

Calibrating the Huff Model Using ArcGIS Business Analyst

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Calibrating the Huff Model Using ArcGIS Business Analyst

An ESRI White Paper

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Calibrating the Huff Model Using ArcGIS Business Analyst

Purpose of This Report

This document is intended to illustrate how the parameters of the generalized version of the Huff Model can be estimated statistically using ArcGIS Business Analyst. Every effort has been made to minimize technical jargon and mathematical proofs. Rather, emphasis is directed toward the application and interpretation of the model in addressing spatial interaction problems. Furthermore, a case study is used to illustrate the steps involved. Maps, diagrams, charts, and graphs generated from ArcGIS Business Analyst are used to facilitate decision making.

The report is divided into seven parts:

- Background
- Technical Review
- Statistical Verification
- Enhanced Capabilities of the Model
- Market Share Analysis
- Steps Involved in Estimating Parameters
- A Case Study

Background

The Huff Model, as it is formally called, is a tool for formulating and evaluating business geographic decisions. The model has had widespread usage. Business and government analysts as well as academicians throughout the world have used the model. With the development of geographic information system (GIS) technology, the model has received even more attention. For example, the model has been used in

- Estimating market potential
- Defining and analyzing trade areas
- Evaluating market penetration
- Assessing economic impact
- Predicting consumer shopping selections
- Profiling and targeting consumers
- Forecasting sales of existing and potential outlets
- Assessing the impact of environmental changes

The model has endured the test of time—more than 40 years have elapsed since it was formally introduced.^{1,2} The reasons for the model's longevity can be attributed to three

The citations noted below are the original publications in which the Huff Model was introduced. These two documents are rarely cited. As a result, significant conceptual material and operational details are often overlooked.

Huff, David L., Determination of Intra-Urban Retail Trade Areas, Real Estate Research Program, Graduate School of Business Administration, University of California, Los Angeles (UCLA), 1963.

principal reasons. First, the model is conceptually appealing. The logical underpinning of the model makes sense and the output can be communicated easily and understandably. Second, the model is relatively easy to make operational. The necessary computations are straightforward once the values of the variables and parameters are specified. The third reason for the model's popularity is its applicability to a wide range of problems and its ability to predict outcomes that would be difficult, if at all possible, without the model. Despite the general applicability of the model, it has not always been employed correctly. Furthermore, the full potential of the model has not been realized. The remainder of this paper will address these issues.

Technical Review

The model is based on the premise that when a person is confronted with a set of alternatives, the probability that a particular item will be selected is directly proportional to the perceived utility of that alternative. Choice behavior can be viewed as probabilistic. It is unlikely that any given alternative will be selected exclusively unless no other alternatives exist. This proposition can be expressed symbolically as follows:

$$P_{ij} = U_{ij} / \sum_{k \in N_i} U_{ik}$$
 [1]

Where P_{ij} is the probability that an individual i will select alternative j given the utility of j relative to the sum of the utilities of all choices n that are considered by individual i.

For the model to be applied, the utility of each alternative must be defined empirically. The first geographic application of the model was an attempt to predict consumer patronage patterns for different classes of products. The utility of a store was defined as the ratio of the square footage of selling area of the store to the distance from a consumer's residence to the store. Each of these variables was weighted by an exponent (parameter) that had to be estimated empirically. Actual shopping preferences were obtained from a survey of individuals residing within the study area.

It was hypothesized that for certain products, the size of the store was more important than it was for others. Thus, the value of the exponent would be expected to be larger. Conversely, the exponent for distance was assumed to be negative. Convenience products could be expected to have a larger exponent while specialty goods would be much smaller. Thus, the utility of a store j to a consumer at i would be derived as follows:

$$U_{ij} = A_j^{\alpha} D_{ij}^{\beta}$$
 [2]

Where S_j is the square footage of selling area of store j, D_{ij} is the distance from i to j, and α and β are parameters that were estimated based on the actual survey data. The probability that a consumer located at i selecting store j can be estimated as follows:

$$P_{ij} = S_j^{\alpha} D_{ij}^{\beta} / \sum_{k \in N_i} S_k^{\alpha} D_{ik}^{\beta}$$
[3]

² Huff, David L., "A Probabilistic Analysis of Consumer Spatial Behavior," *Emerging Concepts in Marketing, Proceedings of the Winter Conference of the American Marketing Association, Pittsburgh, Pennsylvania,* 1962.

Statistical Verification

Originally, the parameters associated with the attraction and proximity variables were estimated using an approximation solution since the application of conventional statistical procedures was considered impossible. The values of the parameters were, therefore, suspect since the statistical significance of the variables could not be determined. Obviously, the lack of statistically validated variables could result in erroneous results. Without an accurate statistical assessment, analysts would be using the model to make predictions based on unverifiable inputs. Thus, the results would be subject to error.

Since the model was introduced, a considerable amount of research has been undertaken related to the issue of parameter estimation. The publications of Nakanishi and Cooper are particularly noteworthy.^{3,4,5} As a result, major breakthroughs have occurred that now make it possible to use standard techniques such as ordinary least squares for calibrating the model.

