How Does Assortment Affect Grocery Store Choice?

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Web Appendix

Simulated Maximum Likelihood Details

We use simulated maximum likelihood estimation, or SMLE, to estimate the parameters given our assumptions about the errors (e.g., Hajivassiliou and Ruud 1994). SMLE employs a structured lower-triangular Cholesky matrix, *C*, by which relationships in the parameter covariance matrix, Σ, are estimated. The Cholesky matrix, *C*, is defined as $C^T C = \Sigma$ so it can be interpreted as the square root of the covariance matrix Σ. Because estimating the full Cholesky matrix is infeasible (there are (57x56)/2 = 1,596 elements in the matrix), we must restrict most off-diagonal elements of the matrix to be zero while still estimating relationships of interest.

We allow for the store intercepts to co-vary with one another ($(S\text{-}1)\times(S\text{-}2)/2$ terms) and to co-vary with the category intercepts from the category needs model ($(S\text{-}1)\times C$ terms). By allowing the store intercepts to co-vary with the category intercepts, we control for any correlation in the error terms between the equations. This result is straight-forward to see as the error terms can be written as having an unique component and a component which is correlated between the equations. This last component is not separately identified from correlation in preferences.

We also allow parameters of four predictor variables in the store choice model—store loyalty, distance, spending and assortment—to covary with one another (6 terms). Finally, we allow the feature advertising parameter in the category needs model, γ_1, to covary with the category intercepts, γ_0 (*C* terms). With S=4 and C=10, we are estimating a total of 36 heterogeneity terms in addition to the 57 main diagonal elements of the Cholesky matrix, which capture unique heterogeneity in the parameters. It is important to note that restricting elements of the lower-diagonal Cholesky matrix to be zero does not imply that the corresponding off-diagonal elements in the parameter covariance matrix, Σ, are zero.

Equation (2.18) implies that each household's likelihood is integrated separately and that the likelihood across households is the product of each household's integrated likelihood. We will therefore focus our discussion on the integration of a single household's likelihood function. The numerical integration is done as follows. Prior to beginning the optimization, a fixed number of draws (*ND*) is made for each household from *K* independent random variates where *K* is the dimension of Θ^0. This results in a $K \times ND$ matrix of random draws (*DRAWS*) for each household. Deviations from the mean vector Θ^0 with the distribution described by Σ is then created by multiplying the lower Cholesky Matrix by the matrix of draws; i.e., $DEVIATIONS = C \times DRAWS$, where the Cholesky matrix is populated by the terms described above.

The integral in equation (2.18) is computed by evaluating the household's likelihood function *ND* times using the mean vector plus the vector of deviations for that draw, then averaging the likelihood over the *ND* draws. Because of the high dimensionality of the integrals in equation (2.18), numerical integration using normal random variates can result in computational problems. For more computational efficiency, we make draws from a quasi-random sequence. Specifically we use 100 draws from a Halton sequence (e.g., Train 1999; Bhat 2001). Bhat argued that 100 draws from a Halton sequence is roughly equal to 1000-1500 draws from a random normal distribution.

The simultaneous estimation of the store choice and category needs models helps us in two ways. First, compared to a two-stage estimation where the category needs model is estimated first and the resulting values "plugged into" the store choice model in a second stage, the joint approach avoids the measurement error associated with the fitted planned purchase probabilities in the first stage. Hence, the standard errors for the estimates that we obtain are the true standard errors for the model parameters. Second, it allows us to specify a joint heterogeneity distribution over parameters across the category needs and store choice models, if we believe that is the true representation of heterogeneity in the marketplace. This represents an extension of previous research, which addressed these distributions separately.

Additional Details of Modeling Assortment

In this section, we provide additional detail about the modeling of assortment. First, we note that we estimated a very simple version of the model presented in the paper (which exploits only cross-sectional variation) to determine whether our findings are entirely dependent on within-household variation over time. They are not. Cross-sectional variation alone is sufficient to find significant effects of product assortment similar to those found in our more general model.

Single Variance Term for All Assortment Factors. We thank an anonymous reviewer for suggesting that parameters of the assortment measures not be deterministic. We therefore modeled the assortment measures as random effects using the parsimonious approach of Erdem (1996, p 365). An artifact of this approach, however, is that the random effects are perfectly correlated. We tested the validity of this approach by estimating a more general specification of heterogeneity with separate random effects for all measures of assortment (recall that the variance of one measure had to be set to one for identification). We also had to set the assortment parameter $_{5h}$ to unity and add covariance terms. The more general specification had a modestly higher likelihood but 14 more variance/covariance terms than the specification detailed in this section, and so was rejected on the basis of CAIC and BIC. We note, however, that this result was for only one dataset and so may not be a general result.

Normalizing Assortment Measures. In the paper, we normalize four of the five assortment measures by market averages (all except the *FavBrand* measure). The number of brands, SKUs/brand, sizes/brand and unique SKUs can only be interpreted in the context of a particular category. For example, is ten brands a large or small number? Clearly the answer depends upon the category. Ten brands is not very many for carbonated beverages but is above average for diapers. Because they are normalized, these assortment measures can be compared across categories. *FavBrand* is a proportion and is independent of the number of brands in the category. It simply captures the concentration of a household's preferences.. As such, it can be compared across the categories without being normalized.

Effects of Stockouts. We thank the Associate Editor for pointing out that stockouts could also cause variation in assortments over time. We contend that, while stockouts could substantially affect the assortment in a particular category in any given week, stockouts would have a limited impact on assortment expectations across categories. In terms of materiality, reported stockout rates are small compared to the range of brand, SKUs/brand and sizes/brand indices across retailers. Moreover, it is unclear how past stockouts would affect shoppers' expectations of category assortments for an upcoming shopping trip. It is quite possible that consumers would expect a product or brand to be available, even if it was out-of-stock on a previous visit. It is also important to note that stockouts cannot be measured using our syndicated data.

Rational Price Expectations

The assumption of rational price expectations requires (i) that shoppers know relative category prices in different stores and (ii) that relative category prices do not change much from week to week. BHT (1998 p. 354) asserted that "consumers develop some prior knowledge about the pricing environment in different stores." We find empirical support for this assertion in our data; shoppers made frequent grocery store visits and switched often among stores. In the "Data" section of the paper, we report that consumers switch stores on 39% of their visits. We also find that households in our dataset shop with frequently, making 1.28 grocery store visits per week. Alba, et al. (1994) showed that, when shoppers compare the prices of many products across stores, their impressions of relative price levels (i.e., higher or lower) are very consistent with actual prices. Thus, in support of requirement (i), frequent grocery shopping and store switching would be expected to result in accurate beliefs about relative category price levels at competing stores. We also find empirical support for requirement (ii) in our data. Using the same dataset, Fox, Metters and Semple (2003, pp. 22-3) conducted pairwise signed-rank tests of weekly category prices across retailers and found that prices at both EDLP retailers were consistently below those at both HiLo retailers (all p-values < 0.0001) in all categories. Thus, relative category prices were consistent over time.

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