Product Launches with New Attributes: A Hybrid Conjoint-Consumer Panel Technique for Estimating Demand

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Abstract

We propose and empirically evaluate a new hybrid estimation approach that integrates choice-based conjoint with repeated purchase data for a dense consumer panel, and show that it increases the accuracy of conjoint predictions for actual purchases observed months later. Our key innovation lies in combining conjoint data with a long and detailed panel of actual choices for a random sample of the target population. By linking the actual purchase and conjoint data, we can estimate preferences for attributes not yet present in the marketplace, while also addressing many of the key limitations of conjoint analysis, including sample selection and contextual differences. Counterfactual product and pricing exercises then illustrate its managerial relevance.

Keywords: Conjoint, Revealed Preference, Stated Preference, Data Fusion, Predictive Validity, Choice Models, Bayesian Hierarchical Models.

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INTRODUCTION

Forecasting new product sales to optimize a product's feature set and price point is a critical marketing research goal. However, product introductions often involve attributes that are new to market, meaning sales forecasts cannot be directly inferred from past purchases. The canonical solution to this problem is a class of conjoint analysis techniques in which a sample of existing consumers are repeatedly tasked with choosing one of several hypothetical products featuring potentially desirable combinations of characteristics (Green and Rao 1971; Green and Srinivasan 1990; Wittink and Cattin 1989; Ben-Akiva et al. 2015). This conjoint choice data is used to estimate preferences and, ultimately, inform decisions related to the new product's attributes and pricing.

However, it is well-known that conjoint can produce biased preference estimates (Ben-Akiva and Morikawa 1990; Horsky and Nelson 1992; Brownstone et al. 2000; Swait and Andrews 2003; Brooks and Lusk 2010) due to sample selection or contextual differences (e.g., Allenby et al. 2005) that can lead to preference distortions and inaccurate choice predictions (Ozer and Kamakura 2007; Swait and Andrews 2003). Dick Wittink wrote in 2000 that "unfortunately, there is not much hard evidence that future market outcomes are predictable [by conjoint]" (Wittink, 2000), echoing previous (Orme et al., 1997) and subsequent (Wittink, 2003) calls for such investigations. Evidence on the predictive accuracy of conjoint for forecasting future choices remains surprisingly limited[1], leading most practitioners to refer to market share simulations as "preference shares", a tacit acknowledgement of their poor forecasting abilities (Orme, 2014). Perhaps the most promising avenue for improving the predictive power of conjoint lies in a growing set of hybrid data-fusion techniques that combine conjoint with actual purchase data (Swait and Andrews 2003; Allenby et al. 2005; Feit et al. 2010). By anchoring stated preferences to actual market choices, such data fusion methods can leverage the strengths of both approaches. This paper is aimed at furthering this goal.

To do so, we develop a new hybrid approach to data fusion that integrates choice-

[1]Papers such as (Orme and Johnson, 2006) and (Gilbride et al., 2008) discuss methods to improve the predictive accuracy from conjoint data alone

based conjoint with a panel of consumer purchase data, and show that it increases the accuracy of conjoint predictions for actual purchases of new products observed months later. Our key innovation lies in combining conjoint data with a long and detailed panel of actual choices for a distinct, random sample of the target population. By linking actual purchases with conjoint data, we can recover preferences for attributes not yet present in the marketplace, while also addressing many of the key limitations of conjoint analysis, including sample selection and contextual differences.

We apply our method to a field study of the Greek yogurt category for a retailer that launched a new private label yogurt following a related conjoint study. We demonstrate that our hybrid approach can link conjoint and loyalty card purchase data successfully, despite the clear presence of preference distortions and selection effects. We characterize the form and quantify the magnitude of these biases and show how our method accounts for them. In so doing, we demonstrate that our model predicts individual-level actual purchases better than both conjoint alone and a strong benchmark approach that combines key earlier data-fusion techniques (Feit et al. 2010; Swait and Andrews 2003). Notably, we can accurately predict actual, individual-level purchases months after the conjoint study, when the new product was in fact launched in stores. Moreover, we do so for a hold-out sample of individuals outside the training set. This challenging predictive task, more involved than most extant evaluations, is critical for establishing the relevance of conjoint for actual managerial decision-making. Finally, we demonstrate via counterfactual exercises that our method can inform decisions regarding optimal product selection and provide profit-enhancing store-level price-setting for products with new to market features.