Most analysts who use the Huff Model incorporate some measure of accessibility such as road distance, travel time, or cost as well as a variable to reflect the attraction of a given destination. The weights, that is, parameters associated with the variables, are often assigned arbitrarily. They are rarely estimated statistically. There are several reasons more analysts do not calibrate the model statistically. First, the nonlinear properties of the model are perceived by some users to be much more difficult to calibrate since it is first necessary to make the model linear with respect to its parameters before standard statistical estimation procedures can be applied.

Another reason is undoubtedly the necessity of having origin-based data as opposed to destination-based data. That is, actual choice decisions must be obtained empirically by a survey of residents of geographic subareas within some larger study area. Choices must be obtained for all alternatives considered by such residents. Unfortunately, most companies collect data only for their facilities. As a result, patronage data for competitors is usually unknown. The task of obtaining actual shopping preferences can be time-consuming as well as expensive since it requires a survey at the household level.

A third reason why statistical calibration is not employed more is the lack of GIS software packages that are uniquely equipped for this type of analysis. The functional requirements of such software must include (1) the ability to execute the necessary operations of the model, (2) a statistical package that will generate the necessary statistics for assessing the significance of variables used to predict choice behavior and will be able to indicate how well the model predicted actual choice frequencies, and (3) the software must have a mapping capability that will enable analysts to examine errors of prediction as well as other geographic patterns that might be suggested by the data.

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³ Nakanishi, Masao, and Lee G. Cooper, "Simplified Estimation Procedures for MCI Models," *Marketing Science*, 1982.

⁴ Nakanishi, Masao, and Lee G. Cooper, "Parameter Estimation for a Multiplicative Competitive Interaction Model—Least Squares Approach," *Journal of Marketing Research*, 1974.

⁵ Cooper, Lee G., and Masao Nakanishi, *Market-Share Analysis* (Massachusetts: Kluwer Academic Publishers), 1988.

Enhanced Capabilities of the Model

As mentioned previously, considerable research has been done on consumer spatial behavior since the original Huff Model was introduced. A few noteworthy examples include (1) multivariate parameter estimation, (2) choice set determination, and (3) detecting and measuring nonstationarity.

It is now possible to include many variables in the Huff Model and be able to determine the associated parameters statistically. In general, variables used in the model can be classified as either controllable or noncontrollable. Controllable variables are those that can be manipulated by decision makers. Examples of controllable variables include advertising, pricing, and store format. Noncontrollable variables are factors that are, for the most part, beyond the firm's control. Accessibility, population distribution, income, and competition are examples of noncontrollable variables. Traditionally, some of these variables have been hypothesized to be determinants of consumer preferences, and attempts have been made to present evidence to support these hypotheses. Being able to examine these variables statistically, however, adds immensely to verifying such hypotheses.

The general form of the Huff Model can be expressed as follows, where P_{ii} = the probability of a consumer at a geographic area i patronizing facility j:

$$P_{ij} = (\prod_{h=1}^{H} A_{hj}^{\gamma_h}) D_{ij}^{\lambda} / \sum_{j=1}^{n} (\prod_{h=1}^{H} A_{hj}^{\gamma_h}) D_{ij}^{\lambda}$$
 [4]

 A_{hj} = a measure of the h_{th} characteristic (h = 1,2,.H) that reflects the attraction of facility j;

 γ = a parameter for the sensitivity of P_{ii} associated with an attraction variable h;

 D_{ii}^{λ} = a measure of accessibility of facility j to a consumer located at i;

 $\lambda =$ a parameter for the sensitivity of P_{ii} with respect to accessibility; and

n = the number of facilities.

The model can be transformed into a linear form in the parameters by applying the following transformation to P_{ii} :

$$\log(P_{ij} / \widetilde{P}_{i}) = \sum_{h=1}^{H} \gamma_{h} \log(A_{hj} / \widetilde{A}_{j}) + \lambda \log(D_{ij} / \widetilde{D}_{i})$$
 [5]

Where \tilde{P}_i , \tilde{A}_j , \tilde{D}_i are the geometric means of P_{ij} , A_{hj} , and D_{ij} , respectively. Once the parameters of the model have been estimated

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($\hat{\gamma}$ and $\hat{\lambda}$), the estimated probability of consumers in any area *i* selecting any facility *j* can be derived by the following equation:

$$\hat{P}_{ij} = (\prod_{h=1}^{H} A_{hj}^{\hat{\gamma}}) D_{ij}^{\hat{\lambda}} / \sum_{j=1}^{n} (\prod_{h=1}^{H} A_{hj}^{\hat{\gamma}}) D_{ij}^{\hat{\lambda}}$$
 [6]

Alternately, one can let the estimate of the dependent variable be denoted by

$$\hat{y}_{ij} = \sum_{h=1}^{H} \gamma_h \log(A_{hj} / \tilde{A}_j) + \lambda \log(D_{ij} / \tilde{D}_j)$$
[7]

It follows then that

$$\left| \hat{P}_{ij} = \exp(\hat{y}_{ij}) / \sum_{j=1}^{n} \exp(\hat{y}_{ij}) \right|$$
 [8]

Market Share Analysis

Once the parameters have been determined statistically, the model can be used to estimate product expenditures by consumers from a given geographic area that are expected to be obtained by store *j* within the study area. That is,

$$E_{ij} = (P_{ij})(B_i)$$
 [9]

where E_{ij} = the expected expenditures that will be made from geographic area i to store j; and B_i = the total expenditures available in i. The total sales of each store in the study area can be determined by summing the expected expenditures from each geographic area for all stores. That is,

$$T_j = \sum_{i=1}^m E_{ij}$$
 [10]

where $T_j=$ the total expected sales of store j. The market share of each store within the study area is each store's total expected sales divided by the total sales of all stores. That is,

$$M_j = T_j / \sum_{j=1}^m T_j$$
 [11]

where M_{j} = the market share of store j.

