatrix} Q_{A,t-1} \\ Q_{B,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{AA} & \beta_{AB} \\ \beta_{BA} & \beta_{BB} \end{bmatrix} \begin{bmatrix} P_{At} \\ P_{Bt} \end{bmatrix} + \begin{bmatrix} \gamma_{AA} & \gamma_{AB} \\ \gamma_{BA} & \gamma_{BB} \end{bmatrix} \begin{bmatrix} P_{A,t-1} \\ P_{B,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{At} \\ \epsilon_{Bt} \end{bmatrix} \quad (2.2)$$

From (2.2), it follows that the effect of change in price of brand A on sales of brand A is given by

$\frac{\partial Q_{At}}{\partial P_{At}} = \beta_{AA}$. If Q and P are log-transformed, then β_{AA} reflects the own price-elasticity of demand.

Similarly, β_{BB} is the own price elasticity for brand B. And, β_{AB} and β_{BA} are cross price elasticities.

With data on multiple markets the above model is estimable using standard procedures.

Suppose there are data on N stores from a city, where consumers can choose to buy from any store. Allowing for cross-store substitution means that the consumers take into account the prices in the nearby stores before making a purchase decision. Extant research on interstore sales displacement (Kumar and Leone, 1988) follow similar logic for empirical formulization and their framework incorporates spatial price in the reduced form model as below:

$$Sales_i(AP) = b_0 + b_1 \Pr_t(AP) + b_2 \Pr_t(AS) + b_3 \Pr_t(CP) + b_4 \Pr_t(CS) + b_5 [F_t(AP) - F_t(AS)] + b_6 [D_t(AP) - D_t(AS)],$$

where $i = \text{store pair}$, $t = \text{time}$, $P = \text{primary (focal store)}$, $S = \text{secondary (competing store)}$, $\{A, B, C\} = \text{brands within the category}$, $\Pr = \text{price}$, $F = \text{feature}$, and $D = \text{Display}$

Walters (1991) proposes empirical framework for inter-store demand dependence as below:

$$Sales(BC) = a_0 + a_1 BC + a_2 PL + a_3 DH + a_4 FBC + a_5 FPL + a_6 KBC + a_7 KPL + a_8 KDH + a_9 KFBC + a_{10} KFPL,$$

$BC, PL, DH = \text{Price of Betty Crocker, Pillsbury and Duncan Hines cake mix in focal store}$,

$FBC, FPL = \text{Price of Betty Crocker and Pillsbury cake frosting respectively in the focal store}$,

$KBC, KPL, KDH = \text{Price of the three cake mix brands in competing store, and}$

KFBC, KFPL= Price of Betty Crocker and Pillsbury cake frosting in competing store

It is also plausible that the consumers consider the inter-store physical distances if they consider cross-store substitution. The longer the distance to an alternative store, lesser should be the chances of cross-store substitution. I propose the following extension of the model in (2.2) which takes such cross-store substitution into account. As is standard in literature, the equations in (2.3) are counterpart of linear demand system of equations put forth in Chapter 1 except that the below model has lagged quantity and price as well.

$$\begin{bmatrix} Q_{At} \\ Q_{Bt} \end{bmatrix} = \begin{bmatrix} \mu_A \\ \mu_B \end{bmatrix} + \begin{bmatrix} \delta_{AA} & \delta_{AB} \\ \delta_{BA} & \delta_{BB} \end{bmatrix} \begin{bmatrix} Q_{A,t-1} \\ Q_{B,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{AA} & \beta_{AB} \\ \beta_{BA} & \beta_{BB} \end{bmatrix} \begin{bmatrix} P_{At} \\ P_{Bt} \end{bmatrix} + \begin{bmatrix} \gamma_{AA} & \gamma_{AB} \\ \gamma_{BA} & \gamma_{BB} \end{bmatrix} \begin{bmatrix} P_{A,t-1} \\ P_{B,t-1} \end{bmatrix} + \begin{bmatrix} \theta_{AA} & \theta_{AB} \\ \theta_{BA} & \theta_{BB} \end{bmatrix} \begin{bmatrix} W P_{At} \\ W P_{Bt} \end{bmatrix} + \begin{bmatrix} \epsilon_{At} \\ \epsilon_{Bt} \end{bmatrix} \quad \dots(2.3)$$

In the above model, $\mathbf{Q}$, $\mathbf{P}$ are $N \times 1$ vectors, since there are N stores. $\mathbf{W}$ is an $N \times N$ zero diagonal graph matrix, with the element in the i -th row and j -th column w_{ij} being the weight of influence of store j on store i . The stronger the influence, greater the potential for substitution from store i to store j , due to any price increase in store i .

Before I discuss more on the $\mathbf{W}$ matrix, it is important to note that the model in (2.3) assumes homogeneity of inter-store substitution across all channels. In our dataset there are two channels – convenience stores and supermarkets. The prices vary significantly across these two channels. Also, the dominant stock keeping units (SKU) sold through the two channels are different. It is prudent to allow the inter-store substitution rate to differ by channel. Therefore, we extend the model in (2.3) to allow the substitution rate to vary by channel. So far I used 2 brands, which led to the system having 2 equations. Now with 2 channels and 2 brands, we have 2 systems and 4 equations as follows:

$$\begin{bmatrix} \mathbf{Q}_{At}^c \\ \mathbf{Q}_{Bt}^c \end{bmatrix} = \begin{bmatrix} \mu_A^c \\ \mu_B^c \end{bmatrix} + \begin{bmatrix} \delta_{AA}^c & \delta_{AB}^c \\ \delta_{BA}^c & \delta_{BB}^c \end{bmatrix} \begin{bmatrix} \mathbf{Q}_{A,t-1}^c \\ \mathbf{Q}_{B,t-1}^c \end{bmatrix} + \begin{bmatrix} \beta_{AA}^c & \beta_{AB}^c \\ \beta_{BA}^c & \beta_{BB}^c \end{bmatrix} \begin{bmatrix} \mathbf{P}_{At}^c \\ \mathbf{P}_{Bt}^c \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^c & \gamma_{AB}^c \\ \gamma_{BA}^c & \gamma_{BB}^c \end{bmatrix} \begin{bmatrix} \mathbf{P}_{A,t-1}^c \\ \mathbf{P}_{B,t-1}^c \end{bmatrix} + \\ \begin{bmatrix} \theta_{AA}^{cc} & \theta_{AB}^{cc} \\ \theta_{BA}^{cc} & \theta_{BB}^{cc} \end{bmatrix} \begin{bmatrix} \mathbf{W}^{cc} \mathbf{P}_{At}^c \\ \mathbf{W}^{cc} \mathbf{P}_{Bt}^c \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{cs} & \theta_{AB}^{cs} \\ \theta_{BA}^{cs} & \theta_{BB}^{cs} \end{bmatrix} \begin{bmatrix} \mathbf{W}^{cs} \mathbf{P}_{At}^s \\ \mathbf{W}^{cs} \mathbf{P}_{Bt}^s \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^c \\ \epsilon_{Bt}^c \end{bmatrix} \quad \dots (2.4)$$

$$\begin{bmatrix} \mathbf{Q}_{At}^s \\ \mathbf{Q}_{Bt}^s \end{bmatrix} = \begin{bmatrix} \mu_A^s \\ \mu_B^s \end{bmatrix} + \begin{bmatrix} \delta_{AA}^s & \delta_{AB}^s \\ \delta_{BA}^s & \delta_{BB}^s \end{bmatrix} \begin{bmatrix} \mathbf{Q}_{A,t-1}^s \\ \mathbf{Q}_{B,t-1}^s \end{bmatrix} + \begin{bmatrix} \beta_{AA}^s & \beta_{AB}^s \\ \beta_{BA}^s & \beta_{BB}^s \end{bmatrix} \begin{bmatrix} \mathbf{P}_{At}^s \\ \mathbf{P}_{Bt}^s \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^s & \gamma_{AB}^s \\ \gamma_{BA}^s & \gamma_{BB}^s \end{bmatrix} \begin{bmatrix} \mathbf{P}_{A,t-1}^s \\ \mathbf{P}_{B,t-1}^s \end{bmatrix} + \\ \begin{bmatrix} \theta_{AA}^{ss} & \theta_{AB}^{ss} \\ \theta_{BA}^{ss} & \theta_{BB}^{ss} \end{bmatrix} \begin{bmatrix} \mathbf{W}^{ss} \mathbf{P}_{At}^s \\ \mathbf{W}^{ss} \mathbf{P}_{Bt}^s \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{sc} & \theta_{AB}^{sc} \\ \theta_{BA}^{sc} & \theta_{BB}^{sc} \end{bmatrix} \begin{bmatrix} \mathbf{W}^{sc} \mathbf{P}_{At}^c \\ \mathbf{W}^{sc} \mathbf{P}_{Bt}^c \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^s \\ \epsilon_{Bt}^s \end{bmatrix} \quad \dots (2.5)$$

Essentially, the model in (2.4-2.5) allows us to estimate the cross-store substitution rates through the parameters θ_{AA} , θ_{AB} , θ_{BA} , and θ_{BB} . Here, θ_{AA} reflects the elasticity of demand due to a change in price in nearby outlet. In the above equations, I use the superscript ‘c’ for convenience stores and superscript ‘s’ for supermarkets. Suppose there are N^c number of convenience stores, and N^s number of supermarkets, with $N = N^c + N^s$. Then $\mathbf{Q}^c$ and $\mathbf{P}^c$ are $N^c \times 1$ vectors, and $\mathbf{Q}^s$ and $\mathbf{P}^s$ are $N^s \times 1$ vectors. And, $\mathbf{W}^{cc}$ matrix denotes the graph matrix capturing the spatial connections of the convenience stores to the other convenience stores, therefore it is an $N^c \times N^c$ matrix. $\mathbf{W}^{cs}$ matrix denotes the graph matrix capturing the spatial connections of the convenience stores to the other supermarkets, therefore it is a $N^c \times N^s$ matrix. Similarly, $\mathbf{W}^{ss}$ is an $N^s \times N^s$ matrix, and $\mathbf{W}^{sc}$ is an $N^s \times N^c$ matrix.

As discussed above, each element w_{ij} of the various $\mathbf{W}$ matrices reflect the spatial connection between 2 stores. Specifically, it is the weight of influence of store j on store i . The spatial weights w_{ij} can be calculated in a manner similar to estimation of retail center patronization probabilities in Huff model (1964). The Huff model of retail gravitation states that the probability of any shopper choosing a particular retail center is directly related to the size of the center and inversely related to the distance separating consumers from the center. The mathematical formulation of Huff’s model is expressed as below:

$$P_{ij} = \frac{\frac{S_j}{T_{ij}^\lambda}}{\sum_{j=1}^n \frac{S_j}{T_{ij}^\lambda}}$$

P_{ij} = the probability of a consumer at a given point of origin i travelling to a shopping center j

S_j = square footage of selling space devoted to the sale of a class of goods by shopping center j ;

T_{ij} = travel time/ distance involved in getting from a consumer's origin i to shopping center j ; and

λ = a parameter that reflect the effect of travel time or distance on various kinds of shopping trips.

n = total number of shopping centers

Following from above, the weights w_{ij} can be plausibly assumed to be inverse function of d_{ij} , where d_{ij} is the physical distance between store i and store j . As is typical in the spatial econometrics literature, we expect this influence to diminish with the distance. In other words, if the distance between 2 stores is really small, then the propensity to substitute stores should be high, and if the distance is large, then it should be negligible.

Given the above model in (2.4-2.5), I need to generate the various $\mathbf{W}$ matrices. In order to generate these matrices, I first calculate the Euclidean distances between all the outlet pairs after extracting coordinates information from each of the outlet location zip codes. I then construct 4 distance matrices, $\mathbf{D}^{cc}$, $\mathbf{D}^{cs}$, $\mathbf{D}^{ss}$ and $\mathbf{D}^{sc}$. The elements d_{ij}^{cc} of the $\mathbf{D}^{cc}$ matrix are the physical distances between a convenience store i to another convenience store j , and $\mathbf{D}^{cc}$ is an $N^c \times N^c$ matrix. The elements d_{ij}^{cs} of the $\mathbf{D}^{cs}$ matrix are the physical distances between a convenience store i to a supermarket j , and $\mathbf{D}^{cs}$ is an $N^c \times N^s$ matrix. The elements d_{ij}^{ss} of the $\mathbf{D}^{ss}$ matrix are the physical distances between a supermarket i to a supermarket j , and $\mathbf{D}^{ss}$ is an $N^s \times N^s$ matrix. The elements

d_{ij}^{sc} of the $\mathbf{D}^{sc}$ matrix are the physical distances between a supermarket i to a convenience store j , and $\mathbf{D}^{sc}$ is an $N^s \times N^c$ matrix.

Then the matrices $\mathbf{W}^{cc}$, $\mathbf{W}^{cs}$, $\mathbf{W}^{ss}$ and $\mathbf{W}^{sc}$ are generated by putting:

$$w_{ij}^{cc} = \frac{\left(\frac{1}{d_{ij}^{cc}}\right)}{\sum_k \left(\frac{1}{d_{ik}^{cc}}\right)}, w_{ij}^{cs} = \frac{\left(\frac{1}{d_{ij}^{cs}}\right)}{\sum_k \left(\frac{1}{d_{ik}^{cs}}\right)}, w_{ij}^{ss} = \frac{\left(\frac{1}{d_{ij}^{ss}}\right)}{\sum_k \left(\frac{1}{d_{ik}^{ss}}\right)}, \text{ and } w_{ij}^{sc} = \frac{\left(\frac{1}{d_{ij}^{sc}}\right)}{\sum_k \left(\frac{1}{d_{ik}^{sc}}\right)}.$$

The normalization with respect to $\sum_k \left(\frac{1}{d_{ik}}\right)$ ensures that the sum of rows of the $\mathbf{W}$ matrices are 1.

