Chapter 14 Alternative-Specific Multinomial Logit Models

14.1 Introduction: Why Alternative-Specific MNL?

In the last chapter, we modeled brand choice using standard multinomial logit (MNL) models, where all predictors were **case-specific**. That is, they described the consumer or choice situation and took the same value for all brands in a given choice set.

In many real marketing applications, however, the most important predictors vary **by brand**. Examples include:

- Price of each brand
- Package size
- Sugar content or nutritional attributes
- Promotional indicators
- Brand-specific features

Alternative-specific multinomial logit (AS-MNL) models allow us to include these variables directly, providing richer managerial insight into how brand attributes drive choice.

In this chapter, you will learn how to:

- Work with long-format choice data
- Split alternative-specific data correctly into training and test samples
- Estimate an alternative-specific MNL model
- Evaluate model fit and classification performance
- Interpret predicted probabilities and marginal effects in a marketing context

Throughout the chapter, we will use the **yogurt** dataset.

14.2 The Yogurt Choice Data

The yogurt dataset records consumer brand choices in repeated choice situations. Each row represents **one alternative within one choice situation**, not a single consumer.

Key implications:

- Each choice situation appears multiple times (once per brand)
- Exactly one alternative is chosen per choice set
- Many predictors vary across brands within the same choice set

This "long" structure is required for alternative-specific MNL models and differs from the wide-format data used earlier in the course.

14.3 Preparing the Data for Modeling

14.3.1 Why Splitting Is Different for Choice Data

With alternative-specific data, we **cannot** randomly split rows into training and test sets. Doing so would break apart choice sets and contaminate model evaluation.

Instead, we must split at the **choice-set level**, ensuring that all rows belonging to the same choice situation stay together.

14.3.2 Creating Training and Test Samples

We still use the `splitsample()` function from the `MKT4320BGSU` package, which supports group-level splitting. Whereas before we didn't use several parameters, will will use them for alternative specific MNL.

Usage:

- `splitsample(data, outcome = NULL, group = NULL, choice = NULL, alt = NULL, p = 0.75, seed = 4320)`
- where:

- `data` is the data frame to split, in long-format.
- `outcome` is NOT (USUALLY) USED FOR ALTERNATIVE SPECIFIC MNL
- `group` is the grouping variable (e.g., choice situation id or respondent id). If provided, splitting is done at the group level. Required for alternative specific MNL.
- `choice` is the 0/1 (or TRUE/FALSE) indicator for the chosen alternative. Used only when `group` is provided. Required for alternative specific MNL.
- `alt` is the optional alternative label/ID. Used with `choice` to stratify at the group level. Required for alternative specific MNL.
- `p` is the proportion of observations to place in the training set. Must be strictly between 0 and 1. Default is 0.75.
- `seed` is the random seed for reproducibility. Default is 4320.

Before, we were interested in the `$train` and `$test` data frames. Now, we are interested in the `train.mdata` and `test.mdata` objects that are saved. They are in the format needed for the using `mlogit` (see below). However, to avoid a console error, you'll access the a slightly different way.

```
sp <- splitsample(data = yogurt, group = "id", choice = "choice", alt = "brand")


train <- sp[["train.mdata"]]
test  <- sp[["test.mdata"]]
```

At this point:

- `train` contains complete choice sets for model estimation
- `test` contains unseen choice sets for out-of-sample evaluation

---

14.4 Specifying an Alternative-Specific MNL Model

In an alternative-specific MNL model:

- Case-specific variables enter once
- Alternative-specific variables enter as brand-varying predictors

