Exploring Heterogeneity in Consumers' Meat Store Choices in an Emerging Market

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Chinese consumers' choices among meat stores are examined through a model that can capture consumer heterogeneities both in their opinion of various store attributes and in how much weight they attach to each attribute. This approach not only informs store managers as to what attributes should receive focus for improving their store images, but also provides insight about which specific attribute could be improved to achieve the most effective result. Based on the individual-level parameters obtained through an empirical Bayes analysis, managers or competitors are able to strategically target their store promotions to specific individual consumers based on their demographic characteristics.

Key Words: heterogeneity, individual-level parameters, logit models, meat store

China has experienced dramatic economic and social changes during the past two decades. Among these changes are notable shifts in meat retailing and consumption patterns (Gale, 2003; Miao, 2003). Although the wet market[1] still remains the major retailing channel for meat products, supermarkets have gained an unprecedented increase in the market share of grocery sales in China, including meat (Access Asia, 2002). Seabridge Marketing Analysis (2003) estimated that by 2005, supermarket chains would likely hold 30% to 50% of the market share, up from only 10% in 2003. Meat wholesalers' role in supplying retail marketers has been declining, and most wholesalers—especially in Northern China—have begun to incorporate retailing into their marketing profile (Miao, 2003). In contrast, for imported meat products, wholesaling is still necessary and important in the supply chain (Seabridge Marketing Analysis, 2003). Given these new trends in the Chinese meat market, an understanding of the role played by consumers in shaping the market becomes very critical.

Consumers' decisions when choosing different meat markets to shop also have direct implications for store managers, foreign store chains, and importers, as well

[1] A "wet market" in China is similar to a "farmer's market" in North America. It refers to a designated area where individual sellers and buyers gather and make transactions. Wet markets can be either open-air or indoors.

as policy makers. Grannis, Thilmany, and Sparling (2002) found that the most important non-service factors for grocery shoppers are features related to meat products, such as their price, quality, and selection. Further, consumers' perceptions of meat products sold in a store are likely to have a significant impact on their overall store choice.

Despite its importance, very little empirical research has been conducted to assess Chinese consumers' choices for various meat shopping places (stores). This study seeks to bridge this gap by investigating consumers' choices among three types of distinct meat shopping places (stores): wet markets, supermarkets, and wholesale markets.

Consumers are assumed to evaluate the objective store attributes according to their own personal characteristics, such as demographic characteristics, motivation, or other idiosyncratic factors (Roy and Tai, 2003) to construct a set of subjective attribute levels. Then, using these subjective evaluations, consumers generate an overall measure of the attractiveness of a certain choice alternative by assigning various weights to each attribute. These weights reflect the relative importance of each attribute. This study describes how subjective store attributes are weighted and combined to form the overall store evaluation as perceived by consumers, and what factors may explain the weights attached to each store attribute.

Heterogeneity in Consumer Choices

Given the subjective nature of the perceived attributes and weights, the key research question is: "Are consumers heterogeneous in the weights of their choices as well as in their evaluations of subjective attributes?" Because the transformation from objective attributes to subjective attributes incorporates consumers' own personal characteristics, it is commonly believed that perceived attributes should contain information reflecting heterogeneity among consumers (Severin, Louviere, and Fin, 2001). By simple analogy, subjective weights attached to these attributes should also reflect the heterogeneous nature of consumers.

Leszczyc and Timmermans (1997) commented that consumers may choose different stores for a variety of reasons: specialty searching, motivation differences, time constraints, or specific tastes of different household members. Under different contexts, consumers' weights on various attributes will be different. These differences contribute to the notion of heterogeneous consumers, recognizing that consumers' choices are likely to be different from one another and may even deviate from their own habits formed previously. Timmermans (1982) cautioned that ignoring this fact may cause serious bias to the understanding of consumer behavior.