Therefore w_{ij} is a reflection of the weight of influence of store j on store i . Note that $\mathbf{W}^{cc}$ and $\mathbf{W}^{ss}$ are zero diagonal matrices (i.e. $w_{ii}^{cc} = 0, w_{ii}^{ss} = 0$), whereas the other two matrices $\mathbf{W}^{cs}$ and $\mathbf{W}^{sc}$ are not necessarily zero diagonal. As is typical in the spatial econometrics literature, beyond a certain distance, I put the spatial weight to be 0. In our empirical analysis, I used 2 km as this cutoff distance. This means that outlets beyond 2 km radius are assumed to have no spatial effect.

2.3.2 Direct and spatial spillover effects

From the model in (2.4-2.5), we can see that within store own price demand elasticities are captured by $\beta_{AA}^c, \beta_{BB}^c, \beta_{AA}^s$ and β_{BB}^s , depending on channel and brand. The within-store cross-price demand elasticities are captured by $\beta_{AB}^c, \beta_{BA}^c, \beta_{AB}^s$ and β_{BA}^s . For instance, in the convenience store channel, a 1% price change in brand B would lead to β_{AB}^c % change in the demand for brand A in the same store. These own and cross-price elasticities are called the direct effects.

The spatial spillover effects are captured by the parameters $\theta = \{\theta_{AA}^{cc}, \theta_{AB}^{cc}, \theta_{BA}^{cc}, \theta_{BB}^{cc}, \theta_{AA}^{ss}, \theta_{AB}^{ss}, \theta_{BA}^{ss}, \theta_{BB}^{ss}, \theta_{AA}^{cs}, \theta_{AB}^{cs}, \theta_{BA}^{cs}, \theta_{BB}^{cs}, \theta_{AA}^{sc}, \theta_{AB}^{sc}, \theta_{BA}^{sc}, \theta_{BB}^{sc}\}$. However, the effect of a price change in outlet j is not symmetric on all other outlets i . The net spatial spillover effect is dependent on the distance between outlets i and j . The spatial weight w_{ij} influences how much

will the effect of a price change in outlet j will be on the demand in outlet i . For instance, if both i and j are convenience stores, then the spillover effect on the demand for brand A in outlet i , due to a price change of brand A in outlet j , will be $\theta_{AA}^{CC} \cdot w_{ij}^{CC}$. Similarly, if i is a convenience store and j is a supermarket, then the spillover effect on the demand for brand A in outlet i , due to a price change of brand A in outlet j , will be $\theta_{AA}^{CS} \cdot w_{ij}^{CS}$. Therefore, the spatial spillover effect will vary from outlet to outlet depending on the distance between the focal outlet and the outlet where price change occurs, and also on the channel types of the two outlets.

The question is then how should we interpret the parameters $\theta = \{\theta_{AA}^{CC}, \theta_{AB}^{CC}, \theta_{BA}^{CC}, \theta_{BB}^{CC}, \theta_{AA}^{SS}, \theta_{AB}^{SS}, \theta_{BA}^{SS}, \theta_{BB}^{SS}, \theta_{AA}^{CS}, \theta_{AB}^{CS}, \theta_{BA}^{CS}, \theta_{BB}^{CS}, \theta_{AA}^{SC}, \theta_{AB}^{SC}, \theta_{BA}^{SC}, \theta_{BB}^{SC}\}$. Note that the row sums of all $\mathbf{W}$ matrices are 1. In other words, the weights of all connected stores of a particular channel sum to 1. Suppose i is a convenience store, and there are several supermarkets it is connected to. The sum of the i -th row elements of $\mathbf{W}^{CS}$ is 1. If there is 1% price change in brand A in any of these supermarkets j , then the spatial spillover effect on outlet i 's demand for brand A will change by $(\theta_{AA}^{CS} \cdot w_{ij}^{CS})\%$ and for brand B will change by $(\theta_{BA}^{CS} \cdot w_{ij}^{CS})\%$. Therefore, if in all connected supermarkets the price of brand A changes by 1% simultaneously, then the total spatial spillover effect on the demand for brand A in outlet i will be $(\sum_j \theta_{AA}^{CS} \cdot w_{ij}^{CS})\%$ and for brand B will be $(\sum_j \theta_{BA}^{CS} \cdot w_{ij}^{CS})\%$. However, $\sum_j w_{ij}^{CS} = 1$. Therefore, this total spatial spillover effect is θ_{AA}^{CS} and θ_{BA}^{CS} . Therefore, the parameters θ reflect the spatial spillover effect (indirect effect) on any outlet if there is a simultaneous change in all other connected outlets. This total effect will vary by brand, by channel of the focal outlet, and by channel of the connected outlets. In Table 2.3, I summarize the parameter interpretations.

Table 2.3: Direct and spatial effect by channel

Type of effect	Channel type of the connected outlets	Channel type of focal outlet	
		Convenience store	Supermarket
Direct effect – own store own and cross price elasticities	NA	$\begin{bmatrix} \beta_{AA}^c & \beta_{AB}^c \\ \beta_{BA}^c & \beta_{BB}^c \end{bmatrix}$	$\begin{bmatrix} \beta_{AA}^s & \beta_{AB}^s \\ \beta_{BA}^s & \beta_{BB}^s \end{bmatrix}$
Indirect effect – spatial spillover effect due to a change in own brand price in all connected outlets	Convenience channel	$\begin{bmatrix} \theta_{AA}^{cc} & \theta_{AB}^{cc} \\ \theta_{BA}^{cc} & \theta_{BB}^{cc} \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{sc} & \theta_{AB}^{sc} \\ \theta_{BA}^{sc} & \theta_{BB}^{sc} \end{bmatrix}$
	Supermarket channel	$\begin{bmatrix} \theta_{AA}^{cs} & \theta_{AB}^{cs} \\ \theta_{BA}^{cs} & \theta_{BB}^{cs} \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{ss} & \theta_{AB}^{ss} \\ \theta_{BA}^{ss} & \theta_{BB}^{ss} \end{bmatrix}$

Note: The first letter in the subscript reflects affected brand, and the second letter in the subscript reflects the brand for which there is a price change. For instance, subscript AB means price change in B and effect on brand A.

2.4. Data

For our empirical analysis we use The Nielsen Company retail scanner panel data for Singapore. This dataset contains weekly data on carbonated soft drinks for two consecutive years (104 weeks, 26 months) across 1151 outlets in Singapore. We matched the retailer data with another dataset that has postal codes and geographical coordinates for 981 outlets in Singapore. We filtered the observations from the dataset for these 981 outlets for our analysis. These 981 outlets come from both channel type- supermarket and convenience stores and spread along the length and breadth of Singapore. They have a representative panel of outlets that belongs to the majority players in organized retail in Singapore- 7-eleven, Cheers (NTUC), Caltex, Starmart, Giant, FairPrice (NTUC), Cold Storage, Sheng Siong and Carrefour.

The carbonated soft drinks category can be bifurcated into cola and other flavors (lemon, berries, orange, club soda etc.). We selected the cola category. Two brands- Coke and Pepsi constitute 99% of the cola market share and the balance 1% is distributed among regional and local players- 365 House brand, My Cola, Loony Tunes, Xndo, Planet Cola etc. Also the smaller brands are present across much selected stores. Based on purchase occasion and nature of product, we categorize cola into 2 SKU volume sub-categories- ≤ 0.6 litre and > 0.6 litre. Next, we impute actual price, month and shop-wise for all the SKUs and use regular price to calculate discount. Combining this with the month and shop wise feature and display data for all the brands, we get a panel dataset that has sales and marketing stimuli information on a monthly and shop wise basis for 26 months and 981 outlets.

I calculated actual price per litre and regular price per litre as it makes comparison easier and also easier to set limits for unrealistic values of regular price and actual price across all observations. I deleted all observations with fractional values of quantity and sales value equal to zero. Then estimated 1% and 99% quantiles of actual and regular price and deleted all observations below largest value of 1% and above smallest value of 99%. First deleted actual price as smaller value of actual price $<$ smaller value of regular price and in case of upper values, did regular price first as upper value of regular price $>$ upper value of actual price.

In Figures 2.1 and 2.2, I show the sales and price trend, respectively, for the category (Cola) and brand-wise (Coke and Pepsi) for SKU volume < 0.6 litre. Coke sales and price trend closely follow the category trend and the series look stationary from the graphs. Coke is higher priced than Pepsi and between the two channels, the price of both the brands is higher in the convenience channel.

Figure 2.1: Sales trend of Coke and Pepsi across channels

Figure 2.2: Price trend of Coke and Pepsi across channels

Coke and Pepsi account for 99% of the category volume with remaining 1% contributed by the regional and local brands. The price of Coke is higher by almost 40% and the price in convenience channel is almost twice the price in supermarket channel for both the brands. The mean and standard deviation for volume sales and price series for Coke and Pepsi² are reported in Table 2.4.

² There is considerable variation among stores within chains. This indicates that the store managers had certain discretion about price promotions

Table 2.4: Mean and std. deviation for the sales and price of Coke and Pepsi across channels

		Total cola			Coke			Pepsi		
		Total	Smkt	Conv	Total	Smkt	Conv	Total	Smkt	Conv
volume (in '000)	<i>Mean</i>	229	138	91	183	110	73	44	27	17
	<i>Std dev</i>	26	27	9	27	24	10	8	7	6
price	<i>Mean</i>	2.87	1.99	4.19	3.04	2.09	4.48	2.22	1.64	3.18
	<i>Std dev</i>	0.16	0.10	0.15	0.22	0.14	0.21	0.18	0.13	0.29

Table 2.5 lists the brand volume and value sales share channel-wise for Coke and Pepsi along with highlighting the retail chains within each channel type and the respective outlets within each chain. An interesting observation is that, though the volume share is lower for convenience channel despite higher number of outlets, the value share is higher mainly due to the higher price in convenience channel as evident from Table 2.4 above.

Table 2.5: Retail outlet distribution, brand sales share across retail chains

Retailer	Outlets		Coke sales		Pepsi sales	
	number	percent	value	volume	value	volume
7-eleven	541	55.1%	43%	26%	41%	27%
Cheers	145	14.8%	12%	9%	12%	9%
Starmart	38	3.9%	3%	3%	1%	2%
Caltex	28	2.9%	2%	2%	1%	1%
Total conv	752	76.7%	59%	40%	55%	39%
Fairprice	104	10.6%	11%	13%	15%	19%
Giant	67	6.8%	5%	5%	5%	5%
Cold Storage	45	4.6%	7%	8%	7%	7%
Sheng Siong	11	1.1%	18%	33%	17%	29%
Carrefour	2	0.2%	1%	1%	1%	1%
Total smkt	229	23.3%	41%	60%	45%	61%
Grand total	981	100%	100%	100%	100%	100%

2.5. Empirical results

2.5.1 Stationarity and unit-root tests

An augmented Dickey-Fuller (ADF) test was conducted on each of the following series: brand sales and price for each of the two brands at aggregate level (weekly and monthly) and at store level (monthly panel data). Additionally, conducted Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests to verify the reverse null hypothesis for the aggregate sales and price series. In case of panel data, all other tests except Fisher (Choi, 2001) and Im–Pesaran–Shin (2003) unit root tests require strictly balanced panels, meaning all panels have same number of observations. Among the above two, Im–Pesaran–Shin further requires no gaps in each of the panels which is not fulfilled by our data. Hence, we use the most unrestricted test, Fisher unit root test to check for stationarity of panel data. It uses both ADF and Phillips-Perron tests panel-wise to check for unit roots and the null hypothesis is that all the panels have unit root. The results for each of the stationarity tests and data type are illustrated in Table 2.6 below. The null hypothesis in case of KPSS test cannot be rejected for all the time series thereby reinforcing the ADF test findings. The results are consistent with the earlier findings that most sales time series are stationary (Nijs et al., 2001; Lim, Currim, and Andrews, 2005).

