

Benchmarking Performance in Retail Chains: An Integrated Approach

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Standardizing performance expectations across different outlets within a chain, differing in their individual features, their consumers, and the nature of competition they face, can be an onerous task. We develop an integrated, nonlinear, block group-level market share model of store expectations that draws upon the existing trade area as well as store performance literatures. By incorporating and normalizing a large number of external and internal factors impacting performance, we are able to offer a means for the retailer to determine equitable standards. The model is estimated using a variation of the maximum-likelihood estimation, on a data set fashioned from several sources and aggregated at the block group and store levels. Finally, we propose a set of indices that allows us to evaluate relative performances of stores and regions given the competitive environments they face. We find that a block group-level model offers a better fit, as well as significantly richer implications, than a traditional store-level model. Results show that a significant number of stores operate well below their expected levels, an insight not obvious from the raw numbers used to report store statistics to upper management.

Key words: retailing; store performance; benchmarking; econometric models

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1. Introduction

The last 50 years has seen an explosion in the operation of chain outlets with one of the most dramatic changes being observed in the grocery retail industry. According to *Progressive Grocer* (2007), the top 50 supermarket chains in the United States have, on an average, 378 stores. Economists have long attributed the success of chain stores to a number of causes—mass production and distribution, standard stocks of merchandise, mass buying, standard business procedures, and systematization of employee training and advertising, to name just a few. Although the large number of chain stores ensures an extensive distribution that maximizes coverage across regions, individual stores may vary tremendously in terms of their physical characteristics such as the size of the store, the services it provides, the products offered, etc. Furthermore, the environment within which the stores operate, in terms of the competition and customers they face, can vary significantly. This variation in stores, as far as management is concerned, is certainly desired and should reflect the customization of stores to meet the needs of its specific consumers, given

the environment in which they exist. Such variation within a single chain also raises several important issues for management as well as for researchers.

First, what expectations should management have with respect to sales for a specific store, given that all stores operate under a different set of conditions? Clearly, what would be considered satisfactory revenue at one store located in an area characterized by strong competition may well be considered unsatisfactory at another store in a relatively isolated location. A second related issue is whether it is possible to determine the kinds of services that add the greatest value, given the specific nature of the competition the store faces and the needs of its consumers. Third, because any given store would be visited by many different consumers, is it possible to identify segments of consumers from whom a satisfactory level of sales has been achieved relative to segments who perhaps shop elsewhere?

These issues have far-reaching implications over several dimensions. Whether the issue is of determining appropriate consumer segments to target, or of formulating strategy to improve store performance,

or indeed for determining what expectations should be regarding performance, the estimation of an equitable expectation of demand at the store level and at the consumer segment level becomes essential. Any such estimation must take into account, and adjust for, differences regarding a variety of factors such as the stores themselves, the areas from which a store draws its consumers, and the nature of the competition faced by the store. Research dealing with such store-specific performance issues, and more specifically consumer segment-specific insights, however, is somewhat scarce, leaving a significant gap in the literature (Bucklin and Gupta 1999). Although a lack of data and technology has been cited as the root cause of this, with information becoming increasingly abundant and methodologies sufficiently sophisticated for handling such data, this important issue of setting “equitable expectations” demands a more satisfactory solution.

The purpose of this paper, then, is to develop an integrated model incorporating store, customer, and competitive characteristics that offer the retailer a means of determining an equitable expectation of demand from the stores as well as the consumers. To address all the issues raised earlier, we construct a unique data set at the block group¹ level rather than at the more traditional store level that enables us to offer a set of indices that not only benchmarks the performance of stores, but can further be disaggregated to offer benchmarks within each block group, thus allowing a variation in performance of the same store over different block groups. Because the benchmarking indices are generated from the same framework, a relative comparison across stores and regions can be undertaken. Thus, in addition to benchmarking stores (as most store models do), we also offer a means of benchmarking block groups. This allows individual stores to determine their overall performance as well as their performance within each of its surrounding areas.

In the next section, we discuss the relevant research work that we draw upon in order to develop our conceptual framework and formulate our model. Subsequent sections deal with the description of data and variables, empirical results, and validation issues. Finally, we conclude with managerial implications and a general discussion of the model, its contributions, and its limitations.

¹ Designed to be a relatively homogeneous segment of consumers with respect to population characteristics and economic status, a census block is the smallest geographic unit for which the Census Bureau tabulates data. Note that this definition of “region” will allow us to use the sociodemographic and demand data so collected.

2. Background

In addressing the issues raised above, we use a conceptual framework that draws from prior research, primarily in the supermarket retailing field. We briefly reference three established areas—namely, the areas focusing on exogenous and endogenous determinants of store performance, and a third stream that studies benchmarking using a variety of methods including empirical, econometric, and operations research methods.²

2.1. Exogenous Determinants of Store Performance

Past research has recognized the importance of various exogenous features such as characteristics of the trading area of the store, nature of the competitive environment, and various other macroeconomic factors that play an important role in determining the performance of the store. Researchers have shown that demographic factors such as income, occupation, and ethnicity of the shoppers have a significant impact on store choice—more specifically, on the importance to choice of specific store-related features (Ghosh 1984, Craig et al. 1984). Some recent work has also shown that determinants of grocery store performance can be identified by such demographic characteristics of the trade area (Kumar and Karande 2000, Reinartz and Kumar 1999). Competitive environment, often modeled as a dummy variable (Ghosh 1984, Hoch et al. 1995, Boatwright et al. 2004), has also been found to play an important role in choice, particularly for differentiation among neighboring stores.

The definition of a trade area within which to consider consumers and competitors becomes a critical issue in the above research. The classic studies by Huff (1963, 1964) define this area by using an infinite function that decreases monotonically with increasing distance in a probabilistic framework. The implied infinite stretching of the market area surrounding a store was subsequently deemed to be a limitation of the model, and several studies tried to resolve this (Reilly 1931, Huff and Rust 1984). Nakanishi and Cooper’s (1974) multiplicative competitive interaction (MCI) model extends Huff’s model by including a set of store attractiveness attributes from which a market share of “store attractiveness” can be computed for a focal store.

Finally, in research focusing on optimizing new retail outlet locations, Hernandez and Bennison (2000) argue that a large number of retailers (within and across sectors) are now adopting more rigorous approaches such as neural networks, data mining algorithms, and artificial intelligence techniques. They

² We would like to thank an anonymous reviewer for this formatting suggestion.

provide a summary of such research and predict an increasing use and diffusion of such techniques.