Several potential methods can be used to capture the heterogeneity in consumers' choices (e.g., Finn and Louviere, 1990; Coughlan and Soberman, 1999). This study seeks solutions from disaggregated behavioral models designed to depict heterogeneities among individual-specific choice processes. The discrete choice literature provides a rich set of analytical tools for this undertaking. The most straightforward approach of incorporating consumers' heterogeneity in their subjective weights is

to treat consumers' characteristics as variables that directly affect consumers' utility functions associated with a store (Moon et al., 1999; Johnston et al., 2001). However, as noted by Vriens, Wedel, and Wilms (1996) and Fennell et al. (2003), simply including consumer characteristic variables into the utility function is generally not a sufficient way to capture the heterogeneity.

Various approaches have been proposed to identify and explain consumer heterogeneity, ranging from the heteroskedastic extreme-value model to mixture models. In this analysis, the mixed logit model (also called the random parameter logit model) specified by Train (1998) is adopted. The mixed logit model is capable of providing invaluable insights into the issue of consumer heterogeneity. Weights from the sampled respondents are assumed to be randomly distributed according to a certain distribution function. Greene and Hensher (2003) showed that if the distribution function is discrete, a mixed logit model can nest a latent class model which is also flexible (e.g., Swait, 1994; Boxall and Adamowicz, 2002). Finally, this study significantly differs from other similar research in that it outlines a way to explain the sources for such heterogeneity through the calculation of individual-level parameters using the empirical Bayes approach.

Data Collection and Processing

The data used in this study were collected using a survey with participants drawn from two Eastern Chinese cities in 2000: Shanghai and Hangzhou.[2] The survey was carried out in two rounds, with a three-week break allowed between the two survey rounds to increase the time coverage of the survey. In addition, to assure inclusion of consumers with different shopping habits or routines, three days of the week were selected for conducting the interviews: Tuesday, Thursday, and a weekend day (Saturday). Four different time slots were also chosen for the interviews in each interviewing day: 7 am to 8 am, 11:30 am to 12:30 pm, 5 pm to 6 pm, and 8:30 pm to 9:30 pm. These time slots generally reflect Chinese consumers' typical shopping patterns of early morning (before work), lunch break, after work, and late evening.

A total of 427 consumers showed serious interest in the survey during the survey period, generating a valid sample of 366 consumers. Based on a representative check of these participants, our sample has a slightly higher-than-average proportion of females and higher-income families for both cities, and slightly fewer younger individuals in Hangzhou. After focus group discussions and a careful review of the relevant literature, seven meat store attributes were selected for incorporation into the survey: meat price, meat quality, convenience of store location, quality of store service, quality of store environment, how well meat products are certified in the store, and meat product selection. These attributes were selected because they can

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[2] These two large cities are located within 200 kilometers of each other, and the "metropolitan belt" formed between them enjoys one of China's strongest economic statuses. We believe consumers in these regions are representative, and can serve as suitable proxies for consumers in other less-developed areas of China. Nevertheless, due to the limited sampling area, results should be interpreted with caution when generalizing to other regions in China.

all be related to the meat shopping places in the study. Additionally, they reflect a fairly comprehensive coverage of meat store attributes which have been commonly considered in recent studies on consumers' store choice behavior (e.g., Bell, Ho, and Tang, 1998; Medina and Ward, 1999; Urbany, Dickson, and Sawyer, 2000; Herrington, 2001; Grannis, Thilmany, and Sparling, 2002; Fox, Metters, and Semple, 2002; Oumlil, 2003; and Coughlan and Soberman, 2005). Respondents were asked to rank each of the three types of stores (wet markets, supermarkets, and wholesale markets) according to these seven attributes using a five-point Likert scale, where 1 = very important and 5 = very unimportant. Finally, the survey collected information on consumers' demographic and social characteristics.

Prior to beginning the empirical analysis, it was apparent from the survey responses that some consumers did not evaluate one or more of the stores according to all seven attributes. In the questionnaire, consumers were allowed to express their opinion if they felt they did not consider certain attributes for a store as important. The survey was worded such that consumers were encouraged to skip the attribute questions only if they truly did not know a type of store well. Consequently, the reason for an omission is not likely due to a consumer's unfamiliarity with a store, but rather to self-selection. Being unfamiliar with a store can be viewed as an indication the consumer has not frequently patronized that store; i.e., the store was not on the "list" of the consumer's potential store choices. This explanation is consistent with the theory of choice set formation in the discrete choice literature (e.g., Finn and Louviere, 1990).

