

Predicting marketplace demand using Volumetric Conjoint Analysis

Nino Hardt
Ohio State University

Peter Kurz
bms marketing research + strategy
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Introduction

Demand predictions in packaged goods

Need to understand *primary* and *secondary* demand

Consumers demand *variety*; do not buy most goods

Consumers trade-offs between *quantity* and *quality*

CPGs need to rely on *choice experiments*, because new features are introduced, or sales data is too expensive or unavailable

Challenges of Marketplace Predictions

Market share predictions are generally well-understood (*secondary* demand)

However, real vs hypothetical choices create challenges

- **Few vs many choice alternatives** (this paper)
- Real vs hypothetical money (incentive-alignment), engagement
- Motivation to buy (goals, consumption occasion, ...)
- ...

Volume predictions (including *primary* demand) create additional challenges, because primary depends on assortment size or variety

→ assortment size elasticity of demand

Demand Models and assortment size elasticity of demand

‘Market Share only’ and ‘quantity-then-choice’

Ignore primary demand, or Poisson/Multinomial

→ inelastic primary demand

‘Latent occasion’

Latent occasion (Dubé, 2004)

→ Containing acceptable choice alternatives

Quantity demand models with economic foundation (Dubé, 2019)

Deal with horizontal variety, corner solutions, any quantity of any alternative (e.g., Kim et al. (2002); Allenby et al. (2017); Bhat (2018))

→ Variety Seeking

Variation in choice-set size

Empirical research suggests mixed results on assortment elasticity (Boatwright and Nunes, 2001; Sloot et al., 2006; Borle et al., 2005).

Behavioral research is rich in theories on choice-set size variation (Meissner et al., 2019; Scheibehenne et al., 2010)

Choice set size often seen as a 'complexity' proxy (Dellaert et al., 2012)

However, no research investigates role of choice-set size in volumetric demand models

Model

The extant volumetric demand model

$$\text{Max } u(x, z) = \sum_{j=1}^N \frac{\psi_j}{\gamma} \ln(\gamma x_j + 1) + \psi_z \ln(z) \quad \text{s.t.} \quad \sum_{j=1}^N p_j x_j + z = E$$

where $\psi_j = \exp(a_j^T \beta + \varepsilon_j)$

- Diminishing marginal returns of inside and outside goods
- Rate of satiation of inside goods γ
- Multiplicative error term ε_j for each of the N inside goods
- $\psi_z = 1$ for identification

Kuhn-Tucker conditions

Use Lagrange approach:

$$\text{Max } L = u(x, z) + \lambda \left\{ E - \sum_{j=1}^N p_j x_j - z \right\}$$

Associating first-order conditions with observed demand yields:

$$u_j = p_j \cdot u_z \quad \text{if} \quad x_j > 0$$

$$u_j < p_j \cdot u_z \quad \text{if} \quad x_j = 0$$

where

$$u_j = \frac{\partial u(x, z)}{\partial x_j} = \frac{\exp(a_j \beta + \varepsilon_j)}{\gamma x_j + 1}$$

$$u_z = \frac{\partial u(x, z)}{\partial z} = \frac{\psi_z}{z} = \frac{1}{z}$$

Likelihood

Applying logarithms:

$$\begin{array}{lll} \varepsilon_j = g_j & \text{if} & x_j > 0 \\ \varepsilon_j < g_j & \text{if} & x_j = 0 \end{array}$$

where

$$g_j = -a_j\beta + \ln(p_j) + \ln(\gamma x_j + 1) - \ln(z)$$

Assuming standard Normal errors, the probability of observed demand where R goods are chosen out of N goods considered can be expressed as:

$$\Pr(x) = |J_R| \left\{ \prod_{i=1}^R \phi(g_i) \right\} \left\{ \prod_{j=R+1}^N \Phi(g_j) \right\}$$

Variation in choice-set size

Given variation in choice-set size, N_t is not a constant anymore

$$u(\mathbf{x}_t, z) = \sum_k^{N_t} \frac{\psi_{kt}}{\gamma} \ln(\gamma \mathbf{x}_{kt} + 1) + \psi_z \ln(z_t)$$

Variation in N_t means variation in choice context

Expected baseline marginal utility ψ_z changes if scale of error variance increases

Larger assortments can imply more uncertainty with respect to the outside good

However, $\psi_z = 1$ is fixed for identification ...