2.2. Endogenous Determinants of Store Performance

Variables impacting consumer shopping behavior include a fairly large array of store-related characteristics that have long been known to play a critical role in impacting store performance. Whether the focus has been on the abstract concepts of store atmosphere such as ambience (Mattila and Wirtz 2001, Baker et al. 1994), or on emotional attributes (Donovan et al. 1994, Darden and Babin 1994, Loken and Ward 1990), or on more concrete structural issues such as assortment and shelf-space allocation issues (Corstjens and Doyle 1989, Grewal et al. 1999, Drèze et al. 1994), research has consistently shown that such features determine a store's image in the consumer's mind and, directly or indirectly, have a significant impact on shopping behavior, sales, and profitability.

Functional attributes such as price and promotions have also been shown to impact store profitability and performance (Bell and Lattin 1998, Lam et al. 2001, Doyle and Saunders 1990, Shankar and Bolton 2004, Fader and Lodish 1990). They have also been shown to strategically create differentiation across stores and improve store performance (Walters and Rinne 1986, Walters and MacKenzie 1988). Some of the specific characteristics studied were the assortment and price of merchandise sold, deal intensity, store hours, as well as various value-added services such as an in-store bakery, banking facilities, and availability of prepared foods. Such value-added services and their impact on creating value and improving performance, in fact, form another substream of literature (e.g., Anderson and Shugan 1991) in this area, where retailers are able to create value for consumers as well as differentiate themselves from the competition. (See Berry et al. 2002 for an excellent overview of the service literature.)

2.3. Benchmarking Research

Finally, a significant volume of work also exists in the area of measuring production efficiency by estimating an "efficient frontier" that serves as a benchmark for evaluating performance. Two broad techniques that have been at the forefront in benchmarking research studies are the stochastic frontier (SF) and data envelopment analysis (DEA) methods. Although the DEA method is a nonparametric, deterministic approach that defines a relationship between multiple spending inputs and outputs by building an efficient frontier, it has been critiqued for not providing fit statistics such as r -square or p -value that can be used for statistical inferences (Donthu and Yoo 1998). The SF method, on the other hand, uses a parametric approach by explicitly taking into account the stochastic properties of

the data. Although able to estimate the overall inefficiency of the retailer by decomposing the error term into two parts to reflect inefficiency as well as the conventional statistical noise (Jondrow et al. 1982, Greene 2000), the SF method has been critiqued for imposing a functional form that restricts the shape of the frontier. Nevertheless, researchers (Kumbhakar and Lovell 2000) show that the decomposition of the error term, which serves to remove much of the bias that occurs in procedures that rely on a single error term, does theoretically help improve the accuracy of parameter estimates.

Some of the previous studies applying frontier methodologies have investigated retailing outlets productivity (Kamakura et al. 1996, Ratchford and Brown 1985); market efficiency and consumer welfare loss (Kamakura et al. 1988, Ratchford et al. 1996); sales-force efficiency (Boles et al. 1995, Horsky and Nelson 1996); channel productivity (Bultez and Parsons 1998); and resource allocation (Chebat et al. 1994), to name just a few.

Although much research has propagated one technique over the other, there has been a lack of consistency in results across approaches. Both methods suffer from drawbacks, however, and comparative studies regarding which method to use have been inconclusive (Luo and Donthu 2005).

3. Model Development

We consider here the case of a supermarket chain having multiple store locations in a given geographical area, which is true of most supermarkets in the United States. We assume that the chain may be competing with other chains and that consumers may come from different regions, and may visit multiple stores.

3.1. Conceptual Framework

In line with the traditional attraction models (such as MCI and logit) that use some form of store attractiveness to determine share, we introduce here the concept of a "core market strength" for a specific store, to reflect the market share that a store can command given its individual features, location, and competition. Note that a major differentiating feature of our model is that the unit of analysis is the block group, whereas prior literature used store-level data. By using block groups at the focus, we can measure its interaction with any store using a distance-based measure, and because consumers do not compete with each other for stores, we do not consider the location of other block groups with respect to the focal block group. Store-level data, on the other hand, will need to model not only the distances between consumers and their store, but also, because the stores compete, the distances between consumers

and competitor stores. As we shall see later, this block group-model estimation provides a number of insights to managers of the focal store chain not otherwise possible with a store-based model, the most obvious of which is the ability to benchmark the performance of a block group in terms of what it contributes to the focal store.

The expected market share (that is, the share that a particular store could be expected to potentially draw) is then defined as the proportion of the core market strength of a given store in the region, relative to the overall market strength exerted in that region. Furthermore, we conceptualize the overall market strength as being comprised of two components—the core market strength discussed earlier (referred to hereafter simply as the market strength) for all known, relatively large stores in the region for which data are available, and the residual local market strength to represent all the remaining stores for which no data are available. Note that because most of the market strength will be exerted by the major stores, it should leave a relatively smaller force to be exerted by the remaining residual stores.

In keeping with the spirit of prior literature (Converse 1949, Huff 1964, etc.), we incorporate distances to reflect decreasing impact of the more distant stores. We also assume that the demand from a specific region is directly proportional to the market strength of the store, relative to all the competing stores over the region. Note that a greater relative force exerted by any neighboring store will result in a lowered market share for the focal store.

The latter component—that is, the residual market strength for each region—is introduced in order to capture the effect of purchases from a variety of other stores, the detailed data for which retailers may not have access to, but which still may capture a significant portion of demand. Note that this residual market strength reflects *unmeasured consumer demand* that is not recorded in the Spectra data. Because the nature of such purchases comprising the unmeasured consumer demand may well be a function of the consumer base, demographics may provide a reasonable approximation of buying power. This in turn becomes a determinant of unrecorded consumer purchasing.

We thus include demographics in our model as a determinant of the unmeasured consumer demand. Note that this is consistent with some earlier findings that the sociodemographic profiles of consumers do in fact influence purchasing behavior (Reinartz and Kumar 1999, Hoch et al. 1995, Boatwright 2004).

We now offer a formal development of the model.

3.2. Formal Development

We define a set of stores, $p = \{1, \dots, P\}$, to include all major chain stores, including the focal stores of interest to us, $s = \{1, \dots, S\}$, on which data are available.

We also define the regions referred to above (from which sales accrue or in which stores are located) as census block groups $r = \{1, \dots, R\}$ as defined by the U.S. Census Bureau. Furthermore, let us define a set of store features $f = \{1, \dots, F\}$ characterizing each store in our chain as well as in the competitive chains $c = \{1, \dots, C\}$.

Following the logic from the conceptual framework above, the market strength of a store is influenced by store features, as well as competition, and monotonically decreases as a function of the geographical distance (e) appearing in the denominator. This decreasing strength reflects the decreasing probability of a consumer travelling to an increasingly distant store. We define the first component (m_{rp}) of the overall strength of a given store “ p ” in block group “ r ” as

$$m_{rp} = \left[\frac{\sum_{f=1}^F \alpha_f x_{pff} + \sum_{c=1}^C \gamma_c z_{pc}}{1 + e(r, p)} \right], \quad r = 1, \dots, R, p = \{1, \dots, P\}, \quad (1)$$

where x_{pff} is the value of the f th store feature at the p th store, $p = \{1, \dots, P\}$, $f = \{1, \dots, F\}$, z_{pc} is a binary dummy for the store signifying chain membership, $c = \{1, \dots, C\}$ $e(r, p)$ is the distance between the p th store and the centroid³ of the r th block group, and α_f and γ_c are parameters to be estimated.