We make three main contributions to the current literature. First, we develop a novel hybrid approach to combining stated and revealed preference data for demand estimation that links conjoint surveys from one sample with rich and detailed panels of consumer choices from a separate, random sample. By fusing such data, we are able to mitigate many of the key biases that arise in conjoint while preserving the ability to forecast demand for products that are not yet present in the market. Second, we provide a new and detailed field evaluation of both conjoint and hybrid approaches that answers the call for greater demonstration of predictive validity.[2] Notably, our approach does best in all prediction tasks. In particular, it reduces the individual-level prediction root mean squared error by 50% compared to standard conjoint. Third, we are also able to evaluate two forms of bias and assess our ability to control for them. Finally, we provide a detailed application showcasing the ability of these approaches to provide concrete managerial insights. We turn now to a more detailed discussion of the challenges of data fusion and our strategy for addressing these issues.

The existing literature has identified two key challenges to combining information from survey and actual purchase data (Adamowicz et al. 1994; Swait and Andrews 2003; Feit et al. 2010; Cherchi and de Dios Ortúzar 2002; Brownstone et al. 2000). First, conjoint respondents are often selected to have previous experience in the category. This can lead to biased coefficient estimates if not properly addressed (Manski and Lerman 1977; Feit et al. 2010).[3] Second, conjoint surveys can present a starkly different contextual environment than actual choices which may affect reported preferences (Swait and Andrews 2003; Allenby et al. 2005).

Our central modeling challenge lies in correcting for these preference distortions while still incorporating unique information from the conjoint data regarding new-to-market features. Building upon the earlier data-fusion frameworks of Swait and Andrews (2003) and Feit et al. (2010), our approach combines information from conjoint and actual purchases. We use the trade-offs revealed in the actual purchase data to inform relative

[2]This predictive validation is worth emphasizing; we were unable to find any predictive validity tests for such difficult prediction tasks. In particular, most existing validations involve hold-out (conjoint) tasks for the same individuals, rather than actual market choices (Wittink, 2000). Such predictions can establish internal, but not external, validity. Those on actual choices are scarce and limited to a single choice for the same (Toubia et al. 2003; Ozer and Kamakura 2007) or other individuals (Feit et al. 2010), or against aggregate market shares (Chang et al. 2009; Rogers and Renken 2003; Orme and Heft 1999; Feurstein et al. 1999). We found only two studies that evaluate predictions against actual repeated (individual-level) purchases; both were for past purchases only (Swait and Andrews 2003; Brooks and Lusk 2010). In contrast, our predictive validation includes (i) repeated individual-level purchases, (ii) both in-sample and a hold-out observations, and (iii) multiple time periods, including cases well after the conjoint data were collected (i.e. the kind of timeline needed for supporting product launch decisions). We contribute to this literature by demonstrating empirically that conjoint performs poorly compared to standard choice models in a setting where both are feasible.

[3]Non-response that is correlated with preferences can also clearly be a problem. We address this concern by conditioning on category-use variables (i.e. we allow for selection on observables).

preferences for attributes already present in the market. We then use the conjoint choices to pin down the tastes for new attributes, using attributes common to both settings to carefully link choices through these relative tastes. Critically, we perform this fusion using only the stated preferences for shared attributes that are believed to be free of distortions. This judgment can be based on a mix of theory, prior research and empirical evidence.

We find that our model is able to identify and address several meaningful preference distortions in the conjoint data. We first estimate models using only conjoint and actual purchase data, and show that the (relative) trade-offs these models imply differ markedly for some attributes, but not others, suggesting that such distortions arise in distinct ways. For example, one clear distortion relates to the relative preference for inside versus outside options. This distortion can arise both because of the selection of participants in the conjoint sample and from differences in the choice contexts. We show that both effects exist in our empirical setting, highlighting the need to correct for each. A second set of distortions relates to weaker relative preferences in the survey data than the actual choice data. Yang et al. (2018) show that consumers become less novelty-seeking and more price-sensitive as the probability of realization of the task increases. We find evidence of such distortions for price sensitivity and state dependence. A third set relates to lower heterogeneity in the survey data preferences relative to those that drive actual choice. We find meaningful distortions for price sensitivity and one brand intercept. The final distortion is that the relative preference for some attributes (e.g., fruit and fat content) are reversed in the conjoint data relative to actual choices. We demonstrate that our model can handle each of these distortions and more accurately represent the actual trade-offs, while still combining the data to produce a credible forecast for new product demand.[4]

[4]We note that our conjoint application did not easily allow the kind of incentive compatibility practices recommended in the literature (Ding (2007)) because the product was both new-to-market and non-storable. In general, there are many settings where incentive compatibility is not feasible (or cost-effective) for the organization sponsoring the conjoint research (Dong et al., 2010). We follow the recommendations of Ding and Huber (2009) for cases when incentives are not possible, while noting that such improvements in conjoint design are a complement to the data fusion approach advocated here.

