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Differential Sourcing of Share in Brand/Price CBC Studies: Market Simulations on HB Lower-Level Point Estimates vs. Draws

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Executive Summary

We compare two common ways for modeling differential sourcing (substitution effects) among 38 SKUs in a brand/price CBC experiment: simulating on the HB respondent-level point estimates and simulating on the HB respondent-level draws. We find that both approaches lead to very similar sourcing patterns, with simulation on the draws maintaining a *slight* edge in terms of demonstrating stronger differential substitution patterns. The two approaches are so similar that we don't hesitate to recommend the common (and simpler) practice of simulating on the point estimates. To confirm our findings, we repeated the analysis with a more sparse second CBC dataset with 51 SKUs.

Background

Brand/Price CBC studies are commonplace in practice today. We often refer to the brands as SKUs (stock keeping units), as the same brand might have multiple forms or flavor variants that are classified by separate SKUs. A well-known potential benefit for CBC analysis is that it can estimate both within-SKU and across-SKU price elasticity. Within-SKU elasticity is the own-price elasticity associated with a SKU as it changes its price. Cross-price elasticity refers to the percent of share lost by, say, SKU B due to a reduction in price of SKU A. We often refer to cross-elasticity in terms of differential competitiveness or substitutability of SKUs, or *sourcing*. Sourcing concerns such questions as, a) when an SKU gains share by reducing price, from which SKUs does it principally source the increased demand? and b) which SKUs are relatively unaffected (non-substitutable)?

Early choice modelers mainly had aggregate MNL at their disposal, and due to the IIA (Independence of Irrelevant Alternatives) property specified cross-effect terms in their models to achieve differential sourcing among SKUs (i.e., mother logit). Otherwise, the IIA property would lead to the naïve and unrealistic result of constant substitution rates. With the introduction of HB (and other individual-level preference models), it wasn't necessary to specify cross-effects between SKUs to see differential substitution between SKUs manifest via market simulations. By capturing individual-level differences in tastes, correlations of preference across people lead to differential sourcing effects when simulating how changes in the price for one SKU affect the shares of competing SKUs. For example, the same people who tend to prefer Coke Light might also demonstrate a strong preference for separate SKU, Coke Zero. When Coke Light reduces its price, Coke Zero will tend to be more affected relative to other more independent SKUs.

Most practitioners applying HB estimation for CBC studies conveniently use the lower-level point estimates (the average of the used draws per respondent) in their market simulators. However, there

are other ways to build market simulators from HB results that might better reflect proper differential sourcing of share among SKUs. At a recent ART Forum, Allenby and Eagle described how one can make draws from the upper-level population means and covariances to simulate market shares. Kurz and Binner later presented a paper at the Sawtooth Software Conference on the same subject (Kurz and Binner, 2016). The principal drawback of this approach for practitioners is that it is hard to deliver market simulators to clients that allow them to filter the data by numerous segmentation variables (as those cuts of the data must initially be specified as covariates in the HB modeling). A practical approach that uses lower-level rather than upper-level draws is to build simulators that leverage, say, 30 to 100 draws per respondent, since respondents and market segments may easily be weighted and filtered *post hoc* (without the need to re-run the HB estimation). Rather than respondents being represented by just one vector of utilities, they now are represented by 30 to 100 proposals (draws) of their utilities. Those within-respondent draws tend to be normally distributed, but with covariances similar to the patterns seen in the upper-level covariance matrix. Thus, simulating on the lower-level draws potentially leads to stronger differences in sourcing among SKUs than when simulating on the point estimates. That is the subject of this investigation.

Whereas the Sawtooth Software community is familiar with Sawtooth Software's default simulation method called Randomized First Choice (RFC) that reduces IIA problems by correcting (penalizing) for product similarity, RFC is unable to address sourcing concerns for the common Brand/Price CBC study. RFC penalizes products that share attribute levels in common, but SKUs often are different levels of the same "brand," and thus RFC sees SKUs as unique and doesn't apply a correction for similarity.