We now define the second, residual component of market strength (l_r) (see §4.1) as a function of the sociodemographic profile of that region, to capture the unmeasured local demand in block group r . We thus define $d = \{1, \dots, D\}$ as the set of demographic variables characterizing each block group r , such that

$$l_r = k + \sum_{d=1}^D \beta_d y_{rd}, \quad r = \{1, \dots, R\}, \quad (2)$$

where y_{rd} is the household average of the d th feature in the r th block group, $r = \{1, \dots, R\}$, $d = \{1, \dots, D\}$ β_d and k are parameters to be estimated.

Note that the constant k serves to capture the impact of unobserved variables on the residual market force and reduce the relative impact of distant block groups. Because sales from distant block groups add only marginally to market share, the impact from them quickly approaches zero. The overall market strength in the block group (m_r) can then be expressed as the sum of the above two components,

$$m_r = \left(\sum_{p=1}^P m_{rp} \right) + l_r, \quad r = \{1, \dots, R\}. \quad (3)$$

³ The centroid is merely the central point of the census block group as defined by the latitude and longitude. Note that the 1 in the denominator ensures that the fraction is still defined even when the store is in the same block group so that $e(r, p) \neq 0$. Also note that using powers of “ e ” did not provide any significant improvement in model fit.

We can now define the expected market share of the focal chain in a given block group (recall that the expected market share expresses the potential market share, given its set of features, customers, and competitors) as being equal to the sum of market strengths of all the focal stores exerted in block group r (m_{rs}) divided by the overall market strength in the same block group (m_r),⁴

$$E(MS_r) = \sum_{s=1}^S m_{rs}/m_r, \quad r = \{1, \dots, R\} \quad (4)$$

Observed market share of our focal chain in each block group can be written as

$$O(MS_r) = E(MS_r) + \varepsilon_r, \quad r = \{1, \dots, R\}, \quad (5)$$

where ε_r may or may not be distributed normally. We substitute Equations (1)–(4) into this to get our nonlinear model for the observed market share for the r th block as

$$O(MS_r) = \frac{\sum_{s=1}^S ((\sum_{f=1}^F \alpha_f x_{sf} + \sum_{c=1}^C \gamma_c z_{sc}) / (1 + e(r, s)))}{\sum_{p=1}^P ((\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc}) / (1 + e(r, p))) + \sum_{d=1}^D \beta_d \gamma_{rd} + k} + \varepsilon_r, \quad r = \{1, \dots, R\} \quad (6)$$

Note that the dependent variable is the market share of the focal store at the block group level, and that the competing stores enter the model as a function of their impact on the shares of the focal stores. We can now estimate the parameters of our market strength model ($\alpha_f, \beta_d, k, \gamma_c$) by minimizing the sum of squared residuals using a quasi maximum-likelihood estimation method (see Appendix A), where residuals can be expressed, from Equation (6), as

$$\varepsilon_r = - \sum_{s=1}^S \left[\frac{\sum_{f=1}^F \alpha_f x_{sf} + \sum_{c=1}^C \gamma_c z_{sc}}{1 + e(r, s)} \right] + O(MS_r) * \left\{ \sum_{p=1}^P \left[\frac{\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc}}{1 + e(r, p)} \right] + \sum_{d=1}^D \beta_d \gamma_{rd} + k \right\}, \quad r = \{1, \dots, R\}. \quad (7)$$

Subject to the constraint,

$$\sum_{p=1}^P \left[\frac{\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc}}{1 + e(r, p)} \right] + \sum_{d=1}^D \beta_d \gamma_{rd} + k > 0, \quad r = \{1, \dots, R\}. \quad (8)$$

(See Appendix A for details of the estimation.)

⁴ Technically, the expected market share value should also have a subscript to indicate the fact that the total chain’s strength is being reflected. However, in the interests of expositional simplicity, we heretofore suppress this additional subscript.

4. Data

The data used in our model have been uniquely fashioned using a variety of sources—frequent shopper data of a large chain in the Northeast, census block group sociodemographic and demand data from the U.S. Census Bureau, and store feature data from the Spectra database. Although much of this information is available, a variety of issues, including computing capacity and privacy concerns, make it a challenge to access, particularly by researchers. For this project, we obtained access to the frequent shopper data from all stores (160) of a large supermarket retail chain located across three states on the East Coast for a period of one quarter (13 weeks) from April 2003 to July 2003. The chain has a loyalty card system such that households could be geocoded (that is, associated with specific block groups). We were thus able to aggregate sales by block group and by focal store in a certain time window. The data record over 200 million transactions of approximately 3 million households during this time period. There are 5,881 census block groups in which consumers reside, with average sales per week for the focal chain of \$3,081. Although the extensive nature of these data was a challenge to set up, it was essential for capturing the variety of effects incorporated in our model. Assembly at the block group level rather than the store level has allowed us to develop some interesting benchmarking indices not possible when using other units of analysis (§§6.1 and 6.1.2).

4.1. Variable Selection

As discussed earlier (§3.1), the market strength of a store is a function of its individual features, consumer base, and the competitive field it faces. Past research emphasized the importance of specific internal and external features that impact the performance of a store. For example, an extensive study by Reinartz and Kumar (1999) found that neighborhood characteristics such as population density and store features such as the presence of banking facilities play a strong role in determining store sales. Similarly, other studies (Kumar and Karande 2000, Hoch et al. 1995, Mace and Neslin 2004, etc.) emphasized additional significant demographic variables and store features. We thus had a basic set of variables to include in our model. Aside from these, discussions with upper-management-level employees of the focal chain also provided us with relevant features. In addition, we also use an average “distance to competition” measure as a store-specific feature to account for the decreased impact of distant competition. Using this set of 23 variables, we ran a correlation analysis to check for multicollinearity issues. We were thus able to drop three variables that were strongly correlated with others in the data set and, in addition, dropped three more that we did not have complete

Table 1 Descriptive Statistics of Census Block Group Sociodemographic Features

Variable	Mean	Std. dev.	Min	Max
Actual sales (\$/week)	3,081.59	3,943.00	1.24	46,873.64
Potential sales (\$/week)	42,533.79	42,393.89	61.54	835,000
Household (hh) size (n)	2.49	0.43	0.95	5
Population density (n /sq. mile)	5,199.58	4,974.45	0	43,710.3
Income (\$/year/hh)	44,982.47	22,178.87	333	150,000
Education (years)	12.05	1.26	0	17
Median age (years)	36.78	5.95	14	92
Married (%)	0.49	0.13	0	1
White collar (%)	0.54	0.17	0	1
White (%)	0.80	0.26	0	1
Unemployed (%)	0.048	0.04	0	0.67
Total block groups	5,881			

information on. Our final list thus included a set of 17 variables meaningful for analysis from both research and managerial perspectives. A descriptive analysis of the demographic characteristics (from the Bureau of Labor Statistics) and store features (from the Spectra database) explored is shown in Tables 1 and 2. Given the set of nine competitor dummy variables, a total of 26 predictor variables representing various store features, demographics, and competitive variables were chosen.