Steps Involved in Estimating Parameters

The steps involved in obtaining the necessary data to calibrate the model are listed below. The relevance of each of these tasks will be discussed, then exemplified through the use of a case study.

- Delineate the study area.
- Divide the study area into subareas.
- Specify the centroids of the subareas.
- Identify all competing facilities within the study area and indicate the coordinates of each facility.
- Determine the distances or travel times between the centroids of all subareas and all facility locations.
- Specify all facility attributes that could influence consumer preferences.
- Indicate economic, social, and demographic data for all subareas.
- Conduct a survey of households within each subarea to determine the frequency at which consumers patronize stores within the study area.

A Case Study

Implementation of the steps outlined in the preceding section can best be understood by relating them to an actual case study. While the case is fictionalized, it is based on an actual situation that closely resembles the setting and problem described in this case.

The Situation

Executives at McCormick, a local supermarket chain located in Parkview, a southwestern city in the United States, are deliberating whether they should acquire property for a new store that has recently come on the market (see map 1). The property in question is located in an affluent area on the western side of the city along a seven-mile, north—south corridor in which McCormick currently has four stores. Four competing stores are also located along this corridor (see map 2).

Proposed Location Proposed Location Proposed Location Loc

Map 1
McCormick's Proposed Location in Northwest Parkview

McCormick's competitive strategy has been to create an upscale image by selecting store sites that are in affluent areas and to acquire properties that may be lacking sufficient sales potential currently but are promising for the future and provide a preemptive competitive tactic. The proposed location is in a developed and affluent area. However, since McCormick has a store located one mile to the north and another a mile south of the proposed location, sales may be restricted.

McCormick Research Sam's Club Wholesome Foods Research Sun Bounty Proposed McCormick Location McCormick Balcones IBP Burnet McCormick 35th

Map 2 McCormick's Existing Locations

The Problem

Inevitably, some cannibalization will occur as a result of the proximity of the stores to one another. The issue that needs to be addressed is whether the cannibalization will be injurious or whether the combined net income of the existing McCormick stores, plus the proposed store, warrant the investment. Another factor that needs to be considered is if McCormick does not acquire the property and it is acquired by a competitor, whether the impact on the sales of the nearby McCormick stores will be severely impaired. The analysis that follows will address each of the steps discussed above with the intent of determining the course of action that McCormick should take.

The Analysis

Delineating the Study Area

The first and perhaps most important step in acquiring relevant and accurate data is defining the study area properly. This is an extremely important task since the geographic extent of the study area will impact the nature and scope of the data that must be collected as well as any conclusions that might be reached based on analyses of such data. Conceptually, the study area can be thought of as an "island" in which buyers and sellers interact to actualize some form of exchange. The majority of transactions should occur within the study area. That is, little trade should come from residents outside the study area, and little trade should occur outside the study area by residents within the study area. Acronyms for these two types of crossover shopping are LOFI (little out from inside) and LIFO (little in from outside). The closer the transactions of the study area mirror these two extremes, the closer the study area resembles an island. Obviously, in metropolitan areas, crossover shopping is bound to occur. The accuracy in delimiting the boundary of the study area is determined by how buyers and sellers are matched. The procedure for making such a match are outlined below.

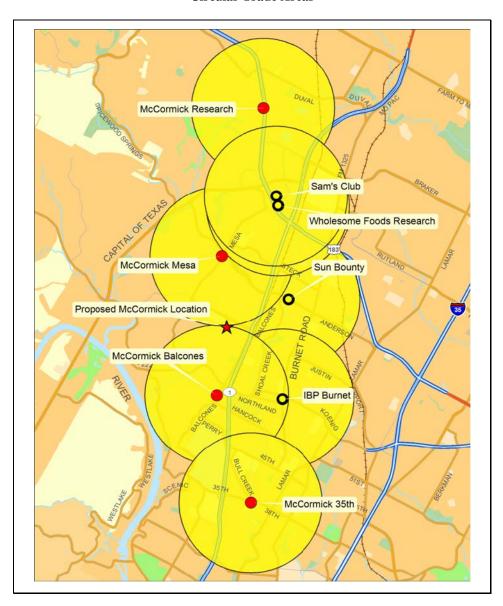
- Identify and locate on a map all facilities under consideration as well as their respective trade areas. The trade areas may have to be estimated (distance bands) rather than derived empirically.
- Draw a boundary around the combined trade areas. This constitutes the first approximation of the study area.
- Modify this initial study area boundary, if necessary, to reflect man-made or natural barriers that limit movement between certain areas. These barriers may be the result of limited access highways as well as restrictive land uses such as cemeteries, parks, ponds, and rivers.
- Divide the initial trade area into smaller geographic units from which patronage patterns can be examined. Normally, analysts will use predefined subareas such as those defined by the Bureau of the Census (e.g., census tracts, ZIP Codes, block groups).
- Demographic data is available for each of these subareas as well as locational information (latitude and longitude) required for electronic mapping.
- Alter the study area, if necessary, to reflect boundaries of the subareas.
- Obtain demographic data to estimate the sales potential of each subarea. Examples of data required to make such assessments include population, number of households, household income, and estimated expenditures for different product groups. Locational information (latitude and longitude) required for mapping must be obtained for the subareas as well.
- Collect data that reflects the relative competitiveness of each store within the study area such as store size, prices, appearance, promotion, service, and store format.

