ASIA MARKETING JOURNAL

Volume 22 | Issue 2 | Article 1

7-31-2020

The Effect of Consideration Set on Market Structure

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http://dx.doi.org/10.15830/amj.2020.22.2.1

The Effect of Consideration Set on Market Structure*

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We estimate a choice-based aggregate demand model accounting for consumers' consideration sets, and study its implications on market structure. In contrast to past research, we model and estimate consumer demand using aggregate-level consumer browsing data in addition to aggregate-level choice data. The use of consumer browsing data allows us to study consumer demand in a realistic setting in which consumers choose from a subset of products. We calibrate the proposed model on both data sets, avoid biases in parameter estimates, and compute the price elasticity measures. As an empirical application, we estimate consumer demand in the camcorder category and study its implications on market structure. The proposed model predicts a limited consumer price response and offers a more discriminating competitive landscape from the one assuming universal consideration set.

Keywords: choice model, demand model, consideration set, limited competition

Ⅰ. Introduction

The choice-based aggregate demand model, a class of demand models by Berry et al. (1995), has been a popular workhorse for many economic analysis and marketing applications (Knittel et al. 2014). In the choice-based aggregate demand model, researchers typically have access to aggregate-level choice data such as sales or market shares. Nonetheless, it takes a bottom-up approach. That is, they first develop an individual-level, random coefficient discrete choice model, and compute individual choice probabilities. Then, they aggregate the choice probabilities across consumers and predict market-level outcomes, which will be used during the estimation. One attractive feature of the choice-based aggregate demand model, compared to the regression-based linear model,

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is the model parsimony (Nevo 2000). That is, the number of parameters to estimate in the choice-based aggregate demand model is usually far smaller than that in linear models, especially when the number of alternatives in the analysis is high. For instance, if one were to estimate the full cross-price elasticity matrix with J number of alternatives in linear models, the number of required parameters is in the order of J^2. The estimation of a very large number of parameters will be very demanding on data, and in some cases it may be impractical.

One common assumption in a vast majority of the choice-based aggregate demand models is that consumers choose from the universe of all available products in the market. However, such an assumption may be less tenable in many empirical settings, especially in the context of differentiated product categories. In Berry et al. (1995), there are more than 100 different nameplates in the automobile market. In our empirical setting, there are over 130 different camcorder models. In both settings, consumers are unlikely to be familiar with and to consider all the products in the market before choice. As such, marketing academics have strongly supported the notion that consumers do not choose from the universal set of products but from a limited set of products.[1] That is, consumers' imperfect and limited information about products and their limited ability to acquire and process the lacking information will affect their decision-making process during choice (Shocker et al. 1991). Despite its intuitive appeal, the modeling of consumer consideration set into empirical research has been challenging due to data limitation: researchers typically do not directly observe consumers' consideration sets. Exceptions in the context of choice-based aggregate demand model are recent research by Bruno et al. (2008) and Goeree (2008), who used product availability and firm-specific advertising variance, respectively, as the source of heterogeneous consideration sets across consumers.

The main contribution of this paper is as follows: we use an additional data set, explicitly incorporate consideration sets into the choice-based aggregate demand model, and study its implications on our understanding of the market structure. Our key premise is that while sales outcome data are informative of consumers' choices, aggregate-level browsing data are informative of consumers' consideration sets. Combined together, they will allow us to better estimate consumer demand and, more importantly, will lead to a better inference on the market competition. By doing so, we demonstrate the importance of modeling consideration sets and add to the growing literature on aggregate

1) In the rest of the paper, we use the words "choice set" and "consideration set" interchangeably to refer to the limited set of products consumers choose from during choice.

demand models and consideration sets.

The rest of the paper is organized as follows. In the next section, we review the related literature followed by a section on data. We then present our empirical model, estimation, and the results. In the application section of the paper, we investigate the impact of consideration sets on the market structure. Then, the paper concludes.

Ⅱ. Related Literature

In this section, we review the past marketing literature in behavioral and empirical research associated with the consideration set. Marketing academics earlier noticed the importance of consideration on consumer purchase (e.g., Alba 1991; Roberts and Lattin 1991). In doing so, behavioral researchers paid attention to the mechanisms behind the consideration set formation. For instance, Chakravarti and Janiszewski (2003) reported that consumers adopted various screening criteria and processes when forming consideration sets. Tversky and Sattath (1979) reported that consumers gather product information either from internal sources such as memory or from external sources such as the consumer environment. Consumers compare this information to cutoffs and include the alternatives that meet these cutoffs. Further research focused on the decision rules consumers adopt during the choice process (e.g., Bettman 1979) and on the determinants of the consideration set formation (Payne 1976; Bettman and Park 1980).