The data were thereafter examined for these missing responses, and a consumer was classified as a non-customer for store *i* if that consumer did not answer at least four attribute questions for store *i*. By this definition, 37 consumer/respondents had only one alternative from which to choose, and they were subsequently excluded from further analysis. Of the remaining 329 consumers retained for the analysis, 247 had a choice set of all three types of stores, and 82 had a choice set of two types of stores. Furthermore, to avoid the problem of multicollinearity, the correlations between the attribute variables were calculated. Variables capturing "how well meat products are certified in a store" and "quality of store environment" had a correlation coefficient higher than 0.8 with other belief variables, and therefore were dropped from the analysis. The final variables used in the analysis are summarized in table 1.[3]

Choice Models for Outlet Selection

Based on random utility theory, and assuming the decision maker's self-evaluated utility and analyst-evaluated utility differ by a random term ε, the utility of consumer *n* choosing store *i* may be expressed as:

$$(1) \qquad\qquad U_{ni} = \beta \mathbf{X}_{ni} + \varepsilon_n,$$

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[3] Additional variables could be used in the analysis. However, given the sample size and the complexity of models to be estimated, the current representative variables are considered to be sufficient.

Table 1. Definitions and Descriptive Statistics of Explanatory Variables ($N=329$)

Explanatory Variable	Description	Mean	Standard Deviation
QUALITY	Quality of meat products (1–5 Likert scale ranking)	3.188	0.896
LOCATION	Convenience of store location (1–5 Likert scale ranking)	3.063	1.100
SERVICE	Within-store quality of service (1–5 Likert scale ranking)	3.392	0.886
SELECT	Meat product selection (1–5 Likert scale ranking)	3.895	1.040
PRICE	Meat product prices (1–5 Likert scale ranking)	2.949	0.966
SUPMKT	Alternative specific constant for supermarket	0.363	0.481
WHSMKT	Alternative specific constant for wholesale market	0.275	0.447
MALE	Dummy variable for male respondents	0.357	0.479
CHILDREN	Continuous variable for number of children in household	1.316	0.661
INCOME	Continuous variable for household income (RMB)[a]	33,948.832	15,046.907
AGE	Continuous variable for respondent's age	53.143	24.037
EDU	Continuous variable for respondent's years in school	12.557	3.405
HSIZE	Continuous variable for household size	3.737	1.232
MARRIED	Dummy variable for married respondents	0.723	0.448

Note: For variables using a five-point Likert scale, 1 = very important and 5 = very unimportant.
[a] RMB denotes Ren Min Bi, the Chinese currency unit (1 RMB = \$0.12 U.S. at the time the survey was conducted in 2000).

where $\mathbf{X}_{ni}$ is a vector of consumer n's subjective evaluation of store i's attributes and $\boldsymbol{\beta}$ is a vector of subjective weights to be estimated. If the error term g_n is distributed i.i.d. and follows a Gumbel distribution, the probability of consumer n choosing store i can be written in the familiar multinomial logit (MNL) form:

$$(2) \qquad P_{ni} = \frac{\exp(\mu V_{ni})}{\sum_{j=1}^{J} \exp(\mu V_{nj})} , \quad J = 2 \text{ or } 3,$$

where $V_{ni} = \boldsymbol{\beta}\mathbf{X}_{ni}$ is the deterministic portion of expression (1), and μ is a scale parameter usually normalized to one.