We use the `mlogit` function from the `mlogit` package to estimate the model. We separate the alternative specific from the case specific variables with a `|`. Alternative specific come first, then the case specific. We can use the base R `summary()` function to get the raw log-odds estimates.

```r
library(mlogit)
as_mnl_fit <- mlogit(choice ~ price + feat | income, data = train)
summary(as_mnl_fit)
```

```

Call:
mlogit(formula = choice ~ price + feat | income, data = train,
    method = "nr")

Frequencies of alternatives:choice
  Dannon   Hiland   Weight  Yoplait
0.401988 0.029818 0.229155 0.339039

nr method
8 iterations, 0h:0m:0s
g'(-H)^-1g = 0.000171
successive function values within tolerance limits

Coefficients :
                      Estimate Std. Error  z-value  Pr(>|z|)
(Intercept):Hiland   0.7587200  0.5677111   1.3365  0.181401
(Intercept):Weight  -0.0263906  0.2078931  -0.1269  0.898986
(Intercept):Yoplait -3.9886941  0.2679762 -14.8845 < 2.2e-16 ***
price               -0.4424450  0.0295572 -14.9691 < 2.2e-16 ***
feat                 0.4230830  0.1491240   2.8371  0.004552 **
income:Hiland       -0.1081164  0.0149201  -7.2464 4.281e-13 ***
income:Weight       -0.0114764  0.0037707  -3.0436  0.002338 **
income:Yoplait       0.0729207  0.0040281  18.1030 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -1618.4
McFadden R^2:  0.23972
Likelihood ratio test : chisq = 1020.6 (p.value = < 2.22e-16)
```

Interpretation notes:

- Coefficients reflect changes in **relative utility**
- Signs and magnitudes should be interpreted in marketing terms

- Alternative-specific variables capture within-choice substitution effects

---

14.5 Evaluating Model Performance

14.5.1 Model Fit and Coefficients

We use the `eval_as_mnl()` function from the `MKT4320BGSU` package to obtain fit statistics, coefficients (both log-odds and odds ratio), and classification diagnostics.

Usage:

- `eval_as_mnl(model, digits = 4, ft = FALSE, newdata = NULL, label_model = "Model data", label_newdata = "New data", class_digits = 3)`
- where:
  - `model` is a fitted mlogit model.
  - `digits` is an integer; decimals to round coefficient and fit results (default 4).
  - `ft` is logical; if TRUE, return coefficient and classification tables as flextable objects (default FALSE).
  - `newdata` is an optional `dfidx` object (e.g., `test.mdata`) for an additional classification matrix. If NULL, only the training-data matrix is produced.
  - `label_model` is a character string label for the training-data classification matrix (default "Model data").
  - `label_newdata` is a character string label for the newdata classification matrix (default "New data").
  - `class_digits` is an integer; decimals to round classification results (default 3).

Key outputs include:

- Log-likelihood χ^2 test
- McFadden's pseudo R^2
- Odds ratios for interpretation
- Classification accuracy and diagnostics

```r
as_eval <- eval_as_mnl(as_mnl_fit, ft = TRUE, newdata = test)
as_eval$coef_table
```

LR chi2 (5) = 1020.5649; p < 0.0001					
McFadden's Pseudo R-square = 0.2397					
term	logodds	OR	std.error	statistic	p.value
(Intercept):Hiland	0.7587	2.1355	0.5677	1.3365	0.1814
(Intercept):Weight	-0.0264	0.9740	0.2079	-0.1269	0.8990
(Intercept):Yoplait	-3.9887	0.0185	0.2680	-14.8845	0.0000
price	-0.4424	0.6425	0.0296	-14.9691	0.0000
feat	0.4231	1.5267	0.1491	2.8371	0.0046
income:Hiland	-0.1081	0.8975	0.0149	-7.2464	0.0000
income:Weight	-0.0115	0.9886	0.0038	-3.0436	0.0023
income:Yoplait	0.0729	1.0756	0.0040	18.1030	0.0000

```
as_eval$classify_model
```

Classification Matrix - Model data					
Accuracy = 0.621					
PCC = 0.330					
	Reference				
Predicted	Dannon	Hiland	Weight	Yoplait	Total
Dannon	577	39	324	97	1037
Hiland	1	12	0	2	15
Weight	18	2	38	18	76
Yoplait	132	1	53	497	683
Total	728	54	415	614	1811
Statistics by Class:					
Sensitivity	0.793	0.222	0.092	0.809	
Specificity	0.575	0.998	0.973	0.845	
Precision	0.556	0.800	0.500	0.728	

```
as_eval$classify_newdata
```

