Modeling Emerging Market Firms' Competitive Retail Distribution Strategies

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Web Appendix A: The Role of Outliers in the Demand Estimation

Since we observe two outlier observations (in terms of marketing mix variables) in our data, we decided to estimate our demand model after dropping these two outliers. We report the estimation results along with our proposed demand model estimates (with outliers) in Table A.

Table A: Demand Estimates for the Models with and without Outliers

Parameters	Demand Model with the Two Outliers	Demand Model without the Two Outliers
$\alpha_{\text{Firm=1 \| Solid Product Form, Paan-plus Stores}}$	1.833842***	1.807700***
$\alpha_{\text{Firm=1 \| Solid Product Form, General Stores}}$	0.823844***	0.802631***
$\alpha_{\text{Firm=1 \| Liquid Product Form, Paan-plus Stores}}$	0.576659***	0.566237***
$\alpha_{\text{Firm=1 \| Liquid Product Form, General Stores}}$	0.189539***	0.173262***
$\alpha_{\text{Firm=2 \| Solid Product Form, Paan-plus Stores}}$	1.089343***	1.089735***
$\alpha_{\text{Firm=2 \| Solid Product Form, General Stores}}$	0.159499***	0.166078***
$\alpha_{\text{Firm=2 \| Liquid Product Form, Paan-plus Stores}}$	-0.957614***	-0.992854***
$\alpha_{\text{Firm=2 \| Liquid Product Form, General Stores}}$	-2.237279***	-2.221228***
β_{Price}	-0.040314***	-0.040079***
$\beta_{\text{Distribution}}$	0.003882***	0.003902***
$\beta_{\text{Price x Distribution}}$	-0.000011***	-0.000011***
θ_{Summer}	-0.102512***	-0.096157***
$\theta_{\text{Minimum Temperature}}$	0.013447***	0.013606***
$\theta_{\text{Maximum Temperature}}$	-0.038686***	-0.038679***
θ_{Rainfall}	-0.000119***	-0.000114***
$\varphi_{\text{Price Residual - Firm =1 \| Solid Product Form}}$	0.004382***	0.002590***
$\varphi_{\text{Price Residual - Firm =1 \| Liquid Product Form}}$	0.010102***	0.009889***
$\varphi_{\text{Price Residual - Firm =2 \| Solid Product Form}}$	0.006749***	0.007781***
$\varphi_{\text{Price Residual - Firm =2 \| Liquid Product Form}}$	0.018552***	0.018214***
$\varphi_{\text{Distribution Residual - Firm =1 \| Solid Product Form, Paan-plus Stores}}$	0.010637***	0.011222***
$\varphi_{\text{Distribution Residual - Firm =1 \| Solid Product Form, General Stores}}$	0.000504***	0.000873***
$\varphi_{\text{Distribution Residual - Firm =1 \| Liquid Product Form, Paan-plus Stores}}$	0.020717***	0.021857***
$\varphi_{\text{Distribution Residual - Firm =1 \| Liquid Product Form, General Stores}}$	0.006529***	0.006223***
$\varphi_{\text{Distribution Residual - Firm =2 \| Solid Product Form, Paan-plus Stores}}$	-0.000830***	-0.000959***
$\varphi_{\text{Distribution Residual - Firm =2 \| Solid Product Form, General Stores}}$	-0.000971***	-0.001109***
$\varphi_{\text{Distribution Residual - Firm =2 \| Liquid Product Form, Paan-plus Stores}}$	0.604806***	0.620739***
$\varphi_{\text{Distribution Residual - Firm =2 \| Liquid Product Form, General Stores}}$	0.058782***	0.059159***
$\sigma_{\text{Firm=1, Solid Product Form, Paan-plus Stores}}$	0.652113***	0.658274***
$\sigma_{\text{Firm=1, Solid Product Form, General Stores}}$	0.751764***	0.730913***
$\sigma_{\text{Firm=1, Liquid Product Form, Paan-plus Stores}}$	3.128853***	3.092251***
$\sigma_{\text{Firm=1, Liquid Product Form, General Stores}}$	0.220675**	0.246824***
$\sigma_{\text{Firm=2, Solid Product Form, Paan-plus Stores}}$	1.388355***	1.378974***
$\sigma_{\text{Firm=2, Solid Product Form, General Stores}}$	0.882325***	0.859093***
$\sigma_{\text{Firm=2, Liquid Product Form, Paan-plus Stores}}$	0.638612***	0.630437***
$\sigma_{\text{Firm=2, Liquid Product Form, General Stores}}$	0.159506***	0.028899***
σ_{Price}	0.010460**	0.010421***
$\sigma_{\text{Distribution}}$	0.000252***	0.000334***