The MNL model imposes one common weight for the weight of each store attribute across all sampled consumers. In addition, this model assumes the property of independence of irrelevant alternative (IIA), which is unlikely in reality. Train (1998) discussed and formalized a random parameter model with a logit kernel and denoted it the mixed logit (ML) model. The ML model assumes weights for store attributes are random variables, and choice probabilities are defined over the density of these random weight parameters. Assuming a particular weight β is normally distributed with density function $f(\beta)$ and the choice probability under a conventional MNL model (P_{ni}), the ML model specifies the choice probability as:

(3) $$P_{ni}^{M} = \int_{m} P_{ni} f(\beta)\, d\beta.$$

Note that since β is a random parameter, $\beta \sim N(\eta_\beta, \sigma_\beta)$, integrating out β in the above expression allows the mean and standard deviation associated with β to be identified. The estimated η_β and σ_β determine the shape of β, which is the distribution the sampled consumers' weights on a particular perceived attribute may follow. In other words, this distribution incorporates the heterogeneity around the sampled consumers' weights on an attribute. If more than one weight is specified as random, each random weight will be integrated simultaneously in the same manner as in expression (3).

The ML model is flexible, and it relaxes the IIA assumption in a conventional MNL model to allow for any type of correlation among choice alternatives.[4] Unlike an MNL model, equation (3) does not have a closed form. Various authors have proposed the simulated approach to approximate P_{ni}^{M} (Boyd and Mellman, 1980; Ben-Akiva and Lerman, 1985). Based on the simulation approach described by Train (1998), the simulated log-likelihood function is defined as follows:

(4) $$SLL = \sum_{n=1}^{N} \sum_{i=1}^{I} c_{ni} \ln(\hat{P}_{ni}^{M}),$$

where $\hat{P}_{ni}^{M}$ is the simulated probability; $c_{ni} = 1$ if store i is chosen by individual n as the most often visited store, otherwise $c_{ni} = 0$. Equation (4) can be maximized via a routine maximization procedure.

Individual Weights

If the consumers in the data are referred to as a population, the distributions of random weights can be defined as the population distributions. Given the population distribution as a prior, and conditional on the choice each consumer makes, the posterior (i.e., individual-level) distribution of a weight can be calculated through the empirical Bayes approach (Tanner, 1993, p. 11). Specifically, defining $f(\beta|\theta)$ as the distribution of a subjective weight in β determined by its distribution parameter vector $\theta(\eta_\beta, \sigma_\beta)$, the probability of consumer n choosing store i conditional on the knowledge of consumer n's weights (β_n) is given by equation (2).[5] The unconditional probability of consumer n choosing store i is conveniently given by equation (3).

Combining this information, Bayes' theorem gives consumer n's subjective weights conditional on his or her own choice(s):

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[4] Revelt and Train (1998) show that although the Gumbel-distributed error term that gives the logit probability P_{ni} is i.i.d. across individuals, alternatives are still correlated due to the interaction between the perceived attributes and random component of weights. The parameters of correlation depend on the type of random terms.

[5] Conditional on our full knowledge of consumer n's subjective weights, no further extra heterogeneity is assumed. Therefore, a conventional logit model is appropriate for calculating choice probabilities.

(5)
$$g\left(\beta_n^c \star C_n^i\right) \cdot \frac{P_{ni}\left(C_n^i \star \beta_n^p\right) f\left(\beta_n^p \star \theta\right)}{P_{ni}^M\left(C_n^i \star \theta\right)},$$

where C_n^i represents consumer n's choice(s), and in a cross-sectional setting, C_n^i represents a choice of store i; β_n^p denotes our prior knowledge of consumer n's individual-level weights being approximated by the population weights β_n; β_n^c represents consumer n's true posterior individual-level weights conditional on his or her past choice(s). Equation (5) can easily be generalized to incorporate a series of previous choices when C_n^i has a time component.

The individual-level parameter distribution $g(\cdot)$ contains individual-related information in which a researcher is interested. Revelt and Train (1999) and Train (2003, p. 209) described a simulation approach to calculate the mean of each individual's weights β_n^c. Given the assumption that the distribution $g(\cdot)$ is continuous, the mean estimator could be calculated as:

(6)
$$\bar{\beta}_n^c \cdot \int_m \beta_n^c g\left(\beta_n^c \star C_n^i\right) d\beta_n^c.$$

By theory, $\bar{\beta}_n^c$ will be different across sampled individuals.[6] This study continues to explain how these differences in consumers' subjective weights may be caused. Specifically, regression models are used to analyze the relationships between individual consumers' demographic characteristics and their subjective weights.