Finally, we also are able to provide insight into the key sources of bias in the conjoint analysis. Because we also observe actual purchases for the survey data sample (i.e. those who completed the conjoint), we can evaluate how and why their preferences differ from the full population. Specifically, we can evaluate the relative importance of selection (who takes part in the conjoint) versus contextual biases (how implied tastes differ across settings), and investigate how effective observable covariates are in mitigating the selection problem. We find that selection bias accounts for less than a third of the total bias in most cases, although it can account for up to half the bias in price sensitivity. This suggests that price elasticities may be understated in conjoint analysis as much due to selection as context effects. We find that information regarding consumer demographic and usage (recency, frequency and monetary value, RFM) variables significantly improves model fit, though simply including these variables is not sufficient to address selection problems. Thus, handling the distortion in preferences that arise from conjoint elicitation is critical for improved prediction. We conclude by performing a suite of counterfactuals that demonstrate the managerial insights from the improved predictive ability.

The paper is organized as follows. Section 2 describes the micro-econometric framework for the model used. The application context and data are presented in Section 3. Section 4 discusses the results, including parameter estimates, model comparison, predictive validity, and disentangles the nature of the conjoint biases. In Section 5, we use our model estimates to evaluate a managerial decision involving product optimization and store-level pricing. Finally, Section 6 concludes.

MODEL AND ESTIMATION

We consider a firm choosing which new-to-market features to include in a new product launch, as well as the optimal prices to set across different spatial locations (e.g. outlets or pricing zones, see section 5). A key decision input is the consumer demand system, which characterizes the level of demand for products, the responsiveness to changes in the product characteristics, and how this responsiveness varies by spatial location. Our estimation task focuses on recovering the structural parameters of this demand system.

The central challenge for demand estimation and prediction is that true 'purchase preferences' for a subset of the variables cannot be inferred from actual purchase data alone. Of central interest are new-to-market-attributes (NTMAs) that are not yet present in the market. For example, in our Greek yogurt application, the store brand is new to the category, as are several new ingredients including fiber and Omega-3. Preferences for such NTMAs cannot be recovered from actual purchases.

To address this challenge, we combine two types of data. First, we employ stated preference (SP) data from a set of choice-based conjoint tasks. Conjoint experiments involve manipulating a set of product "profiles" that a consumer can choose in a series of "choice tasks". Because the set of attributes (and attribute levels) for each product is chosen by the researcher, these can include the NTMAs of interest here, but inference may be subject to distortions from the survey context. To address this concern, we include a second set of revealed preference (RP) data that are drawn from actual purchase histories. Such data can generally be obtained from a retailer's loyalty card program, consumer panel data, or online shopping histories.

Note that RP and SP data typically contain two distinct types of individuals (or segments): a random sample of consumers from the full population and a survey sample of respondents that complete the conjoint tasks. The first group, which we distinguish by the subscript 'ss', are often invited to complete the conjoint survey based on past purchases or stated category interest, adding an element of selection. The notation SP_{ss} emphasizes the fact that this first data type reflects *stated preference* outcomes for the selected *survey sample* group. In contrast, the second data type reflects *revealed preferences* from actual purchases for a *random sample* of the full population, and is denoted RP_{rs}. Assuming the structural choice model is correctly specified, the preferences revealed by these choices are assumed to represent the ground truth. Throughout the text, we use D to index the different datasets.

While one could, in principle, use SP_{ss}-type data alone to estimate the demand system, preferences obtained from survey data may include "distortions" that can bias predictions. These biases can include distortions in mean preferences or the predictability of choices, and may arise from differences in either the respondents selected into the survey sample or contextual differences in the choice tasks themselves. In particular, survey respondents are often heavy users of the category, so they might have more experience with the relevant trade-offs (Ben-Akiva et al., 2015) or stronger tastes for the products considered. Furthermore, actual choice contexts may differ from the artificial setting of a survey (Allenby et al., 2005). Such differences could arise directly from the decision context (store location, signage, number of options, physical product vs. simple survey design with radio buttons) or indirectly through the choice context inducing different information processing modes or invoking other incentives. For example, the hypothetical nature of the conjoint tasks could result in a higher level of construal when making decisions (Trope and Liberman, 2010) that alters the nature of preferences. Likewise, social desirability and related motivations may lead individuals to prefer options in a survey that they might not actually consume in practice, such as a choice that serves the public good or constitutes a healthier food option (Whitehead et al., 2008). Such choice context effects may be more salient for certain attributes than others. For example, the relevant outside option might be different in actual versus conjoint settings (due to the absence of a clear budget constraint) and inferred price sensitivity may depend on the context (Horsky and Nelson, 1992).