Nested logit, Top-N Share of Preference, and *post hoc* nested Share of Preference are other approaches that have been proposed for better handling differential sourcing for Brand/Price CBC studies (Lattery and Hardon 2018, van der Wagt 2014). Examining their effectiveness is beyond the scope of this current investigation.

CBC Study Details

One of our colleagues shared a CBC dataset with us that has good properties for investigating how simulators built on respondent-level HB point estimates vs. draws lead to stronger or weaker differential sourcing effects among SKUs. We cannot show the attribute levels or discuss the product category due to client confidentiality. The key aspects of this CBC study were:

- 39 SKUs, plus a separate price attribute
- 15 tasks per respondent
- N=1080 respondents, prior to cleaning
- 32 concepts per task + None; 4% of choices were of the None
- Discrete Choice format

Prior to delivering the data to us, our colleague told us that many of the SKUs represented multiple offerings from the same brand and should be expected to compete strongly with one another.

"Tail Effect" Reversals on Quantitative Attributes Like Price

We ran HB estimation on all 1080 respondents, saving every 400th draw after convergence, for 50 saved draws per respondent (i.e., 20000 draws after convergence). The point estimates averaged all 20000 used draws per respondent. Although it wouldn't be the default procedure using Sawtooth Software, to illustrate a potential pitfall when leveraging draws, we fit a single linear term to price, unconstrained. 16% of the 1080 respondents had a reversed (positive) price coefficient (examining the point estimates). When examining the 1080 respondents x 50 = 54000 draws, 25% of those draws showed a reversal in Price.

For our 39-SKU dataset and an unconstrained HB run, we found that simulating on individual-level draws (where 25% of the draws were reversed on Price, compared to 16% for point estimates) resulted in an even greater magnitude of reversal for the price curve in the aggregated shares of preference. The simulated shares of preference for five price levels (holding SKU constant) are shown in Exhibit 1:

Exhibit 1:

Shares of Preference across 5 Price Points

(Reversals at Price 5)

	Pr1	Pr2	Pr3	Pr4	Pr5
Point Estimates	62.7%	16.0%	8.1%	6.3%	6.9%
Draws	63.5%	12.2%	6.5%	6.4%	11.3%

At the 2011 Turbo CBC conference, Kevin Karty described this simulated price reversal effect: "(The) distribution of individual level utilities for price often have a significant number of individuals with positive utilities on price, causing share gain at high price points even when aggregate utility is negative." In his presentation, he noted how these problems were exacerbated by individual-level models such as HB. He stated, "moving from aggregate to individual level models can introduce subtle bias in certain types of results -- notably those relying on simulators."

Based on our simulation results that include 16% sign reversals on the linear-coefficient for price for point estimates and 25% sign reversals among draws, we urge special caution regarding preference reversals for quantitative attributes fit with linear terms when simulating on the lower-level HB draws[1]. Reversals on other quantitative attributes modeled as linear terms such as speed, weight, etc. can lead to similar reversals in simulated shares of preference that are exacerbated with draws compared to simulating on the point estimates. We examined a separate recent CBC data set to see if the "tail effect" problems noted above are seen with effects-coded price functions, and the common effects-

[1] Kevin Lattery at SKIM, recommended log-linear price terms rather than linear price terms, which we also tried and found that it can reduce the "tail effect" bias we see here for price 5. The concavity of a positive sloping price function reduces the "runaway" share of price 5, somewhat. But, the bias remains with this dataset for the reversal seen from price 4 to 5, especially when operating on the draws. Standard effects-coding or dummy-coding of part-worth utilities for price seems to avoid this "tail effect" bias. To avoid the bias with linear or log-linear price coefficients might require constraining the sign to be negative during HB estimation (a facility provided by Sawtooth Software's utility estimation tools).

coded price functions (the default option in Sawtooth Software's CBC systems) don't seem to manifest this effect as much.