Proposed location adjustment

We adjust the location of *inside good baseline marginal utilities*, yielding consistent estimates of β across assortment sizes; adjustment is a function of N (similar to Akerberg and Rysman (2005))

We use a simple log specification

$$\psi_{kt}^* = \exp(\mathbf{a}_k\beta + \varepsilon - \ln(\delta N_t + 1))$$

where $\delta > 0$

This is equivalent to:

$$u(\mathbf{x}_t, z_t) = \sum_k \frac{\psi_{kt}}{\gamma} \ln(\gamma \mathbf{x}_{kt} + 1) + (\delta N_t + 1) \ln(z_t)$$

Ignoring the location shift would lead to a shift in inside good intercepts across different choice-set sizes

Proposed model

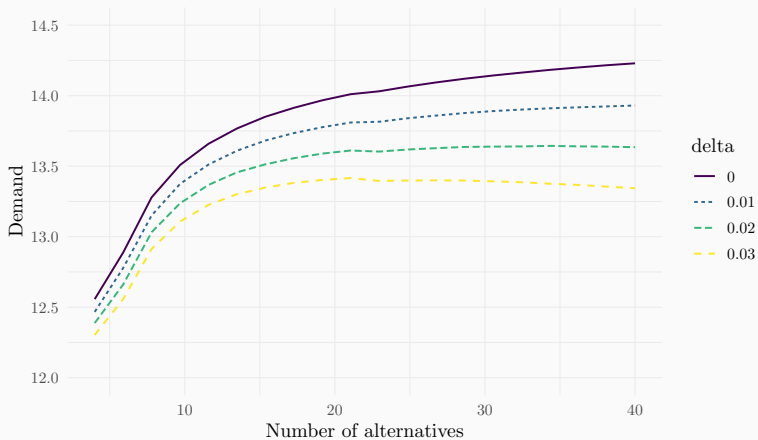
Now the marginal utility of the outside good is:

$$u_{zt} = \frac{\partial u(\mathbf{x}_t, z_t)}{\partial z_t} = \frac{\delta N_t + 1}{z_t}$$

The resulting likelihood function comprises mass and density contributions based on g_{kt} :

$$g_{kt} = -\mathbf{a}_{kt}\beta + \ln(\delta N_t + 1) + \ln(\mathbf{p}_{kt}) + \ln(\gamma \mathbf{x}_{kt} + 1) - \ln(z_t)$$

Number of alternatives, δ , and primary demand (simulation)



Empirical Application

Germans consume a lot of chocolate

The World's Biggest Chocolate Consumers

Pounds of chocolate consumed per capita each year



Source: Euromonitor

Forbes statista

Experimental Setup

Condition	Choice	Number of alternatives during		sample size
		first 8 tasks	second 8 tasks	
1	Volumetric	8	8	314
2	Volumetric	18	18	278
3	Volumetric	8	18	302

All respondents see 16 choice tasks

Choice task (8 alternatives)

Wenn Sie lediglich diese Auswahl an Schokoladentafeln hätten, welche Tafeln und wieviele davon würden Sie kaufen?

Bitte tragen Sie die Anzahl an Schokoladentafeln die Sie kaufen würden unterhalb des Produktes ein:

 Alpia Milchsokolade Nüsse - - 100 gr 0,70€ 	 Lindt Schwarze Schokolade - - 100 gr 1,12€ 	 Lindt Dunkle Schokolade - Früchte - 150 gr 2,49€ 	 Milka Milchsokolade - Keks 100 gr 0,99€
 Milka Milchsokolade - - Schokostücke 100 gr 0,99€ 	 Nestle Weisse Schokolade - - 100 gr 0,99€ 	 Ritter Sport Milchsokolade Nüsse - 100 gr 1,82€ 	 Sarotti Milchsokolade - Caramel 100 gr 1,14€

0 Total:

Wenn Sie bei diesem Angebot lieber keine Schokolade kaufen, dann tragen Sie einfach eine "0" in eines der Antwortfelder ein.