4.2. Correctional Factors

To avoid any estimation or measurement bias resulting from households that may have moved, have missing addresses, etc., we apply some correction factors.

First, keeping in mind that we conduct the analysis from the perspective of a focal store, we find that 70%–80% of their sales (v_s) can be traced to a specific loyalty card and address. In the remaining cases, either the purchases were made without a loyalty card, or it was not possible to geo code the

Table 2 Descriptive Statistics of Store Features

Store feature	Percentage of stores with the feature
Presence of ATM machines	45.18
Presence of banking office	18.67
Selling beer	49.45
Presence of film lab	15.6
Presence of floral center	28.13
Presence of food service	40.24
Store remodeled	8.09
Presence of bulletin board	32.22
Selling wine	16.37
Presence of everyday low price	20.92
Located within a plaza	25.75
Avg. distance to closest 5 competitors (miles)*	3.36 (3.32)
Total selling area (sq. ft.)*	42,264.90 (16,866.42)

*Note that these variables represent averages and standard deviations over the entire set of stores.

addresses (that is, identify the address with a specific block group). Therefore, we use a correction factor (γ_s) for a given store s , to include nontraceable sales as some proportion of total sales. Note that this enables us to incorporate data from some households (20%–30%) that would otherwise have been ignored, thereby resulting in biased estimates, by employing a reasonable scaling factor. Defining “ h ” as the household unit such that $h = \{1, \dots, H\}$, we get

$$\lambda_s = v_s / \left(\sum_{h=1}^H v_{hs} \right), \quad s = \{1, \dots, S\}. \quad (9)$$

We then use this to compute the total corrected sales of a store s in block group r (v_{rs}),

$$v_{rs} = \lambda_s \left(\sum_{h|h \in r} v_{hs} \right), \quad r = \{1, \dots, R\}, s = \{1, \dots, S\}. \quad (10)$$

Note that the observed market share of the focal chain in each block group r , defined as the proportion of sales of the focal stores to the demand in the whole block group (Q_r , obtainable from the Bureau of Labor Statistics⁵), is

$$O(MS_r) = \left(\sum_{s=1}^S v_{rs} \right) / Q_r, \quad r = \{1, \dots, R\}. \quad (11)$$

Second, in some instances, the most convenient store location for a household may not be the one closest to the residence. We would expect to see this, for example, when no store is located in their block group, or when they work at a distance from home and regularly shop at the store close to their workplace. To preserve the integrity of the data in terms of aggregation issues, we identify the store from which maximum purchases were made, and if its distance from the block group of residence exceeds a certain threshold (δ),⁶ we transfer its share of demand and the sociodemographic data of the block group of residence to the block group of its best-selling store.

5. Analysis and Results

5.1. Parameter Estimation and Significance

We estimate the parameters of our market strength model ($\alpha_f, \beta_d, k, \gamma_c$) by minimizing the sum of squared residuals using maximum-likelihood estimation method, where residuals are expressed as in

⁵Note that in referring to the demand obtained from the BLS data, we refer only to total grocery spending.

⁶We used threshold values ranging between 3 miles (prior research shows that average distance between households and a supermarket chain in the United States ranges around 3 miles—see Fox and Hoch 2005, Bell et al. 1998, etc.) and 10 miles, at which point no significant changes in the dependent variable were observed. Thus, a value of 10 miles was used.

Table 3 Estimated (Normalized) Coefficients of Store Features

Variables	Full data set ($N = 5,881$ block groups)	Estimation sample ($N = 3,921$ block groups)
Internal variables (store features)		
• Total sales area, sq. ft.	0.940*	0.831*
• Presence of ATM machines	0.127*	0.141*
• Presence of banking office	0.099*	0.087*
• Selling beer	0.232*	0.228*
• Presence of film lab	0.028	0.021
• Presence of floral center	0.051	0.078
• Presence of food service	0.061	0.046
• Store remodeled	0.067	0.041
• Presence of bulletin board	0.039	0.044
• Selling wine	0.119*	0.151*
• Presence of everyday low price	0.022	0.018
• Located within a plaza	0.109*	0.126*
• Avg. distance to closest 5 competitors	0.011*	0.009*
External variables (demographics)		
• Population density (n /sq. mile)	0.978*	0.967*
• Income (\$/year/hh)	0.224*	0.235*
• White collar rate (%)	0.027	0.021
• Unemployed rate (%)	0.056	0.042
Chain dummies		
• Chain 1	0.043	0.041
• Chain 2	0.569*	0.607*
• Chain 3	0.292*	0.231*
• Chain 4	0.181	0.177
• Chain 5	0.176	0.173
• Chain 6	0.161	0.159
• Chain 7	0.217*	0.237*
• Chain 8	0.202	0.201
• Chain 9	0.445*	0.384*
Pseudo R^2	0.77	0.71
Log likelihood (LL)	-2,388.23	-2,454.06
Akaike's information criterion (AIC)	4,828.26	4,960.12

*Denotes significant at 0.05 level, $k = 0.014$.

Equations (7) and (8). The parameter estimates for the full model are given in Table 3 (LL = -2,388.23; AIC = 4,828.26). Note that when the model is run without the adjustment factors, LL increases to -2,392.45 and the AIC = 4,836.90, indicating that the adjustments have a small, positive impact on model fit. We find that 7 of the 13 store features (total sales area, presence of ATM machines, presence of banking office, selling beer, selling wine, located within a plaza, and average distance of five closest competitors) and two of the four demographic variables (population density and income) were significant. These results are discussed in greater detail in §6.1.

Using the estimated parameters, we also compute differences between the observed and expected market shares in block groups (ϵ_r) (see Equation (5)). Having accounted for a set of variables and incorporated some correction factors, we may now interpret these differences (ϵ_r) as reflecting the effect of

different performance levels of management in the different block groups, or other unobservable factors. We can thus compute a pseudo R^2 to test the overall fit of the model, such that

$$R^2 = \frac{\text{Var}(O(MS_r)) - \text{Var}(\epsilon_r)}{\text{Var}(O(MS_r))}. \quad (12)$$

An R^2 of 0.70, for example, can then be interpreted as reflecting the degree to which the internal store features and competitive environment can explain the difference in actual and expected performance for our focal chain. Note that the purpose for determining a pseudo R^2 statistic in addition to the log-likelihood value that we estimate for the model is to facilitate comparisons with previous models that have been estimated using regression methods. The model was a good fit, with a pseudo R^2 of 0.77.