Classification Matrix - New data					
Accuracy = 0.607					
PCC = 0.331					
	Reference				
Predicted	Dannon	Hiland	Weight	Yoplait	Total
Dannon	199	14	104	38	355
Hiland	2	2	1	1	6
Weight	8	1	12	13	34
Yoplait	33	0	21	152	206
Total	242	17	138	204	601
Statistics by Class:					
Sensitivity	0.822	0.118	0.087	0.745	
Specificity	0.565	0.993	0.952	0.864	
Precision	0.561	0.333	0.353	0.738	

14.5.2 Classification Performance

Classification is evaluated at the **choice-set level**:

- The predicted brand is the one with the highest predicted probability
- Accuracy reflects correct brand predictions
- PCC provides a baseline comparison

This approach mirrors how managers think about predicting actual consumer choices.

14.6 Predicted Probabilities and Marginal Effects

14.6.1 Why Predicted Probabilities Matter

Coefficients are not always intuitive. Predicted probabilities translate the model into outcomes managers care about:

- Market shares
- Brand switching
- Competitive responses

14.6.2 Why Marginal Effects Are Useful

Marginal effects quantify how much choice probabilities change in response to a small change in an attribute, holding everything else constant. Marginal effects can be computed in two common ways:

- **At observed values (Average Marginal Effects, AME)**
  Marginal effects are calculated for each observation using its actual attribute values and then averaged.
- **At means (Marginal Effects at the Mean, MEM)**
  Marginal effects are calculated at a single "average" profile, where each attribute is set to its sample mean.

Both approaches summarize how sensitive choice probabilities are to changes in attributes, but they differ in interpretation.

Marginal effects **at observed values**:

- Reflect the full distribution of the data
- Avoid relying on a potentially unrealistic "average consumer"
- Are often preferred for descriptive and policy interpretation

Marginal effects **at means**:

- Are easier to reproduce by hand or with software defaults
- Provide a clear, single reference point
- Can be useful for illustrating model mechanics and comparing effects across variables

The marginal effects tables can therefore answer questions such as:

- "On average, how does a $1 increase in price affect brand choice?"
- "How would choice probabilities change for a typical consumer if an attribute increased slightly?"
- "Which brands are most sensitive to changes in a specific attribute?"

In practice, the choice between observed values and means depends on the goal of the analysis. For interpretation and real-world impact, average marginal effects at observed values are often preferred. For teaching, demonstration, or simplified comparisons, marginal effects at means can be equally informative.

14.6.3 The `pp_as_mnl()` Function

For both case-specific and alternative-specific predictors, we use the `pp_as_mnl()` function from the `MKT4320BGSU` package to get both predicted probabilities and marginal effects.

Usage:

- `pp_as_mnl(model,focal_var, focal_type = c("auto", "alt", "case"), grid_n = 25, digits = 4, ft = FALSE, marginal = TRUE, me_method = c("observed", "means"), me_step = 1)`
- where:
    - `model` is a fitted mlogit model.
    - `focal_var` is a character string name of the focal variable.
    - `focal_type` is a character string; one of "case", "alt", or "auto" (default = "auto").
    - `grid_n` is an integer; number of points used to construct the grid of focal values for predicted probability plots when the focal variable is continuous (default = 25).
    - `digits` is an integer; rounding for numeric output (default = 4).
    - `ft` is logical; if TRUE, return tables as flextable objects (default = FALSE).
    - `marginal` is logical; if TRUE, compute marginal effects (default = TRUE).
    - `me_method` is a character string; one of "observed" AME or "means" (default = "observed").
    - `me_step` is numeric; finite-difference step size for AME (default = 1).