Table 2.6: Unit root tests results

Data	Test	Time-series variables			
		<i>Volume_Coke</i>	<i>Volume_Pepsi</i>	<i>Price_Coke</i>	<i>Price_Pepsi</i>
Aggregate weekly	ADF	Null Hypothesis:	<i>Series has a unit root</i>		
		Test-statistic	-6.052	-6.159	-4.848
		p-value	0	0	0
	KPSS	Null Hypothesis:	<i>Series is stationary</i>		
		Test-statistic	0.149	0.297	0.184
		Test-statistic at p=0.1	0.347	0.347	0.347
Aggregate monthly	ADF	Null Hypothesis:	<i>Series has a unit root</i>		
		Test-statistic	-2.663	-3.281	-3.089
		p-value	0.007	0.002	0.003
	KPSS	Null Hypothesis:	<i>Series is stationary</i>		
		Test-statistic	0.0981	0.103	0.19
		Test-statistic at p=0.1	0.347	0.347	0.347
Panel data	xtunitroot	Null Hypothesis:	<i>All panels contain unit roots</i>		
		Test-statistic	-69.885	-75.741	-88.624
		p-value	0	0	0

2.5.2 Estimation results

Essentially, the model that I use is a dynamic panel data model with spatial components. The system of equations to be estimated is same as equations 2.4 and 2.5 (please refer to section 2.3.1):-

$$\begin{aligned}
 \begin{bmatrix} Q_{At}^c \\ Q_{Bt}^c \end{bmatrix} &= \begin{bmatrix} \mu_A^c \\ \mu_B^c \end{bmatrix} + \begin{bmatrix} \delta_{AA}^c & \delta_{AB}^c \\ \delta_{BA}^c & \delta_{BB}^c \end{bmatrix} \begin{bmatrix} Q_{A,t-1}^c \\ Q_{B,t-1}^c \end{bmatrix} + \begin{bmatrix} \beta_{AA}^c & \beta_{AB}^c \\ \beta_{BA}^c & \beta_{BB}^c \end{bmatrix} \begin{bmatrix} P_{At}^c \\ P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^c & \gamma_{AB}^c \\ \gamma_{BA}^c & \gamma_{BB}^c \end{bmatrix} \begin{bmatrix} P_{A,t-1}^c \\ P_{B,t-1}^c \end{bmatrix} + \\
 &\begin{bmatrix} \theta_{AA}^{cc} & \theta_{AB}^{cc} \\ \theta_{BA}^{cc} & \theta_{BB}^{cc} \end{bmatrix} \begin{bmatrix} W^{cc} P_{At}^c \\ W^{cc} P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{cs} & \theta_{AB}^{cs} \\ \theta_{BA}^{cs} & \theta_{BB}^{cs} \end{bmatrix} \begin{bmatrix} W^{cs} P_{At}^s \\ W^{cs} P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^c \\ \epsilon_{Bt}^c \end{bmatrix} \quad \text{..... (2.4)}
 \end{aligned}$$

$$\begin{aligned}
 \begin{bmatrix} Q_{At}^s \\ Q_{Bt}^s \end{bmatrix} &= \begin{bmatrix} \mu_A^s \\ \mu_B^s \end{bmatrix} + \begin{bmatrix} \delta_{AA}^s & \delta_{AB}^s \\ \delta_{BA}^s & \delta_{BB}^s \end{bmatrix} \begin{bmatrix} Q_{A,t-1}^s \\ Q_{B,t-1}^s \end{bmatrix} + \begin{bmatrix} \beta_{AA}^s & \beta_{AB}^s \\ \beta_{BA}^s & \beta_{BB}^s \end{bmatrix} \begin{bmatrix} P_{At}^s \\ P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^s & \gamma_{AB}^s \\ \gamma_{BA}^s & \gamma_{BB}^s \end{bmatrix} \begin{bmatrix} P_{A,t-1}^s \\ P_{B,t-1}^s \end{bmatrix} + \\
 &\begin{bmatrix} \theta_{AA}^{ss} & \theta_{AB}^{ss} \\ \theta_{BA}^{ss} & \theta_{BB}^{ss} \end{bmatrix} \begin{bmatrix} W^{ss} P_{At}^s \\ W^{ss} P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{sc} & \theta_{AB}^{sc} \\ \theta_{BA}^{sc} & \theta_{BB}^{sc} \end{bmatrix} \begin{bmatrix} W^{sc} P_{At}^c \\ W^{sc} P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^s \\ \epsilon_{Bt}^s \end{bmatrix} \quad \text{..... (2.5)}
 \end{aligned}$$

Note that the systems of equations in the model (2.4-2.5) can be estimated equation by equation using a dynamic panel data estimator. I apply the Arellano and Bond (1991) GMM method for estimation. Arellano and Bond (1991) and Blundell and Bond (1998) developed the generalized method of moments estimator, and discussed how lagged data can be used for instrumentation in order to address endogeneity that manifests not only due to the lagged dependent variable, but also any other endogenous variable, under certain assumptions. An important assumption is that the idiosyncratic disturbances are uncorrelated across individuals after differencing or orthogonalization. The model is particularly suitable where T , may be small. (i.e., “small T , large N .”). Arellano and Bond (1991) propose the test for testing autocorrelation, which is then used to determine up to which level the lagged variables cannot be used as instruments. In all cases, I found that null hypothesis ‘no autocorrelation’ up to lag 2 are rejected, however, ‘no autocorrelation’ at lag 3 cannot be rejected. Therefore, I selected instruments starting from lag 3 onward.

Tables 2.7(a) and 2.7(b) report the results using three models- model without spatial price variables (non-spatial), model with own and cross-brand spatial price variables, and model with own brand spatial price variables for convenience and supermarket channels respectively.

Table 2.7(a): Model comparison- convenience channel

Variables	Model					
	<i>Non-spatial</i>		<i>With own and cross-brand spatial price</i>		<i>With own brand spatial price</i>	
	<i>Conv</i>		<i>Conv</i>		<i>Conv</i>	
<i>Lagged volume</i>	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Coke	0.951*** (0.00809)	0.137*** (0.0228)	0.946*** (0.0109)	0.178*** (0.0191)	0.944*** (0.0112)	0.175*** (0.0189)
Pepsi	0.0261*** (0.00870)	0.550*** (0.0164)	0.0189** (0.00815)	0.573*** (0.0148)	0.0202** (0.00787)	0.565*** (0.0150)
<i>Price</i>						
Coke	-1.619*** (0.0478)	0.898*** (0.0856)	-1.656*** (0.0474)	0.771*** (0.0827)	-1.665*** (0.0468)	0.873*** (0.0787)
Pepsi	0.117*** (0.0265)	-2.825*** (0.0537)	0.142*** (0.0331)	-2.643*** (0.0605)	0.123*** (0.0252)	-2.764*** (0.0598)
<i>Lagged Price</i>						
Coke	1.504*** (0.0474)	-0.0167 (0.0913)	1.492*** (0.0476)	0.0238 (0.0803)	1.518*** (0.0450)	0.0468 (0.0827)
Pepsi	0.00381 (0.0400)	1.433*** (0.0622)	-0.0196 (0.0384)	1.447*** (0.0571)	-0.00455 (0.0363)	1.428*** (0.0576)
<i>Spatial lagged price convenience outlets</i>						
Coke			0.146** (0.0601)	0.208 (0.110)	0.145** (0.0735)	
Pepsi			-0.0626 (0.0352)	-0.181*** (0.0671)		-0.106 (0.0641)
<i>Supermarkets</i>						
Coke			-0.158 (0.0953)	0.858*** (0.223)	0.0737 (0.0868)	
Pepsi			0.325** (0.126)	-0.974*** (0.278)		0.309** (0.154)
Observations	17,398	17,398	17,398	17,398	17,398	17,398
abar(3)	0.0700	0.599	0.0597	0.555	0.0668	0.564
J-statistic	0	0	0.983	1	0.987	0.917
AIC	-42185	-20058	-42276	-22099	-42320	-22165
BIC	-42030	-19903	-42090	-21913	-42149	-21994
LL	-106051	-94987	-106100	-96012	-106120	-96043

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$

Table 2.7(b): Model comparison- supermarket channel

Variables	Model					
	<i>Non-spatial</i>		<i>With own and cross-brand spatial price</i>		<i>With own brand spatial price</i>	
	<i>Smkt</i>		<i>Smkt</i>		<i>Smkt</i>	
<i>Lagged volume</i>	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Coke	0.952*** (0.0227)	0.195*** (0.0456)	0.931*** (0.0224)	0.168*** (0.0385)	0.925*** (0.0222)	0.179*** (0.0420)
Pepsi	0.0207 (0.0126)	0.760*** (0.0343)	0.0294** (0.0113)	0.800*** (0.0253)	0.0211 (0.0109)	0.776*** (0.0313)
<i>Price</i>						
Coke	-1.813*** (0.430)	2.105*** (0.634)	-1.311*** (0.428)	1.794*** (0.593)	-1.673*** (0.408)	1.993*** (0.611)
Pepsi	0.354 (0.190)	-2.758*** (0.534)	0.346 (0.192)	-2.615*** (0.476)	0.297 (0.175)	-2.711*** (0.518)
<i>Lagged Price</i>						
Coke	1.997*** (0.395)	-1.270** (0.514)	1.223*** (0.411)	-0.877 (0.488)	1.677*** (0.384)	-1.168** (0.504)
Pepsi	-0.303 (0.210)	1.087** (0.445)	-0.154 (0.210)	1.162*** (0.396)	-0.277 (0.190)	1.104** (0.433)
<i>Spatial lagged price convenience outlets</i>						
Coke			0.207*** (0.0662)	0.169 (0.0980)	0.197*** (0.0607)	
Pepsi			-0.137*** (0.0353)	-0.0540 (0.0554)		-0.00235 (0.0583)
<i>Supermarkets</i>						
Coke			0.506 (0.330)	-0.759 (0.516)	0.298 (0.163)	
Pepsi			-0.228 (0.248)	0.326 (0.437)		-0.0853 (0.338)
Observations	5,094	5,094	5,094	5,094	5,094	5,094
abar(3)	0.698	0.188	0.750	0.202	0.760	0.185
J-statistic	1	1	1	1	1	1
AIC	-15482	-8556	-15615	-8773	-15641	-8893
BIC	-15351	-8425	-15458	-8616	-15497	-8749
LL	-29502	-26039	-29572	-26151	-29583	-26209

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$

From the above tables, we see that the information criterion statistics (AIC, BIC and LL) decrease as we move from non-spatial to full model (third and fourth column) to model with own brand spatial price variables (fifth and sixth columns). The statistical evidence favors the more parsimonious model. In addition to the above factors, there were certain sign reversals in the spatial price parameters in the full model that were not interpretable. Hence, for reasons of parsimony, favorable statistical evidence and interpretable parameter estimates, I chose the model with own brand spatial price variables. Hence, the system of equations to be estimated becomes:

$$\begin{bmatrix} Q_{At}^c \\ Q_{Bt}^c \end{bmatrix} = \begin{bmatrix} \mu_A^c \\ \mu_B^c \end{bmatrix} + \begin{bmatrix} \delta_{AA}^c & \delta_{AB}^c \\ \delta_{BA}^c & \delta_{BB}^c \end{bmatrix} \begin{bmatrix} Q_{A,t-1}^c \\ Q_{B,t-1}^c \end{bmatrix} + \begin{bmatrix} \beta_{AA}^c & \beta_{AB}^c \\ \beta_{BA}^c & \beta_{BB}^c \end{bmatrix} \begin{bmatrix} P_{At}^c \\ P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^c & \gamma_{AB}^c \\ \gamma_{BA}^c & \gamma_{BB}^c \end{bmatrix} \begin{bmatrix} P_{A,t-1}^c \\ P_{B,t-1}^c \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{cc} & 0 \\ 0 & \theta_{BB}^{cc} \end{bmatrix} \begin{bmatrix} W^{cc} P_{At}^c \\ W^{cc} P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{cs} & 0 \\ 0 & \theta_{BB}^{cs} \end{bmatrix} \begin{bmatrix} W^{cs} P_{At}^s \\ W^{cs} P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^c \\ \epsilon_{Bt}^c \end{bmatrix} \quad \dots (2.6)$$

$$\begin{bmatrix} Q_{At}^s \\ Q_{Bt}^s \end{bmatrix} = \begin{bmatrix} \mu_A^s \\ \mu_B^s \end{bmatrix} + \begin{bmatrix} \delta_{AA}^s & \delta_{AB}^s \\ \delta_{BA}^s & \delta_{BB}^s \end{bmatrix} \begin{bmatrix} Q_{A,t-1}^s \\ Q_{B,t-1}^s \end{bmatrix} + \begin{bmatrix} \beta_{AA}^s & \beta_{AB}^s \\ \beta_{BA}^s & \beta_{BB}^s \end{bmatrix} \begin{bmatrix} P_{At}^s \\ P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \gamma_{AA}^s & \gamma_{AB}^s \\ \gamma_{BA}^s & \gamma_{BB}^s \end{bmatrix} \begin{bmatrix} P_{A,t-1}^s \\ P_{B,t-1}^s \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{ss} & 0 \\ 0 & \theta_{BB}^{ss} \end{bmatrix} \begin{bmatrix} W^{ss} P_{At}^s \\ W^{ss} P_{Bt}^s \end{bmatrix} + \begin{bmatrix} \theta_{AA}^{sc} & 0 \\ 0 & \theta_{BB}^{sc} \end{bmatrix} \begin{bmatrix} W^{sc} P_{At}^c \\ W^{sc} P_{Bt}^c \end{bmatrix} + \begin{bmatrix} \epsilon_{At}^s \\ \epsilon_{Bt}^s \end{bmatrix} \quad \dots (2.7)$$

I restrict cross-brand-cross-store substitution in equations 2.6 and 2.7 to be zero. In addition, it is plausible that when a consumer wishes to buy brand A, if there is any price change in brand A, the consumer would consider buying brand B from the same store, or, if the consumer is brand-loyal, would consider buying brand A from another store.

In Tables 2.8(a) and 2.8(b), I report the estimation results using three specifications—a time series specification with brand-level monthly data aggregated to the market level without spatial interaction (specification 1), a panel data specification with brand- and store-level monthly data without spatial interdependence (specification 2), and a panel data specification with brand- and store-level monthly data with spatial interdependence (specification 3).