Finally, because the need for modeling the unmeasured local demand for block groups may only arise if there is a substantial proportion of purchases being made by consumers from unaccounted-for sources, we first take the difference between actual sales aggregated by block group using our focal retail chain data and potential sales as reported in the census data. This average gap, or unmeasured local demand, across all block groups was 27%. Because this is clearly not an insignificant amount, there needs to be some means of modeling it. Running our model without the local demand term (thus eliminating demographics) causes a drop in pseudo R^2 to 0.51, thereby validating the use of demographics to represent unmeasured local demand.⁷

Upon running the model without the adjustment of migrating loyalty card owner households, a small decrease in pseudo R^2 confirms the finding from the likelihood estimation, that the adjustment has a small positive effect on model fit. We also checked for heteroscedasticity (using scatterplots), ruling out correlation of the error term with the variables, which would potentially result in biased estimates.

We now validate our model in several ways.

5.2. Validation

We offer a validation of our model at several levels. First, in a more traditional validation technique, we use a holdout sample to test the accuracy of predictions using estimated parameters. Second, we compare results from two other relevant models in the literature with our model estimations. Third, we

⁷ Note that in cases where the unmeasured local demand is significant but not captured by demographics—that is, unmeasured local demand would vary over regions for reasons unrelated to their buying power or demography—alternate means of representation would have to be found. We thank an anonymous reviewer for pointing this out.

provide a measure of external face validity to our model by comparing results with syndicated data. Finally, we offer comparisons with two more traditional models—an efficiency model and a store-level model.

5.2.1. Validation Using Holdout Sample. Of the total 5,881 block groups in the database, we randomly choose a 33% sample of 1,960 block groups to isolate in a holdout sample. Estimating our model on the remaining 3,921 block groups, we find all 13 original significant parameters remain significant, and coefficient values are comparable as well (see Table 3). Using these estimates to predict sales for the holdout sample, we obtain a correlation coefficient of 0.71 for actual and predicted sales. Furthermore, estimation using several alternative random samples of block groups yielded correlations between 0.70 and 0.71, indicating stability of the results over the data set.

5.2.2. Validation Against Prior Models. Using our data, we use a prior model existing in the literature for comparison against our market strength model. Note that the choices of previous models available for such a comparison are somewhat limited. For example, the use of market share as a dependent variable in block group data has not been previously feasible because of the lack of potential demand information as well as the complexity involved in aggregating data at the block group level. As a result, previous research has necessarily used sales volume as the dependant variable, whereas we have been able to use a share model that serves to minimize seasonality effects as well as to include demand potential effects. Furthermore, some of the prior research (e.g., Hoch et al. 1995, Boatwright et al. 2004) focuses on different issues such as price and promotional elasticities, making a comparison with them less meaningful for our work.

We thus use Reinartz and Kumar's (1999) model as being the most relevant to our study in terms of model objectives and implications, for comparison. It uses a polygonal finite trading area approach involving multiple internal store features and demographic variables,⁸ with sales and sales per square foot as dependent variables in a linear model. Results from the two models show some consistency in the set of significant parameters across model estimations lending face validity to our approach. For example, the two highest impact variables (store area and population density) are common across both models. In addition, our model offers an improved fit ($R^2 = 0.77$

versus 0.51; $RMAE^9 = 0.36$ versus 0.44). Furthermore, unlike prior models, which take just the focal store characteristics into account, our model incorporates characteristics of all the stores (including the focal stores), thus offering richer insights.

5.2.3. Validation Using Syndicated Data. To provide a measure of external validity for the model, we use the estimated coefficients to predict block group sales for all the competitive stores. We then aggregated the block group sales to the corresponding competitive sales at the store level. A correlation of this aggregated sales value with the syndicated sales value of each store (obtained from the Spectra database) resulted in a value of 0.66 (significant at 0.01 level), indicating a satisfactory fit, particularly given the fact that the correlation is for competitive sales estimated with only store features, with no specific block group-level sales data on competitive stores.

5.2.4. Validation Against Traditional (Stochastic Frontier and Store-Level) Models. We also compare results from our model with those from a stochastic frontier model that uses the more traditional production-based methodology discussed earlier. The stochastic nature of this model and its explicit treatment of random noise and efficiency that serves to remove much of the bias, which occurs in procedures that rely on a single-error term, offer an advantage over alternative models of the efficiency frontier genre.¹⁰ Furthermore, although stochastic frontier estimates are expected to vary by the specific distributional assumptions imposed on the error term, research shows that the impact of such assumptions on results is limited (Greene 2000, Luo and Donthu 2005).

To keep the comparison consistent, we use the same set of input variables, including market strength of the focal store, for the stochastic frontier model. Although a direct comparison of coefficients will not be possible because the model formulations are quite distinct, a ranking of the census block groups as computed by our model shows a 72.2% overlap in the top decile of block groups from the stochastic frontier model. Furthermore, a correlation of rankings from the two models is 0.92 ($p < 0.001$), indicating a high level of consistency with our model. Similarly, for the stochastic frontier store-level model (once again we include a variable, average distance to the five nearest competitors to keep the comparison consistent) the overlap in the top decile of stores is 60%

⁸ Note that because some of the variables used in the original model were not available, we used proxies such as population density for the number of households.

⁹ Because R^2 cannot be used for comparison unless the units of the dependent variable are the same, we also determine the relative mean absolute error (RMAE) for this model.

¹⁰ We thank the area editor for suggesting the stochastic frontier approach.

and a correlation of store rankings from both models is 0.548 ($p < 0.001$). Note that whereas the frontier models just the focal store characteristics into account, our model takes the characteristics of all the stores into account while removing the constraint requiring a normal error term.

Finally, to justify the additional effort involved in constructing a block group-level data set to run our model, we also formulate a traditional store-level model with each store representing an observation. Note that store features enter the model simply as dependent measures for this model, but for the competitive effect, we take the stores within a five-mile radius as competitors (represented by n) to each of our focal stores. Observed market share of the stores of our focal chain can be written as

$$O(MS_s) = E(MS_s) + \xi_s, \quad s = \{1, \dots, S\} \quad (13)$$

$$O(MS_s) = \frac{\sum_{f=1}^F \alpha_f x_{sf} + \sum_{c=1}^C \gamma_c z_{sc}}{\sum_{p=1}^n (\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc} + \sum_{d=1}^D \beta_d y_{pd}) + k} + \xi_s \quad (14)$$

We estimate the parameters of this store-level market strength model ($\alpha_f, \beta_d, k, \gamma_c$) in the same manner (minimizing sum of squared residuals using the quasi MLE (QMLE) method).