14.6.4 Case-Specific Predictors

We first examine how a consumer-level variable affects brand choice probabilities.

```
pp_income <- pp_as_mnl(as_mnl_fit, focal_var = "income", ft = TRUE, me_method="means")
pp_income$me_table
```

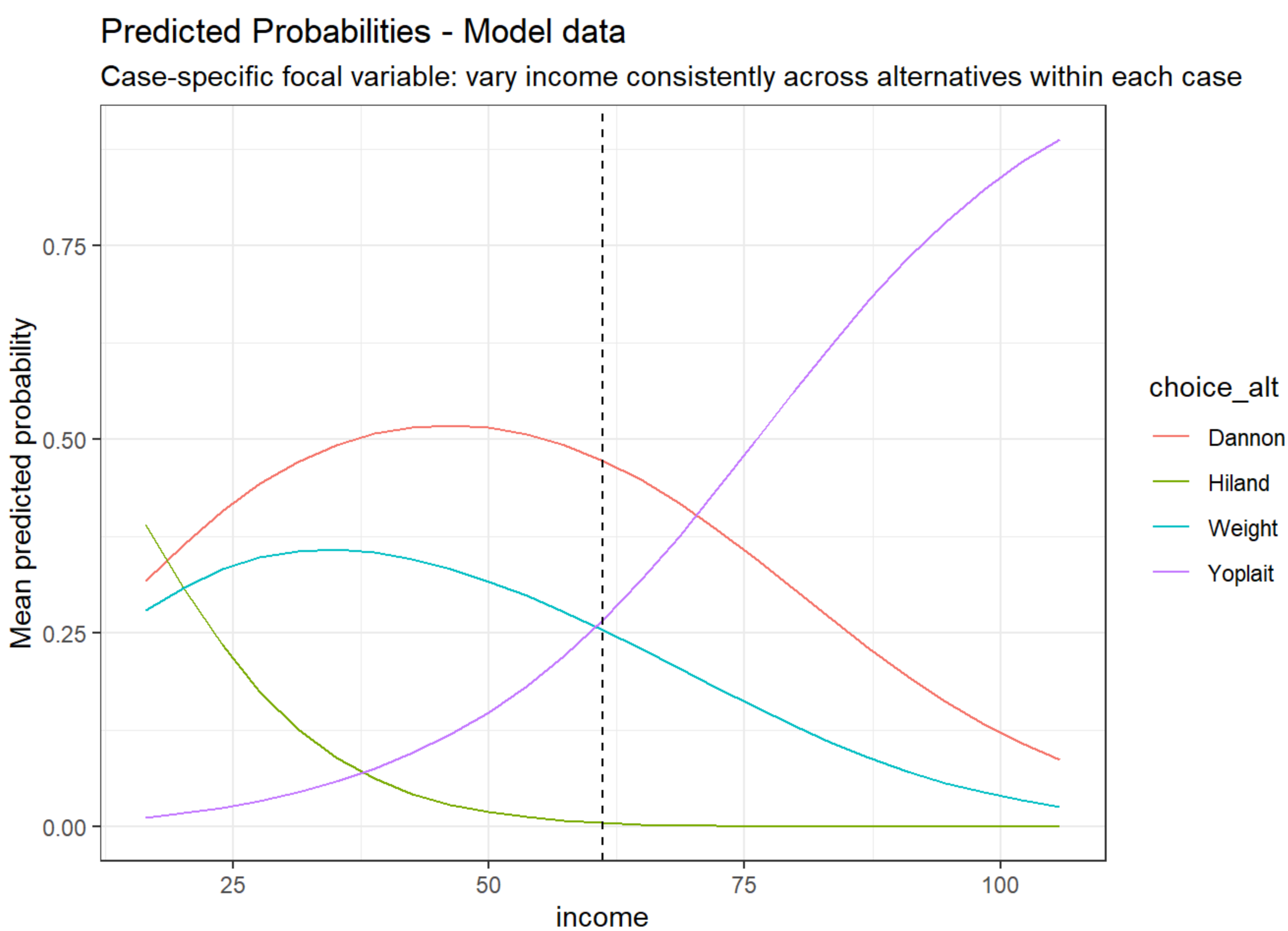
Marginal effects for ***income*** (at means)			
Dannon	Hiland	Weight	Yoplait
-0.0073	-0.0006	-0.0068	0.0147

```
pp_income$pp_table
```