Modeling researchers also accepted the importance of incorporating consideration sets into empirical models. To begin with, from a statistical perspective, explicit modeling of consideration set allows researchers to recover unbiased parameters with higher efficiency in choice models (Horowitz and Louviere 1995). Nonetheless, the incorporation of consideration sets in empirical models was challenging due to the data limitation: analysts usually do not observe consumers' consideration sets during their choice process. As such, earlier research operationalized consideration sets from the past choices of consumers: consideration set was calibrated using consumers' choices in the past. Under such an operationalization, Siddarth et al. (1995) reported that firms' promotions could help expand consideration sets, which will in turn affect consumers' choice. Adopting a similar operationalization, Bronnenberg et al. (1996) found that product competition is limited or localized once consideration sets were fully accounted for. From a statistical perspective, Chiang et al. (1998) offered a comprehensive study that illustrates the effects of heterogeneous consideration sets on numerous statistical and substantive areas. A separate stream of research adopted cost-benefit analysis in modeling consideration set in the context of choice model.

For instance, Shugan (1980) focused on the cost side of product evaluation while Roberts and Lattin (1992) applied a cost-benefit framework to study consumers' consideration and choice decisions in consumer packaged goods category. The recent availability of individual-level clickstream data facilitates researchers to include consideration sets into choice models in an online setting (e.g.,Moe 2006).

So far, we focused our discussion on consideration set models that are calibrated on individual-level data. However, most relevant to our work are Bruno et al. (2008) and Goeree (2008), who modeled consideration sets in choice-based aggregate demand models. Before their work, the vast majority of research in aggregate demand models assumed universal choice set for consumers (e.g., Berry et al. 1995; Nevo 2001; Petrin 2002). However, Bruno et al. (2008) modeled limited product distribution as the source of consideration sets across consumers. Goeree (2008) modeled advertising spending variance across PC manufacturers as the source of heterogeneous awareness sets. In contrast, we directly observe consumers' aggregate-level product browsing behaviors in our empirical data, which we believe is more informative of consumers' consideration sets. They will allow us to estimate consumer demand and study market competition in a more realistic setting. In the next section, we discuss our empirical setting and data in detail.

Ⅲ. Data

For our empirical analysis, we use public data sets available at Amazon.com. Our empirical setting is similar to that in Kim (2019), who used Amazon.com's longitudinal sales rank and product characteristics data in estimating consumer demand in the camcorder category. In addition to sales rank and product characteristics data, however, we use additional data - aggregate-level consumer browsing data - in our model development and estimation. Consumer browsing data plays a key role in our model and facilitates the incorporation of consideration sets into the demand model. Our key premise is that the products online consumers browsed are correlated with the products in their consideration sets in the model. In the remaining section of this paper, we provide a brief overview of the public data set available at Amazon.com. We then move our discussion to view-list data, the additional data source, we use in our empirical model and analysis.

Amazon.com publishes aggregate-level data that summarize product browsing and purchase behaviors of its customers. The following is a short description of the data. First, the SKU-level sales rank data are available in a vast number of product categories. Although the sales rank data are ordinal and hence is limited compared to continuous data such as sales data or market shares, they are informative of aggregate-level consumer choices. In addition, detailed product characteristics data are available at Amazon.com. These data, free to acquire, are published and updated on a regular basis. For our empirical analysis, we use data in the camcorder category with $J=131$, starting from the middle of 2006 for about 11 months. Please refer to Table 1 for the summary statistics of products in our empirical analysis. Next, we discuss the aggregate-level consumer browsing data that are also available at Amazon.com.

Amazon.com provides a list of products consumers browsed together with a focal product. That is, if a number of consumers browsed products A and B together, either A will appear on B's list and/or vice versa. We call this data set view-list data. As a concrete example, consider a case in which more consumers jointly browse products A and B together than products A and C. In the view-list for A, product B is more likely to appear on A's view-list than product C appears on A's view-list. Figure 1 is a screenshot of the view-list for a camcorder from Panasonic SDR-S100. As a summary of view-list data, an average product has about 24.4 products on its view-list with a standard deviation of 10.0 across products and time. The key premise in our approach is that the view-list data are informative of products' browsing popularities conditional on a focal product. Further, they are informative of consumers' consideration set formation and can be used to approximate consumers' consideration sets in our model. Note that the time duration in our longitudinal data is shorter than that in Kim (2019): there are some periods during which we do not observe consumers' browsing behaviors due to technical issues during the data collection period. We exclude such periods in our empirical analysis.

〈Table 1〉 Summary statistics of products in the empirical analysis. Mean and standard deviations for continuous variables are computed across products ($J=131$) and periods ($T=41$)