Estimation and Random Weights Specification

To determine which store attributes should be allowed with random weights, the test proposed by McFadden and Train (2000) is used. Given the predicted probability of consumer n choosing store i, $(\hat{P}_{ni})$ from equation (2), a vector of artificial variables **z** is defined as:

(7)
$$z_j \cdot \tfrac{1}{2}\left(X_j \& \sum_i^I X_{ij}\hat{P}_{ni}\right)^2, \quad \text{œ}n \cdot 1, 2, ..., N,$$

where j indexes various perceived store attributes. This set of artificial variables is then incorporated into a conventional MNL model, and the estimation results are reported in table 2. *SUPMKT* and *WHSMKT* are two alternative specific constants (ASCs) for supermarket and wholesale market, respectively; *PRICE*, *QUALITY*, *LOCATION*, *SERVICE*, and *SELECT* are the perceived price level, quality, degree of location convenience, service level, and selection of meat products, respectively. Variables z_1 to z_7 are artificial variables corresponding to these seven variables.

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[6] In this particular application using cross-section data, each element of $\bar{\beta}_n^c$ is not necessarily different for *each* individual in the sample. Only in a situation involving panel data, and when the choice situations faced by individuals approach infinity, will each element of $\bar{\beta}_n^c$ be different across each sampled individual for any finite sampled population.

Table 2. Estimation Results of Test for the Existence of Mixing Structures

Explanatory Variable	Coefficient	t-Ratio	Artificial Variable	Coefficient	t-Ratio
SUPMKT	! 2.118*	! 2.207	z_1	0.750	0.278
WHSMKT	! 2.512	! 1.276	z_2	2.257	0.429
PRICE	! 0.315*	! 1.958	z_3	0.022	0.146
QUALITY	0.405**	2.142	z_4	! 0.288*	! 1.901
LOCATION	0.171	1.265	z_5	! 0.223*	! 1.944
SERVICE	0.232	1.425	z_6	0.143*	0.998
SELECT	! 0.080	! 0.575	z_7	0.232**	2.006

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Based on the t-ratio, a significant z_j indicates that X_j may need a random weight β_{nj}. McFadden and Train (2000) demonstrated that the power of this test is relatively low when random terms are tested independently, and the critical value of one should be used rather than two as the diagnostic criteria for determining whether z_j is significant. Following this rule, artificial variables z_4, z_5, and z_7 are all significant (table 2). Given the t-ratio of z_6 (0.998) is reasonably close to 1, we consider z_6 to be significant as well. According to these figures, the corresponding variables *QUALITY*, *LOCATION*, *SERVICE*, and *SELECT* all may be estimated with a random weight.

Estimation Results

Coefficient Estimates

Table 3 provides the estimation results of both the conventional MNL model and the ML model (after 100 Halton replications). Compared with the MNL model, the ML model has a better model fit, with an adjusted pseudo-R^2 statistic of 0.063—which is low but not surprising for a cross-sectional discrete choice model (Louviere, Hensher, and Swait, 2000, p. 54). Both models predict a negative weight associated with the price attribute. The ASCs representing supermarket and wholesale market (*SUPMKT* and *WHSMKT*) are both significant and negative in the two models. This finding indicates, holding all other factors constant, when compared with wet markets, both supermarkets and wholesale markets bring negative values for consumers, and thus they are less likely to choose these two types of shopping places. This result is consistent with evidence observed in China that the wet market is still by far the most popular choice for Chinese consumers.