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- Determine the distances or travel times between the subareas and all stores within the study area.
- Conduct a survey to determine the shopping patterns of residents of the subareas. Further refinement of the study area may be necessary once actual shopping preferences are known. This is particularly true in the outer reaches of the study area where competitive influences may be more pronounced.

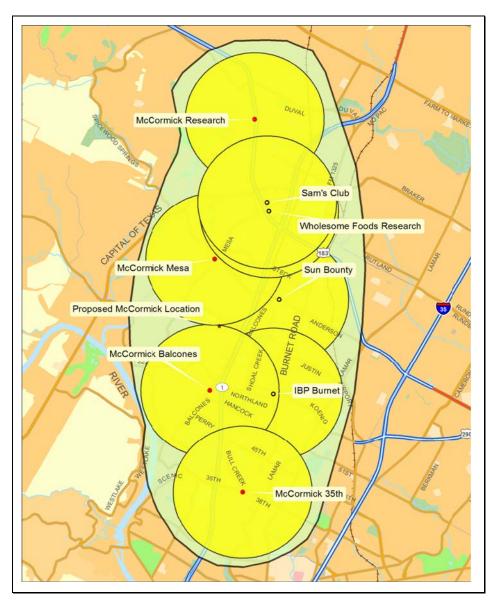
The four McCormick stores; the four competing stores; and their estimated trade areas, expressed as circles with a 1.25-mile radius, are shown on map 3.

Map 3 Circular Trade Areas



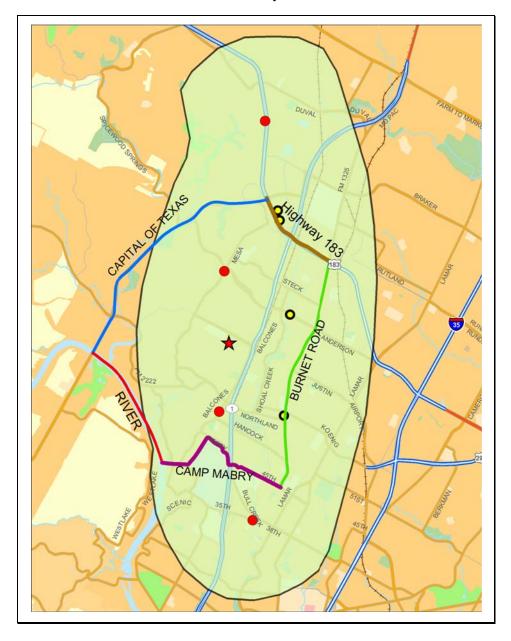
A first approximation of the study area is obtained by drawing a freehand boundary around the trade areas of the outermost stores (map 4). Natural and man-made barriers that restrict movement also limit the geographic scope of the study area.

Map 4
First Approximation of the Study Area



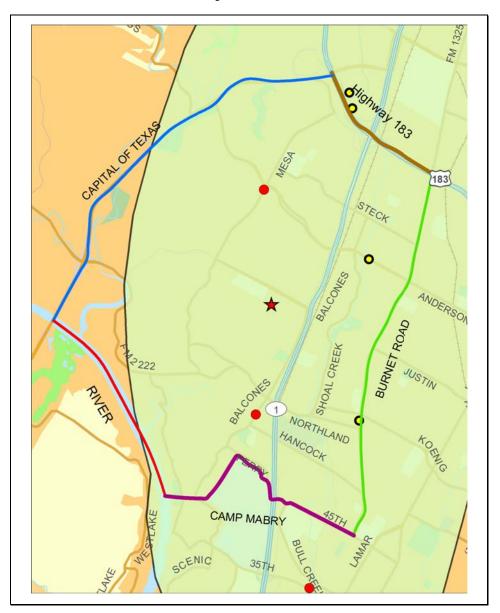
It can be seen from maps 5 and 6 that the limited access expressways to the west, north, and east and the river to the south reduce the area of the initial study area significantly.