0% 100%

Choice task (18 alternatives)

Wenn Sie lediglich diese Auswahl an Schokoladentafeln hätten, welche Tafeln und wieviele davon würden Sie kaufen?

Bitte tragen Sie die Anzahl an Schokoladentafeln die Sie kaufen würden unterhalb des Produktes ein:

 Alpia Milchsokolade - Beeren Jogurth 100 gr 0,99€ 	 Feodora Milchsokolade - Kaffee 100 gr 1,82€ 	 Feodora Milchsokolade - Früchte - 100 gr 1,82€ 	 Feodora Milchsokolade - Nüsse - 100 gr 1,82€ 	 Lindt Dunkle Schokolade - Nüsse - 150 gr 3,32€ 	 Milka Milchsokolade - Beeren Jogurth 100 gr 0,85€
 Milka Milchsokolade - Caramel 100 gr 0,85€ 	 Milka Milchsokolade - spezielle Füllung 100 gr 0,85€ 	 Milka Milchsokolade - Schokostücke 100 gr 0,85€ 	 Ritter Sport Milchsokolade - Nüsse Trauben 100 gr 1,82€ 	 Ritter Sport Milchsokolade - - 100 gr 1,82€ 	 Ritter Sport Milchsokolade - - 100 gr 1,82€
 Sarotti Schwarze Schokolade - - 80 gr 1,12€ 	 Schogetten Milchsokolade - Milchcreme 100 gr 0,70€ 	 Schogetten Milchsokolade - Milchcreme 100 gr 0,70€ 	 Schogetten Milchsokolade - Nougat 100 gr 0,70€ 	 Schogetten Milchsokolade - schwarzweiss 100 gr 0,70€ 	 Trumpf Milchsokolade - Nüsse - 100 gr 1,59€

Attributes and Levels

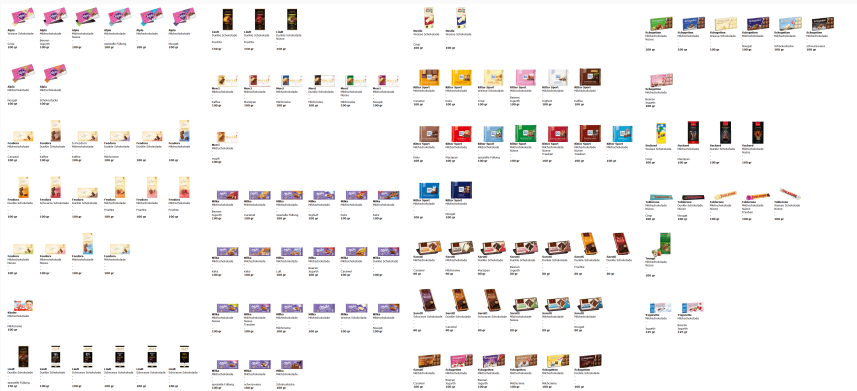
Attribute space based on existing features on market:

Attributes	Levels
Brand	Alpia, Feodora, Kinder, Lindt, Merci, Milka, Nestle, Ritter, Sarotti, Schogetten, Suchard, Tobler, Trumpf, Ferrero/Yogurette
Chocolate	Milk, Dark, Black, White
Nut	Nut, No Nut
Fruit	Fruit, Berry, Grape, No Fruit
Filling	None, Yogurt, Choc Chunk, Coffee, Cookie, Black and White, Crisp, Nougat, Caramel, Milk Ccreme, Special, Marzipan

Able to capture 80% of sales using this attribute space

Few SKUs are merged to keep attribute space manageable (e.g. 70% and 72% dark chocolate)