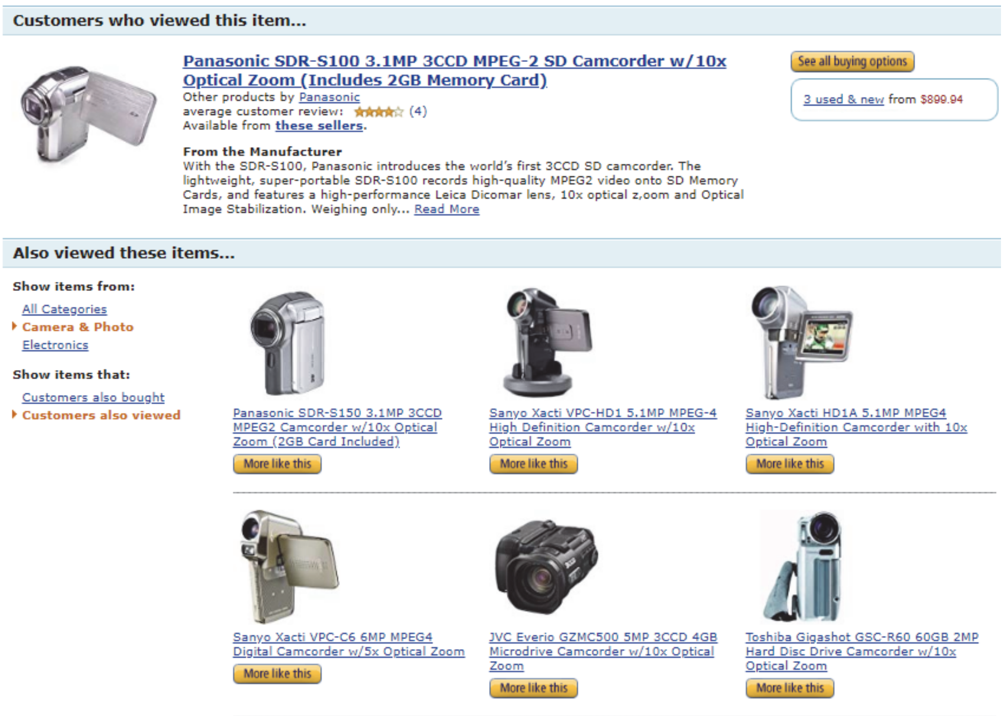
Product Characteristics	Values
Brand	Sony (40), Panasonic (30), Canon (23), JVC (26), Samsung (13)
Media Formats	MiniDV (57), DVD (38), HD (27), FM (10)
Form Factor	Compact (11), Conventional (121)
High Definition	Yes (12), No (120)
Number of Pixels	1.38M (1.00M)
Zoom	19.10 (10.35)
Price	\$524 (\$264)
Out-of-stock	0.001 (0.03)
Number of reviews	9.29 (10.22)
Average consumer ratings	3.07 (1.56)

Our modeling approach for consideration set requires the marginal distribution of products' browsing popularities. Intuitively, if product A is more popular than B among the consumers during the process, A is more likely to enter consumers' consideration sets than B. With such a marginal distribution on hand, we can simulate consumers' consideration sets during the estimation. However, the challenge with this approach is that while the view-list data are informative of conditional browsing popularities among the products, they do not offer products' marginal browsing popularities. Given such a challenge, our empirical strategy is to approximate the marginal browsing popularity distribution from the view-list data. We discuss our approach in detail in the estimation section of the paper.

Ⅳ. MODEL

Our goal in this paper is to introduce consideration sets into the choice-based aggregate demand model. By doing so, we aim to relax the assumption of the universal product set commonly adopted in past research. Our utility framework

〈Figure 1〉 An example of a view-list which shows the set of products co-browsed with the focal product of Panasonic SDR-S100



in this section is a standard one found in choice-based aggregate demand models. Due to the similarities in empirical settings, the first part of this section broadly follows Kim (2019), who used sales rank as dependent variables in demand model estimation. In the second part of the section, we discuss our approach to modeling heterogeneous consumer consideration sets with view-list data.

Utility for consumer i $(=1,\cdots, I)$ for product j $(=1, \cdots, J_t)$ at week t $(=1, \cdots, T)$ is represented as,

$$u_{ijt} = [\, Z_j \,;\, X_{jt} \,]' \cdot \beta_i - p_{jt} \cdot \alpha_i + \xi_j + e_{ijt}, \quad (1)$$

where Z_j is a vector of time-invariant product characteristics (e.g., brands), X_{jt} is a vector of j's time-varying product characteristics at t (e.g., consumer reviews), and p_{jt} is j's price at t. β_i is a vector of consumer-specific sensitivities for product characteristics, and α_i is i's price sensitivity. ξ_j is unobservable product characteristics, a structural error term that is observed by consumers but not by analysts during the time of consumers' choice.[2)] The last term of e_{ijt} represents idiosyncratic consumer taste and is an i.i.d. GEV type I random error term across i, j, and t. Following the approach in choice-based aggregate demand models (e.g., Berry et al. 1995), we assume a normal distribution for heterogeneous consumer tastes,

$$\beta_i \sim \mathrm{N}(b, \Sigma_b), \quad (2\text{-}1)$$

where b is a vector and Σ_b is a diagonal matrix. We assume a log normal distribution for the price coefficient,

$$\log(\alpha_i) \sim \mathrm{N}(\alpha, \sigma_\alpha^2). \quad (2\text{-}2)$$

In our utility specification, one expects ξ_{jt} with subscripts of j and t and not ξ_j as in Equation (1). However, the sales rank data as our dependent variables do not allow us to fully estimate ξ_{jt}. Therefore, we follow Kim (2019), decompose $\xi_{jt} = \xi_j + \xi_t + \triangle\xi_{jt}$, and estimate ξ_j only. The intuition behind this approach is as follows. First, among the decomposed terms, the estimation of $\triangle\xi_{jt}$ still requires continuous dependent variables in contraction mapping (Berry et al. 1995). However, our sales rank data are discrete. Next, our sales rank data do not allow us to estimate ξ_t. Although the sales rank data are informative of relative sales popularities across products within the same time window, they are not informative of their popularities across time windows. For instance, top-ranked product in each time period will have higher sales quantity compared to any other products within