Table 4 shows the results of this store-level model. We find here that the coefficients for some of the variables (such as total selling area, presence of banking office, and average distance to the competitors) remain significant as they were in the block group-level model. This is consistent with the past research on store-level models (Reinartz and Kumar 1999, Kumar and Karande 2000). However, other coefficients (e.g., presence of ATM machines, selling beer, and location in a plaza) do not remain significant in this model. Income of households (typically found to be significant in prior research) has no significant impact in the store-level model. More critically, the RMAE shows a lower value for our block group model (0.36) as opposed to the store-level model (0.49). The pseudo R^2 of the store-level model also shows a significant drop in fit to 0.34, compared with 0.77 of our block group-level model.

Finally, it should be noted that a significant contribution of our block group model, beyond these or other previous models, is that it can be used as a means of generating a fairly comprehensive set of benchmarking indices that can provide a relative evaluation not just of the stores, but also of block groups and the competition (discussed below).

5.3. Benchmarking Measures

The benchmarking indices are developed in the following way. Using the estimated parameters, we can

Table 4 Comparison with Store-Level Model

Variables	Block group model results	Store-level model
Internal variables (store features)		
• Total sales area, sq. ft.	0.940*	0.107*
• Presence of ATM machines	0.127*	0.105
• Presence of banking office	0.099*	0.105*
• Selling beer	0.232*	0.112
• Presence of film lab	0.028	0.119
• Presence of floral center	0.051	0.101
• Presence of food service	0.061	0.116
• Store remodeled	0.067	0.113*
• Presence of bulletin board	0.039	0.105
• Selling wine	0.119*	0.093
• Presence of everyday low price	0.022	0.103
• Located within a plaza	0.109*	0.105
• Avg. distance to closest 5 competitors	0.011*	0.956*
External variables (demographics)		
• Population density (n /sq. mile)	0.978*	0.109*
• Income (\$/year/hh)	0.224*	0.110
• White collar rate (%)	0.027	0.084
• Unemployed rate (%)	0.056	0.072
Competitor chain dummies		
• Chain 1	0.043	0.090
• Chain 2	0.569*	0.470*
• Chain 3	0.292*	0.101*
• Chain 4	0.181	0.619*
• Chain 5	0.176	0.337
• Chain 6	0.161	0.686*
• Chain 7	0.217*	0.483
• Chain 8	0.202	0.714*
• Chain 9	0.445*	0.095
Pseudo R^2	0.77	0.34
Log likelihood	-2,388.23	-3,012.63
AIC	4,828.26	6,077.26
RMAE	0.36	0.49

*Denotes significant at 0.05 level.

compute the expected market share of the s th store in the r th block group:

$$E(MS_{rs}) = m_{rs}/m_r, \quad r = \{1, \dots, R\}, s = \{1, \dots, S\}. \quad (15)$$

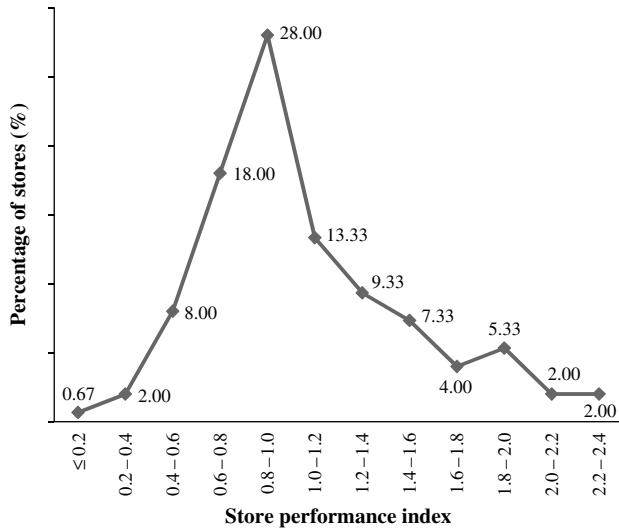
This expected market share therefore represents the share that a given store in a given block group with an average level of quality (for that chain) of its management, can be expected to achieve, given its internal store features and competitive environment. If the expected market share is higher than the actual, performance of the store management can be said to be below average, and vice versa. This comparison provides the following performance index for the s th store in the r th block group (q_{rs}) (where 100% is average performance):

$$q_{rs} = O(MS_{rs})/E(MS_{rs}), \quad r = \{1, \dots, R\}, s = \{1, \dots, S\}, \quad (16)$$

such that

$$O(MS_{rs}) = v_{rs}/Q_r, \quad r = \{1, \dots, R\}, s = \{1, \dots, S\} \quad (17)$$

Figure 1 Store Performance Indices



and represents the observed market share of the s th store in the r th block group. These group and store-specific measures can be aggregated in several ways to benchmark stores, regions, and competitive environment.

5.3.1. Store Indices. We compute performance indices for the s th store (q_s), representing how well this store does in terms of achieving the total expected share from all the block groups:

$$q_s = v_s / \sum_{r=1}^R Q_r * E(MS_{rs}), \quad s = \{1, \dots, S\}. \quad (18)$$

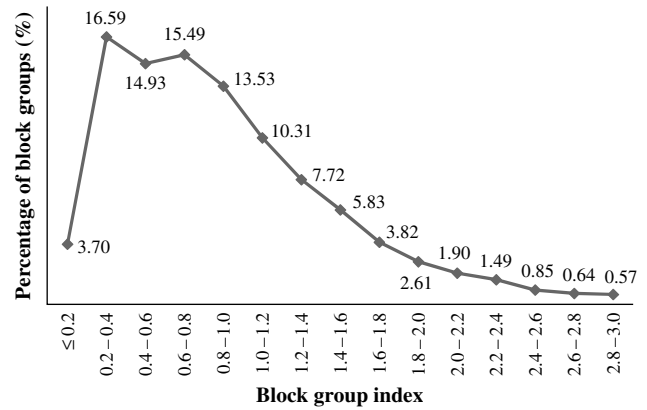
Figure 1 shows the distribution of stores over the range of store indices. We find that about 41% of the stores lie in the 0.8–1.2 range, or the “middle” range, implying that these stores are performing in the average range and that given the externalities, the actual sales of these stores are more or less equal to the expected sales. Also, about 4% of the stores have an index greater than 2.0 (or “high” range), implying that these stores are doing very well, with shares exceeding expectations. (Note that the ranges were picked after studying the distribution of indices and in consultation with management, to reflect the two extremes of the distribution as well as an average.)

5.3.2. Region Indices. The performance index of the r th block group (q_r), representing how well our focal chain store does in terms of extracting sales from this block group, can be computed as

$$q_r = O(MS_r) / E(MS_r), \quad r = \{1, \dots, R\}. \quad (19)$$

We show the performance indices of all the block groups in Figure 2. We find that about 24% of the block groups lie in the midrange, implying that these block

Figure 2 Block Group Performance Indices



groups are performing on par with expectations. Furthermore, about 5% of the block groups have a high index, implying that these block groups are generating greater-than-expected sales for the focal store.