Our model leverages both RP_{rs} data and SP_{ss} data to solve this dual problem of recovering preferences about new-to-market attributes while minimizing the potential biases from sample selection and choice context differences. In what follows, we first introduce a micro-founded model of consumer decision-making and then discuss how we link the RP_{rs} and SP_{ss} datasets. We then present our estimation approach and discuss our identification strategy. Throughout, we refer to units of analysis as individuals, but these could also represent households or any other "micro-segments" classified a priori using demographic, location, and other observable features.

Model Of Consumers

For each dataset D, consumers indexed $i = 1, \ldots, N^D$ make choices over goods j in a series of decision opportunities $t = 1, \ldots, T_i^D$. These decision opportunities may represent either actual purchases ($D = RP_{rs}$) or tasks in a conjoint study ($D = SP_{ss}$). Goods are represented as preferences for bundles of attributes, denoted X_{ijt}, one component of which is price. Individual i's choices, y_{it}^D, and indirect utilities, U_{ijt}^D, at t, over a set of options, C_{it}^D, are indexed by a vector of preference parameters, β_i^D, as follows:

$$U_{ijt}^D = X_{ijt}^D \, \beta_i^D + \epsilon_{ijt}^D. \quad j \in C_{it}^D \tag{1}$$

The datasets (and choice contexts) have two key differences reflected in the structure of equation (1). First, the characteristics X_{ijt}^D may differ in the set of included features. As mentioned earlier, the SP_{ss} data may include new-to-market attributes (or bundles of such attributes) that are not found in the RP_{rs} data. Conversely, there may be features or products in the RP_{rs} data that are not included in the conjoint design (which we refer as "*RP*-only" attributes).[5] Such missing attributes yield an additional source of randomness that can increase the scale of the errors, $\epsilon_{ijt}^{SP_{ss}}$, or bias parameters if these missing attributes are correlated with ones in the model. Moreover, it is clear that preferences for the missing attribute levels cannot be estimated using data from which they are absent (Islam et al., 2007).

Second, the choice set C_{it}^D itself varies across the datasets with the SP_{ss} choice sets designed by the researcher and the RP_{rs} choice sets determined by the marketplace. An important implication of this is that the relevant "outside good" for the given choice setting differs. Conjoint studies usually provide a "none-of-the-above" option, assumed to convey zero utility in the stated preference (SP_{ss} data) context. However, in revealed preference RP_{rs} data, the outside good is often defined (by the analyst) as purchases in

[5]This can occur, for example, when the actual choice context involves too many options to include in the conjoint design. Additionally, there might be features reflected in both datasets that are perfectly collinear in the actual context but can be varied independently in the survey (which we refer to as "*Confounded*" variables). For instance, if *all of exactly one brand's* products are organic, purchase data cannot separately identify brand from organic preference (see also Swait and Andrews (2003)).

a related sub-category or categories. For our Greek yogurt application, we follow these conventions and construct a price index for the outside option (p_{i0t}), which captures purchases of non-Greek yogurt products, and normalize the constant for these purchases to 0, as detailed below:

$$
\begin{aligned}
U_{i0t}^{SP_{ss}} &= 0 + \epsilon_{i0t}^{SP_{ss}} \\
U_{i0t}^{RP_{rs}} &= \beta_{i,price}^{RP_{rs}} p_{i0t} + \epsilon_{i0t}^{RP_{rs}}
\end{aligned} \tag{2}
$$

Returning now to the overall choice problem, assuming ϵ_{ijt}^{D} is distributed iid logit yields a familiar formulation for the individual choice probabilities implied by equation (1):

$$
P_{ijt}^{D} = \frac{\exp(X_{ijt}^{D}\ \beta_i^{D})}{\sum_{h=0}^{C_{it}^{D}} \exp(X_{iht}\ \beta_i^{D})}. \tag{3}
$$

To account for heterogeneity in tastes, we allow consumer preferences to be a function of observed individual characteristics[6], Z_i^D, and an unobserved component, ν_i^D. In particular,

$$
\beta_i^D = Z_i^D \Delta^D + \nu_i^D. \tag{4}
$$

where ν_i^D is assumed to be distributed multivariate[7] normal with mean zero and variance, Σ^D.