2) We discuss this term further in the next paragraph.

the same period. However, sales rank data are not informative of relative popularities among the products across time. For a detailed discussion on this topic, please refer Kim (2019). Conditional on data and model parameters, we can express i's choice probability for j at t as,

$$p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi}) = \frac{exp\left([\,z_j\,;\,x_{jt}\,]' \cdot \beta_i - \mathrm{p}_{jt} \cdot \alpha_i + \xi_j\right)}{\sum_{k=1}^{J_t} exp([\,z_k\,;\,x_{kt}\,]' \cdot \beta_i - \mathrm{p}_{kt} \cdot \alpha_i + \xi_k)}. \tag{3}$$

Now, we must add the element of consideration set to the choice probability. Let α_{it} be a vector of consideration set membership of products for consumer i at t,

$$\boldsymbol{a}_{it} = \left\{a_{i1t}, \ldots, a_{ijt}, \ldots, a_{iJ_t t}\right\}, \tag{4}$$

where each element of $a_{ijt} \in \{0, 1\}$ is a binary variable that is equal to 1 if j enters i's consideration set at t, and 0 otherwise. The choice probability conditional on membership vector α_{it} is (e.g., Bruno et al. 2008),

$$p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi} | \boldsymbol{a}_{it}) = \frac{a_{ijt} \cdot exp\left([\,z_j\,;\,x_{jt}\,]' \cdot \beta_i - \mathrm{p}_{jt} \cdot \alpha_i + \xi_j\right)}{\sum_{k=1}^{J_t} a_{ikt} \cdot exp([\,z_k\,;\,x_{kt}\,]' \cdot \beta_i - \mathrm{p}_{kt} \cdot \alpha_i + \xi_k)}. \tag{5}$$

To compute the marginal choice probability, we need to sum Equation (5) across all possible vectors of $\boldsymbol{\alpha}_{it}$,

$$p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi}) = \textstyle\sum_{\boldsymbol{a}_{it}} p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi} | \boldsymbol{a}_{it}) \cdot \pi(\boldsymbol{a}_{it}). \tag{6}$$

Finally, we can compute j's sales once we integrate Equation (6) over the distribution of consumers characterized by the parameter set of $\Theta = \left\{b, \Sigma_b, \alpha, \sigma_\alpha^2\right\}$,

$$\begin{aligned} s_{jt} &= \int p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi}) \cdot f(\theta_i|\Theta) d\Theta \\ &= \int \textstyle\sum_{\boldsymbol{a}_{it}} p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi} | \boldsymbol{a}_{it}) \cdot \pi(\boldsymbol{a}_{it}) \cdot f(\theta_i|\Theta) \cdot d\Theta. \end{aligned} \tag{7}$$

For our empirical estimation, we implement an analog version of Equation (7) with a draw of I=*1,000* consumers from the joint distribution defined by Θ. We now present our estimation strategy and the result in the next section.

Ⅴ. Estimation and Result

Given the empirical similarity, we broadly adopt the estimation approach in Kim (2019) but with a major additional component: we incorporate consideration sets into the model and estimation. Accordingly, it requires additional steps in the estimation. In this section, we first discuss our approach for the consideration set, followed by a discussion on the main model estimation.

5.1 Consideration Set

To incorporate consideration sets in the choice model, we need to estimate the marginal distribution of the consideration set membership vector of $\pi(\boldsymbol{a}_{it})$ at t defined by Equation (4). However, since we do not have the data that are directly informative of the marginal browsing popularities, we approximate them from the view-list data. First, following the earlier research by Bruno et al. (2008) and Goeree (2008), we assume independence among the products in the consideration set formation. That is, we model that the probability of one product entering the consideration set is independent across products and time. More formally,

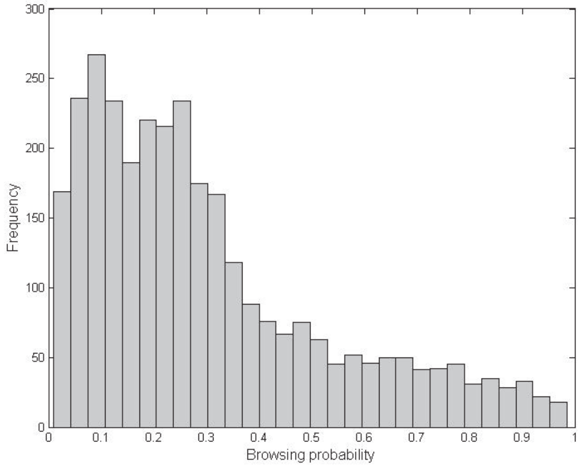
$$\pi(\boldsymbol{a}_{it}) = \pi(a_{i1t}, \dots, a_{ijt}, \dots, a_{iJ_t t}) = \prod_{k=1}^{J_t} \Pr(a_{ikt}) . \tag{8}$$