Map 5
Reduction in the Initial Study Area Due to Barriers



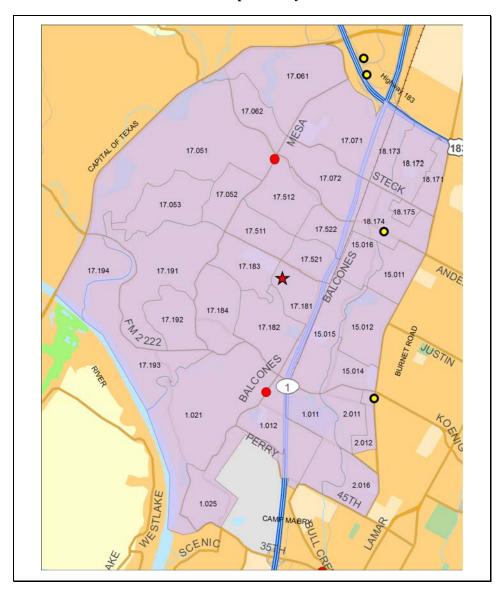
McCormick stores at 35th and Research are outside the study area. This reduced study area is then divided into smaller geographic units for which demographic data is available.

Map 6 Closeup View of Barriers



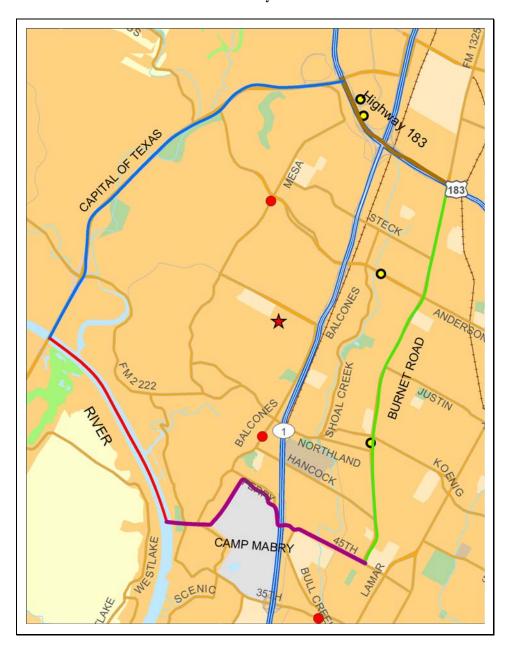
For the present analysis, block groups, as defined by U.S. Bureau of the Census, were superimposed over the modified study area (map 7).

Map 7 Block Groups in Study Area



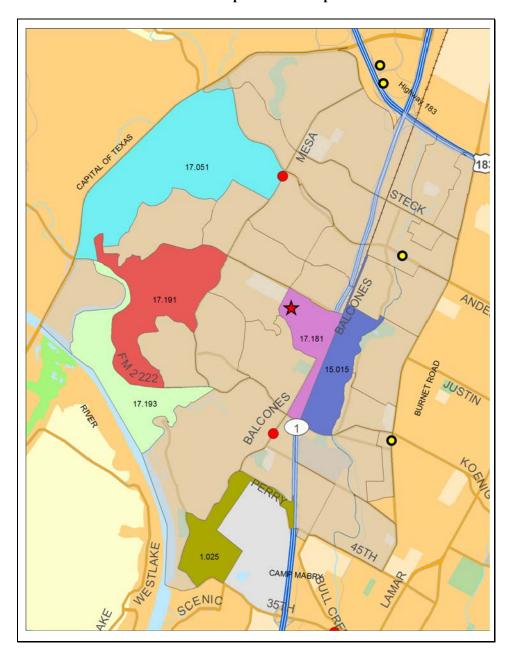
The final study area is shown on map 8. Using block groups can present a problem because of the irregularity of their shapes and size differences.

Map 8 Final Study Area



This is very apparent with a number of block groups shown in map 9. Obviously, such distortions can affect calculations and conclusions.

Map 9 Odd-Shaped Block Groups



Using a Grid Analysis

An alternative method for subdividing the study area so that geographic distortions are minimized is to construct a grid with equally sized cells for which census data can be obtained. Census data reported at the block level is available as block points. Block points are the centroids of city blocks.

As a result, data can be summarized for a cell of any size by simply summing the number of dots observed in the cell. There are several methods for determining the appropriate cell size.

For the purposes of this case study, the cells are .25 x .25-mile squares. The results are shown in maps 10 and 11. The number of cells within the boundary of the study area is 218.

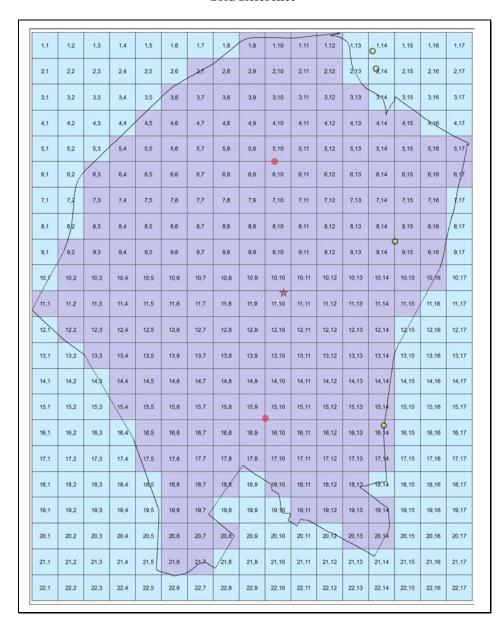
Block Folitis in Study Area

Map 10 Block Points in Study Area

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Map 11 Grid Reference



Fifty-three cells were eliminated since they did not have anyone residing within them. The total number of cells within the study area is 165.