Common marketplace offering



100+ items can be mapped to attribute space

Many more alternatives than presented on typical choice experiment task

Empirical Application

Descriptive Analysis

Descriptive Statistics

Data	Units per task		Varieties per task		EUR spent		Maximum spent		Units where $\sum_i x_i > 0$	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
# Alternatives										
18	2.27	0.48	1.67	0.27	2.73	0.61	8.50	3.40	2.73	0.53
18 after 8	2.38	0.80	1.78	0.44	2.84	1.02	7.30	4.10	2.80	0.84
8	1.66	0.45	1.22	0.26	1.98	0.65	7.21	5.78	2.25	0.54
8 before 18	1.61	0.54	1.22	0.35	1.90	0.65	5.37	2.32	2.19	0.62

Primary demand is higher in 18 alternative condition

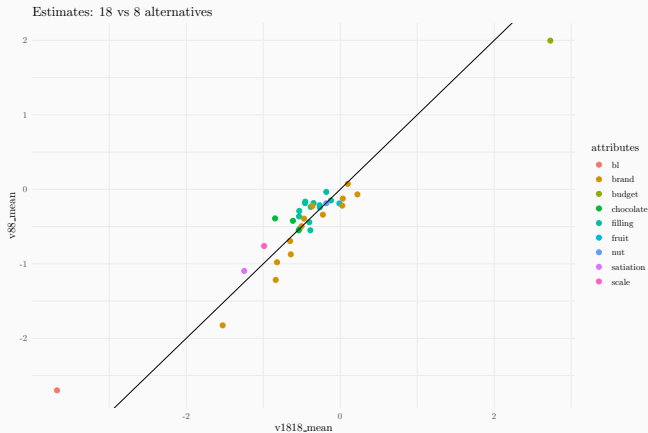
Demand for variety is higher, total expenditure is higher in 18 alternative condition

Empirical Application

Comparing 8 vs 18 alternatives

Estimates: Using 18 vs 8 alternatives

par	18		8	
	mean	sd	mean	sd
baseline	-3.68	0.12	-2.70	0.09
Brand				
Alpia	-0.65	0.07	-0.69	0.07
Feodora	-1.53	0.11	-1.83	0.11
FerreroYogu	0.03	0.13	-0.12	0.13
Kinder	0.22	0.14	-0.07	0.19
Lindt	0.03	0.12	-0.22	0.14
Merci	-0.36	0.09	-0.22	0.09
Nestle	-0.50	0.09	-0.49	0.11
Ritter	0.10	0.08	0.07	0.08
Sarotti	-0.82	0.10	-0.98	0.12
Schogetten	-0.47	0.08	-0.39	0.07
Suchard	-0.84	0.14	-1.22	0.19
Tobler	-0.23	0.10	-0.34	0.14
Trumpf	-0.64	0.12	-0.87	0.20
Chocolate				
black	-0.85	0.15	-0.39	0.11
dark	-0.61	0.11	-0.42	0.10
white	-0.54	0.09	-0.55	0.10
Fruit and Nut				
nut	-0.18	0.06	-0.19	0.07
berry	-0.27	0.08	-0.21	0.08
fruit	-0.53	0.12	-0.53	0.16
grape	-0.01	0.06	-0.19	0.07
Filling				
blackwhite	-0.40	0.09	-0.44	0.12
caramel	-0.46	0.08	-0.19	0.08
chocchunk	-0.35	0.08	-0.18	0.08
coffee	-0.54	0.08	-0.36	0.13
cookie	-0.27	0.07	-0.24	0.07
crisp	-0.39	0.09	-0.55	0.11
marzipan	-0.38	0.10	-0.24	0.12
milkcreme	-0.45	0.06	-0.16	0.07
nougat	-0.12	0.07	-0.15	0.08
special	-0.18	0.06	-0.03	0.08
yog	-0.53	0.07	-0.29	0.08
InE	2.73	0.10	2.00	0.06
Ing	-1.25	0.06	-1.10	0.06
Insig	-0.99	0.04	-0.76	0.04