Note that the view-list data provide some degree of information about the dependencies among the products' browsing popularities. However, the view-list data do not quantify how frequently a product is browsed together with other products and without such information, it is not clear how we can transform the strength of relationship implied in the view-list data into a marginal one and preserve the dependencies among the products. Therefore, we take a pragmatic approach: we assume independence among the products and approximate the marginal browsing popularity of j by aggregating its appearance frequencies across view-lists of other products. Therefore, in our approach, we depend on the variance across the view-lists to quantify the browsing popularities across the products. Product j will be more popular during the browsing process if j appears more frequently on the view-lists of other products, $k \neq j$. For instance, if product j appears on the view-lists of N different products while k appears on the view-lists of M different products in which $N > M$, we interpret that j is more popular than k during consumers' browsing process. Accordingly, we assign a higher membership probability to j in the consideration sets. Formally, we approximate the marginal browsing probability for j, ν_{jt}, from the set of view-lists as,

$$\nu_{jt} = \Pr(a_{ijt} = 1 | \{VL_{kt}\}) = \frac{\sum_{k=1}^{J_t} I(j \in VL_{kt})}{J_t} , \tag{9}$$

where $k(=1, \dots, J_t, k \neq j)$ indexes product, VL_{kt} is the view-list of k at t, and $I(j \in VL_{kt})$ is an indicator variable that is equal to 1 if j appears on VL_{kt}. For instance, if j appears on the view-lists on 40 products at t and $J_t = 100$, we set $v_{jt} = 0.4$. This in turn means that j's inclusion probability to consideration sets is 40%. Figure 2 shows the histogram of marginal browsing probabilities across products and time, directly simulated

〈Figure 2〉 Histogram of browsing probabilities approximated from the view-list data across products and time



from Equation (9). Using our marginal distribution, we compute that an average product appears on 30% of other products' view-lists with a standard deviation of 23%. Therefore, an average product appears on other products' view-lists in a limited way with a large variance. We interpret this large variance as a sizable difference across browsing popularities of products. The histogram constructed at t will serve as a sampling distribution for heterogeneous consideration sets in our estimation, which we discuss in the next subsection.

5.2 Main Model Estimation

For the estimation of the main model, we closely follow the empirical approach in Kim (2019). The key difference is that we must introduce additional modeling component and impose consideration set in the model and estimation. To that end, we modify Equation (7) as,

$$\begin{aligned} s_{jt} &= \int \sum_{\boldsymbol{a}_{it}} p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi} | \boldsymbol{a}_{it}) \cdot \pi(\boldsymbol{a}_{it}) \cdot f(\theta_i | \Theta) d\Theta \\ &= \int \frac{1}{H} \sum_{\widehat{\boldsymbol{a}}_{it}} p_{ijt}(\mathbf{Z}, \mathbf{X}, \theta_i, \boldsymbol{\xi} | \widehat{\boldsymbol{a}}_{it}) \cdot f(\theta_i | \Theta) d\Theta \end{aligned}, \quad (10)$$

where $\Theta = \{b, \Sigma_b, \alpha, \sigma_\alpha^2\}$ is the set of model parameters.[3] $\hat{\boldsymbol{a}}_{it}$, a vector of ones and zeros, is a realization drawn independently from a multidimensional Bernoulli distribution of,

$$\hat{\boldsymbol{a}}_{it} \sim Bernoulli(\boldsymbol{v}_t, 1),$$

3) An alternative approach to implement the consideration set may be to use the estimated value of v_{jt} in Equation (5) similar to Bronnenberg et al. (1996). However, following the recent papers, we adopt the conditional probability approach in model estimation.

where $\boldsymbol{v}_t = (v_{1t}, \ldots, v_{jt}, \ldots, v_{J_t t})$. Each element of v_{jt} is defined in Equation (9), and H is the number of simulation draws for $\hat{\boldsymbol{a}}_{it}$. Figure 3 shows the histogram of the set sizes simulated across consumers with $J=64$ at $t=1$. At $t=1$, the average set size is 11, with a standard deviation of 2.93. Therefore, the use and approximation of the product browsing popularity from the view-list data allow us to impose product-specific restrictions on the consideration sets in our estimation. With every realized value of $\hat{\boldsymbol{a}}_{it}$, we can compute the logit choice probability for a consumer.