5.3.3. Competitive Indices. We also compute a measure to represent the competitive environment faced by any given store. By using the market strength of a block group and subtracting from it the market strength of the block group-specific store, we arrive at a measure that can then be scaled for distance to represent the average market strength of competition faced by a store (mc_s):

$$mc_s = \left(\sum_{r=1}^R \frac{m_r - m_{rs}}{1 + e(r, s)} \right) / \left(\sum_{r=1}^R \frac{1}{1 + e(r, s)} \right), \quad s = \{1, \dots, S\}. \quad (20)$$

Note that we use proximity-weighted averages here to reflect lower impact of competitive stores from block groups that are more distant to the focal store “ s .” Thus, a greater value indicates stronger competitive effects operating in the environment. We can now create clusters from the computed indices of stores, thus forming three segments such that each comprises a set of stores facing weak, medium, or strong competitive environments. Our data indicate that although many of the stores fall into the “medium competitive environment” category (47%), a substantial number (30% and 23%) fall into the low and high competitive categories, respectively. Obviously, this will be a significant element to consider when setting expectations of performance.

6. Managerial Implications and Insights

By developing a model that recognizes sales potential, store features, demographic characteristics, and the competitive environment, we offer the retailer a market strength model at the block group level

that can be used to benchmark sales performance of chain stores, market share of stores in different block groups, and the intensity of competition in different block groups faced by each store. Because the benchmarking indices generate from the same framework, a relative comparison across stores and regions can be undertaken to see different parts of the same picture and tell a cohesive story.

6.1. Model Insights

The estimated importance weights of store features, sociodemographic variables of block group parameters, and competitive chain dummies can help managers determine which of them have a significant impact on sales (Table 3). We find that store area, the sale of beer and wine,¹¹ the presence of an ATM or bank, population density, and income are some of the more important characteristics influencing market share. Note that in the case of the competitive chain estimates, a higher value indicates greater force being exerted on the focal chain, resulting in a lower market share for the latter. Thus, Chains 2 and 9 were the most significant competitors to our focal store of analysis. Discussions with the upper-level management of our focal store provided qualitative evidence that revealed that Chain 9 was seen as a strong competitor given its standing as the second-largest grocery chain in the region and its relatively higher quality of products (particularly in certain categories), whereas Chain 2 was frequented for the same perceived benefits of low price as the focal store, and thus overlapped somewhat in their consumer base.

6.2. Benchmarking Insights

Aside from the model estimates, the benchmarking indices also offer some interesting managerial insights. The indices developed for benchmarking block groups indicate the degree to which each block group contributes, relative to what they could potentially contribute, to the focal store. Figure 2 reveals that the tail is longer at the high-performance end, but that the majority of block groups fall into the poorly contributing group. Clearly, the block groups could be contributing substantially more to the focal stores.

To further explore the analysis possible, we choose three segments of block groups with the same ranges—poor performing, with an index of 0–0.4; average performing, with an index of 0.8–1.2; and superior performing, with an index greater than 2.0.

Table 5 Block Group Performance Index

Block group variable means	Low (0–0.4)	Medium (0.8–1.2)	High (>2.0)
Population density (<i>n</i> /sq. mile)	3,651.07	6,095.11	4,201.00
Income (\$/year/hh)	53,125.31	40,997.48	45,859.97
Household size (<i>n</i>)	2.52	2.47	2.55
Age (years)	37.37	36.61	37.26
White race rate	0.87	0.76	0.88
Unemployed rate	0.04	0.05	0.04
Market share (%)	0.01	0.09	0.21

Table 5 selects the relevant block groups and studies average sociodemographic profiles for these three segments. It can be seen that block groups with an average index are more densely populated compared with the block groups with either a low or a high index. The average market share of the focal chain in the high-index block group is the highest, which is to be expected. It is interesting to note, however, that the low-index block groups (contributing lower-than-expected sales) have the highest average incomes (\$53,000/household) and the lowest population density. These findings have significant managerial implications. These appear, then, to be consumers that are predominantly shopping elsewhere. This is very much in line with upper-management thinking, that a majority of their consumers come from the lower-income segment. With some strategic targeting, this segment could potentially be one from which a greater share of sales could be extracted.

Furthermore, Table 5 also reveals that the low- and high-index segments (that is, purchasing either very little or a lot) are more similar to each other than to the middle-index segments. (Compare, for example, the average incomes across the groups—\$53,125 and \$45,860 for the low- and high-index segments, and \$40,998 for the middle-index segment.) This interesting result confirms management intuition (that higher-income shoppers tend to shop at competitor 9, whereas the low-income segment shops at Chain 2) as well as our competitive benchmarking results (that the two strongest competitors are indeed Chain 9 and Chain 2).

Based on the competitive environments faced by the stores, we classified stores in three clusters of low, medium, and high competitive environment. Table 6 offers some statistics regarding the environment faced by each focal store. We see that a higher competitive index reflects a larger number of competitors in the 20-mile radius (the low competitive index cluster shows 6 competitors, whereas the medium and high clusters show 141 and 226, respectively). Furthermore, the lowest competitive index also implies the maximum average distance of the competition, as well as the smallest selling area. The competitive index thus serves as a valuable benchmark for the

¹¹ Note that because of legal restrictions placed on the sale of such products, this variable has to be treated with some caution because it may lead to endogeneity problems. In our data set, because only 4 of the 160 focal stores were barred from selling wine, and of the remaining 156, 54 chose not to, we were able to circumvent the problem.

Table 6 Descriptive Statistics for Stores in Different Competitive Environments

Competitive environment of focal store	Number of competitors	Avg. total selling area	Avg. grocery selling area	Avg. grocery weekly volume	Avg. total weekly volume	Avg. distance
Low	6	6,571.43	6,571.43	45,142.86	45,142.86	14.56
Medium	141	31,404.25	26,624.11	202,304.96	232,659.60	13.52
High	226	32,800.88	27,398.23	217,092.92	252,292.00	11.47

relative evaluation of store-specific issues for a variety of managerial purposes. Note, finally, that this development of indices and the ensuing implications directly addresses the research questions raised earlier regarding the identification of segments of consumers and regions and their varying expectations.