Empirical Application

Applying the proposed model

Applying the proposed and competing models

Respondents were shown 8 tasks with 8 alternatives, then 8 tasks with 18 alternatives

We estimate a pooled model and then allow β_0 , γ , E to differ between the 8 and 18 alternative tasks, while 'part-worths' are assumed to be identical across the 8 and 18 alternative settings

Finally, we estimate the proposed model with location adjustment

Model fits

model	In-sample	Out of sample		
	LMD	mse	mae	rae
pooled	-11384.75	0.143	0.134	0.799
b	-11161.54	0.145	0.130	0.771
bg	-11205.18	0.147	0.131	0.777
bgE	-10954.32	0.147	0.131	0.777
proposed	-11164.97	0.140	0.129	0.770

In-sample fit favors more flexible models

Overall, out-of-sample fit is very similar

Estimates: Using 18 vs 8 alternatives

$\hat{\theta}$ posterior	pooled		b		bg		bgE		proposed	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
baseline	-3.16	0.12	-2.92	0.12	-2.92	0.13	-2.55	0.12	-2.55	0.15
baseline2			-3.22	0.11	-3.25	0.12	-3.46	0.13		
Brand (reference=Milka)										
Alpia	-0.65	0.11	-0.82	0.09	-0.80	0.11	-0.79	0.09	-0.70	0.10
Feodora	-2.22	0.19	-2.42	0.17	-2.45	0.20	-2.56	0.17	-2.07	0.21
FerreroYogu	-0.10	0.17	-0.04	0.16	-0.10	0.18	0.10	0.14	0.04	0.21
Kinder	0.32	0.16	0.23	0.17	0.52	0.18	0.72	0.19	0.25	0.16
Lindt	-0.24	0.17	-0.45	0.17	-0.37	0.22	-0.44	0.20	-0.24	0.19
Merci	-0.46	0.12	-0.56	0.14	-0.52	0.15	-0.48	0.13	-0.41	0.14
Nestle	-0.71	0.20	-0.46	0.13	-0.60	0.16	-0.43	0.20	-0.46	0.15
Ritter	-0.06	0.11	-0.08	0.11	-0.09	0.12	-0.06	0.12	-0.03	0.11
Sarotti	-1.24	0.15	-1.22	0.13	-1.32	0.13	-1.38	0.13	-1.13	0.13
Schogetten	-0.54	0.09	-0.59	0.09	-0.54	0.10	-0.57	0.10	-0.49	0.09
Suchard	-1.78	0.27	-1.26	0.23	-1.46	0.23	-1.52	0.21	-1.27	0.16
Tobler	-0.50	0.16	-0.50	0.16	-0.44	0.14	-0.47	0.15	-0.53	0.15
Trumpf	-0.67	0.16	-0.87	0.19	-0.83	0.23	-0.56	0.16	-0.82	0.23
Chocolate (reference=milk)										
black	-0.34	0.20	-0.23	0.19	-0.33	0.19	-0.09	0.16	-0.29	0.18
dark	-0.61	0.16	-0.67	0.15	-0.79	0.15	-0.73	0.15	-0.66	0.13
white	-0.80	0.14	-0.80	0.17	-0.83	0.13	-0.87	0.12	-0.78	0.12
Fruit and Nut										
nut	-0.12	0.09	-0.13	0.08	-0.19	0.09	-0.18	0.10	-0.14	0.08
berry	-0.36	0.13	-0.25	0.11	-0.32	0.12	-0.31	0.12	-0.30	0.11
fruit	-0.89	0.14	-0.77	0.14	-0.68	0.21	-0.73	0.20	-1.15	0.13
grape	-0.13	0.08	-0.08	0.08	-0.10	0.09	-0.07	0.09	-0.08	0.08
Filling										
blackwhite	-0.52	0.13	-0.55	0.15	-0.62	0.15	-0.53	0.11	-0.57	0.17
caramel	-0.29	0.10	-0.27	0.11	-0.29	0.12	-0.35	0.11	-0.33	0.11
chocchunk	-0.49	0.14	-0.48	0.10	-0.53	0.12	-0.42	0.15	-0.58	0.13
coffee	-0.51	0.11	-0.49	0.12	-0.54	0.14	-0.65	0.14	-0.61	0.14
cookie	-0.36	0.10	-0.40	0.11	-0.43	0.11	-0.51	0.13	-0.40	0.11
crisp	-0.30	0.12	-0.45	0.16	-0.40	0.10	-0.55	0.10	-0.42	0.12
marzipan	-0.41	0.13	-0.49	0.10	-0.47	0.12	-0.46	0.14	-0.43	0.13
milkcreme	-0.32	0.09	-0.34	0.10	-0.40	0.09	-0.43	0.10	-0.34	0.09
nougat	-0.04	0.10	-0.03	0.09	-0.08	0.09	-0.03	0.09	-0.06	0.09
special	-0.29	0.10	-0.29	0.10	-0.37	0.09	-0.39	0.11	-0.28	0.09
yog	-0.47	0.10	-0.55	0.11	-0.61	0.10	-0.64	0.10	-0.57	0.11
lnE	1.91	0.07	1.86	0.07	1.84	0.07	1.49	0.06	1.94	0.07
lnE2							1.90	0.08		
lng	-1.06	0.07	-1.04	0.07	-0.91	0.07	-1.11	0.09	-1.10	0.07
lng2					-1.05	0.07	-0.98	0.07		
lnsig	-0.62	0.04	-0.61	0.05	-0.57	0.04	-0.50	0.05	-0.67	0.04
lndelta									-3.62	0.27