The rest of the estimation approach is a typical one in choice-based aggregate demand models (e.g., Berry et al. 1995). That is, we locate a set of parameters that minimizes the gap between the predicted and actual sales ranks. The detailed estimation steps in which we use the sales rank data as dependent variables are similar to Kim (2019). Therefore, in this subsection we just provide the core idea behind the estimation approach. First, note that we can predict the market share of product j from Equation (10) as,

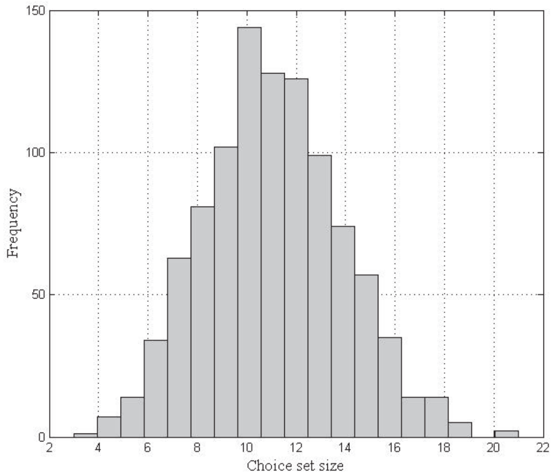
$$\hat{S}_{jt}(\boldsymbol{Z}, X; \Theta, \xi).$$

Assume j's sales rank is smaller than that of k at t in the data,[4]

$$r_j < r_k .$$

From the proposed model, we can predict the share difference between j and k as,

〈Figure 3〉 Histogram of the consideration set sizes from simulations at $t=1$ with $I=1,000$ consumers



4) In other words, product j sold more than k at t.

$$\hat{S}_{jt}(\boldsymbol{Z}, X; \Theta, \xi) - \hat{S}_{kt}(\boldsymbol{Z}, X; \Theta, \xi). \quad (11)$$

Under some regulatory conditions, we can express the probability of observing the sales rank inequality of $r_j < r_k$ in the data as,

$$\Phi\left(\frac{\hat{S}_{jt}(\mathbf{Z},\mathbf{X};\Theta,\boldsymbol{\xi}) - \hat{S}_{kt}(\mathbf{Z},\mathbf{X};\Theta,\boldsymbol{\xi})}{\sigma_\epsilon}\right),$$

where Φ is CDF of standard normal distribution, and σ_ϵ represents the accuracy of the sales rank relationship between j and k. Note that, as the share difference in Equation (10) increases, our chance to match the observed inequality of $r_j < r_k$ also increases. Our likelihood function for MLE is,

$$L = \prod_{t=1}^{T}\prod_{j=1}^{J_t}\prod_{k \neq j}^{J_t}\Phi\left(\frac{\hat{s}_{jt}(\mathbf{Z},\mathbf{X};\Theta,\boldsymbol{\xi}) - \hat{s}_{kt}(\mathbf{Z},\mathbf{X};\Theta,\boldsymbol{\xi})}{\sigma_\epsilon}\right).$$

We maximize the above likelihood function during the estimation.

5.3 Estimation Result

Table 2 shows the model parameter estimates. Among the estimated model parameters, the

〈Table 2〉 Estimated model parameters. For model parsimony, all brands share one heterogeneity parameter and all media formats also share another heterogeneity parameter

Variable	Mean (s.e.)	Heterogeneity (s.e.)
Panasonic	-2.04 (0.05)	0.45(0.09)
Canon	-3.44(0.08)	0.45(0.09)
JVC	-5.44(0.13)	0.45(0.09)
Samsung	-3.16(0.09)	0.45(0.09)
DVD	-0.20(0.01)	0.18(0.05)
Flash Memory	4.96(0.10)	0.18(0.05)
Hard Drive	0.13(0.01)	0.18(0.05)
Compact	-4.16(0.42)	0.67(0.55)
Hi-def	1.83 (0.32)	2.87(0.38)
Zoom	0.17(0.004)	0.00(0.001)
Pixel (in MM)	1.56(0.03)	0.12(0.02)
Xi	0.75(0.02)	NA
log(Price in hundred)	-0.96(0.03)	0.02(0.03)
Average consumer rating	0.10(0.004)	0.14(0.01)
Number of reviews	-0.01(0.004)	0.02(0.001)
Out of stock	-2.17(0.07)	0.80(0.36)
Aggregation error	0.01(5e-5)	
Loglikelihood	-39,593	

mean coefficients of Sony among the brands, and of mini-DV among the storage types, are normalized to 0, respectively. Note that most of the estimated parameters make an intuitive sense. For instance, an average consumer prefers products with higher zoom and pixel numbers among the continuous product characteristics. In addition, consumers prefer high values for the unobservable product characteristic. In the next section, we compute various price measures using the estimated parameters, and conduct a comparative study on market structure inference between the limited and full consideration set models.