To further compare the two models, marginal effects of three representative attributes for the wet market are presented in table 4. These marginal effects show how much the probability of choosing a particular store changes when the ratings of the

Table 3. Estimation Results for the MNL and ML Models

	MNL Model		ML Model			
Variable	Mean Coefficient	*t*-Ratio	Mean Coefficient	*t*-Ratio	Std. Dev. Coefficient	*t*-Ratio
PRICE	! 0.287**	! 2.123	! 0.327**	! 2.089	—	—
SUPMKT	! 1.860***	! 8.364	! 2.098***	! 7.477	—	—
WHSMKT	! 1.766***	! 7.697	! 1.943***	! 7.256	—	—
QUALITY	0.300**	2.030	0.323*	1.837	0.014	0.046
LOCATION	0.207*	1.780	0.248*	1.864	0.000	0.001
SERVICE	0.232	1.600	0.156	0.870	0.586*	1.745
SELECT	! 0.135	! 1.037	! 0.084	! 0.480	0.767**	2.024
Log Likelihood	! 207.130		! 193.417			
Adjusted Pseudo-R^2	0.029		0.063			

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Marginal Effects on Own- and Cross-Alternative Choice Probabilities by Three Wet Market Attributes

Wet Market Attribute	Change of Choice Probabilities Predicted by the MNL Model			Change of Choice Probabilities Predicted by the ML Model		
	Wet Market	Supermarket	Wholesale	Wet Market	Supermarket	Wholesale
PRICE	! 0.048	0.031	0.019	! 0.128	0.080	0.048
QUALITY	0.050	! 0.032	! 0.018	0.136	! 0.086	! 0.050
LOCATION	0.034	! 0.022	! 0.012	0.115	! 0.073	! 0.042

three attributes for wet market change by one unit (i.e., higher price, higher quality, and better location for the wet market). All own- and cross-alternative effects were calculated for each individual and then averaged. These marginal effects do indicate moderate differences between the two models.

The variables *QUALITY* and *LOCATION* are significant and positive in both models (*QUALITY* is significant at the 10% significance level in the ML model). These findings suggest Chinese consumers prefer shopping at stores that provide higher quality meat and stores with convenient access. Within each model, the relative magnitude of the weight for *QUALITY* is greater than that for *LOCATION*.[7] In their shopping decisions, consumers therefore place a higher value on meat quality than the location of a store. Knowing this information can be beneficial to

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[7] Both *QUALITY* and *LOCATION* are measured on a five-point Likert scale. Therefore, one can compare the relative weights of these variables. In addition, since we are comparing two variables in the same model, the scale difference between logit models does not apply.

store managers. Of course, it would be considered difficult to improve the conven-ience of a store's location, unless the manager wishes to relocate the store or to build a new one; however, improving meat quality may be relatively easier to achieve. Although it is not possible to infer from the current model how many more customers a particular managerial improvement may attract (given that the attributes are perceived), clearly managers can choose one approach if the other is too difficult to accomplish.

The service level of a store (*SERVICE*) and the variety of types of meat products available (*SELECT*) in a store are not significant in either model, perhaps suggesting Chinese consumers are not placing enough attention on either of these two attributes when forming their attitudes and choice decisions toward a meat store. However, as will be observed from the ML model estimation results, the interpretation of these two variables may depend on the model used, and interpreting them as being insig-nificant may be misleading.

Standard Deviation Estimates and Implications

In the ML model, standard deviation estimates for the weights associated with the attributes *QUALITY* and *LOCATION* do not appear to be significantly different from zero (table 3). This reveals a lack of variation across consumers in terms of the respective weights they assign to these two attributes. Despite the random parameter specification test, consumers implicitly "agreed" with one another regarding the weights placed on these two attributes. In other words, consumers are homogeneous in terms of their evaluation of the importance of a store's meat quality and conven-ience of location, just as they are relative to the price attribute and the store-specific indicators.

The variables *SERVICE* and *SELECT* are not significant in either model (table 3). In the conventional MNL model, this leads to a conclusion that consumers do not think the service in a store and the selections available are important factors for their store-choice decision. Yet, as found in other studies on consumers' heterogeneity, this conclusion is misleading (Train, 2003, pp. 275–276). In the ML model, although the mean weights for *SERVICE* and *SELECT* are not significant, the standard devia-tions of these two estimates are significantly different from zero (at the 10% and 5% significance levels, respectively). This finding indicates the existence of a significant variation around the overall sample mean weight estimates, which is the average of the weights from all individual consumers. Importantly, having the knowledge of the mean and standard deviation for the weights associated with *SERVICE* and *SELECT* allows us to calculate the shares of consumers who have positive or negative weights associated with these two store attributes based on the normal distribution cumula-tive distribution function.