Predicted Probability Table (income) - Model data				
focal_value	Dannon	Hiland	Weight	Yoplait
60.1438	0.4788	0.0060	0.2608	0.2544
61.1438	0.4729	0.0053	0.2545	0.2672
62.1438	0.4667	0.0047	0.2482	0.2804

Because ***income*** is continuous, the values shown include the mean and +/- 1 unit.

```
pp_income$pp_plot
```



14.6.5 Alternative-Specific Predictors

Now we examine a brand-specific variable such as price (a continuous variable) and feature (a categorical variable).

```
pp_price <- pp_as_mnl(as_mnl_fit, focal_var = "price", ft=TRUE, me_method="means")
pp_price$me_table
```

Marginal effects for ***price*** (at means)				
Alternative	Dannon	Hiland	Weight	Yoplait
Dannon	-0.1105	0.0010	0.0550	0.0545
Hiland	0.0010	-0.0021	0.0005	0.0005
Weight	0.0550	0.0005	-0.0845	0.0290
Yoplait	0.0545	0.0005	0.0290	-0.0840

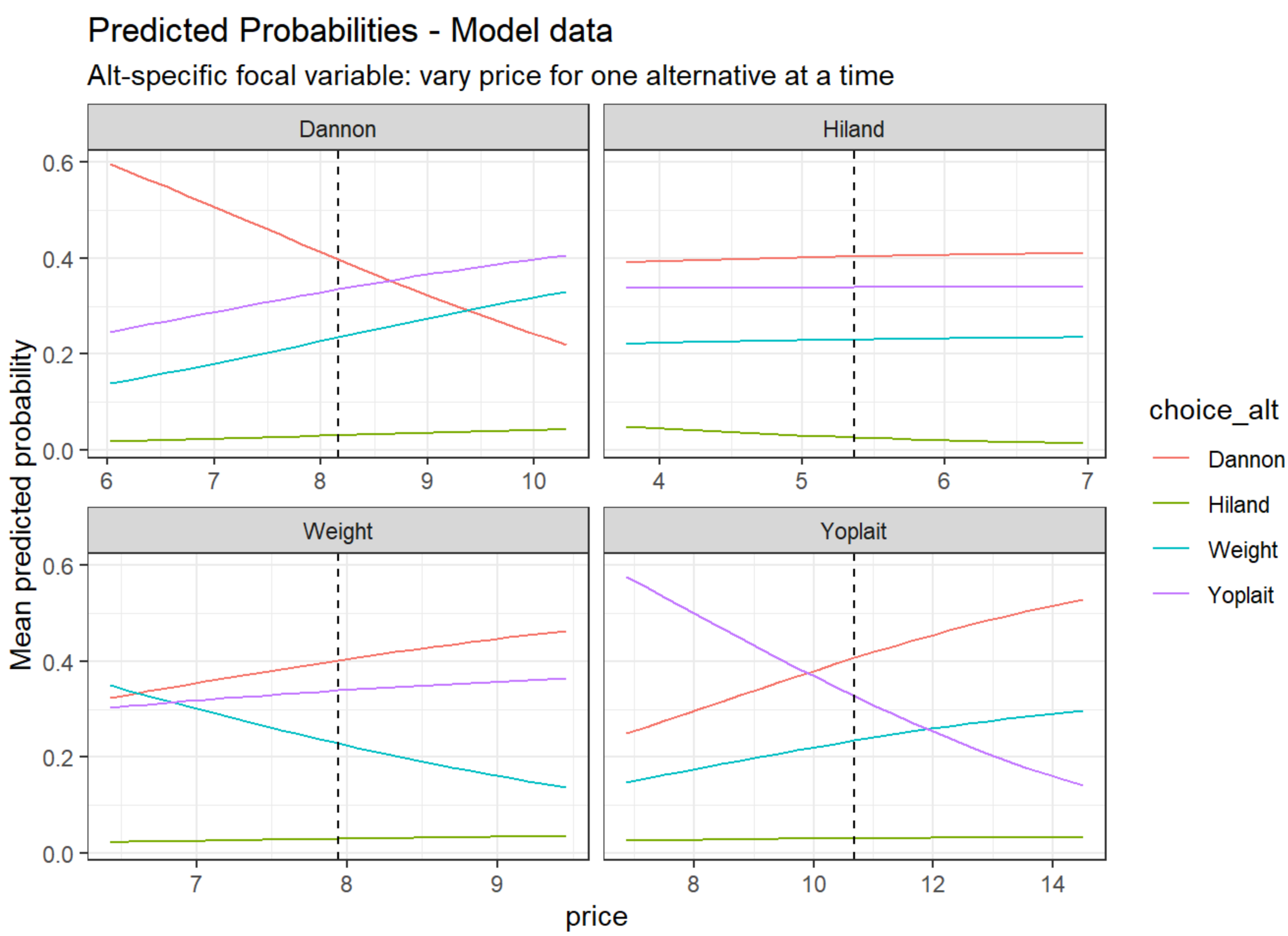
```
pp_price$pp_table
```

Predicted Probability Table (price) - Model data					
varied_alt	focal_value	Dannon	Hiland	Weight	Yoplait
Dannon	7.1628	0.4918	0.0250	0.1883	0.2949