To treat this reversals problem with price and to continue our investigation to compare simulations on HB point estimates vs. draws, we deleted the 16% of respondents with price reversals in their point estimates and re-ran the HB model on the remaining 904 respondents. We used 20000 burn-in iterations, followed by 20000 used iterations. As mentioned before, we saved every 400th used iteration per respondent, for 50 draws per respondent. The HB run took about 2.5 hours on a standard laptop computer.

Even after deleting 16% of respondents, still 12% of the draws for the remaining respondents showed price reversals (but this was better than the previous 25% of draws with price reversals). Because we wanted to focus our analysis on sourcing patterns (where we planned to conduct simulations using only on the lower half of the prices in the price function), we decided not to further treat the reversals in price with utility constraints.

Top-Line HB Model Parameters

The upper-level mean (alpha) estimate of the parameters is shown in Exhibit 2:

Exhibit 2

HB Upper-Level (Alpha) Point Estimates of Utility for 39 SKUs, Price, and the None

SKU1	1.45
SKU2	1.87
SKU3	1.19
SKU4	1.94
SKU5	-0.23
SKU6	0.77
SKU7	0.43
SKU8	-0.17
SKU9	1.46
SKU10	-0.66
SKU11	-0.54
SKU12	-0.55
SKU13	-0.40
SKU14	-0.54
SKU15	-0.61
SKU16	1.82
SKU17	-2.99
SKU18	-1.47
SKU19	-1.81
SKU20	-2.32
SKU21	-1.81
SKU22	1.31
SKU23	1.09
SKU24	2.21
SKU25	2.82
SKU26	0.79
SKU27	-0.51
SKU28	1.33

SKU29	-0.08
SKU30	-0.71
SKU31	-0.68
SKU32	1.01
SKU33	-0.48
SKU34	-1.57
SKU35	-0.70
SKU36	0.52
SKU37	0.53
SKU38	0.23
SKU39	-3.95
Price	-2.03
None	0.19

The point estimate of the upper-level covariance matrix for the SKUs is shown in the next table, Exhibit 3. (We isolate the off-diagonal elements for reporting, since we are focusing this investigation on the sourcing between SKUs.) SKUs that are more competitive and sourcing to a higher degree from one another have higher covariances.