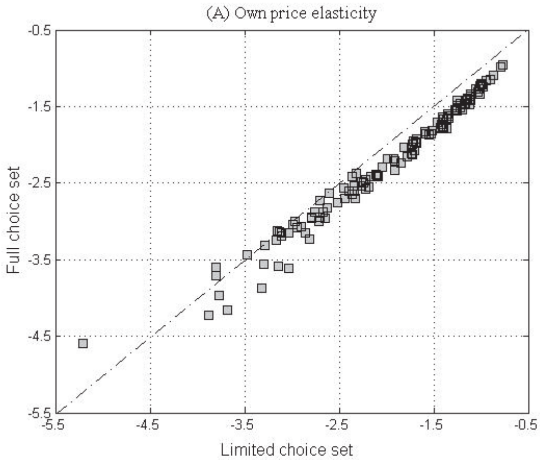
Ⅵ. Consideration Set and Market Structure

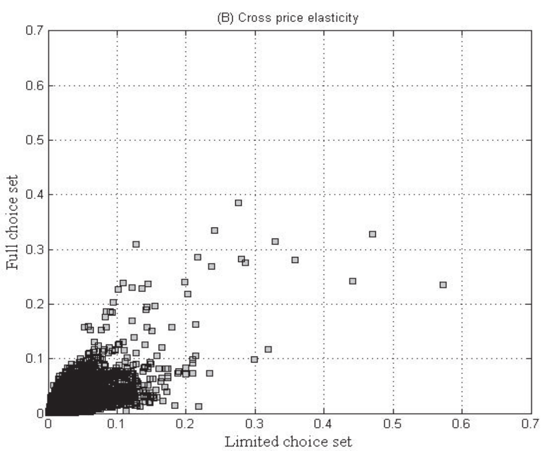
Our primary goal in this paper is to understand the implications of the consideration set on the market structure. Since the consideration set better reflects the consumer choice behaviors, we expect substantial differences on our inferences between limited and full consideration set models. To that end, we compute and use price elasticity measures from both models and draw inferences on the underlying market structure. As a first step, we separately estimate the full consideration set model. Then, we compute and compare the own-price elasticities of demand from both models.

Figure 4(A) shows own-price elasticities estimated from both models. In this figure, each point is a product, and the X-axis and Y-axis values are own-price elasticities computed from the limited and full consideration set models, respectively. From this figure, we note that the vast majority of points are scattered below 45-degree line, indicating that the demand is projected to be more elastic (larger absolute value) under the full consideration set model than the consideration set model. As a summary statistic, the average own-price elasticity computed from the full consideration set model is -2.2 (with a standard deviation of 0.81) while that from the consideration set model is -1.96 (with a standard deviation of 0.86). Therefore, the estimated own-price elasticities from the full consideration set model are biased downwards (larger absolute value) by more than 10% compared to the consideration set model. The intuition behind this bias is as follows. Under the full consideration set scenario, consumers can switch away to the full array of products in the market. With more alternatives, consumers are more likely to switch away to other products in the presence of the focal product's price increase. More switching consumers mean higher share loss and higher price elasticity for the focal alternative. On the other hand, consumers will have a smaller number of alternatives to switch to under the limited consideration set. Therefore, fewer consumers are likely to switch to other products, which means a smaller share loss and less elastic demand. In sum, the implication of a consideration set model aligns well with the notion of local consumer response and limited competition. Unless products enter consumers' consideration sets, they cannot effectively compete against other products. Less competition means less elastic demand.

Now we compare the cross-price elasticity measures between two models in Figure 4(B). In this figure, each point is a product, and the X-axis and Y-axis values are the cross-price elasticities from the limited and full consideration models, respectively. Unlike Figure 4(A), the patterns in this figure are mixed since some of the points are above 45-degree line while others are below 45-degree line. However, we can see that the estimated cross- price elasticities are quite different between these two models. This difference implies that the market structure inferred by both models may be quite different. To gain more insights on this matter, we adopt the clout and vulnerability chart by Kamakura and Russel (1984). Clout and vulnerability chart is a concise way to visualize the market structure using the cross-price elasticity measures: while clout measures a brand's impact on its competitors in the presence of its own price changes, vulnerability measures the impacts of other bands' price changes on the focal brand. In detail, high clout means that a product can steal away other brands' shares when it lowers its price while high vulnerability means that a focal brand will lose a higher fraction of its sales to other brands when they lower their prices. Figure 5 compares the clout and vulnerability

〈Figure 4〉 Scatter plots of price elasticities estimated from consideration set (X-axis) and full consideration set (Y-axis) models
Panel (A) shows own elasticities while panel (B) shows cross-price elasticities