The coefficients of price variables in specification 1 reflect the standard price elasticity estimates at the market level. The Hansen J-statistic improves from specifications 2 to 3, clearly indicating that specification 3 is a valid and better fit for the brand- and store-level monthly panel data. In specification 3, the spatial weights matrix has been bifurcated into supermarkets and convenience outlets connected to the focal outlet. Hence, we consider the spatially lagged price in both channels for each of the brands. The cut-off distance between the outlets for specification 3 is 2km. The deeper temporal lags of the variables are used as instruments in the estimation. The spatially lagged price variable coefficients are significant and positive in specification 3, which means an increase in the price of the brand in adjoining stores increases the sales of the brand in the focal store. Because the model is log-log linear, the coefficients imply price-elasticity measures.

Referring to Table 2.8(a) and specification 3, a price increase in adjoining convenience stores benefits the focal convenience store in the case of Coke (θ_{AA}^{CC} (0.145) is significant and positive). Coke is the market leader, with an 89% market share, and charges a price premium to the tune of 40% in both channels as compared to Pepsi. Gabor and Granger (1966) found strong evidence that consumers use price as an indicator of quality at the individual level. Higher priced brands are believed to offer better quality and evoke high brand loyalty (Allenby and Rossi, 1991; Horvath and Fok, 2013); hence, store substitution and brand substitution (though to a relatively lesser extent) both happen in response to a price change. If an individual has strong brand loyalty, it is possible that the individual may be willing to substitute the store rather than substitute the brand. As long as the cost (of effort along with monetary) of substituting the store is less than the cost of substituting the brand, intuitively the person may be willing to move to another store for the same brand rather than simply choose an alternative brand.

There is no effect of a price change in adjoining supermarkets on the demand for Coke in the focal convenience store (θ_{AA}^{cs} is insignificant). The price increase in adjoining supermarkets does not cause consumers to switch to the focal convenience store to buy Coke as the price gap between the two channels is almost to the tune of 40% and, despite a price increase in supermarkets, the price will still be lower than the convenience store price.

For Pepsi, demand in the focal convenience store is unaffected by price changes in neighboring convenience stores (θ_{BB}^{cc} is insignificant). This could be explained by the lower brand loyalty for Pepsi. Pepsi has a 9% share of the cola market as compared to market leader Coke which has a 90% market share. This asymmetry in market shares implies differences in the customer base, such that high-quality (high-priced) brands usually have more loyal customers than do low-quality (inexpensive) brands (Sethuraman et al., 1999). Consumers who buy Pepsi may be more willing to switch to another brand than to shift to another store in the event of a price change in the focal convenience store. θ_{BB}^{cs} (0.309) is significant and positive, which means that the demand for Pepsi in the focal convenience store increases (decreases) when the price of Pepsi increases (decreases) in adjoining supermarkets. At first glance, it is little bit surprising to notice potential substitution from supermarket to convenience channel given that supermarket price is lower. However, this is not inconsistent from microeconomic point of view if considered within the purview of demand response to relative price changes between two substitutes, in this case price of Pepsi in supermarket and convenience stores. Yet, it is difficult to explain from practical point of view since there is large difference in price of Pepsi between the two channels.

With reference to estimation results for specification 3 in Table 2.8(b), it is observed that a price increase (decrease) in adjoining convenience stores does increase (decrease) the demand in the focal supermarket (θ_{AA}^{sc} (0.197) is significant and positive) for Coke. There is no impact on the

demand for Coke in supermarkets due to the price change in adjoining supermarkets (θ_{AA}^{SS} is insignificant). For Pepsi, there is no spatial spillover from adjoining convenience stores or supermarkets to the focal supermarket (θ_{BB}^{SC} and θ_{BB}^{SS} are insignificant). The lack of spatial spillover between supermarkets can be explained by the sparse supermarket-to-supermarket density. Supermarket-supermarket distances are usually longer than convenience-supermarket or convenience-convenience store distances. This is further compounded by the fact that amount of purchases are higher in supermarkets with long purchase lists and large basket sizes. Both the above factors lead to greater time and effort that goes into buying from a supermarket. Customers usually plan well ahead of time for a supermarket shopping trip and these are planned purchases. Thus it is perhaps plausible to assume that switching stores is more costly for the customers if there is a price change for single item or so. Hence, I believe that it is reasonable to find lower store substitution for supermarket purchases relative to convenience store purchases.

Table 2.8(a): Estimation results—convenience channel

Variables	Specification					
	1		2		3	
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Lagged volume						
Coke	0.611*** (0.147)	-0.528 (0.276)	0.951*** (0.00809)	0.137*** (0.0228)	0.944*** (0.0112)	0.175*** (0.0189)
Pepsi	-0.0627 (0.0927)	0.528*** (0.174)	0.0261*** (0.00870)	0.550*** (0.0164)	0.0202** (0.00787)	0.565*** (0.0150)
Price						
Coke	-1.645*** (0.201)	0.548 (0.377)	-1.619*** (0.0478)	0.898*** (0.0856)	-1.665*** (0.0468)	0.873*** (0.0787)
Pepsi	0.0847 (0.176)	-1.159*** (0.332)	0.117*** (0.0265)	-2.825*** (0.0537)	0.123*** (0.0252)	-2.764*** (0.0598)
Lagged Price						
Coke	0.773** (0.317)	-1.352** (0.596)	1.504*** (0.0474)	-0.0167 (0.0913)	1.518*** (0.0450)	0.0468 (0.0827)
Pepsi	-0.184 (0.208)	0.519 (0.390)	0.00381 (0.0400)	1.433*** (0.0622)	-0.00455 (0.0363)	1.428*** (0.0576)
Spatial lagged price convenience outlets						
Coke					0.145** (0.0735)	
Pepsi						-0.106 (0.0641)
Supermarkets						
Coke					0.0737 (0.0868)	
Pepsi						0.309** (0.154)
Observations	25	25	17,398	17,398	17,398	17,398
R-square	0.818	0.616				
abar(3)			0.0700	0.599	0.0668	0.564
Hansen J-statistic			0	0	0.987	0.917

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$

Table 2.8(b): Estimation results—supermarket channel

Variables	Specification					
	1		2		3	
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Lagged volume						
Coke	0.611*** (0.147)	-0.528 (0.276)	0.952*** (0.0227)	0.195*** (0.0456)	0.925*** (0.0222)	0.179*** (0.0420)
Pepsi	-0.0627 (0.0927)	0.528*** (0.174)	0.0207 (0.0126)	0.760*** (0.0343)	0.0211 (0.0109)	0.776*** (0.0313)
Price						
Coke	-1.645*** (0.201)	0.548 (0.377)	-1.813*** (0.430)	2.105*** (0.634)	-1.673*** (0.408)	1.993*** (0.611)
Pepsi	0.0847 (0.176)	-1.159*** (0.332)	0.354 (0.190)	-2.758*** (0.534)	0.297 (0.175)	-2.711*** (0.518)
Lagged Price						
Coke	0.773** (0.317)	-1.352** (0.596)	1.997*** (0.395)	-1.270** (0.514)	1.677*** -0.384	-1.168** (0.504)
Pepsi	-0.184 (0.208)	0.519 (0.390)	-0.303 (0.210)	1.087** (0.445)	-0.277 (0.190)	1.104** (0.433)
Spatial lagged price convenience outlets						
Coke					0.197*** (0.0607)	
Pepsi						-0.00235 (0.0583)
Supermarkets						
Coke					0.298 (0.163)	
Pepsi						-0.0853 (0.338)
Observations	25	25	5,094	5,094	5,094	5,094
R-square	0.818	0.616				
abar(3)			0.698	0.188	0.760	0.185
Hansen J-statistic			1	1	1	1

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$

2.5.3 Robustness check

I analyzed alternative specifications of the spatial weights matrix (binary and linear in ' d '). The alternative specifications of the W matrix that I empirically investigated are listed below:

1. W matrix elements equal to inverse of physical distance between outlets for distances upto 500m, 1km, and 2km.
2. W matrix as binary contiguity matrix for distances upto 500m, 1km, and 2km.
3. W matrix as a linear function of ' d ' upto 500m, 1km, and 2km and zero beyond that point.

Tables 2.9(a) and 2.9(b) compare nine specifications along three information criterion-AIC, BIC and log likelihood (LL) channel-wise for Coke and Pepsi respectively. I choose $d < 2\text{km}$ owing to superior statistical evidence.

Table 2.9(a): Model comparison- Coke

W specification	Brand	AIC (conv)	AIC (smkt)	BIC (conv)	BIC (smkt)	LL (conv)	LL (smkt)
$w=(1/d)$, $d < 500\text{m}$	Coke	-42181	-15630	-42010	-15486	-106051	-29578
$w=(1/d)$, $d < 1\text{km}$	Coke	-42181	-15575	-42010	-15431	-106051	-29550
$w=(1/d)$, $d < 2\text{km}$	Coke	-42320	-15641	-42149	-15497	-106120	-29583
$w_{\text{binary}} < 500\text{m}$	Coke	-42181	-15575	-42010	-15431	-106051	-29550
$w_{\text{binary}} < 1\text{km}$	Coke	-42142	-15553	-41971	-15409	-106031	-29539
$w_{\text{binary}} < 2\text{km}$	Coke	-36990	-15608	-36819	-15464	-103455	-29567
$wd_wd2 < 500\text{m}$	Coke	-42213	-15622	-42011	-15452	-106070	-29578
$wd_wd2 < 1\text{km}$	Coke	-42272	-15578	-42070	-15408	-106100	-29556
$wd_wd2 < 2\text{km}$	Coke	-42232	-15633	-42031	-15463	-106080	-29583

Table 2.9(b): Model comparison- Pepsi

W specification	Brand	AIC (conv)	AIC (smkt)	BIC (conv)	BIC (smkt)	LL (conv)	LL (smkt)
w=(1/d), d<500m	Pepsi	-20903	-8893	-20732	-8749	-95411	-26209
w=(1/d), d<1km	Pepsi	-22103	-8864	-21932	-8720	-96012	-26195
w=(1/d), d<2km	Pepsi	-22165	-8893	-21994	-8749	-96043	-26209
w_binary<500m	Pepsi	-22165	-8835	-21994	-8691	-96043	-26180
w_binary<1km	Pepsi	-22103	-8835	-21932	-8691	-96012	-26180
w_binary<2km	Pepsi	-22041	-8864	-21870	-8720	-95981	-26195
wd_wd2<500m	Pepsi	-21910	-8769	-21708	-8599	-95919	-26151
wd_wd2<1km	Pepsi	-21848	-8798	-21646	-8628	-95888	-26166
wd_wd2<2km	Pepsi	-21910	-8683	-21708	-8513	-95919	-26108

From the above tables, w=(1/d) for d<2km emerges as the best fit among the nine models.

I also estimate another specification (4) with a cut-off distance for the outlets as <1km in the spatial weights matrix. Specifications 3 and 4 are reported in Table 2.10 below for comparison. The magnitude and sign of the price and spatial price variables are comparable and in the same direction, which lends support to the robustness of my results. In specification 4, we see that lesser spatial price coefficients are significant. This means that spatial spillover reduces within close clusters. This sounds counter-intuitive, as conventional wisdom would dictate that the closer the stores, the greater the opportunities for store substitution. A possible explanation for this could be that stores in close vicinity to each other match their prices, thereby reducing spatial price competition and reducing the incentive for consumers to cross-shop.

Table 2.10: Robustness check

Variables	Specification							
	3 Conv		4 Conv		3 Smkt		4 Smkt	
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Lagged volume								
Coke	0.944*** (0.0112)	0.175*** (0.0189)	0.867*** (0.0105)	0.168*** (0.0191)	0.925*** (0.0222)	0.179*** (0.0420)	0.899*** (0.0237)	0.173*** (0.0381)
Pepsi	0.0202** (0.00787)	0.565*** (0.0150)	0.0321*** (0.00626)	0.568*** (0.0154)	0.0211 (0.0109)	0.776*** (0.0313)	0.0257** (0.0104)	0.786*** (0.0280)
Price								
Coke	-1.665*** (0.0468)	0.873*** (0.0787)	-1.692*** (0.0397)	0.865*** (0.0792)	-1.673*** (0.408)	1.993*** (0.611)	-1.291*** (0.423)	1.776*** (0.583)
Pepsi	0.123*** (0.0252)	-2.764*** (0.0598)	0.135*** (0.0226)	-2.753*** (0.0595)	0.297 (0.175)	-2.711*** (0.518)	0.0354 (0.158)	-2.620*** (0.499)
Lagged Price								
Coke	1.518*** (0.0450)	0.0468 (0.0827)	1.451*** (0.0424)	0.0272 (0.0826)	1.677*** -0.384	-1.168** (0.504)	1.550*** (0.373)	-1.069** (0.501)
Pepsi	-0.00455 (0.0363)	1.428*** (0.0576)	0.0294 (0.0285)	1.438*** (0.0586)	-0.277 (0.190)	1.104** (0.433)	-0.129 (0.168)	1.172*** (0.387)
Spatial lagged price convenience outlets								
Coke	0.145** (0.0735)		0.103*** (0.0390)		0.197*** (0.0607)		0.0884 (0.0534)	
Pepsi		-0.106 (0.0641)		-0.0735 (0.0625)		-0.00235 (0.0583)		-0.0337 (0.0465)
Supermarkets								
Coke	0.0737 (0.0868)		-0.0112 (0.0355)		0.298 (0.163)		0.0652 (0.112)	
Pepsi		0.309** (0.154)		0.299*** (0.0954)		-0.0853 (0.338)		0.0271 (0.165)
Observations	17,398	17,398	17,398	17,398	5,094	5,094	5,094	5,094
abar(3)	0.0668	0.564	0.0748	0.540	0.760	0.185	0.660	0.189
Hansen J-statistic	0.987	0.917	1	1	1	1	1	1

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$

2.5.4 Impact of spatial spillover on elasticity estimates

The impact of spatial interdependence on elasticity estimates is outlined in Table 2.11 below. The own-price elasticity of Coke remains consistent across aggregate and channel-wise estimates. The demand for Pepsi becomes far more elastic as we move from specification 1 to specification 3 (-1.15 vs. -2.7) with spatial interdependence. The cross-brand price elasticity estimates are insignificant for the aggregate model (specification 1). Looking at specification 1, one might simply conclude that there is no brand substitution between the competing brands in the cola category and that any change in demand due to price increase goes to brands within the non-cola beverages category. The cross-brand price elasticities become significant for specification 3; when that is combined with the spatial spillover effect, we can say that both brand and store substitution happen once the price of the brand changes in any outlet.