Exhibit 3: HB Upper-Level Point Estimate of (off-diagonal) Covariance Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
2	9.0																																					
3	8.9	8.5																																				
4	8.7	9.6	11.4																																			
5	-2.2	-1.2	-0.6	-0.1																																		
6	0.1	0.4	0.0	-0.1	1.8																																	
7	-3.0	-2.8	-2.0	-2.5	3.9	8.4																																
8	-1.3	-0.9	-2.0	-2.1	0.9	3.7	4.5																															
9	3.1	2.5	3.0	3.2	-1.2	-3.3	-1.3	-0.3																														
10	0.5	-0.5	-0.9	-0.5	0.1	-0.4	-2.4	-0.7	1.0																													
11	3.2	2.7	1.2	1.3	-1.5	-0.3	-2.2	0.7	0.1	1.8																												
12	-0.7	-0.6	-0.9	-1.3	-0.5	-6.1	-2.7	-1.3	0.7	0.8	0.8																											
13	-0.3	-0.3	0.3	-0.4	-1.2	-3.2	-2.3	-1.6	1.3	0.3	-0.5	5.9																										
14	-0.3	-0.9	-0.5	-2.2	0.0	-3.8	-2.4	0.0	-0.7	1.5	-0.7	1.2	0.3																									
15	-2.1	-1.9	-0.3	-0.1	1.3	1.8	1.7	1.7	0.1	0.3	-1.7	-4.6	-4.2	0.2																								
16	1.5	1.5	1.6	2.4	-1.0	3.4	2.7	3.7	1.2	-1.4	1.8	-2.9	-3.4	-1.8	2.4																								
17	-5.0	-4.2	-3.6	-3.5	1.1	-7.9	-3.3	-2.9	-1.0	-0.1	-4.3	3.3	2.9	2.2	-1.0	-5.9																						
18	-5.4	-3.8	-4.8	-4.9	-2.1	-8.6	-4.6	-2.1	-1.3	-2.3	-1.2	4.7	4.9	0.3	-3.4	-5.5	9.4																					
19	-6.6	-4.7	-7.8	-7.2	-1.5	-8.9	-6.1	-3.6	-2.3	-0.9	-1.5	5.9	5.6	-0.6	-5.4	-8.6	11.1	16.3																				
20	-7.8	-6.5	-10.0	-10.0	-0.5	-8.0	-2.2	-3.2	-3.1	-3.3	-4.4	5.1	4.2	-1.7	-4.7	-9.2	9.8	14.7	20.7																			
21	-6.8	-5.0	-5.8	-5.9	1.2	-10.0	-2.3	-3.2	-2.5	-5.6	-3.5	5.0	4.2	-1.4	-3.4	-5.4	8.4	12.3	15.7	19.6																		
22	1.3	0.4	0.3	0.6	-2.0	-5.2	-4.3	-2.5	0.1	-0.2	-0.1	0.6	-0.9	1.1	-1.1	-0.9	1.3	1.5	2.5	2.5	2.8																	
23	0.4	-1.2	0.3	0.5	-1.7	-7.1	-3.8	-4.1	0.0	-0.7	0.7	2.0	0.4	-0.1	-1.5	-0.9	2.8	3.0	2.0	2.4	4.6	4.4																
24	-1.6	-2.2	-1.7	-0.3	-1.1	-7.8	-2.7	-4.9	-0.2	-3.9	-3.3	1.0	-0.1	-3.1	-1.1	-1.1	3.3	3.9	4.1	9.2	11.7	5.7	9.9															
25	-2.4	-2.1	-1.8	-1.8	-2.7	-6.2	0.1	-0.6	2.2	-4.3	-0.1	1.6	1.5	-3.5	-0.9	2.3	0.6	4.8	3.5	6.2	8.8	1.1	4.0	8.6														