$\lambda_{\text{Solid Product Form}\mid\text{Paan-plus Stores}}$	1.018519***	1.057025***
$\lambda_{\text{Solid Product Form}\mid\text{General Stores}}$	3.132429***	3.074303***
$\lambda_{\text{Liquid Product Form}\mid\text{Paan-plus Stores}}$	2.609761***	2.612888***
$\lambda_{\text{Liquid Product Form}\mid\text{General Stores}}$	0.976303***	0.986200***
$\lambda_{\text{Paan-plus Stores}}$	1.547152***	1.531355***
$\lambda_{\text{General Stores}}$	1.140543***	1.146316***
Log-Likelihood	20,045.1M	20,044.2M
BIC	40,090.2M	40,088.4M

***significant at 1%|**significant at 5% level

As seen in Table A, the two demand models (with and without outliers) yield estimates that are very close in magnitude. Thus, we use the model with the outliers as our main model in the rest of our analysis.

Web Appendix B: Model Identification

Identification of Response Parameters (Stylized Example)

In this section, we discuss how observed variations in price and distribution variables can be used to identify the marketing mix response parameters (i.e., main price - β_P - and distribution - β_D - coefficients and coefficient of price-distribution interaction-β_{PxD}). We illustrate our empirical identification strategy with the following stylized example.

For simplicity, assume there are two products (i=1, 2) that are priced at p_1 and p_2 (that can take two values: high (H) – 2 and low (L) – 1), and distributed through d_1 and d_2 (that can take two values: high – 2 and low – 1) stores. Further, assume that the intrinsic preferences for the products are zero (i.e., intercepts of the deterministic indirect utilities are zero). In addition, assume that the marketing mix vector in the market place is defined as (p_1, p_2, d_1, d_2). Thus, possible marketing mix vectors can be one of the 16 combinations shown below.

Combination Number	Marketing Mix Combinations	Deterministic Utility for Product 1: V_1	Deterministic Utility for Product 2: V_2
1	L, L, L, L	$\beta_P + \beta_{PxD} + \beta_D$	$\beta_P + \beta_{PxD} + \beta_D$
2	L, L, L, H	$\beta_P + \beta_{PxD} + \beta_D$	$\beta_P + 2\beta_{PxD} + 2\beta_D$
3	L, L, H, L	$\beta_P + 2\beta_{PxD} + 2\beta_D$	$\beta_P + \beta_{PxD} + \beta_D$
4	L, L, H, H	$\beta_P + 2\beta_{PxD} + 2\beta_D$	$\beta_P + 2\beta_{PxD} + 2\beta_D$
5	L, H, L, L	$\beta_P + \beta_{PxD} + \beta_D$	$2\beta_P + 2\beta_{PxD} + \beta_D$
6	L, H, L, H	$\beta_P + \beta_{PxD} + \beta_D$	$2\beta_P + 4\beta_{PxD} + 2\beta_D$
7	L, H, H, L	$\beta_P + 2\beta_{PxD} + 2\beta_D$	$2\beta_P + 2\beta_{PxD} + \beta_D$
8	L, H, H, H	$\beta_P + 2\beta_{PxD} + 2\beta_D$	$2\beta_P + 4\beta_{PxD} + 2\beta_D$
9	H, L, L, L	$2\beta_P + 2\beta_{PxD} + \beta_D$	$\beta_P + \beta_{PxD} + \beta_D$
10	H, L, L, H	$2\beta_P + 2\beta_{PxD} + \beta_D$	$\beta_P + 2\beta_{PxD} + 2\beta_D$
11	H, L, H, L	$2\beta_P + 4\beta_{PxD} + 2\beta_D$	$\beta_P + \beta_{PxD} + \beta_D$
12	H, L, H, H	$2\beta_P + 4\beta_{PxD} + 2\beta_D$	$\beta_P + 2\beta_{PxD} + 2\beta_D$
13	H, H, L, L	$2\beta_P + 2\beta_{PxD} + \beta_D$	$2\beta_P + 2\beta_{PxD} + \beta_D$
14	H, H, L, H	$2\beta_P + 2\beta_{PxD} + \beta_D$	$2\beta_P + 4\beta_{PxD} + 2\beta_D$
15	H, H, H, L	$2\beta_P + 4\beta_{PxD} + 2\beta_D$	$2\beta_P + 2\beta_{PxD} + \beta_D$

16	H, H, H, H	$2\beta_P + 4\beta_{PxD} + 2\beta_D$	$2\beta_P + 4\beta_{PxD} + 2\beta_D$

First, comparing the market shares under combinations 1 and 3 helps one to understand $\beta_{PxD}+\beta_D$. Second, comparing the market shares under combinations 9 and 11 helps one to understand $2\beta_{PxD}+\beta_D$. The comparing the market share differences between 1 and 3, and 9 and 11 helps one to understand β_{PxD} (i.e., β_{PxD} can be identified). Once β_{PxD} is identified, by comparing combinations 1 and 3, one can identify β_D since β_{PxD} is already identified. Last, using any combination, one can identify β_P since both β_D and β_{PxD} are already identified. Thus, the identification of response parameters depends on observing variations in the marketing mix variables (among different periods) for a given product while the remaining alternatives have relatively small (to no) variations in their marketing mix variables during those periods. Comparison of market shares among the corresponding periods can be used to identify the response parameters.