6.3. Store-Tracking Insights

An interesting aspect of the indices we develop from our market strength model is that any given store can be tracked in terms of its own ranking, the rankings of the surrounding block groups and the competitive cluster into which it falls. As an illustration, we pick two focal stores for a detailed study of their comparative standing on various dimensions. The first one ranked highly on the store index dimension (4th), whereas the second ranked much lower (122nd). An initial look at the store features showed some similarity between the two stores in that both offered banking facilities, were not located in a plaza, did not employ an EDLP strategy, and both block groups had similar average incomes (\$51,000 versus \$49,000). However, a more careful study revealed that whereas the first store was placed in a highly competitive cluster (which lowered expectation for sales), the second store was in a low competitive cluster. Furthermore, the first store also placed in the high block group index cluster (implying that a major portion of the shopping is done at the focal store), whereas the second store was located in a medium index cluster. This analysis serves to demonstrate the microlevels at which an individual store’s performance can be evaluated. Thus, because the block groups can be spatially charted, it would be possible to study the surrounding block groups as well.

In summary, the incorporation of specific store features, demographic profiles of block groups, as well as individually characterized competitive environments have allowed our market strength model to offer a means by which evaluation of specific programs or store managers, across stores and chains, can be conducted equitably.

7. Contributions, Limitations and Future Research

We contribute to this literature along two dimensions. First, our model addresses the issue of specific store analysis by integrating the existing trade

area and store performance literature and then formulating an underlying theoretical and conceptual basis that determines relative performance. Second, by formulating the model at the block group level, we offer a detailed, block group-specific level of analysis not possible in earlier studies. The three levels of benchmarking determined by our market strength model provide the ability to view different aspects of the same integrated industry picture resulting in rich managerial implications. The benchmarking reveals not just how well a store is doing overall, but also how well it does in each block group. Such performance evaluation of consumer block groups has not previously been possible with the more traditional store-level models. We thus add to the seminal work on performance at the store level using polygonal trading areas both theoretically and methodologically.

We also provide estimates about the attractiveness of different store features for customers, supporting decisions on store improvement (Reinartz and Kumar 2000), as well as estimates about the competitive force of chains, thereby supporting the development of competitive strategies. Using the Spectra database allows us to examine a comprehensive set of internal and external store features. Examining the significant parameters (see Tables 3 and 4), we see evidence of consistency with previous literature in our results. Store area and the availability of banking facilities, for example, have both been previously found to be highly significant in having a positive impact on store sales (Ghosh and McLafferty 1982, Ghosh 1984, Reinartz and Kumar 1999). The importance of this attribute is also reflected in the actions of management in that the average size of grocery stores in the United States has increased by 30% from 35,100 sq. ft. in 1994 to 45,561 sq. ft. in 2004.¹²

A limitation of our model is that it requires loyalty card, census block, and store feature information. However, most chains do have a loyalty card system in place, census data are publicly available, and aggregate syndicated data are also routinely collected by companies such as Spectra and AC Nielsen. While there is a danger of introducing measurement error as a result of using information from different sources, it should be noted that we try to minimize it by applying suitable corrections and statistically

¹² Source: Food Marketing Industry Speaks 1994–2005.

checking correlations between independent variables and the dependent variable. Finally, although the model in its present form does include some store-specific features such as store area, presence of service features, and price strategy followed by the store, it does not consider the effect of other endogenous determinants of store performance such as store-level advertising, price indices, promotional activity, etc. Although these data were not available for any but our focal stores, and as such were not incorporated, such marketplace dynamics at the store/chain level can be included as an extension to enhance insights from our model. Another interesting application of the model would be a practical method to estimate expected sales for a new store in a given location with given features (Drezner 1994).

In closing, our market strength model adds to the stream of benchmarking performance literature by offering a means of using data dissected at the block group level to develop indices for evaluating stores, block groups as well as the competition within an integrated framework. The focus at the block group level, as opposed to the more traditional store level, not only offers a superior fit, but also serves to provide richer managerial insights at a more disaggregated level.

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Appendix A

We estimate the parameters of our market force model ($\alpha_f, \beta_d, k, \gamma_c$) using the quasi maximum-likelihood estimation¹³ method, where residuals can be expressed, from Equation (7), as

$$\begin{aligned} \epsilon_r = & - \sum_{s=1}^S \left[\frac{\sum_{f=1}^F \alpha_f x_{sf} + \sum_{c=1}^C \gamma_c z_{sc}}{1 + e(r, s)} \right] + O(MS_r) \\ & * \left\{ \sum_{p=1}^P \left[\frac{\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc}}{1 + e(r, p)} \right] + \sum_{d=1}^D \beta_d y_{rd} + k \right\} \\ & r = \{1, \dots, R\} \end{aligned} \tag{20}$$

The quasi likelihood function can therefore be expressed as

$$L = \left[\prod_{r=1}^R \left(\frac{1}{\sigma_{O(MS_r)} \sqrt{2\pi}} \exp(-(\epsilon_r)^2/2) \right) \right], \tag{21}$$

¹³Note that we use the QMLE method as opposed to the more traditional MLE method, because errors from market share are subject to constraints and therefore may not be normally distributed. The resulting estimates will be consistent, but may not be efficient (White 1982).

where $\sigma_{O(MS_r)}$ is the standard deviation of actual market shares across regions. The log-linear function simplifies to

$$\begin{aligned} Ln(L) = & R * (\ln(l) - \ln(\sigma_{O(MS_r)}) - 0.5 \ln(2\pi)) \\ & + \sum_{r=1}^R (-(\epsilon_r)^2/2). \end{aligned} \tag{22}$$

We can omit the constant from above to get

$$\sum_{r=1}^R (-(\epsilon_r)^2/2), \tag{23}$$

subject to

$$\begin{aligned} \sum_{p=1}^P \left[\frac{\sum_{f=1}^F \alpha_f x_{pf} + \sum_{c=1}^C \gamma_c z_{pc}}{1 + e(r, p)} \right] + \sum_{d=1}^D \beta_d y_{rd} + k > 0, \\ r = \{1, \dots, R\}. \end{aligned} \tag{24}$$

Furthermore, to determine significance levels, we take the inverse of the Hessian matrix of the likelihood function, which at the optimum point is equal to the variance-covariance matrix of the estimated parameters. Standard errors of parameters can now be obtained from the trace of the matrix. We then perform a two-sided *t*-test to determine the significance of the parameters (degrees of freedom are $R - (F + D + C + 1) - 1$):

$$t_f = \alpha_f / h_{ff}^{0.55}, \quad f = 1, \dots, F \tag{25}$$

$$t_d = \beta_{F+d} / h_{F+d, F+d}^{0.5}, \quad d = 1, \dots, D \tag{26}$$

$$t_c = \gamma_{F+D+c} / h_{F+D+c, F+D+c}^{0.5}, \quad c = 1, \dots, C \tag{27}$$

$$t_k = k / h_{F+D+C+1, F+D+C+1}^{0.5}, \tag{28}$$

where

$$\begin{aligned} H_{(C+D+F+1)(C+D+F+1)}^{-1} \\ = \{h_{uv}, u, v = 1, \dots, C + D + F + 1\}, \end{aligned} \tag{29}$$

that is, the inverse of the Hessian matrix at the optimum point.

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