26	-0.1	0.1	-2.5	-1.2	-1.1	-8.2	-2.2	0.9	-1.2	-2.4	3.6	3.0	-0.7	-0.9	-2.2	1.9	1.0	4.5	5.1	6.4	8.6	3.1	4.3	7.1	6.9													
27	1.5	1.9	0.6	2.0	-1.8	-1.7	-3.6	-0.4	0.2	1.2	5.4	-0.2	-0.7	-0.2	-0.2	0.1	-2.0	0.2	0.5	-2.0	-2.2	0.7	0.5	-1.8	-0.5	2.0												
28	3.7	2.8	3.2	3.2	-2.3	3.8	-0.6	-0.4	1.2	1.5	-0.1	-3.2	-2.4	-0.5	1.7	2.7	-4.7	-6.0	-6.7	-7.5	-8.2	-0.1	-1.5	-3.1	-2.6	-4.6	1.3											
29	-2.8	-2.3	-1.2	-0.5	0.7	-0.9	2.1	1.9	0.8	-0.7	-1.3	-3.2	-3.7	-0.1	5.0	4.2	-1.2	-2.6	-4.7	-3.2	-1.2	-0.1	0.2	1.4	2.5	0.3	-0.2	1.4										
30	0.3	0.3	1.0	1.5	-0.6	-4.1	-4.3	-1.3	1.2	3.4	3.9	2.0	1.5	1.3	0.0	-0.8	1.8	1.2	1.5	-3.1	-2.6	0.0	1.0	-3.2	-2.4	-0.4	3.4	0.3	-0.9								
31	-2.0	-1.9	-1.0	-2.5	0.0	-5.8	-2.5	-0.4	0.4	1.4	-3.1	1.9	1.1	7.6	0.5	-1.8	3.3	0.8	0.7	0.3	0.9	1.2	-0.4	-2.6	-1.3	-1.5	-1.2	-0.3	1.3	0.9							
32	1.4	0.0	0.2	-0.8	-2.6	-6.4	-3.5	-1.8	1.4	-0.9	0.7	0.1	-1.1	0.8	-0.3	-1.1	0.8	2.1	1.8	3.4	3.0	3.6	4.2	5.6	3.4	2.8	1.2	0.2	0.9	-0.1	1.0						
33	1.5	0.3	0.4	-0.8	-0.8	2.1	-2.0	-0.4	0.9	5.4	0.8	-0.3	0.0	3.1	0.4	-0.5	-1.1	-4.0	-3.2	-6.3	-8.2	-0.7	-2.2	-6.8	-6.0	-5.9	0.3	3.6	-0.7	2.6	3.3	-1.2					
34	-0.2	-1.1	-0.4	-1.8	1.0	1.0	0.0	0.3	-0.6	2.7	-1.5	-0.8	-1.6	5.5	1.4	-0.9	-0.2	-4.5	-4.9	-5.0	-5.2	0.0	-1.2	-3.4	-5.5	-4.2	-1.2	1.5	0.3	0.6	5.2	-0.3	4.8				
35	-2.6	-3.0	-2.7	-3.4	0.8	-1.7	-0.9	-0.5	-0.4	3.0	-4.2	0.7	0.1	4.2	0.9	-1.9	3.0	-0.9	0.5	0.8	-0.7	0.6	-0.8	-1.3	-2.9	-3.1	-2.7	0.4	0.6	0.1	5.7	-0.5	3.7	4.9			
36	1.4	1.8	1.1	1.1	2.3	20.3	9.0	4.3	-3.2	0.2	0.1	-6.5	-3.8	-3.8	2.2	4.0	-9.6	-11.4	-11.8	-11.1	-12.9	-6.0	-8.4	-9.9	-8.1	-9.4	-1.7	5.0	-1.3	-3.7	-6.0	-7.4	3.2	2.2	-1.3		
37	-2.1	-1.9	-0.4	-1.4	4.1	12.3	11.7	4.8	-2.6	-2.3	-2.7	-4.0	-2.3	-1.6	2.4	2.5	-3.8	-5.8	-7.9	-5.3	-5.8	-5.7	-5.9	-6.4	-3.8	-6.0	-3.9	1.1	1.3	-4.1	-2.9	-5.5	-0.4	1.0	-0.8	13.6	
38	-0.2	0.0	-0.3	-0.3	2.2	21.6	10.0	4.7	-4.0	0.1	-0.6	-7.5	-4.2	-4.2	3.0	3.7	-8.7	-10.2	-11.0	-10.2	-13.0	-6.5	-8.5	-10.0	-7.9	-10.2	-1.7	5.1	-0.7	-4.2	-6.8	-7.6	2.9	1.5	-1.7	23.8	15.1	
39	-3.4	-3.3	-4.0	-4.4	1.9	15.4	6.3	3.1	-2.2	1.5	-0.8	-7.7	-5.0	-3.3	5.2	0.5	-4.4	-5.9	-5.4	-4.9	-8.8	-5.2	-7.1	-8.3	-5.6	-9.8	-0.5	3.2	0.4	-1.9	-4.6	-4.4	3.1	1.7	0.3	16.9	9.2	19.3