In many existing applications, Z_i^D includes demographic variables such as income and family size (see Feit et al.). We include measures of past purchase behavior such as the Recency, Frequency or Monetary value (RFM) of past category purchases. This inclusion is worth emphasizing here, as it can potentially correct for one source of preference distortion: selection into the conjoint study itself. Since invitation to the survey sample was based on these past purchase behaviors directly, including these variables allows us

[6]The Z^D matrix in each dataset is mean-centered and includes an intercept term.

[7]In principle, one could extend this formulation to include a semi-parametric distribution for the mixing distribution, such as a mixture of normals, to allow for even richer substitution patterns.

to construct conditional mean shifts along the primary basis of selection. We evaluate the actual reduction in bias due to their inclusion in section 4.4.[8]

Returning to the choice model, a straightforward option is to simply estimate the preference parameters (Δ^D, Σ^D) for the two datasets RP_{rs} and SP_{ss} separately, using equations (3) and (4). However, given the discussion above, we expect the estimates of the common parameters recovered from these separate procedures to differ sharply along at least some dimensions, degrading the ultimate quality of prediction. To obtain accurate estimates of the full demand system, we seek to link the two datasets together, pooling information in a way that leverages the strengths of each. Because we are focused on predicting outcomes in the actual context, we assume that the parameters $\beta_i^{RP_{rs}}$ represent the true (revealed) preferences for the attributes and attribute levels observable in the market for the overall population. In contrast, the conjoint estimates, $\beta_i^{SP_{ss}}$, represent the stated preferences given the choice tasks, and are observed for the survey sample alone. Therefore, the aim for our linking method is two-fold: obtain preferences for new-to-market variables that are absent from the actual context, and reduce the known preference distortions between the two datasets to make accurate predictions. The test of success will be based on out of sample prediction performance.

Linking Stated Choices And Actual Purchases

To flexibly fuse the conjoint and purchase data together, we introduce additive "mean preference shifters" and multiplicative "variance shifters" to equation (4), which we refer to jointly as "distribution shifters". The full parameterization is

$$\Delta^{RP_{rs}} = \lambda\ (\mu + \Delta^{SP_{ss}});\ \Sigma^{RP_{rs}} = \lambda^2\ (\Phi \Sigma^{SP_{ss}} \Phi') \tag{5}$$

where λ is a a positive scaling parameter that adjusts the relative variances of choice unobservables ϵ_{ijt}^D across datasets. The matrix μ shifts the weights of the demographic/RFM variables on shaping individual preferences β_i^D between the RP_{rs} and SP_{ss} datasets. In

[8]While the estimated Δ^D on these Z^D variables should not be interpreted causally, they still prove useful for predicting future demand.

our application, we focus on the mean shift in preferences for the "average" individual. For instance, an additive mean shifter for the outside good shifts all the inside options in the RP_{rs} dataset, relative to the inside goods in the SP_{ss} data. Similarly, the scaling matrix Φ shifts the variances (and in general covariances) for product attributes between the RP_{rs} and SP_{ss} datasets. Thus, the distribution shifters μ and Φ allow for changes in average preferences, unobserved heterogeneity, and covariances between product attributes, leading to different attribute tradeoffs across the RP_{rs} and SP_{ss} contexts.

Our linkage method improves on the existing standard of linking RP and SP datasets via a single scaling constant λ (which can be expressed as a special case of our model in which $\mu = 0$ and Φ is unit diagonal matrix). A single scaling constant requires that respondents fully reveal their true preferences in survey contexts and that sample selection play no material role. Unfortunately, significant preference distortions appear to be the norm in most settings. Thus, to link the SP_{ss} and RP_{rs} data, we allow the scale to adjust, incorporate observable heterogeneity in the form of demographic and RFM variables, and allow some subset of preferences to have distribution shifts between the two datasets. We turn now to the details of estimation.