- Estimates of part-worths are consistent across models
- Need for location adjustment visible from difference in β_0 estimates; location shift will be larger with larger differences in choice set size

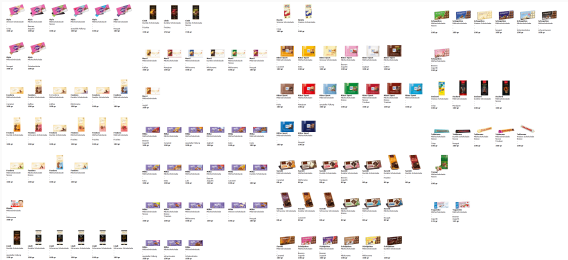
Empirical Application

Marketplace Predictions

Marketplace Prediction

Product offerings based on typical supermarket, >100 SKUs,
average prices

Predictions based on proposed and pooled models



Extrapolating marketplace demand in t – actual: 240,000

Annual primary demand prediction, assuming 25m households, 3 shopping trips/week:

model	mean	median	centile 5	centile 95	sd
b	411,453	411,095	393,778	430,124	11,184
bg	414,355	414,066	395,323	434,303	11,905
bgE	440,239	440,491	414,383	466,117	15,852
pooled	435,315	434,782	415,240	456,749	12,740
proposed	257,076	255,315	227,662	294,244	19,944
$\bar{x}$ - 18 alternatives	206,100				
$\bar{x}$ - 8 alternatives	150,300				
stated 'last purchase'	217,617				

Actual annual demand: 240,000t

Models without location adjustment overpredict demand

Primary demand depends on choice-set size

Brand-name level predictions – per trip

brand	demand quantity				demand share			
	only18	only8	pooled	proposed	only18	only8	pooled	proposed
Milka	2.323	1.839	1.483	0.805	0.267	0.289	0.307	0.282
Ritter	1.674	1.167	0.845	0.485	0.193	0.184	0.175	0.170
Lindt	1.106	0.615	0.553	0.372	0.127	0.097	0.114	0.130
Alpia	1.170	0.708	0.606	0.356	0.134	0.111	0.125	0.125
Schogetten	0.739	0.575	0.392	0.237	0.085	0.090	0.081	0.083
Tobler	0.406	0.354	0.269	0.169	0.047	0.056	0.056	0.059
Sarotti	0.364	0.273	0.169	0.119	0.042	0.043	0.035	0.042
FerreroYogu	0.240	0.230	0.132	0.078	0.028	0.036	0.027	0.028
Kinder	0.162	0.088	0.119	0.072	0.019	0.014	0.025	0.025
Merci	0.208	0.217	0.108	0.060	0.024	0.034	0.022	0.021
Nestle	0.115	0.113	0.077	0.045	0.013	0.018	0.016	0.016
Feodora	0.092	0.079	0.041	0.026	0.011	0.013	0.008	0.009
Suchard	0.055	0.051	0.019	0.017	0.006	0.008	0.004	0.006
Trumpf	0.045	0.047	0.025	0.014	0.005	0.007	0.005	0.005