From the covariance matrix, it appears (as isolated examples) that SKU36 has a wide range in sourcing effects compared to the other SKUs. SKU36 is highly substitutable (competitive) with SKUs 6, 37-39. And, it appears to be not very substitutable (competitive) with SKUs 17-21. SKU6 also seems to show potentially strong differential substitutability (particularly positive relative to SKUs 36-38 and particularly negative relative to SKUs 17-21).

Sourcing Sensitivity Simulations

We built two market simulators in Excel: one leveraging the 904 respondent-level point estimates and the other leveraging the 904 x 50 = 45200 respondent-level draws. We used the Share of Preference (logit) simulation rule for both simulators. We simulated a base case scenario that included the first 38 SKUs plus None (we omitted SKU39 due to its low choice likelihood). We set all SKUs at the middle price point for this base case, then one-at-a-time decreased the price for each SKU to the lowest price point while holding all other SKUs at the middle price point. We compared the share of preference for the SKUs before and after the price changes.

For better comparability between the results of the point estimates vs. draws simulators, we first tuned the exponent (scale factor) so that the sensitivity to changes in SKUs and prices was as close as we could make it. Holding the scale factor of the points simulator at 1.0, the scale factor adjustment to the draws simulator was 1.25 to near equalize the sensitivity of the simulated share results. In other words, without any adjustment for scale, simulating on the draws would lead to flatter simulation sensitivities relative to simulating on point estimates.

For illustration, let's examine the sourcing results for SKU4 from our simulation sensitivity analysis. What happens to the shares for the other SKUs as we lower the price for SKU4 from the middle to the lowest price? And, how do those substitution patterns compare to the patterns we see in HB's upper-level covariance matrix? In the chart below, we show the loss in share for the remaining SKUs when SKU4 lowers its price. For example, SKU1 loses 33% of its share according to the simulator built on the point estimates and 41% of its share according to the HB draws simulator. The covariance between SKU4 and SKU1 (from the HB upper-level estimate) is 8.7.

Exhibit 4:

Sourcing Results, SKU 4

(Loss in Share Due to Decrease in SKU4's Price, With HB Covariances Shown for Reference)

	Point Estimates	Draws	HB Covariances
SKU1	33%	41%	8.7
2	49%	54%	9.6
3	42%	49%	11.4
4			
5	9%	14%	-0.1
6	9%	15%	-0.1
7	7%	11%	-2.5
8	12%	10%	-2.1
9	21%	24%	3.2
10	12%	15%	-0.5
11	14%	14%	1.3
12	8%	10%	-1.3
13	11%	14%	-0.4
14	11%	12%	-2.2
15	10%	13%	-0.1
16	19%	30%	2.4
17	2%	6%	-3.5
18	3%	4%	-4.9
19	2%	3%	-7.2
20	0%	1%	-10.0
21	2%	3%	-5.9
22	19%	20%	0.6
23	9%	12%	0.5
24	7%	12%	-0.3
25	6%	10%	-1.8
26	8%	11%	-1.2
27	26%	19%	2.0
28	25%	36%	3.2
29	19%	19%	-0.5
30	17%	15%	1.5
31	12%	13%	-2.5
32	12%	13%	-0.8
33	12%	16%	-0.8
34	9%	12%	-1.8
35	10%	13%	-3.4
36	10%	18%	1.1
37	8%	12%	-1.4
38	6%	11%	-0.3

If the share simulation results were bound entirely by IIA, the percentages in the first two columns above would be identical across SKUs. However, due to capturing heterogeneity in the data and simulating choices at the individual level, we see large differences in sourcing across the SKUs (even though IIA holds within each respondent's results). For example (draws results), when SKU4 lowers its price, SKU2 loses 54% of its share while SKU20 loses 1% of its share. This is very impressive that main-effects HB utility estimation (without any cross-effects) can achieve such differential results for sourcing patterns.

Taking standard deviations of the first two columns in Exhibit 4 can summarize the degree of differential sourcing due to changes in SKU4's price. The column standard deviations are 10.5% and 11.8% for the points and draws simulations, respectively. Thus, at least for SKU4, the differential sourcing effects are a bit more pronounced for the simulator built on the draws. We repeated this analysis across the 38 SKUs and the average standard deviation was more similar: 6.1% for the point estimates simulator and 6.2% for the draws. So, the results are nearly identical, with a *slight* edge toward the draws simulator for enhancing the differential sourcing among SKUs.