Table 2.11: Price elasticity estimates with spatial spillover

Type of effect	Channel type of the connected outlets	Channel type of focal outlet	
		Convenience store	Supermarket
Direct effect – own store own and cross price elasticities	NA	$\begin{bmatrix} \beta_{AA}^c & \beta_{AB}^c \\ \beta_{BA}^c & \beta_{BB}^c \end{bmatrix} = \begin{bmatrix} -1.665 & 0.123 \\ 0.873 & -2.764 \end{bmatrix}$	$\begin{bmatrix} \beta_{AA}^s & \beta_{AB}^s \\ \beta_{BA}^s & \beta_{BB}^s \end{bmatrix} = \begin{bmatrix} -1.673 & 0 \\ 1.993 & -2.711 \end{bmatrix}$
Indirect effect – spatial spillover effect due to a change in own brand price in all connected outlets	Convenience channel	$\begin{bmatrix} \theta_{AA}^{cc} \\ \theta_{BB}^{cc} \end{bmatrix} = \begin{bmatrix} 0.145 \\ 0 \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{sc} \\ \theta_{BB}^{sc} \end{bmatrix} = \begin{bmatrix} 0.197 \\ 0 \end{bmatrix}$
	Supermarket channel	$\begin{bmatrix} \theta_{AA}^{cs} \\ \theta_{BB}^{cs} \end{bmatrix} = \begin{bmatrix} 0 \\ 0.309 \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{ss} \\ \theta_{BB}^{ss} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

Note: The first letter in the subscript reflects affected brand, and the second letter in the subscript reflects the brand for which there is a price change. For instance, subscript AB means price change in B and effect on brand A. Brand A is Coke and brand B is Pepsi.

From Table 2.11, we see that the demand for Coke in the convenience channel outlet decreases by 1.66% when the price of Coke increases by 1%. However, the demand for Coke in the convenience store increases by 0.123% upon a price increase of Pepsi in the same outlet (brand substitution effect) and by 0.145% upon a price increase of Coke in nearby convenience stores (store substitution effect). In the supermarket channel, the demand for Coke decreases by 1.67% upon a price increase of 1% but does not gain anything from a price increase in Pepsi at the same store. It does gain from spatial spillover (0.197%) upon the price increase of Coke in nearby convenience stores.

Pepsi demand is more elastic than Coke demand, indicating lower brand loyalty for Pepsi (2.7% vs. 1.6%). An own-price increase in either channel leads to a decrease in the demand for Pepsi to the tune of approximately 2.7%. A price increase in Coke triggers a brand substitution to Pepsi, 0.87% within the convenience channel and 1.9% within the supermarket channel. The spatial spillover effect is present only for the convenience channel. Consumers switch to the nearest convenience store to buy Pepsi when the price of Pepsi increases (by 1%) in nearby supermarkets, leading to a 0.309% increase in the demand for Pepsi in the convenience store.

2.5.5 Outlet-wise store substitution effect

Figures 2.3(a) and 2.3(b) provide the distribution of the channel-wise store substitution corresponding to a price change in each of the outlets for Coke and Pepsi. For a price change in focal convenience store/supermarket, there will be spatial spillover of demand to nearby convenience stores and supermarkets. I calculate the spatial spillover effect channel-wise for 1% price change in focal outlet for each of the outlet. For Coke, price change in focal convenience store causes spatial spillover of demand to both convenience and supermarket channel. However, spatial spillover effect is equal to zero in both channels for price change of Coke in focal

supermarket. From the distributions we can see that for price change in any outlet belonging to convenience channel, the intra-channel (conv-conv) store substitution is higher than the inter-channel (conv-smkt) store substitution.

Figure 2.3(a): Outlet-wise store substitution for Coke

If we take the average of channel-wise store substitution, 70% of the store-substitution is claimed by nearby convenience channel outlets while 30% of the store substitution is claimed by nearby supermarket channel outlets for Coke. The channels are not exactly substitutable and each channel offers different shopping benefits, which can partly explain the lower inter-channel store substitution from the convenience channel to the supermarket channel despite the lower price in the supermarket channel. Supermarket-to-supermarket channel substitution is zero, as average distances between supermarkets are longer and consumers may not be willing to make that extra effort, especially when they go to supermarkets with long shopping lists; the trade-off between saving some money and putting in extra effort and time to go to another store may not be that great.

Figure 2.3(b): Outlet-wise store substitution for Pepsi

For Pepsi, no store substitution happens due to a price change in any outlet in the convenience channel to either of the channels. Pepsi accounts for only 9% of the market share, leading to a lower proportion of brand-loyal consumers who would be willing to shift stores rather than switch brands in the event of a price change in the focal convenience store. An exception to this rule is the inter-channel store substitution that happens to the convenience channel due to a price change in any outlet in the supermarket channel.

2.5.6 Intra-chain and inter-chain spatial spillover effects

The channel-wise spatial spillover effects can be further split into intra- and inter-chain-level effects. The chain-level breakdown helps us assess the relative importance of own-chain store cannibalization vs. competitor-chain store substitution. Table 2.12(a) shows the chain-level split of the change in demand for Coke in response to a price change in Coke in nearby 7-Eleven, Cheers, Caltex, and Starmart stores, respectively. The first row below the table shows that sales displacement in a 7-Eleven store is maximum (0.103) due to the price change in nearby 7-Eleven stores rather than in Cheers, Caltex, or SPC stores. Hence, for 7-Eleven stores, own-chain

cannibalization is stronger than competitor-store switching. For other retail firms in the convenience channel (Cheers, Caltex, and SPC), the own-chain cannibalization effect is weaker than competitor switching and the main competitor is 7-Eleven. A similar conclusion holds true for chains within the supermarket channel—FairPrice, Cold Storage, Sheng Siong, Giant, and Carrefour. Coke demand in all chains is strongly influenced by price levels in nearby 7-Eleven stores.

Table 2.12(a): Intra and inter-chain spatial spillover effects for Coke

Retailer	Price change				
	7-eleven	Cheers	Caltex	SPC	Total
7-eleven	0.103	0.030	0.005	0.007	0.145
Cheers	0.103	0.027	0.006	0.008	0.145
Caltex	0.097	0.032	0.007	0.009	0.145
SPC	0.093	0.036	0.009	0.006	0.145
FairPrice	0.139	0.046	0.006	0.006	0.197
Cold Storage	0.146	0.033	0.010	0.008	0.197
Sheng Siong	0.127	0.049	0.007	0.014	0.197
Giant	0.156	0.031	0.005	0.005	0.197
Carrefour	0.149	0.045	0.002	0.001	0.197

Intra-channel spatial spillover effects (conv-conv and smkt-smkt) are insignificant for Pepsi. Hence, we do not see an own-chain store cannibalization vs. competitor store switching phenomenon for Pepsi.

Table 2.12(b) shows the chain-level split of the change in demand of Pepsi in the convenience channel in response to a price change in Pepsi in nearby FairPrice, Cold Storage, Sheng Siong, Giant, and Carrefour stores, respectively (inter-channel spatial spillover effect).

Table 2.12(b): Intra and inter-chain spatial spillover effects for Pepsi

Retailer	Price change					
	FairPrice	Cold Storage	Sheng Siong	Giant	Carrefour	Total
7-eleven	0.137	0.068	0.010	0.082	0.006	0.303
Cheers	0.155	0.054	0.013	0.077	0.004	0.303
Caltex	0.136	0.078	0.009	0.074	0.001	0.298
SPC	0.131	0.060	0.023	0.070	0.000	0.285

For Pepsi, the maximum change in demand in 7-Eleven (0.137) is due to a price change in nearby FairPrice stores, followed by Giant, Cold Storage, and Sheng Siong. Other retail firms in the convenience channel—Cheers, Caltex, and SPC—also exhibit a similar price change pattern with FairPrice as the main contributor to the spatial spillover effect. Thus, convenience stores should closely watch Pepsi price levels in nearby FairPrice stores.

2.6. Managerial implications

The results of the current study have important managerial and academic implications. Many key marketing decisions in the consumer packaged goods industry are based on elasticity estimates—pricing, promotion, and advertising decisions. From the results, it is obvious that stores do not operate in isolation but that spatial spillover in demand exists and prices in different stores interact with each other. Marketing metrics that look at price elasticity estimates that do not consider spatial interdependence among stores can be misleading and result in erroneous future planning. Our results are relevant primarily to three key stakeholders in the marketing landscape: individual store managers, brand marketing managers, and retail chain managers.

For the brand marketing manager, market-level price elasticity estimates usually suffice for making marketing input decisions for a sales impetus in the market. However, it is known that the

two channels existing in the market are distinct in terms of the shopping benefits they offer, locations, product assortment, store density, and the kinds of shoppers they attract. This presents a case for a clear price differential that exists between the two channels. Plus, proximity encourages spatial interaction between outlets in the two channels. Under such a scenario, treating both of them alike in price elasticity estimates and ignoring spatial interdependence between outlets (both intra-channel and inter-channel effects) gives rise to a mixed picture and to suboptimal decisions.

Table 2.13: Price elasticity estimates with spatial spillover

Specification	Type of effect	Channel type of the connected outlets	Channel type of focal outlet	
			Convenience store	Supermarket
Specification 3	Direct effect – own store own and cross price elasticities	NA	$\begin{bmatrix} \beta_{AA}^C & \beta_{AB}^C \\ \beta_{BA}^C & \beta_{BB}^C \end{bmatrix} = \begin{bmatrix} -1.665 & 0.123 \\ 0.873 & -2.764 \end{bmatrix}$	$\begin{bmatrix} \beta_{AA}^S & \beta_{AB}^S \\ \beta_{BA}^S & \beta_{BB}^S \end{bmatrix} = \begin{bmatrix} -1.673 & 0 \\ 1.993 & -2.711 \end{bmatrix}$
	Indirect effect – spatial spillover effect due to a change in own brand price in all connected outlets	Convenience channel	$\begin{bmatrix} \theta_{AA}^{CC} \\ \theta_{BB}^{CC} \end{bmatrix} = \begin{bmatrix} 0.145 \\ 0 \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{SC} \\ \theta_{BB}^{SC} \end{bmatrix} = \begin{bmatrix} 0.197 \\ 0 \end{bmatrix}$
		Supermarket channel	$\begin{bmatrix} \theta_{AA}^{CS} \\ \theta_{BB}^{CS} \end{bmatrix} = \begin{bmatrix} 0 \\ 0.309 \end{bmatrix}$	$\begin{bmatrix} \theta_{AA}^{SS} \\ \theta_{BB}^{SS} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
	Net effect	NA	$\begin{bmatrix} -1.520 & 0.123 \\ 0.873 & -2.455 \end{bmatrix}$	$\begin{bmatrix} -1.476 & 0 \\ 1.993 & -2.711 \end{bmatrix}$
Specification 2	Net effect	NA	$\begin{bmatrix} -1.619 & 0.117 \\ 0.898 & -2.825 \end{bmatrix}$	$\begin{bmatrix} -1.813 & 0 \\ 2.105 & -2.758 \end{bmatrix}$

Note: The first letter in the subscript reflects affected brand, and the second letter in the subscript reflects the brand for which there is a price change. For instance, subscript AB means price change in B and effect on brand A. Brand A is Coke and brand B is Pepsi.

Our channel-level price elasticity estimates, which take into account spatial spillover among the outlets, provide a more realistic picture of the market response to pricing inputs, thus allowing brand managers to make better decisions.

If the brand manager looks at the elasticity estimates from specification 2 (without spatial interdependence), he/she will conclude that a 1% price decrease in Coke leads to a 1.62% increase in the demand for Coke in the convenience channel and to a 1.81% increase in the demand for Coke in supermarkets. Once we take into account spatial interdependence (specification 3), a 1% price decrease in Coke will lead to a 1.52% ($1.665-0.145$) demand increase in the convenience channel due to the spillover effect of 0.145% to other convenience stores. The increase in demand in supermarkets will be 1.48% ($1.673-0.197$) due to the spillover effect of 0.197% to other convenience stores. This would mean that the demand for Coke in both channels is less elastic to price change.