Brand-name level sales prediction (actual: EUR 240m)

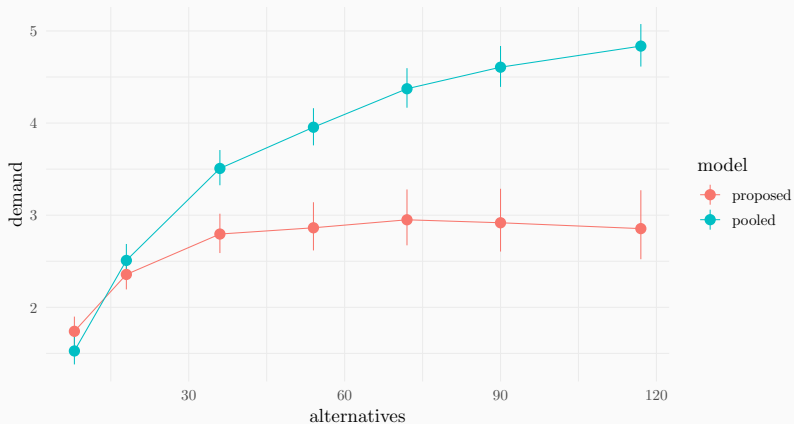


Domestic Sales of Ritter Sport: EUR 240m (actual)

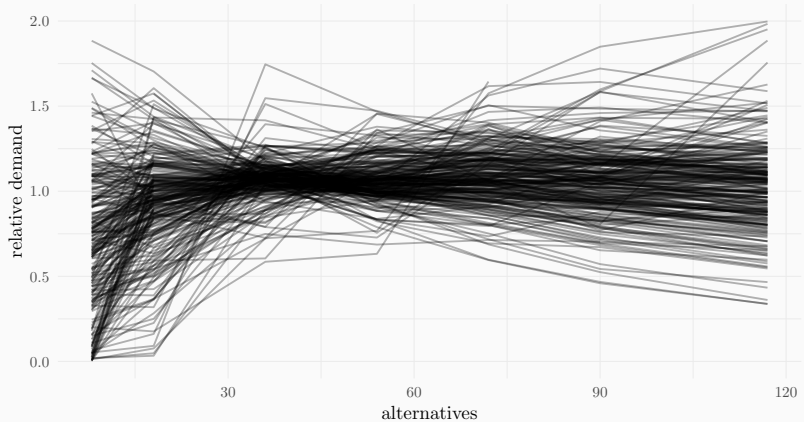
Prediction, assuming 50% sales margin, 25m households, 3 shopping trips/week:

model	mean	median	centile 5	centile 95	sd
b	352.89	351.62	295.51	416.79	37.52
bg	354.89	353.07	292.74	421.64	39.21
bgE	378.02	376.41	312.51	449.50	41.81
pooled	380.50	379.51	315.21	447.20	40.18
proposed	217.53	216.28	165.12	276.17	34.24

Comparing assortment elasticity of demand



Heterogeneity in assortment elasticity



Conclusion

Implications, Future Research, Limitations

Assortment size elasticity of demand matters

Proposed model can also be applied to purchase transaction data with dynamic assortment sizes

Screening rules

More variation in number of alternatives

Apply to sales data

Integer choices vs continuous quantities (not solvable in high dimension, since NP-hard)