Exhibit 5: Strength of Differential Sourcing, Summary across 38 SKUs

Point estimates simulator: 6.1%
Draws simulator: 6.2%

A related question is how much the patterns of sourcing seen in the HB covariance matrix are reflected in the sensitivity simulation results from the two simulator approaches. The correlation among the three columns in Exhibit 4 is very high for SKU4:

Exhibit 6: SKU 4 Sourcing Patterns Correlation

	Point Estimates	*Draws*	*HB Covariances*
Point Estimates	1.00		
Draws	0.96	1.00	
HB Covariances	0.90	0.93	1.00

To stabilize the results (in case SKU4 was an outlier), we repeated this correlation analysis by stacking the results for a sampling of seven SKUs and the summary correlations were as follows:

Exhibit 7: Average of Seven SKUs Sourcing Patterns Correlation

	Point Estimates	*Draws*	*HB Covariances*
Point Estimates	1.00		
Draws	0.95	1.00	
HB Covariances	0.77	0.81	1.00

Thus, we see that the sourcing patterns are very highly correlated (0.95) between simulations on the point estimates and the draws. And, simulations on the draws are a bit more correlated with the patterns seen in the HB Covariance matrix relative to simulations on the point estimates (0.81 and 0.77, respectively).

A Second CBC Dataset

To confirm our findings from the first dataset, we examined a second brand/price CBC study that was more sparse at the individual level than the previous dataset, featuring:

- 51 SKUs, plus a separate price attribute
- 11 tasks per respondent
- N=788 respondents
- 10 concepts per task + None; 15% of choices were of the None

In this dataset, each SKU appeared from 1-3 times per respondent—much sparser than the previous dataset where each item appeared about 12 times per respondent.

Despite the sparseness of this dataset, we still observed large differential sourcing effects among the SKUs using HB estimation with main effects (and no cross effects). The key findings regarding strength of sourcing effects and the patterns of sourcing effects between simulators built on point estimates or draws were confirmed. The correlation between sourcing effects was 0.96 between simulators built on the point estimates and the draws (compared to 0.95 with the previous CBC dataset).

Conclusions:

Whether simulating on the lower-level point estimates or the draws, the patterns of sourcing among 38 SKUs and 51 SKUs for two commercial datasets are very similar. Simulating on the draws leads to *slightly* higher differential sourcing patterns, but not nearly enough for these data sets to warrant the extra work involved in simulating on the draws. The sourcing patterns seen in HB's upper-level covariance matrix are highly correlated with the sourcing sensitivity results seen whether simulating on the point estimates or the draws, with a *slight* edge in pattern correlation for simulating on the draws.

Regarding fitting unconstrained continuous price functions, a “tail effect” bias leads to a biased upward share for the highest price point leading to a strong reversal in the simulated price curve. This is especially manifest when running simulations on the draws. Fitting a log-linear rather than a linear function to price can ameliorate, but not eliminate, the “tail effect” bias for this data set. This leads us to caution practitioners regarding building simulators on the draws involving linear or log-linear price effects, unless applying sign (utility) constraints on price.

References:

Kurz, Peter and Stefan Binner (2016), “Simulating from HB Upper Level Model,” 2016 Sawtooth Software Conference Proceedings, Orem, UT.

Lattery, Kevin and J. Hardon (2018), “Tools for Dealing with Correlated Alternatives,” Sawtooth Software Conference, Provo, UT.

van der Wagt, K. (2014), “Red Bus/Blue Bus: Toward Results with Higher Validity,” Presentation at the 2014 Turbo Choice Event. Amsterdam, The Netherlands: Sawtooth Software.