Similarly, for Pepsi, a 1% price decrease (increase) leads to a 2.455% ($2.764-0.309$) increase (decrease) in demand for Pepsi in the convenience channel due to a spatial spillover of 0.309% to supermarkets. The increase (decrease) in demand in supermarkets will be 2.711% ($1.673-0.197$). When spatial interdependence is not considered (specification 2), the change in demand predicted in the convenience channel is 2.825% for Pepsi. This means that the demand in the convenience channel is less elastic to price change for Pepsi when spatial spillover effects are taken into account. The shifts of 0.33% ($1.81-1.48$) for Coke and 0.37% ($2.825-2.455$) for Pepsi may look small but, when converted to actual volume (litres), constitute a considerable number. This would mean that brand managers are either undercutting prices or overspending on promotion.

For the individual store manager, the store-level price elasticities are more relevant. From the expanded spatial price elasticity matrix, the manager can identify the key influencers and

beneficiaries among the neighboring outlets and can be more watchful of the actions and reactions of these outlets in particular. This leads to more efficient planning and more targeted decisions.

As an example, let us consider that the focal store is a 7-Eleven store in Marina Square in Singapore. Eighty-five other convenience stores are connected to this 7-Eleven store. When the price of Coke changes by 1% in the neighboring convenience stores, the spatial spillover effect of demand on this store is 0.145%. The majority of the spillover, to the tune of 56%, is driven by another 7-Eleven store in the same pin code. This would mean that the focal 7-Eleven store loses 56% of 1.45% of its Coke sales to the nearest 7-Eleven store in the case of a 10% price promotion. The average monthly Coke sales for this store are \$2500, which would translate into a loss of \$18. The dollar impact or the cost of inaction by the focal store manager is for just one brand within a category. A convenience store typically stocks an average of 40-50 categories and four to five brands within a category. If at least one brand within each category runs a promotion every month, the overall cost of inaction will multiply and have a substantial effect on store revenues.

Consider another example, this one from the supermarket channel. The focal supermarket is a Sheng Siong in the Telok Blangah area in Singapore. It is connected to 41 neighboring convenience stores. When the price of Coke changes by 1% in the neighboring convenience stores, the spatial spillover effect of demand on this store is 0.197%. The majority of the spillover, to the tune of 38%, is driven by two 7-Eleven stores in the vicinity. This would mean that the focal Sheng Siong store loses 38% of 1.97% of its Coke sales to the nearest 7-Eleven stores in the event of a 10% price promotion. The average monthly Coke sales for this store are \$114, which would translate into a loss of \$1. A similar argument holds true for the Sheng Siong store. A supermarket typically stocks, on average, >100 categories and four to five brands within a category. If at least one brand within each category runs a promotion every month, the overall cost of inaction will multiply and

have a substantial effect on store revenues. The current analysis gives the store manager target stores to watch out for, measures their effect on the sales of the focal store, and facilitates timely price matching to minimize the loss of revenue.

For the third kind of stakeholders, who are mainly retail chain managers, chain-level interactions are more informative than either store- or channel-level interactions. The current study clearly indicates that in the event of spatial spillover effects, 7-Eleven outlets are major influencers. For 7-Eleven, own-chain cannibalization is stronger than that of any other retail chain (Cheers, Caltex, SPC). For Cheers, the main influencers are neighboring 7-Eleven outlets. For Caltex and SPC stores, the main influencers are neighboring 7-Eleven and Cheers outlets. For inter-channel effects, the change in sales of 7-Eleven, Cheers, Caltex, and SPC outlets due to spatial spillover effects is mainly and almost equally contributed to by a price change in neighboring FairPrice outlets, followed by Cold Storage and Giant. The change in the sales of FairPrice, Cold Storage, Sheng Siong, Giant, and Carrefour stores due to spatial spillover effects is driven mainly by a price change in spatially connected 7-Eleven and Cheers outlets. This kind of information can be very handy for a firm's pricing and promotion decisions when combined with the spatial distribution information of the other chain outlets.

2.7. Summary and discussion

This study offers evidence of spatial spillover owing to own-brand store substitution and its impact on price elasticity estimates. Earlier research has focused on aggregate data for estimating brand price elasticities and does not account for store-level interaction. Time-series methods have been employed to assess the impact of marketing inputs on market response variables. Studies in the social influence, product adoption, and firm strategic interaction domains have taken into account spatial dependence among agents, though the spatial map representation is different and not based

on the actual physical location of entities. This study sheds light on the impact of spatial interdependence among stores on store-level demand and own-brand price elasticity estimates. An important implication of our findings is that consumers can switch either brands or stores in the event of a price increase in a brand. Store substitution is more pronounced for the brand with a higher market share and a price premium (market leader) owing to a higher percentage of brand-loyal consumers.

Intra- and inter-channel store substitution effects are asymmetric. Same-channel store substitution is significant in the case of the convenience channel but insignificant for the supermarket channel. Convenience-store-to-supermarket sales displacement happens for Coke only, when the price gap between channels is large, whereas supermarket-to-convenience-store substitution happens in the case of Pepsi as channel benefits (‘grab and go’) supersede the price gap between the two channels. At the retail firm level, store density does matter and the chain with larger coverage gets more benefit from the spatial spillover effect.

2.7.1 Limitations and future research

In our context, there is considerable variation in prices among stores within chains. This indicates that the store managers had certain discretion about price promotions. If the prices are fixed across stores within a chain, it can lead to high correlation that would make estimates inefficient which could be problematic. Even if they are not fixed, one can expect a high degree of correlation, which can lead to larger standard errors. If the prices are fixed across stores within chain, any spatial interaction across stores within chain can be ruled out. The current model can be extended to estimate spatial effect for price setting practice by retail chains (standardized pricing) and include

only competitive chains in the spatial components of the model to see if any spatial effect exists or not.

There are several ways in which this study can be extended. We used a very narrow definition of the category, that is, the cola category within the carbonated soft drinks category. Within the cola category, Coke and Pepsi accounted for 98% of the market. Hence, we considered only two brands. Going ahead, it would be interesting to expand the category definition, include multiple brands, and estimate the price elasticities in the presence of spatial spillover. This would also mean extending the model used in this study to accommodate multiple brands, as the almost-ideal demand system kind of model (Deaton and Muellbauer, 1980) used here has limitations in terms of the number of parameters that can be identified and, hence, the number of brands that the model can include.

Previous research (Crask and Olshavsky, 1983) and conventional wisdom in retailing indicate that, to save time and enhance convenience, consumers attempt to minimize the number of visits they make to different stores during a particular shopping trip. Consequently, purchases of promoted products and their complements (as well as nonrelated products) in one store eliminate the need to purchase those products in a competing store. The promotion of one product in a store may result in a decrease in sales of that product and its complements in a competing store, as consumers find it efficient to purchase those products in the same store (Walters, 1991). This requires multi-category sales and price data. The study of the effect of a price change on one brand in the focal store on the sales of complementary products in neighboring stores could be investigated with the availability of such data.

In addition, our analysis is based on a data set from the Singapore market, which is quite contained and developed, and we use column-normalized inverse Euclidean distances between stores as

spatial weights. One possible extension of the current study could be to consider different geographies and different operationalizations of the spatial weights matrix (nearest 'q' neighbors, binary contiguity etc.). Last but not the least, our analysis pertains solely to fast-moving consumer goods. An important question is whether our findings can be generalized to other categories, such as durable goods or categories that induce greater involvement among customers.

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Chapter 3

A spatial econometric model for demand system
estimation in the differentiated goods market

3.1. Introduction

In the previous chapter, we estimated brand price elasticities for two brands—Coke and Pepsi. The category definition was adopted as the “cola” flavor within the carbonated soft drinks category. The consideration of the above category helped us establish the existence of a spatial influence among retailers using a linear system of equations. The main disadvantage of this model is that as the number of brands within a category increases, the number of parameters to be estimated increases exponentially. It becomes increasingly difficult to estimate the brand-level own- and cross-price elasticity due to the sheer number of coefficients that might have to be estimated depending on the number of brands—more commonly referred to as the dimensionality problem in the empirical literature.

One way to circumvent this problem is to place certain restrictions on coefficients using the assumption of the weak separability of coefficients. The main drawback of this approach is that elasticity estimates rely on the separable structure of the utility function and, hence, cannot be empirically verified. The projection of products on a characteristic space offers some respite from the dimensionality problem by reducing the number of coefficients that must be estimated. Consumer heterogeneity of preferences is modeled over product characteristics in discrete choice demand models. However, these models have certain disadvantages such as the independence of irrelevant alternatives (IIA) encountered in logit and nested logit models and the computational complexity in the estimation of the Berry et al. (1995) model.

Pinkse et al. (2002) put forth a different approach to overcoming the dimensionality problem of the neo-classical demand model. In this approach, the authors adopted a new method for cross-price coefficient specification. A variety of distance metrics (based on continuous or discrete attributes) can be constructed among brands and used as weights to create cross-price indices for

each distance metric. From the estimated cross-price indices and the distance metrics between brands, one can calculate the cross-price coefficients and elasticity measures. The main advantages of the Pinkse et al. (2002) model over the discrete choice model are that the former allows for easy estimation, accounts for the location of brands in characteristic space, and allows for the verification of various product groupings as potential sources of competition.

In this chapter, I use the distance-metric (DM) method to estimate a demand system in the characteristic space in the presence of spatial interaction among outlets. The use of a characteristic space alleviates the limitation of the linear demand system model of Chapter 2 when there is a large number of brands. Using the DM method, one can map the brands into a low-dimensional characteristic space; therefore, increasing the number of brands poses few problems in terms of estimation. Similar to the model discussed in Chapter 2, I consider only own-brand-cross-store spatial substitution in the model that this chapter discusses. The spatial spillover effects are captured by one parameter for each brand and the spatial weight matrix. Because the competitive brands are mapped onto the characteristic space, the total number of parameters is not very high. To the best of our knowledge, this is the first study on spatial spillover effects in demand system estimation for differentiated goods with a large number of brands.

I see this chapter as a contribution to the literature on dimension reduction in the demand system estimation (the seminal article being the one by Pinkse et al. (2002)). In this chapter, I demonstrate how the model can be extended to include spatial price competition in the presence of a large number of differentiated goods. While the famous BLP model (Berry et al, 1995) is popular in the Marketing literature, the Pinkse et al. (2002) is less so. However, it is well known that the BLP model estimation faces numerical challenges, whereas the numerical challenges for Pinkse et al (2002) model estimation is less. Adding the spatial component would make BLP even more

numerically challenging, and therefore, I believe the Pinkse et al (2002) offers a suitable less challenging alternative. I do wish to highlight that even with extending the Pinkse et al (2002) model to incorporate spatial price competition may be challenging. A few counterintuitive results in this chapter actually indicate that there are more work that need to be done to make the model more functional. This chapter is only the first step. And I hope to continue to conduct research in this area to examine many more statistical challenges that I may not have discussed in this chapter. Having said that, I do agree that the appeal of this model may not be widespread. But I do believe that researchers examining spatial price competition may find this research useful, even if it is for identifying lacunas and potential solutions.

The remainder of the chapter is structured as follows. Section 3.2 illustrates the empirical model; section 3.3 describes the data; section 3.4 discusses the estimation and results; section 3.5 discusses the managerial implications; and section 3.6 contains the summary and discussion.

3.2. Empirical model

The main intent of this chapter is to estimate a store-level demand model with spatial interdependence that incorporates multiple brands within a category. With an increase in the number of brands, the parameter space explodes in a linear model, as in Chapter 2, or in ALIDS- (Deaton and Muellbauer, 1980) type models, making those models unsuitable for application. Discrete demand models use a more efficient approach by projecting products in a characteristic space. This reduces the number of cross-price coefficients to be estimated. On the other hand, such models bring with them a certain computational complexity and constraints of their own, such as the purchase of a single product in a single shopping trip (Berry et al., 1995).

Pinkse et al.'s (2002) model alleviated concerns about the above two models. It can include multiple brands and does not impose any restrictions on purchase quantity. In an application of the Pinkse et al. (2002) model in demand estimation for beer markets, Rojas and Peterson (2008) showed that the DM method can be applied to the Almost Ideal Demand System (Deaton and Muellbauer, 1980) to reduce the problem of the dimensionality of the parameter space. The ALIDS model can be written as:

$$s_{jt} = \alpha_{jt} + \sum_{k=1}^J \beta_{jk} \log P_{kt} + \delta_j \log \left(\frac{x_t}{PI_t} \right) + \epsilon_{jt} \quad \dots\dots\dots(3.1)$$

where $t = \{1, \dots, T\}$ is the index for market, $j = \{1, \dots, J\}$ is the index for brand, P_{jt} is the price for brand j in market t , Q_{jt} is the quantity sold for brand j in market t , $s_{jt} = \left[\frac{(P_{jt} * Q_{jt})}{x_t} \right]$ is the market share, and $x_t = \sum_{j=1}^J P_{jt} * Q_{jt}$ is the total expenditure. PI_t is the Stone price index in market 't' given by: $\log PI_t = \sum_{j=1}^J s_{jt} \log P_{jt}$.