Sales Potential

Table 1 summarizes the geographic and demographic characteristics of the study area utilizing the grid system. It can be seen that the sales potential is limited. Six stores are competing for part of the \$145 million estimated to have been spent by the 46,027 residents of the study area on food products prepared at home.

Table 1 Quarter-Mile Cells Profile of the Study Area Using Grid Analysis

Geographic Characteristics

Boundaries: (extreme boundary points)
North-South: 5.50 miles
East-West: 4.25 miles

Total Area: 23.375 square miles
Number of Block Points: 489
Total Number of Cells: 374
Cells in Study Area: 218
Populated Cells: 165

Demographic Characteristics

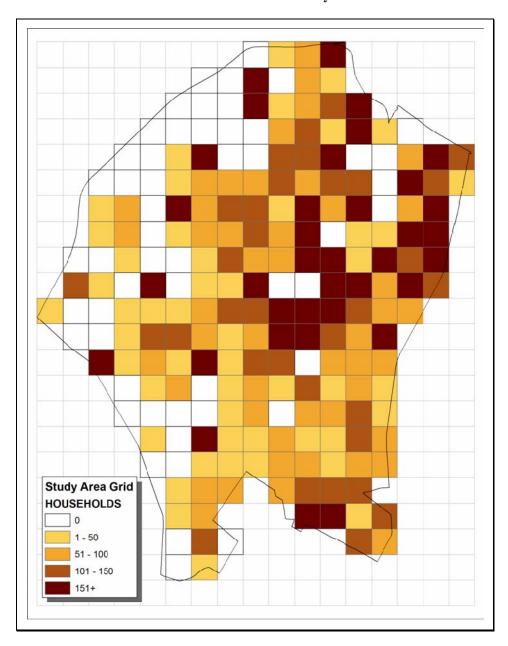
Households: 22,904 Population: 46,027

Household Income: \$109,864

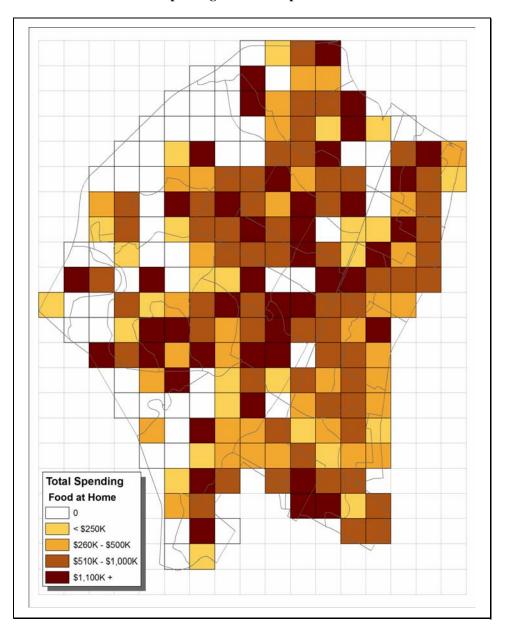
Total PH Food Expenditures: \$145,377,197

Furthermore, the sales potential is not uniform geographically as shown in maps 12 and 13. What is the current market share of each store, and how will these shares change if the new store is added?

Map 12 Number of Households in Study Area



Map 13
Total Spending on Food Prepared at Home



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Store Competitiveness

The proximity of each store to each subarea will affect store patronage patterns. All things being equal, the more centrally located a store is to its target population, the greater is the likelihood that consumers will patronize the facility over others. The attraction of a store to consumers is, for the most part, attributable to variables that are controllable by management. They include promotion, pricing, the product offering, and the overall appearance of the store. The variables used in this case study were limited to proximity, the square footage of the store, and age. These variables are summarized for each store in table 2.

Table 2
Store Attributes

Name	Age	Size	Distance*
McCormick (B)	23	26,000	-
McCormick (M)	33	26,000	-
IBP (B)	22	38,000	-
Sun Bounty	21	24,000	-
Wholesome Foods	11	30,000	-
Sam's Club	14	50,000	-

^{*} Distances are available from a separate file.

Survey of Consumer Preferences

The calibration of the model requires that actual shopping preferences be obtained from a household survey. The objective of the survey is to determine the frequency at which residents patronize different stores for each subarea. Normally, residents are selected at random from each subarea and surveyed either by telephone or personal interviews. The results of the survey provide actual patronage data that can be compared to the estimates generated by the model. Household interviews are relatively expensive to conduct, given the geographic coverage and the sample size required since each cell within the study area must be included in the sample. Normally, telephone interviews are conducted to obtain consumer preferences. Typical questions that are often asked of respondents are

- At which stores do you normally purchase food items prepared at home?
- Out of 10 shopping trips, how often do you go to each store?
- What do you particularly like about each of these stores?
- Are you aware of any promotional activities by any of these stores or other marketing programs?

Parameter Estimation

Equation 5 shows how the Huff Model becomes linear in its parameters by applying the log-centering transformation. Table 3 shows a partial listing of the regression-ready data for 36 cells. Ordinary least squares was used to estimate the parameters of the regression model. Collectively, the three independent variables were able to explain 81 percent of the variance. The parameter estimates are shown in table 4. The proximity of a store to a cell is obviously the most significant variable in predicting store choice. The remaining variables were also statistically significant and the signs made sense.