Dannon	8.1628	0.3980	0.0313	0.2353	0.3355
Dannon	9.1628	0.3088	0.0375	0.2821	0.3716
Hiland	4.3663	0.3966	0.0394	0.2258	0.3382
Hiland	5.3663	0.4035	0.0268	0.2305	0.3392
Hiland	6.3663	0.4083	0.0179	0.2338	0.3399
Weight	6.9421	0.3516	0.0256	0.3060	0.3169
Weight	7.9421	0.4019	0.0301	0.2287	0.3392
Weight	8.9421	0.4446	0.0340	0.1648	0.3566
Yoplait	9.6874	0.3673	0.0302	0.2138	0.3886
Yoplait	10.6874	0.4069	0.0311	0.2350	0.3269
Yoplait	11.6874	0.4438	0.0318	0.2545	0.2699

Predicted Probability Table (price) - Model data					
varied_alt	focal_value	Dannon	Hiland	Weight	Yoplait

Because ***price*** is continuous, the values shown include the mean and +/- 1 unit.

```
pp_price$pp_plot
```




```
pp_feat <- pp_as_mnl(as_mnl_fit, focal_var = "feat", ft=TRUE, me_method="means")
pp_feat$me_table
```

Marginal effects for ***feat*** (at means)				
Alternative	Dannon	Hiland	Weight	Yoplait
Dannon	0.1057	-0.0010	-0.0526	-0.0521
Hiland	-0.0010	0.0020	-0.0005	-0.0005
Weight	-0.0526	-0.0005	0.0808	-0.0277