Results show that 41.1% of the surveyed consumers have negative values associ-ated with higher service quality (*SERVICE*), and 58.9% of these respondents think oppositely. For the attribute of meat product selection (*SELECT*), consumers are more divided in their weights, as 52.2% and 47.8% of the surveyed consumers value

the selection attribute negatively and positively, respectively. These divisions on both sides of zero, which would average to zero, clearly reveal that consumers differ from one another regarding their subjective weights attached to the *SERVICE* and *SELECT* attributes.

Revelt and Train (1998) observed a similar situation in consumers' evaluation of rebates associated with household appliances. Therefore, an insignificant weight in an MNL model may not necessarily mean that consumers do not care; rather, an explanation for this result may be that consumers do not all assign a similar weight to the attribute, and averaging among the sampled consumers' weights associated with these two attributes leads to statistical insignificance. The ML model thus allows us to observe the heterogeneity which would otherwise be clouded in the MNL model results.

For store managers, an understanding of the actual underlying preferences of consumers is critical. Results from the ML model essentially indicate there may be two distinct store promotion strategies surrounding either the *SERVICE* or the *SELECT* attribute. If managers can obtain specific information as to which consumers may place negative or positive weights on these two attributes, these managers can better position their store image campaign to compensate for consumers with negative views, and to attract the other half who have positive views. This information would also save managers a significant amount of cost from unnecessary promotion practices. This information is especially important to competitors, either domestic or foreign stores, who wish to enter the market. A more targeted strategy may assist them in gaining a faster and smoother entry. Later in this study, we describe how to predict each individual consumer's opinion on these two attributes.

Individual-Level Parameters

Individual parameters are obtained according to equation (7).[8] These individual-level parameters are further regressed against consumers' demographic and socio-economic characteristics. Generalized least squares (GLS) regression analysis is used to account for the possible existence of heteroskedasticity in this cross-sectional analysis.

Table 5 reports the GLS results for the weights of the *SERVICE* and *SELECT* attributes. Household size (*HSIZE*) is significant with opposite signs in the two regressions, indicating shoppers for larger families do not place high priority on quality of service in their meat store; instead, they prefer a shopping place offering an abundant selection of meat products. This result might be due to the following reasons. First, in larger families, household members' demand for meat cuts may

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[8] To calculate individual-level parameters, we assume parameters $\boldsymbol{\theta}$ are jointly distributed as multivariate normal. We take draws from this multivariate normal distribution, and after each draw, we simulate the mean of each random weight in $\bar{\beta}_n^c$ according to equation (7). Theoretically, when the number of replications used for calculating $\bar{\beta}_n^c$ [based on equation (7)] is large enough, the simulation error can be ignored and the variation of β_n^c surrounding $\bar{\beta}_n^c$ can be viewed as being introduced only by drawing vector $\boldsymbol{\theta}$ from its multivariate normal density function. We used 1,000 replications for both types of simulation.

Table 5. GLS Analysis of Attribute Weights on the *SERVICE* and *SELECT* Variables

Variable	SERVICE		SELECT	
	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
Constant	0.203	5.961	! 0.091*	! 1.684
MALE	0.002	0.127	0.040*	1.721
CHILDREN	0.026*	1.775	! 0.040	! 1.536
INCOME	! 0.006	! 1.151	! 0.022***	! 3.380
AGE	! 0.011	! 1.357	0.010	0.717
EDU	0.009	1.424	0.002	0.231
HSIZE	! 0.022**	! 2.157	0.026**	2.094
MARRIED	0.029	1.273	0.012	0.371
Adjusted R^2	0.045		0.061	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

vary across a relatively greater range than in a small family. Shoppers for larger families would necessarily patronize stores providing more meat product selections (Leszczyc and Timmermans, 1997). Second, larger families may have limited financial means. Because higher service standards are normally associated with higher prices, shoppers from larger families may place greater emphasis on their grocery budget, and consequently forego shopping at stores promoting higher service quality.