Estimation

We estimate the model using a Bayesian Hybrid Monte Carlo technique (STAN). Using equations (3), we can write the likelihood contribution for a single choice occasion given individual parameters β_i^D as follows:

$$\mathcal{L}(y_{it}^D|\beta_i^D) = P_{ijt}^D = \frac{\exp(X_{ijt}^D\beta_i^D)}{\sum_{j=0}^{C_{it}^D}\exp(X_{ijt}^D\beta_i^D)}, \quad i \in D \tag{6}$$

Using (4) and (5), we define the set of aggregate parameters as $\Theta = \{\Delta^{SP_{ss}}, \Sigma^{SP_{ss}}, \lambda^{RP_{rs}}, \mu^{RP_{rs}}, \Phi^{RP_{rs}}\}$. Note that this set links the individual parameters β_i^D across datasets. For this parameter set, we can now write out the total posterior distribution (given the datasets), which is provided below in equation (7). In Web Appendix B, we provide additional details regarding the choice of prior and overall estimation procedure. The likelihoods for SP_{ss} and RP_{rs} datasets are shown in equations (8)-(9), and the mixing distributions in equations (10)-(11):

$$\mathcal{L}(\Theta|y) \propto \mathcal{L}(y|\Theta)\mathcal{L}(\Theta) \tag{7}$$
$$\propto \mathcal{L}(y^{SP_{ss}}|\Theta)\ \mathcal{L}(y^{RP_{rs}}|\Theta)\mathcal{L}(\Theta)$$

$$\mathcal{L}(y^{SP_{ss}}|\Theta) \propto \prod_{i\in ss}\big(\prod_{t=1}^{T_i^{SP_{ss}}} \mathcal{L}(y_{it}^{SP_{ss}}|\beta_i^{SP_{ss}})\big)\mathcal{L}(\beta_i^{SP_{ss}}|\Theta) \tag{8}$$

$$\mathcal{L}(y^{RP_{rs}}|\Theta) \propto \prod_{i\in rs}\big(\prod_{t=1}^{T_i^{RP_{rs}}} \mathcal{L}(y_{it}^{RP_{rs}}|\beta_i^{RP_{rs}})\big)\mathcal{L}(\beta_i^{RP_{rs}}|\Theta) \tag{9}$$

$$\beta_i^{SP_{ss}}|\Theta \sim \mathbb{N}(Z_i^{SP_{ss}}\Delta^{SP_{ss}}, \Sigma^{SP_{ss}}) \tag{10}$$

$$\beta_i^{RP_{rs}}|\Theta \sim \mathbb{N}\big(\lambda^{RP_{rs}}\ Z_i^{RP_{rs}}(\mu^{RP_{rs}} + \Delta^{SP_{ss}}), (\lambda^{RP_{rs}}\Phi^{RP_{rs}})\Sigma^{SP_{ss}}(\lambda^{RP_{rs}}\Phi^{RP_{rs}})'\big) \tag{11}$$

We will now provide some intuition regarding how the linking parameters μ and Φ are identified across the two datasets.

Selection And Identification Of The Scaling And Distribution Shifter Parameters

We begin by discussing the practical aspects surrounding the set of shifters to include in the model. First, notice that we can only apply the distribution shifters, μ and Φ to the set of attributes common to the two datasets (as these are the only ones for which both datasets are informative). Second, in order to pool information across the two datasets, we force equality to hold for a non-empty set of the parameters on these common attributes (up to the scaling parameter, λ). Third, the parameter set that is forced to equality should be (relatively) free of preference distortions. If a distorted preference parameter is assumed equal, pooling will contaminate the other (non-distorted) parameters.

To identify distortion in the conjoint parameters, one can rely on managerial experience, theory, or prior empirical findings. For example, past research and theory suggests alternative specific constants may differ (Louviere et al., 2000), price sensitivity likely differs (Horsky and Nelson, 1992), and that other parameters might differ due to question context or social desirability bias (Whitehead et al., 2008). One can also leverage empirical information from the setting at hand by inspecting the estimates obtained from calibrating the preference parameters separately on the two datasets or by applying a series of likelihood ratio tests for whether or not to pool on specific parameters (Brownstone et al. 2000). We also note that, in principle, one could select the set of distribution shifters via a systematic model-selection routine that uses cross-validation over holdout samples from both the conjoint and actual purchase data. Unfortunately, we found this to be computationally impractical in our empirical setting.

We now discuss the intuition for how information from the two datasets is pooled and refer the reader to Web Appendix C for a formal discussion. The preference parameters for the common attributes that are assumed equal provide the link between the datasets and generate a benchmark magnitude. All other parameters within a dataset then have their magnitudes defined relative to that benchmark. Hence, the relative magnitude of one attribute in the conjoint, say organic, is relative to the common pooled parameter, say fat level. In this way, by pooling on attribute preferences that are believed to be distortion free, one can obtain the full set of parameters distortion free. As this essentially amounts to "dummying out" the distorted components, doing so requires including shifters for the parameters with distorted preferences in the conjoint data, so that distortions in the shared attribute preferences do not infect the other preference estimates.