Consider the inclusion of the spatial spillover effect in the above model. Using the approach employed in Chapter 2, one can develop the following model to incorporate this effect:

$$s_{jt} = \alpha_{jt} + \sum_{k=1}^J \beta_{jk} \log P_{kt} + \theta_j^{cc} \sum_{t' \in c} \omega_{tt'} \log P_{jt'} + \theta_j^{cs} \sum_{t^* \in s} \omega_{tt^*} \log P_{jt^*} + \delta_j \log \left(\frac{x_t}{PI_t} \right) + \epsilon_{jt} \quad \dots\dots\dots(3.2)$$

Here, superscript 'c' and 's' denote convenience store and supermarket, respectively. Meanwhile, $\omega_{tt'}$ is the spatial weight between outlet t and t' when both outlets are convenience stores; ω_{tt^*} is the spatial weight between outlet t and t^* when the focal outlet is the convenience store and outlet t^* is a supermarket. Similarly, one can estimate an equation when the focal market is a supermarket.

Estimating equation (3.1) or (3.2) as above for multiple brands in a category will still require $J(J-1)/2$ coefficients to be estimated for price. Many coefficients remain to be estimated if ' J ' is large. Hence, I consider the distance-metric method to overcome this problem.

3.2.1 Distance-metric (DM) method

Rojas and Peterson (2008) showed that instead of using competitive brand prices directly in equation (3.1), one can map the competitive brand prices on a set of observable characteristics. For instance, any carbonated soft drink brand can be described according to its flavor, packaging type, sugar content, etc. The core idea of the DM method is to calculate the distance between the focal brand and the competitive brands in the same store for each characteristic. These distances are then used as weights to calculate the weighted average price of that characteristic. This way, if there are L characteristics, we can calculate L weighted average prices. Thus, even if the number of brands J is very large, the competitive brands can be mapped onto L dimensional characteristic prices.

Let the distance between brand j and a competitive brand k on characteristic l be δ_{jk}^l . Suppose the store has K competitive brands. Then the weighted average price of the characteristic can be calculated as $g(\delta_j^l) = \sum_{k=1}^K \delta_{jk}^l \cdot \log P_k / K$. For characteristics that are continuous variables, the Euclidean distance can be calculated. For characteristics that are discrete, the distance can be either 0 or 1. It is useful to take the inverse of the distance. Therefore, if two brands have the same discrete characteristic, then δ_{jk}^l between them should be 1; if they are different, then δ_{jk}^l should be 0. For continuous characteristics, one can take the inverse of the Euclidean distance as δ_{jk}^l .

With these distance metrics, one can use the following model for demand estimation:

$$s_{jt} = \alpha_{jt} + \beta_{jj} \log P_{jt} + \sum_l \lambda_l g(\delta_j^l) + \delta_j \log \left(\frac{x_t}{P_{It}} \right) + \epsilon_{jt} \quad \dots\dots\dots(3.3)$$

Using the above model, one can estimate the cross-characteristic substitution. Suppose that cola flavor is one of the characteristics on which we wish to estimate the demand function parameters for a carbonated soft drink brand. If the competitive cola brand prices increase, some of the

competitive brand consumers may switch to the focal brand. When competitive cola brand prices increase, then $g(\delta_j^l)$ should increase. Meanwhile, if λ_l is positive, that would reflect a substitution to the focal brand. Thus, the use of a model on characteristic space has the advantage of ensuring that the consumer's switch to a similar characteristic brand is easily captured.

3.2.2 Distance-metric (DM) method with spatial interaction

I propose to include the spatially weighted prices of own brands in Equation (3.3) to estimate whether there is also a cross-store substitution. Similar to the model in Chapter 2, I restrict the model to include only own-brand-cross-store substitution. The argument being it is unlikely that *ceteris paribus* if there is a price change in the focal brand, a consumer would switch to a competitive brand in another store. The logical choices would be a competitive brand in the same store or, if the consumer is brand-loyal, the person may decide to switch stores to buy the same brand.

In addition to incorporating cross-store substitution, I wish to allow for the substitution rate to differ by the focal store and connected store channels. The substitution rate from a convenience store to a convenience store may differ from the substitution rate from a convenience store to a supermarket. To accommodate these differences, I modify Equation (3.3) to the following:

$$s_{jt} = \alpha_{jt} + \beta_{jj} \log P_{jt} + \theta_j^{cc} \sum_{t' \in c} \omega_{tt'} \log P_{jt'} + \theta_j^{cs} \sum_{t' \in s} \omega_{tt'} \log P_{jt'} + \sum_l \lambda_l g(\delta_j^l) + \delta_j \log \left(\frac{x_t}{p_{lt}} \right) + \epsilon_{jt} \quad ..(3.4)$$

The above equation is for convenience stores. The estimation equation for supermarkets can be developed similarly. The advantage of the model in Equation (3.4) over the linear demand system model discussed in Chapter 2 is that this model can capture the spatial effects exactly the same way but with a manageable number of parameters for cross-price substitution. The direct and spatial spillover effects are to be interpreted in the same way for both the model in Chapter 2 and

the model in this chapter. Therefore, we do not discuss the direct and spatial spillover effects separately in this chapter.

3.3. Data

The data comes from The Nielsen Company retail scanner panel data for Singapore and comprises of weekly price, volume sales (quantity of units sold), value sales for each SKU and outlet for 982 outlets in Singapore for carbonated soft drinks category. The data is from 2010-2012 for a total of 26 months (weekly data aggregated into months). The volume sales have been converted to litres and the unit for price is \$/litre. The data also contains many store-level variables- channel, region, chain, postal code information and brand-level variables-manufacturer, pack size, packaging, flavor.

For current analysis, top 19 stock keeping units (SKUs) in the overall carbonated soft drinks market are considered. The 20th category is considered to be the ‘outside good’. These 19 SKUs differ by brand, flavor and pack sizes. In order to limit the number of parameters to a reasonable level, SKUs are categorized into three flavor types – cola, lemon-lime and others, and into four pack-types small cans, small bottles, large bottles and multipack (of more than 1.8 liters).

Table 3.1 lists the 19 SKUs and their main characteristics, along with average per store market share. Although the sum of the average per store market shares is almost 98%, the overall (all stores combined) market share of these 19 SKUs turns out to be approximately 68%. In Table 3.1, the top 4 SKUs are all variants of Coke (Coca-Cola). These four SKUs vary due to their pack-sizes. The 5th largest SKU is Sprite large bottles, and the 6th one is Bundaberg small bottles. However, Pepsi cola’s 2 SKUs-small bottles and large bottles, in combination, hold more market share than Sprite, essentially making Pepsi the second largest brand. F&N has 2 SKUs, and in

combination this brand also has more market share than Sprite. Thus, the market has one strong leader in Coke, and there are several follower brands with similar market shares.

Table 3.1: SKU descriptions and average per store market shares

SKU no.	Brand	Cola	Lemon-lime	Small pack	Large pack	Mean market share per store
1	Coke	1	0	0	0	18.37%
2	Coke	1	0	0	1	18.19%
3	Coke	1	0	1	0	17.78%
4	Coke	1	0	0	0	6.19%
5	Sprite	0	1	0	1	3.75%
6	Bundaberg	0	0	1	0	3.65%
7	Pepsi	1	0	1	0	3.64%
8	F&N	0	0	0	1	3.23%
9	Mountain Dew	0	0	1	0	2.92%
10	Fanta	0	0	1	0	2.67%
11	Sprite	0	1	1	0	2.51%
12	7-up	0	1	1	0	2.49%
13	Pepsi	1	0	0	1	2.43%
14	Pokka	0	0	1	0	2.36%
15	Schweppes Soda	0	0	0	0	1.98%
16	A&W	0	0	1	0	1.87%
17	Schweppes Tonic	0	0	0	0	1.61%
18	Pepsi	1	0	0	0	1.26%
19	F&N	0	0	1	0	1.18%

Table 3.2 reports the average, minimum and maximum market share by store by channel. The market comprises of two channels – supermarkets and convenience stores. There are substantial variations in the market shares of the 19 SKUs in the 2 channels. While the 4 Coke SKUs retain their strong leadership position, the dominance of the SKUs differ between the 2 channels. Interestingly, given the strong position of Coke, it appears that a few retailers in the convenience store channel sell only Coke SKUs in certain months, giving the brand 100% market-share during those months.

Table 3.2: Average market share per store by channel

Brand no.	Average per store market share - supermarkets			Average per store market share – convenience stores		
	Mean	Min	Max	Mean	Min	Max
1	19.15%	0.04%	59.30%	17.67%	0.05%	63.67%
2	20.49%	1.86%	48.97%	17.47%	0.27%	100.00%
3	4.51%	0.03%	24.45%	21.84%	0.82%	100.00%
4	3.23%	0.01%	84.65%	7.25%	0.01%	66.17%
5	3.33%	0.18%	15.17%	3.92%	0.05%	26.36%
6	2.32%	0.02%	10.59%	4.04%	0.04%	40.27%
7	0.97%	0.00%	8.22%	4.47%	0.03%	62.70%
8	4.04%	0.02%	47.54%	2.69%	0.02%	28.49%
9	0.49%	0.01%	9.07%	3.47%	0.02%	22.97%
10	0.93%	0.00%	23.74%	3.29%	0.04%	29.26%
11	0.91%	0.00%	10.48%	3.07%	0.03%	43.90%
12	0.58%	0.00%	8.01%	3.09%	0.03%	35.99%
13	2.62%	0.01%	9.34%	2.34%	0.02%	20.00%
14	0.31%	0.00%	7.14%	2.87%	0.02%	34.31%
15	0.71%	0.00%	5.34%	3.24%	0.02%	22.38%
16	0.50%	0.00%	7.02%	2.30%	0.03%	30.87%
17	1.36%	0.00%	6.40%	1.93%	0.03%	10.88%
18	1.08%	0.00%	58.40%	1.38%	0.02%	23.92%
19	0.20%	0.00%	3.70%	1.53%	0.02%	47.45%

Table 3.3 reports the average prices of these 19 SKUs by channel. Price per liter varies significantly in the 2 channels for all the SKUs. Notably, the variation in price per liter among the supermarket stores is generally much smaller than that among the convenience stores. The large difference in the average price in the two channels suggests that they cater to different needs of the consumers. The convenience stores cater to ‘impulse purchase’ needs, whereas the supermarkets cater to ‘planned purchase’ needs in general. The price difference suggests that these two channels should be separately examined in the empirical analysis.

Table 3.3: Price distribution by channel

Brand no.	Distribution of price/liter – supermarkets				Distribution of price/liter – convenience stores			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
1	1.97	0.16	1.16	2.50	2.06	0.31	1.52	3.43
2	1.27	0.06	1.04	1.68	1.93	0.26	1.15	2.51
3	2.64	0.16	1.80	3.23	4.34	0.75	2.54	6.02
4	2.47	0.42	1.25	6.19	4.94	0.83	1.65	6.67
5	1.16	0.06	1.02	1.50	1.87	0.31	1.14	2.40
6	4.81	0.52	3.05	6.67	5.67	0.56	3.97	7.35
7	1.87	0.17	1.32	2.33	3.15	0.57	1.67	5.00
8	1.08	0.08	0.53	1.31	1.64	0.29	0.35	2.13
9	2.06	0.27	1.11	2.50	3.45	0.66	1.20	5.00
10	2.32	0.12	0.24	2.80	3.85	0.71	2.28	5.20
11	2.35	0.11	1.80	2.83	4.08	0.65	2.30	5.00
12	1.83	0.13	1.46	2.38	3.02	0.53	1.00	6.67
13	1.12	0.08	0.88	1.96	1.67	0.32	0.87	2.75
14	2.27	0.29	0.93	2.88	3.69	1.08	1.52	5.40
15	2.78	0.55	1.76	10.33	5.63	0.56	4.09	6.67
16	2.35	0.11	1.80	2.74	4.03	0.65	2.27	5.00
17	2.67	0.27	2.07	7.02	5.46	0.58	3.64	6.67
18	1.93	0.21	1.00	2.64	4.46	1.20	1.25	6.67
19	2.19	0.22	1.18	2.75	3.84	0.71	1.98	5.20

Geo-location of the outlets is extracted from postal code information and converted into Euclidean distances between outlets. This gives an $N \times N$ (N =total number of outlets) matrix of distances where non-diagonal elements give distance between outlets and diagonal elements are zero. The column normalized inverse of distances in this matrix gives spatial weights matrix. The column vector for the respective outlet from the above matrix when multiplied by price vector of each brand for all stores for a particular month gives the spatially weighted price for each brand in that month for the respective outlet. This way we create the spatial price variables used in the model.

3.4. Estimation and results

The empirical model in current study is a reduced form demand model inspired by ALIDS (Deaton and Muellbauer, 1980) and Pinkse, Slade and Brett (2002) models as illustrated in the framework section. Since the explanatory variables are mostly prices, these are potentially endogenous. Therefore, we use GMM on first difference for estimation. First differencing eliminates store specific fixed effects. However, prices may still be endogenous due to manufacturers' choices. Therefore, we use second and third lags of the variables as instruments. The large panel dataset means approximately 15-25K observations for each SKU, thus making it possible to estimate the model separately for each SKU. The current model also allows us to have variable distance-metric parameters across SKU's unlike the Rojas and Peterson (2008) model that estimates one set of ' λ 's' for all the brands.