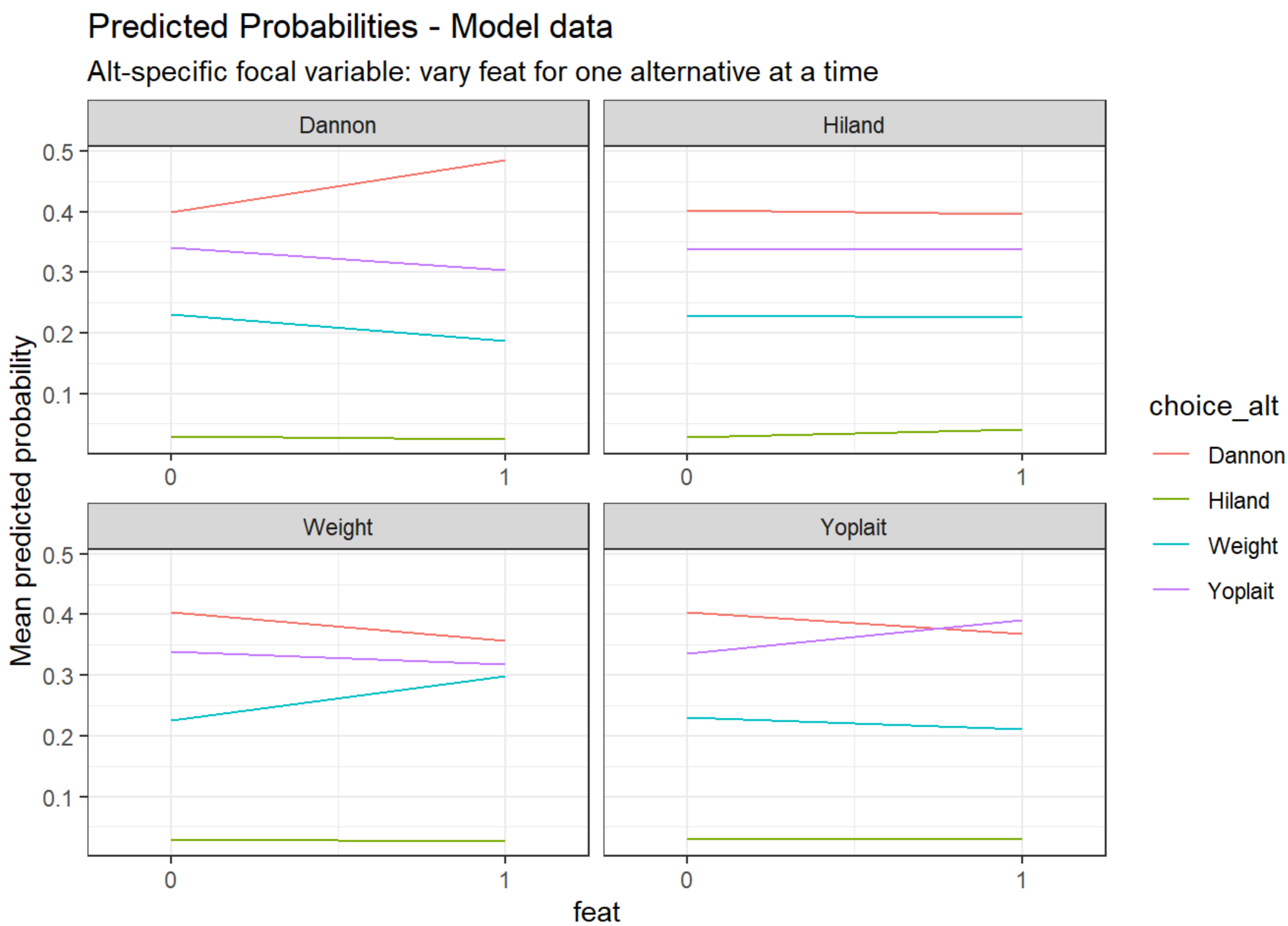
Marginal effects for ***feat*** (at means)				
Alternative	Dannon	Hiland	Weight	Yoplait
Yoplait	-0.0521	-0.0005	-0.0277	0.0804

```
pp_feat$pp_table
```

Predicted Probability Table (feat) - Model data					
varied_alt	focal_value	Dannon	Hiland	Weight	Yoplait
Dannon	0	0.3988	0.0301	0.2308	0.3403
Dannon	1	0.4853	0.0244	0.1870	0.3033
Hiland	0	0.4027	0.0285	0.2297	0.3391
Hiland	1	0.3960	0.0407	0.2251	0.3381
Weight	0	0.4038	0.0300	0.2264	0.3398
Weight	1	0.3565	0.0257	0.2990	0.3188
Yoplait	0	0.4043	0.0299	0.2306	0.3352
Yoplait	1	0.3681	0.0289	0.2112	0.3918

Because ***feat*** is binary, only the two observed values are shown.

```
pp_feat$pp_plot
```



14.7 Managerial Insights

Alternative-specific MNL models allow managers to:

- Evaluate pricing and promotion strategies
- Understand competitive substitution patterns
- Predict market share changes under different scenarios

Compared to standard MNL models, AS-MNL models provide more realistic insights when brand attributes vary within choice sets.