Given the stylized nature of this example, we conduct a micro-simulation study to see whether we are able to identify our model parameters. We discuss this simulation study next.

Identification of Preference Parameters: A Micro-Simulation Study

To check that whether we can identify the customer preference parameters, we first simulate the choices of N=100,000 customers with heterogeneous preferences (in term of both the intrinsic preferences and marketing mix responses) for T=250 periods. Similar to our current setting, we allow customers to make their decisions sequentially (channel choice first, product form next, brand last). Once, we simulate the choices, we sum the choices up over customers to simulate the sales for each period t=1,2,…,T. We use that simulated sales data and estimate the assumed parameters back by maximizing the simulated likelihood with a set of R=1000 i.i.d. standard normal draws (for the random components of intercept, price and distribution coefficients) at the seed=1. Please see Table B for the results of this simulation study.

Table B: Micro-Simulation Showcasing the Identification of the Preference Parameters

Parameters	Assumed Values	Estimated Parameters	Standard Errors of the Estimated Parameters
$\alpha_{\text{Firm=1 \| Solid Product Form, Paan-plus Stores}}$	0.00000	-0.10417	0.04277
$\alpha_{\text{Firm=1 \| Solid Product Form, General Stores}}$	1.00000	1.00096	0.03127
$\alpha_{\text{Firm=1 \| Liquid Product Form, Paan-plus Stores}}$	2.00000	1.92809	0.03848
$\alpha_{\text{Firm=1 \| Liquid Product Form, General Stores}}$	1.00000	1.20431	0.03153
$\alpha_{\text{Firm=2 \| Solid Product Form, Paan-plus Stores}}$	1.00000	0.98306	0.02075
$\alpha_{\text{Firm=2 \| Solid Product Form, General Stores}}$	2.00000	2.12682	0.04007
$\alpha_{\text{Firm=2 \| Liquid Product Form, Paan-plus Stores}}$	1.00000	1.00753	0.02319
$\alpha_{\text{Firm=2 \| Liquid Product Form, General Stores}}$	2.00000	1.99681	0.02851
β_{Price}	-0.00500	-0.00552	0.00013
$\beta_{\text{Distribution}}$	0.00500	0.00494	0.00002
$\beta_{\text{Price x Distribution}}$	-0.00002	-0.00002	0.00000
$\sigma_{\text{Firm=1, Solid Product Form, Paan-plus Stores}}$	1.00000	1.00096	0.02573
$\sigma_{\text{Firm=1, Solid Product Form, General Stores}}$	2.00000	1.88610	0.01916
$\sigma_{\text{Firm=1, Liquid Product Form, Paan-plus Stores}}$	3.00000	3.06063	0.02905
$\sigma_{\text{Firm=1, Liquid Product Form, General Stores}}$	2.00000	2.11124	0.03904
$\sigma_{\text{Firm=2, Solid Product Form, Paan-plus Stores}}$	2.00000	2.09534	0.01308
$\sigma_{\text{Firm=2, Solid Product Form, General Stores}}$	3.00000	2.93104	0.03428
$\sigma_{\text{Firm=2, Liquid Product Form, Paan-plus Stores}}$	4.00000	4.19919	0.03415

$\sigma_{\text{Firm=2, Liquid Product Form, General Stores}}$	3.00000	3.12184	0.05321
σ_{Price}	0.00500	0.00493	0.00011
$\sigma_{\text{Distribution}}$	0.01000	0.01031	0.00013
$\lambda_{\text{Solid Product Form}\mid\text{Paan}-\text{plus Stores}}$	1.00000	0.93778	0.00828
$\lambda_{\text{Solid Product Form}\mid\text{General Stores}}$	1.00000	0.89971	0.00681
$\lambda_{\text{Liquid Product Form}\mid\text{Paan}-\text{plus Stores}}$	1.00000	0.95687	0.02127
$\lambda_{\text{Liquid Product Form}\mid\text{General Stores}}$	1.00000	0.97908	0.02385
$\lambda_{\text{Paan}-\text{plus Stores}}$	1.00000	1.10009	0.01706
$\lambda_{\text{General Stores}}$	1.00000	1.05630	0.02518

As seen in Table B, we recover all preference parameters (intercepts, price, distribution and interaction coefficients, and the heterogeneity parameters) very closely to their assumed values.