Table 3 A Partial Listing of the Regression-Ready Values

Grid Cell	Store	Log (Proportion/ GM)	Log (Distance/ GM)	Log (Store Age/GM)	Log (Store Size/GM)
1, 10	Sam's	0.306	-0.184	-0.143	0.212
1, 10	IBP Burnet	-0.539	0.313	0.054	0.093
1, 10	McCormick Balcones	-1.042	0.249	0.073	-0.072
1, 10	McCormick Mesa	1.132	-0.315	0.230	-0.072
1, 10	Sun Bounty	-0.585	0.069	0.033	-0.107
1, 10	Wholesome Foods	0.727	-0.132	-0.247	-0.055
1, 11	Sam's	0.736	-0.231	-0.143	0.212
1, 11	IBP Burnet	-0.919	0.335	0.054	0.093
1, 11	McCormick Balcones	-0.204	0.267	0.073	-0.072
1, 11	McCormick Mesa	0.135	-0.273	0.230	-0.072
1, 11	Sun Bounty	0.223	0.068	0.033	-0.107
1, 11	Wholesome Foods	0.029	-0.167	-0.247	-0.055
1, 12	Sam's	0.312	-0.246	-0.143	0.212
1, 12	IBP Burnet	-0.747	0.340	0.054	0.093
1, 12	McCormick Balcones	-0.530	0.270	0.073	-0.072
1, 12	McCormick Mesa	1.163	-0.252	0.230	-0.072
1, 12	Sun Bounty	0.081	0.067	0.033	-0.107
1, 12	Wholesome Foods	-0.279	-1.178	-0.247	-0.055
2, 9	Sam's	-0.155	-0.051	-0.143	0.212
2, 9	IBP Burnet	-0.836	0.343	0.054	0.093
2, 9	McCormick Balcones	-0.272	0.287	0.073	-0.072
2, 9	McCormick Mesa	1.921	-0.478	0.230	-0.072
2, 9	Sun Bounty	-0.611	-0.081	0.033	-0.107
2, 9	Wholesome Foods	-0.047	-0.020	-0.247	-0.055
2, 11	Sam's	0.867	-0.180	-0.143	0.212
2, 11	IBP Burnet	-0.364	0.356	0.054	0.093
2, 11	McCormick Balcones	-1.001	0.289	0.073	-0.072
2, 11	McCormick Mesa	0.782	-0.361	0.230	-0.072
2, 11	Sun Bounty	-0.184	0.018	0.033	-0.107
2, 11	Wholesome Foods	-0.100	-0.122	-0.247	-0.055
2, 12	Sam's	0.251	-0.183	-0.143	0.212
2, 12	IBP Burnet	-0.058	0.352	0.054	0.093
2, 12	McCormick Balcones	-0.463	0.285	0.073	-0.072
2, 12	McCormick Mesa	0.845	-0.343	0.230	-0.072
2, 12	Sun Bounty	-0.493	0.025	0.033	-0.107
2, 12	Wholesome Foods	0.919	-0.135	-0.247	-0.055

Table 4 Regression Results

Model Summary

Model	R	RSquare(a)
1	.898(b)	.806
2	.899(c)	.809
3	.900(d)	.810

- (a) For regression through the origin (the no-intercept model), RSquare measures the proportion of the variability in the dependent variable about the origin explained by regression. This *cannot* be compared to RSquare for models that include an intercept.
- (b) Predictors: Log(Dist/GM)
- (c) Predictors: Log(Dist/GM), Log(StoreAge/GM)
- (d) Predictors: Log(Dist/GM), Log(StoreAge/GM), Log(StoreSize/GM)

Coefficients (a,b)

Mo	odel	Coefficients		Sig.
		(b)		
1	Log(Dist/GM)	-2.743		.000
2	Log(Dist/GM)	-2.644		.000
	Log(StoreAge/GM)	.356		.000
3	Log(Dist/GM)	-2.661		.000
	Log(StoreAge/GM)	.403		.000
	Log(StoreSize/GM)	.245		.000

- (a) Dependent Variable: Log(Prop/GM)
- (b) Linear Regression through the Origin

Impact Analysis

If it is assumed that the sales leakage from the study area is offset by purchases made by consumers who reside elsewhere, then the total estimated sales would be equal to total expenditures for food within the study area as shown in table 1. Once the parameters have been derived, the model can be used to estimate the sales of a different set of stores or the competitive impact of some change that has occurred within the study area. For example, the actual sales of the six stores currently operating within the study area are shown in table 5. If the proposed store is included in the dataset as a new McCormick store, and the expected sales of seven rather than six stores are estimated from the model, the impact can be assessed as shown in table 5. It can be seen that the two existing McCormick stores are estimated to lose \$9.6 million to cannibalization by the new store. The estimated sales of the proposed store is \$21.2 million. The total sales of all three McCormick stores would amount to \$99 million. Despite the cannibalization, the net increase in total sales of the three McCormick stores amounts to \$11.9 million. If McCormick elects not to open a store at the proposed location and a competitor does, the impact amounts to an estimated annual loss in sales of \$21.2 million. As a consequence, it would seem that the best course of action would be for McCormick to open a new store at the proposed site not only as a preemptive strategy but also to

solidify its position as the market leader in West Parkview. Market share would increase from 60.0 to 68.2 percent.