As an example, assume an actual vehicle-purchase dataset contains information about prices, cost per mile, and a number of other attributes unique to the actual purchase dataset. A corresponding conjoint purchase set has information about prices, mileage costs, and includes a new electric vehicle. If the conjoint price preferences are believed to be biased but mileage cost is distortion free, then pooling could occur on the cost per mile attribute. In this case, within the actual purchase data, the calibration of the price sensitivity will be relative to the mileage cost preference *within* the actual purchases. Similarly, for the conjoint data, the evaluation of the new electric vehicle will be relative to cost per mile. Hence, the relationships that are key to estimating accurate trade-offs are the relative comparison of cost per mile to price and cost per mile to the new electric vehicle. Of course, in practice, more than one attribute may be used for pooling, and the parameters can affect both the intercept and the Z_i coefficients. Although this makes the estimation a more complicated projection, the intuition remains the same.

We note that the more parameters that are restricted to be the same across datasets, the more the information on relative preferences can be used to inform the linkage. This implies a tradeoff between (1) including more restrictions (and minimizing the bias from preference distortions that can infect the other estimates) and (2) including fewer restrictions (but decreasing the error from linking on less informative attributes). This requires practical judgment guided by past research, theory, and empirical insights.

DATA AND SETTING

Our application is to single-cup Greek yogurt in a leading grocery retailer in 2011. Greek yogurt sales grew from 3% of all yogurt unit sales in 2008 to 18% in 2012. The growth leading up to 2011 was largely fueled by the entry of Chobani, the leading national brand. The successful growth of Chobani led the retailer to launch its own private label Greek yogurt product. We study the period after Chobani's entry (January 2011) to after the retailer launched their private brand in this category (February 6 to October 15 2011).

The retailer had a long-running and successful private label program in place in other categories. At the planning stage for its private label launch in Greek yogurt, the retailer was debating what products to offer in the category, including a potential "high-end" offering that would include additional nutrients and/or be organic. Preferences for these attributes, along with the private brand itself, were not yet observable in the market. To support managerial decisions related to product selection and the launch (e.g., pricing), the retailer undertook a conjoint analysis that involved sending online surveys to members of their loyalty card club in May 2011. Below we describe the conjoint design and dataset followed by the related loyalty card data. Figure 1 shows the relationship between the samples and datasets.

Conjoint Data

The conjoint survey was launched in May 2011, with over 2200 invited respondents (see Figure 2). The customers invited to participate were required to have at least one Greek yogurt purchase in the past 6 months. Of these invited participants, 510 respondents completed the full survey within a week of its launch. Participants were offered the chance to win a $100 retailer gift card upon completion.

The survey was designed as a choice-based conjoint questionnaire fielded via Qualtrics. Respondents were initially asked their propensity to consume Greek yogurt, what attracts them to the category, and how they use it (cooking/snacking). Following these questions were some generic instructions about the conjoint tasks including, "Now you will be asked to select between multiple options of Greek yogurt. For each of these choices, assume your preferred flavor(s) are available within each of the options presented." These instructions were intended to avoid including the large variety of flavor options. Seven different sets of 12 tasks were designed using Sawtooth Software's design module and were assigned randomly to respondents. Each task had four profiles of Greek yogurt and a "None-Of-These" option. Web Appendix figure 12 includes an example question.

The profiles varied attributes such as brand, fat content, plain/fruit flavors, organic/all natural content, healthy attributes (probiotic/vitamins/omega-3/fiber), packaging styles and price. The full set of attributes is listed in Web Appendix Table 14 along with the set of attributes in the marketplace. We characterize these based on the confounded, new-to-market, RP-only, and common designations defined in section 2. In the actual marketplace, consumers could choose over brand, fat content, fruit/plain, cup styles, and price. Some brands only carried organic or all natural options. For example, Oikos was the only organic brand and it carried only organic products. Hence, the preference for these attributes was confounded with brand preferences in actual choices, i.e., the confounded attributes. The new-to-market attributes (NTMA) include healthy ingredients (probiotic/vitamins/omega-3/fiber) as well as a new attribute level for the private label brand and new packaging styles. The conjoint questionnaire, therefore, elicits preferences for these confounded and NTMA attributes which cannot be obtained from revealed preference data. The only attribute level in the actual data that was not included in the conjoint analysis was the Brown Cow brand value.