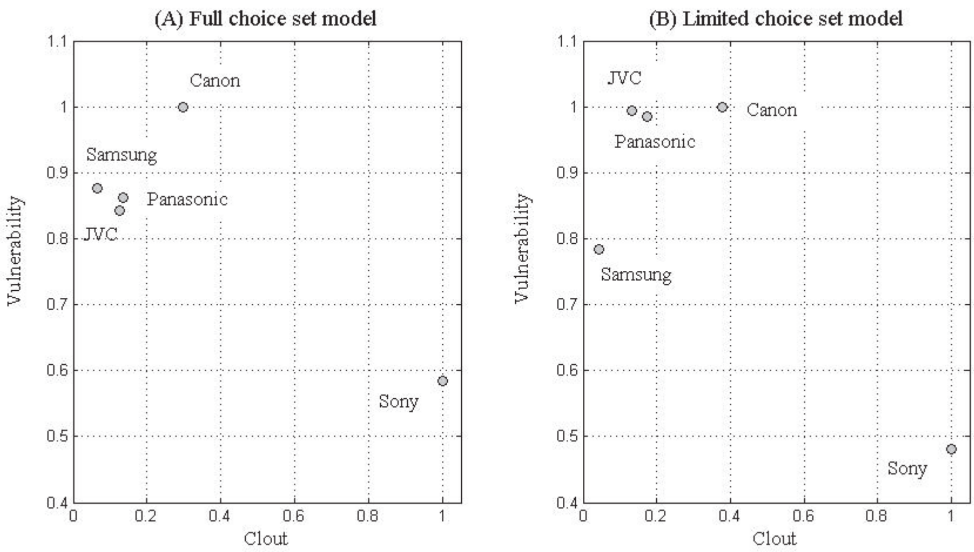




charts constructed using the cross-price elasticity measures from the full consideration set model (panel A) and the limited consideration set model (panel B). Note that in clout and vulnerability chart, only the relative positions matter in understanding the competitive landscape. There are a few similarities and differences in the charts between the two models. Common to both charts is that Sony is well positioned in the competitive landscape: it has the highest clout and the lowest vulnerability among the brands. Another similarity is that the rest of the products are all positioned relatively close to each other, implying similar levels of brands' power. That is, besides Sony, the rest of the brands exhibit comparable levels of clout and vulnerability. Among them, we project Samsung to have the least level of clout, which is consistent with the intuition that consumers highly valued Japanese brands during our data collection period.

There are some key differences between these two charts. First, Sony's vulnerability may be over-estimated with the full choice model. Besides, although the rest of the brands are positioned all relatively close among themselves in both charts, they are more closely clustered in the full consideration set model. That is, the full consideration model predicts that all brands except Sony will have very similar levels of clout and vulnerability. In contrast, the limited consideration model still distinguishes these

〈Figure 5〉 Clout and vulnerability charts implied by the full consideration set (panel A) and consideration set (panel B) models. Note that all the values are normalized for comparison purposes within charts (A) and (B)



manufacturers in the chart. As an example, the limited consideration set model projects Samsung to be less vulnerable compared to other brands. This difference may be due to the observation that Samsung is the least known and least expensive brand at the time of our data collection period. Therefore, Samsung is likely to attract price-sensitive consumers, and they would not consider other expensive products in the presence of a marginal price decrease from the expensive brands. Our consideration set model is likely to reflect such a scenario. Second, while the relative levels of clout among the five manufacturers are overall similar between the two models, their vulnerability levels exhibit different patterns between the two models.[5] For instance, while Canon is predicted to be the most vulnerable brand in our full choice model, Canon, JVC and Panasonic all show similar levels of vulnerability in consideration set model. Therefore, the key difference in market structure between these two models comes mainly from vulnerability and less from clout.

In summary, our consideration set model implies "local" competition among the manufacturers in the competitive landscape. This "local" or "limited" competition leads to two key differences between the two models. First, we find own-price elasticities are over-estimated under full consideration set model. Second, the limited consideration set implies a market structure that is more discriminating among the brands than the full consideration set model.

Ⅶ. Conclusion

In this paper, we develop and estimate a choice-based aggregate demand model with consideration sets. The incorporation of consideration sets is a significant departure from the past research in which consumers are assumed to choose from the universal set of products. Using aggregate-level browsing data as an additional data source, we first model and approximate the marginal distribution of products' browsing popularity and incorporate them into the choice model. We apply the proposed model to aggregate-level browsing and sales rank data at Amazon.com and estimate consumer demand. With the price elasticity measures computed from the model estimates, we investigate its implications on our understanding of market structure.

Compared to a model that assumes full consideration sets, our proposed model with a consideration set offers a different inference on the competitive landscape. First, we find that own-price elasticities are biased downwards (or a larger absolute value) under the full

5) We thank an anonymous reviewer for this interpretation and insight.

choice model than the consideration set model. Second, cross price elasticity measures are quite different between the two models. We find that the market structure inferred from the consideration set model better distinguishes the manufacturers in the competitive landscape. For instance, we find that Samsung, probably least known at the time of our data collection, is estimated to be less vulnerable under the proposed model than under a full choice set model. These findings are consistent with the intuition that a consideration set model aligns well with the notion of "local" competition. In contrast, the full consideration model forces universal competition among all the products.

One of the limitations of the proposed model is that we had to assume independence among the products in their consideration set membership. Although past research adopted the same assumption, it would be desirable to model the dependencies among the products in the consideration set. Such a model may better reflect the consumers' decision process and allow recovery of more realistic estimation of demand and substitutions among the products.

〈Received March 19. 2020〉
〈Accepted June 16. 2020〉

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