In the analysis of the service-level attribute (table 5), the variable *CHILDREN* was significant at the 10% level. This finding suggests the presence of children in a family may lead shoppers to choose a store characterized by a better level of service. When weighting *SELECT*, male shoppers seem to prefer (at the 10% significance level) a store with more product selections, suggesting male consumers may be more adventurous or variety seeking. The results also show higher-income families systematically avoid stores providing a wide variety of selection. This finding is not surprising given the fact that supermarkets are almost exclusively visited by higher-income families in China, and one of the major characteristics of supermarkets in China (especially in comparison to wet markets) is their lack of product selection (Seabridge Marketing Analysis, 2003). A possible reason for this outcome may be that in higher-income families, both the male and female household heads work, and therefore cooking time has a higher opportunity cost. Supermarkets usually provide more ready-to-cook products, thereby offering consumers the value of reduced cooking time. Another possible explanation for this finding is that shopping at a store with large product selections may involve longer searching times by the consumer, and the opportunity cost of searching is also relatively high for families with higher incomes.

The practical implication from the analysis of individual-level parameters is promising. Once store managers know where different consumers stand in terms of the weights they place on the service and meat product selection attributes, managers can strategize or even personalize their marketing plans in order to increase profits. This can be accomplished by focusing on the most efficient sales promotion action with respect to a particular individual or a group of individuals. For example, in relatively affluent areas of the city, managers may want to improve attributes such as meat quality (e.g., by offering more ready-to-cook products), but not increase the meat product selection, as the cost for consumers with higher incomes to search among a large selection of products may be high. Another strategy example might involve targeting consumers who shop for large families. In this case, an efficient way to increase sales is not to direct resources toward improving customer service, but instead to use these resources to increase the number of meat product selections available in the store. This type of information is especially valuable for new market competitors to position their management strategies for gaining access to the market.

Conclusions and Implications

This study has examined Chinese consumers' meat store preferences. Results show that Chinese consumers place considerable weight on the attributes of price, meat quality, and the convenience of the store location. Accordingly, store managers should identify ways to improve consumers' perceived levels of these attributes. It is also demonstrated in this study that in addition to the heterogeneity reflected through consumers' perceived store attributes, there is further heterogeneity in their subjective evaluation of the relative importance of these attributes. A mixed logit model was adopted in this analysis, which reveals the heterogeneity among sampled individual consumers for their weights on the service and range of product selection in a meat store. The conventional multinomial logit model does not provide these details.

Sampled consumers were roughly equally divided in terms of their assessment of the desirability of meat store service level and product selection: half of the consumers attached positive weights to these attributes, while the other half reported negative opinions. Knowing this information, store managers can direct their resources to strategies that best fit this heterogeneous situation, thereby avoiding unnecessary costs associated with misdirected marketing practices.

The ability to employ these strategies requires knowledge as to what types of consumers are more likely to belong to either group (i.e., hold a positive or negative view). Results of this study also provide an insight into this issue. Obtained through the application of Bayes' theorem to an ML model, individual-level parameter estimation enables further analysis of the source of consumers' preference heterogeneity. Consumers' income, household size, gender, and whether children are present in the household are all found to affect consumers' weights on the two attributes of quality of service and meat product selection. With this information at hand, store managers can perform detailed market segment analysis and strategically

design a marketing tool or a store promotion campaign to achieve the best result for each particular type of consumer.

Although this study focuses on Chinese consumers' meat shop choices, it employs a general model that can be applied to other situations. For example, the approach outlined here can be applied to other types of stores, products, and/or a different country. Due to the rich empirical results implied by this approach, managers can benefit from the revealed information on consumers and their perceptions. Finally, the method described here is built upon traditional shopping occasions; i.e., consumers have to pay physical visits to various stores. In the new e-commerce era, many currently important store attributes, such as location or convenience, may become less of a concern, while some new attributes, such as payment method or delivery service, may become more important (Larson and Steinhofer, 2005). This approach offers a promising venue for analyzing these emerging attributes in the new market structure.

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