Table 5
Market Shares Before and After the
Addition of the Proposed Store

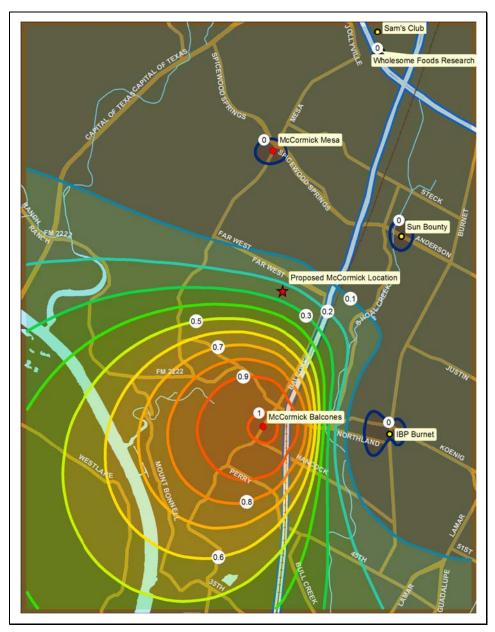
Store	Market	Share
	Before	After
Sam's	3.04%	2.74%
McCormick Mesa	34.13	30.56
Wholesome Foods	3.02	1.92
Sun Bounty	20.64	16.86
IBP Burnet	13.27	10.30
McCormick Balcones	25.90	22.90
	100.00%	84.98%
Proposed Store		15.02%

Trade Area Comparisons

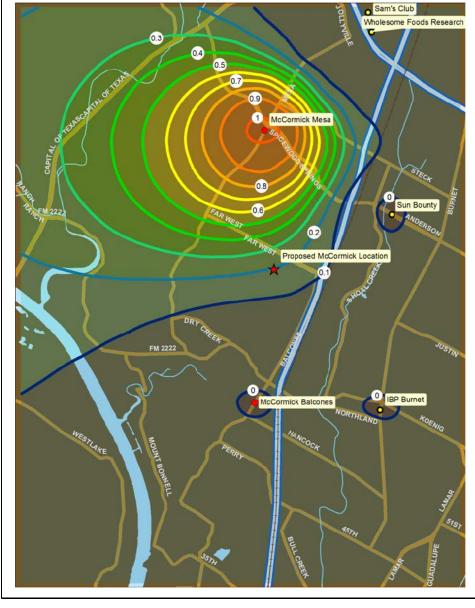
A visual assessment of the proposed store's impact on existing stores can be made by comparing the trade areas of the stores before and after the inclusion of the proposed store. Knowing where expected geographic changes in penetration are likely to occur provides management with a geographic target to direct their marketing efforts. Furthermore, while the analysis of penetration is important, the expected purchases from subareas within the trade areas of the stores are even more important. It is possible to have high penetration but little purchasing potential.

As a result, it is important to not only examine each geographic subarea in terms of penetration but also expected purchases. Maps 14 and 15 show the penetration contours surrounding the McCormick Balcones store and the McCormick Mesa store.

Map 14
Penetration Contours* for Balcones Location



^{*} Contours created using ArcGIS® Spatial Analyst extension

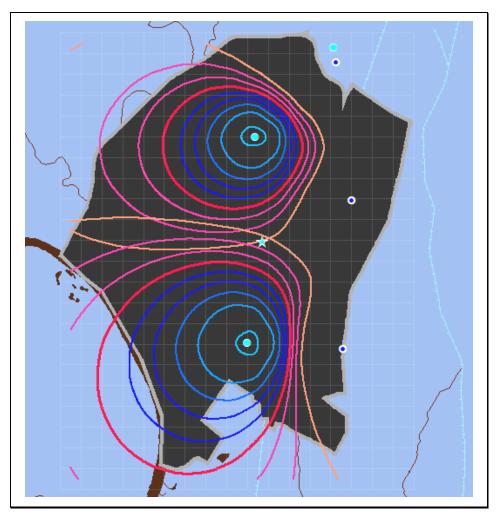


Map 15 Penetration Contours* for Mesa Location

^{*} Contours created using ArcGIS Spatial Analyst extension

Map 16 shows the penetration contours for the same two McCormick stores but with the proposed store open. It can be seen where the penetration values have changed and what is likely to be the long- and short-term impact of such changes.

Map 16 Penetration Contours* Surrounding the Mesa and Balcones Stores



^{*} Contours created using ArcGIS Spatial Analyst extension



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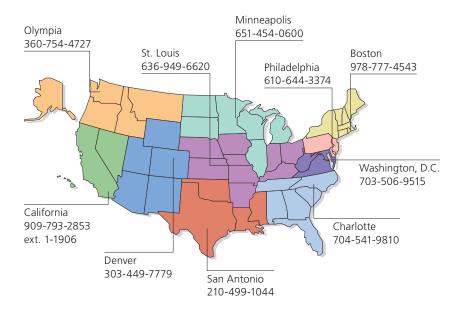
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