The results are reported in Tables 3.4 and 3.5. As indicated previously, the nature of price competition appears to be quite different. Prices in convenience stores are significantly higher. While, both supermarkets and convenience stores can be within very short physical distances, the large price difference suggest that there may be considerable differences in the demand side factors. Thus, we estimate the parameters of our empirical model for the two channels separately. Table 3.4 reports the parameter estimates using the market shares in the supermarkets as the dependent variable, and Table 3.5 reports the estimates using market shares in the convenience stores as the dependent variable.

For both channels, we estimate the parameters for the top 5 products. Each product is a stock keeping unit (SKU) and characterized by brand, flavor and pack-size. There are 10 specifications in each table. Each pair of specification (1, 2), (3, 4), (5, 6), (7, 8) and (9, 10) pertains to each of the 5 SKUs. The odd numbered specifications exclude the spatial variables and even numbered specifications include the spatial variables. The independent variables on the left hand side of each

of the tables include, own-store own brand price, own-brand spatially weighted average of convenience stores price, own-brand spatially weighted average of supermarkets price, cross-brand price of colas (other than focal brand, Coke), cross-brand price of lemon-lime flavored drinks, cross-brand price of small bottles, cross-brand price of large bottles and the price index.

All the cross-brand prices' are based on characteristic space calculation using discrete distance metrics of two characteristics- flavor and packaging. The neighborhood matrices are created based on these two characteristics. The flavors are-cola, lemon-lime and others and packaging is either small or large bottle. If brand (j, k) belong to the same group, the (j, k) element of the neighborhood matrix is equal to one else zero. Referring to Table 3.4, four out of five specifications with spatial variables have significant coefficients for either or both the spatial variables (Spatial price-conv and Spatial price-smkt) which lends support to the hypothesis that demand does depend on spatially weighted prices apart from own price.

Supermarket-supermarket spatial competition- As seen in Table 3.4, the coefficients for the spatially weighted price of own brand in adjoining supermarkets are positive and significant for specifications 4, 8 and 10 which means that as price of own brand goes up in adjoining supermarkets, the market share in focal store goes up. The spatial spillover effect is positive. For example, for specification 4, it can be said that when spatially weighted price of own brand in nearby supermarkets goes up by 1%, the market share of own brand in focal supermarket goes up by 5.3% of the current market share (log-log model used).

Supermarket-convenience store spatial competition- From Table 3.4, we see that coefficients for spatially weighted price of own brand in adjoining convenience stores are significant and positive for specifications 2 and 4 which has similar implications on the market share of own brand in focal supermarket as listed above. The spatial spillover effect is again positive. One point to

note at this stage is the relative difference in the magnitude of the coefficients of spatially weighted own brand price in supermarkets and convenience stores respectively. For example, for specification 4, a 1% increase in spatially weighted price of own brand in nearby supermarkets leads to an increase in market share equal to 5.3% of the current market share. However, a 1% increase in spatially weighted price of own brand in nearby convenience stores leads to an increase in market share equal to 1.5% (approximately) of the current market share which is much lesser than 5.3% impact. This would imply that intra-channel price change has higher impact on market share than inter-channel price change in case of supermarkets.

Convenience-convenience store spatial competition- Referring to estimates in Table 3.5, we see that all own brand-own store price elasticities are negative (coefficient of Own price variable). For the spatially weighted price in adjoining convenience stores, only one coefficient estimate is significant (for specification 8) and it is negative. A negative spillover effect is counter-intuitive. It means that a price increase of own brand by 1% in spatially connected convenience stores leads to decrease in market share of own brand in focal convenience store equal to 1.5% (approximately) of the current market share. Currently, I do not have a foolproof and plausible explanation for the negative coefficients that I am getting after estimation. I am still working on the estimation model and may be, I get more reasonable results in the future work.

Convenience store-supermarket spatial competition- In Table 3.5, the coefficient for spatially weighted price in adjoining supermarkets is significant for specification 2, 8 and 10. The coefficient is positive for specification 2 and 8. Thus, if the spatially weighted price of own brand in supermarkets goes up by 1%, the market share of own brand in focal convenience store increases by a magnitude equal to 1.5% (specification 2) of the current market share.

Table 3.4: Estimates for supermarkets

VARIABLES	Coke small can		Coke large bottle		Coke small bottle		Coke multipack		Sprite large bottle	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Own price	-2.614*** (0.678)	0.123 (1.166)	-4.655*** (0.376)	-5.287*** (0.570)	-4.962** (2.417)	-2.967 (5.043)	-0.694 (1.164)	-8.385*** (2.813)	-0.605 (0.387)	-0.941*** (0.283)
Spatial price – conv		1.267*** (0.412)		1.493*** (0.569)		-1.279 (0.422)		-0.378 (0.370)		-0.175 (0.215)
Spatial price – smkt		-0.383 (3.346)		5.314*** (1.944)		3.428 (1.987)		7.475*** (2.879)		3.264*** (1.105)
DM – cola	0.885 (4.049)	1.898** (0.768)	-3.295 (2.389)	-7.762*** (2.418)	-30.391*** (5.373)	-11.463 (10.274)	-10.646 (7.203)	3.361 (3.961)	-5.393*** (1.456)	-5.276*** (1.181)
DM – lemon	20.776** (9.022)	0.260 (1.631)	6.869 (4.363)	3.400 (5.301)	63.461*** (12.039)		8.242 (20.834)	-5.650 (8.542)	9.341*** (3.221)	3.400 (2.324)
DM – small bottle	-18.244** (8.648)	-1.519 (1.739)	-3.617 (5.522)	0.851 (5.668)	-58.747*** (12.083)	-84.493*** (18.045)	-12.854 (22.283)	3.909 (10.426)	-6.046** (3.000)	1.496 (2.262)
DM – large bottle	7.244** (3.212)	-1.067 (0.637)	1.186 (1.768)	0.273 (1.821)	24.688*** (4.815)	35.561*** (11.988)	17.680 (9.666)	9.434 (5.608)	4.621*** (1.216)	-0.203 (1.008)
Price adjusted expenditure	-0.152*** (0.015)	-0.169*** (0.014)	0.212*** (0.032)	0.101*** (0.029)	-0.425*** (0.036)	-0.354*** (0.070)	-0.386*** (0.043)	-0.439*** (0.033)	-0.352*** (0.017)	-0.238*** (0.017)
Observations	4,329	4,780	4,503	4,731	4,491	4,491	4,321	4,546	4,554	4,781
R-squared	-0.547	0.115	0.155	0.172	-3.096	-2.862	-0.516	-0.217	0.054	0.239
Kleibergen-Paap F-stat	0.699	3.787	8.303	9.777	11.29	0.333	0.579	0.763	8.367	11.72
Hansen's J-stat	7.428	135.4	34.47	0	29.07	15.45	10.31	11.40	8.230	37.09
Hansen's J-stat p-value	0.191	0	1.92e-06		2.25e-05	0.0170	0.0669		0.0835	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05. DM = distance metric.

Table 3.5: Estimates for convenience stores

VARIABLES	Coke small can		Coke large bottle		Coke small bottle		Coke multipack		Sprite large bottle	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Own price	-1.821*** (0.269)	-1.333*** (0.250)	-1.564*** (0.318)	-3.273 (1.951)	-0.983*** (0.158)	-0.891** (0.422)	-0.830*** (0.070)	-0.426** (0.204)	-1.043*** (0.125)	-0.670*** (0.169)
Spatial price – conv		0.686 (0.381)		4.804 (6.309)		0.257 (0.540)		-1.491*** (0.305)		-0.373 (0.314)
Spatial price – smkt		1.561** (0.761)		17.287 (14.875)		0.410 (1.061)		1.885*** (0.471)		-1.320** (0.644)
DM – cola	1.356 (0.820)	-1.860*** (0.469)	-0.778 (1.694)	-2.905 (4.666)	-2.235*** (0.646)	-1.293*** (0.414)	-1.085** (0.465)	-3.400*** (0.686)	1.271 (0.717)	1.345** (0.620)
DM – lemon	-0.634 (0.885)	3.068*** (0.555)	-2.600 (1.860)	-6.033 (4.423)	1.382 (0.717)	0.488 (0.557)	2.283*** (0.557)	2.536*** (0.952)	-1.270 (0.959)	-1.376 (0.891)
DM – small bottle	1.085 (0.903)	-2.096*** (0.535)	2.386 (2.547)	12.896 (9.088)	0.585 (0.589)	0.194 (0.613)	0.371 (0.525)	0.261 (1.693)	1.428*** (0.496)	1.564*** (0.491)
DM – large bottle	1.507*** (0.543)	0.091 (0.339)	2.955*** (1.137)	-0.866 (4.527)	-0.921** (0.404)	-0.261 (0.426)	1.916*** (0.384)	2.734** (1.081)	-0.719 (0.473)	-0.441 (0.494)
Price adjusted expenditure	0.073*** (0.023)	-0.027 (0.016)	0.109** (0.054)	0.019 (0.225)	-0.140*** (0.021)	-0.154*** (0.026)	-0.024 (0.015)	-0.069*** (0.017)	-0.032 (0.023)	-0.008 (0.025)
Observations	13,777	15,282	4,253	4,253	13,621	13,621	14,789	14,789	12,484	12,484
R-squared	-0.108	-0.173	0.039	-0.221	-0.053	0.004	-0.237	-0.609	0.036	0.032
Kleibergen-Paap F-stat	3.691	12.88	6.146	0.674	11.73	13.58	20.51	2.675	16.03	14.90
Hansen's J-stat	30.19	54.30	9.695	2.171	11.44	21.66	2.415	4.012	63.05	62.63
Hansen's J-stat p-value	1.35e-05	0	0.0843	0.704	0.0433	0.00559	0.120	0.404	0	0

Robust standard errors in parentheses; *** p<0.01, ** p<0.05. DM = distance metric

3.5. Managerial implications

There are many ways to use the above empirical findings. From the brand manager's perspective, the above findings clearly highlight the efficacy of price change/promotion for Coke and Sprite by packaging, product size, and channel. The large bottles/multipacks are positioned as family-value packs and have a higher demand in the supermarket channel. For Coke and Sprite, the intra-channel spatial spillover effect is higher than the inter-channel spatial spillover for large bottles and multipacks in supermarkets. The decrease in the market share of Coke large bottle, multipack, and Sprite large bottle in the supermarket channel for an own-brand price increase is compensated for, to a large extent, by an intra-channel spatial spillover effect for these products. This brings to light the notion that demand for these products is fairly inelastic in supermarkets if the bigger picture is seen (own-store price elasticity estimates + spatial spillover). This gives leverage to the brand manager to increase prices without hurting the market share to the extent that was thought earlier. This also helps the brand manager channelize the promotion money to a more effective marketing instrument.

For Coke small can, only an inter-channel spatial spillover effect is seen, i.e., the market share of Coke small can in a supermarket is affected by a price change in neighboring convenience stores, while the reverse is true for market share in a convenience store. Increasing the price of Coke small can in supermarkets (lower priced-low margin channel) leads to an increase in the market share of Coke small can in a convenience store (higher priced-high margin channel). This translates into additional revenues and profit margins for the product. Price promotion on Coke small can in supermarkets should be avoided, as it reduces the market share in the higher-margin channel (convenience stores). Also, Coke small bottle demand in both channels is not affected by any price change in either neighboring convenience stores or supermarkets. The own-brand price elasticity is also low. The brand manager can clearly infer that a price increase in Coke small bottle in the

supermarket or convenience channel will not decrease the market share. At the same time, a price promotion in Coke small bottle in either channel will not help in gaining market share. All this information shows that giving a price promotion to Coke small bottle might not be a great idea to increase market share; the money for promotion can be used on a more effective alternative marketing instrument.

3.6. Summary and discussion

The intent of this chapter is to illustrate the phenomenon of spatial interaction among stores and its impact on demand estimation, moving from the brand space to the characteristic space. The current study accommodates multiple brands within a category. The spatial coefficient estimates show that spatial interaction exists among the outlets and that the spatially weighted price of adjoining outlets affects the sales/market share of the brand in the focal outlet. The positive spatial coefficients indicate that the demand for the brand in the focal store increases if the price of the same brand in spatially connected outlets increases, while the demand decreases if the spatial price decreases. The above findings highlight the efficacy of price change/promotion for Coke and Sprite by packaging, product size, and channel. This gives leverage to the brand manager to increase the price without hurting the market share to the extent as thought earlier. This also helps the brand manager channelize the promotion money to a more effective marketing instrument.

One study limitation is that few coefficients are negative, which is counter-intuitive to logic and requires further examination. Also, Hansen's J-statistic is significant, which could be in part due to a high correlation among variables and this makes it difficult to find perfect instruments. Although this approach allows for the estimation of a large number of brand elasticities, inclusion of spatial weights and characteristic space weights in the same equation introduces computational complexity that makes variable operationalization difficult. Again, within the distance-metric

method, taste is subjective and there is much more to it than just two variables (size of bottle and flavor) that current analysis has used. If there were certain continuous variables, for example, sugar content or may be the color that would have created clearer difference between products. Ideally, more variables and dimensions would sufficiently discriminate between brands but at the price of increase in number of parameters to be estimated.

Despite these limitations, this study presents evidence for spatial interaction, and is the first study to include spatial interaction in demand estimation. This study is set in a new geography (Singapore market), while most of the earlier literature regarding on demand system estimation has utilized the US market. It will be interesting to determine if our findings are generalizable to other countries. Also, we can use this demand system estimation on other product category data to determine if category characteristics or country characteristics affect these findings.

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