Backup

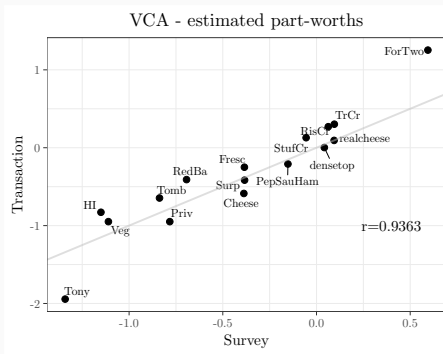
Secondary demand analysis works

Despite challenges, secondary demand analysis works well

For instance, in packaged goods, people know what they like

Recap from volumetric demand study on frozen Pizza purchases

- Relative preferences are identical between Conjoint and Transaction data
- Choice experiments are capable of predicting market *shares*



Transforming from random-utility error (ε) to the likelihood of the observed data (x), we need to consider the Jacobian $|J_{R_t}|$:

$$|J_{R_t}| = \prod_{i=1}^{R_t} \left(\frac{\gamma}{\gamma x_{i,t} + 1} \right) \left\{ \sum_{i=1}^{R_t} \frac{\gamma x_{i,t} + 1}{\gamma} \cdot \frac{p_i}{z_t} + 1 \right\}$$

Priors & Estimation

$\theta_h = \{\beta_h, \ln \gamma_h, \ln E_h, \ln \sigma_h, \ln \delta_h\}$ is respondent h 's vector of parameters of length M governing the individual-level demand model.

We assume:

$$\theta_h \sim \text{Normal}(\bar{\theta}, \Sigma)$$

Hyperparameters:

$$\bar{\theta} \sim \text{Normal}(0, 100I_M)$$

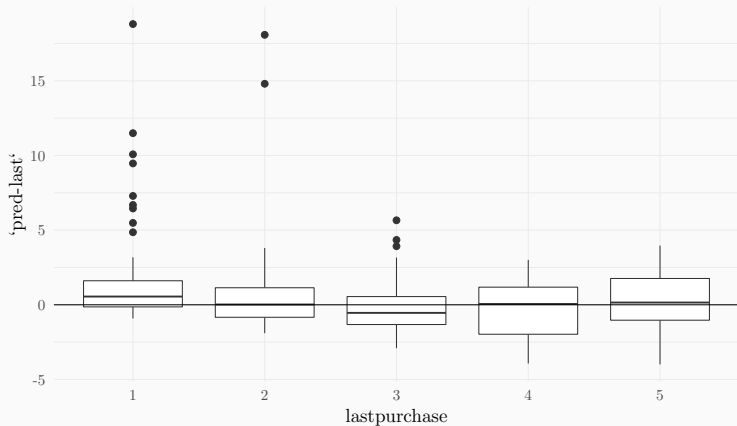
$$\Sigma \sim \text{IW}(M + 4, (M + 4)I_M)$$

Estimation of this model is easy using standard Monte Carlo Markov Chain methods, including the Metropolis-Hastings algorithm

Hold-Out fit statistics

$$\begin{aligned}\text{MSE}(\mathbf{x}, \hat{\mathbf{x}}) &= \frac{\sum_{i=1}^n (\hat{\mathbf{x}}_i - \mathbf{x}_i)^2}{n} \\ \text{MAE}(\mathbf{x}, \hat{\mathbf{x}}) &= \frac{\sum_{i=1}^n |\hat{\mathbf{x}}_i - \mathbf{x}_i|}{n} \\ \text{RAE}(\mathbf{x}, \hat{\mathbf{x}}) &= \frac{\sum_{i=1}^n |\hat{\mathbf{x}}_i - \mathbf{x}_i|}{\sum_{i=1}^n |\bar{\mathbf{x}} - \mathbf{x}_i|}\end{aligned}$$

Individual-level primary demand predictions



Chocolate bars in Germany

Common packaged good

Variety

We do not expect choice anomalies: easy tasks, familiar brands and features

I like chocolate

Median response times

Respondents are quick to adjust to changing choice-set size