Loyalty Card Data

The loyalty card data consists of actual purchases for a random sample of 4,288 customers and 510 survey sample participants between February and October 2011 across 79 stores. The study period was marked by expansion in Greek yogurt share (of total yogurt sales), and multiple brand entries and exits. In particular, Chobani and Dannon launched in the retailer's stores in January 2011, just prior to our data window; Brown Cow exited Greek yogurt in July 2011, and the private label Greek yogurt was introduced in September 2011.

In addition to purchase and related choice-specific variables, we use the loyalty card data to construct three measures of past category usage - days since last Greek yogurt purchase (Recency), number of store visits with Greek yogurt purchase in past 90 days (Frequency), average expenditure in Greek yogurt given yogurt category purchase in past 90 days (Monetary value). These RFM measures are time-invariant in the estimation, and calculated at the start of the observation window. Consequently, the RP_{rs} and SP_{ss} datasets use different time periods to construct the RFM variables. We also include two pure demographic variables - whether the household annual income is below $\$75,000$, and whether the consumer belongs to a small family (with less than 3 members).

We split the total February-October 2011 period into three groups: estimation period (24 weeks between February 6-July 23, 2011) before Brown Cow exit, forecast period 1 (6 weeks between July 24-Sept 3, 2011) after Brown Cow exit and before private brand entry, and forecast period 2 (6 weeks between Sept 4-Oct 15, 2011) after the private label entry. This allows us the rare opportunity to evaluate model performance in settings with and without the new-to-market attributes.

Another unique feature of our application is access to actual choice data for both a random sample of consumers (RP_{rs}) and actual choice data for the same survey sample participants that took part in the conjoint experiment (RP_{ss}). Although our model only requires the RP_{rs} and SP_{ss} data, we use the RP_{ss} data to describe the sample differences below and to evaluate the magnitude of selection and context biases in section 4.4.

Figure 2 depicts the timing of our estimation and forecast periods as well as the time series of Greek yogurt purchase shares out of total single cup yogurt unit sales for the RP_{rs} and RP_{ss} datasets.[9] Greek yogurt market shares for the RP_{rs} data increased from 16% in February to 28% by July, 2011, whereas the survey sample shares rose from 47% in February to 69% in the same period. The difference between samples reflects the fact that the survey was sent to individuals that were more likely to have bought Greek yogurt in the last three months than the overall population of chain customers.

We now examine the sample differences between the RP_{ss} and RP_{rs} data (further details are provided in the Web Appendix). Focusing on the estimation period, the revealed preference brand shares (of sold units) for the random sample (RP_{rs}) and survey sample (RP_{ss}) differ: survey sample participants are three times more likely to purchase Greek yogurt than the random sample (67.28% vs 20.14%). However, conditional on purchase, brand shares are similar across samples. The samples also differ in their demographic and usage variables, with the survey sample having higher income and higher RFM variables (as expected). In the Web Appendix, we show that the survey sample observations span the range of the RFM variables in the random sample, but that the overlap is thin for the less recent, more frequent and low monetary value individuals.

To ensure the estimation weights the information in the RP_{rs} and SP_{ss} datasets similarly, we select 510 individuals from the random sample. These individuals were selected to have at least one category purchase in the estimation and two forecast periods, which we demonstrate in the Web Appendix poses little threat to representativeness. We define a choice occasion as an instance where the consumer chooses any cup of yogurt (Greek or regular). The average choice occasions per individual for the RP_{rs} data is 56.34, for a total of $28,731$ purchase occasions.

During a single shopping trip, consumers choose between an outside option (regular yogurt) and up to 14 available single-cup Greek yogurt options. We identify the available

[9]Throughout, we treat club-pack purchases as multiple single-cup purchases.

products based on non-zero store sales from aggregate data and treat multiple single-cup or club-pack purchases within the same shopping trip as a series of independent single-cup choices. The choice options vary on dimensions such as brand, whether the yogurt is zero-fat or low-fat, is plain or fruit-flavored (including other flavors, e.g., honey), whether the brand was purchased in the previous shopping trip (state dependence), and the price (calculated as the average store-week price from aggregate data). Following Dubé et al. (2010), state dependence is calculated only for inside options, and captured via an indicator for the last brand purchased (that increments that brand's utility). We also include state dependence in the conjoint data, based on the respondent's last purchase prior to the survey, similar to Swait and Andrews (2003).

RESULTS

We divide this section into four parts. First, we present baseline results for choice models estimated separately, that is using the actual purchase (RP_{rs}) and conjoint (SP_{ss}) data independently. This initial exercise provides insight into the preference distortions that must be accounted for in our proposed data-fusion model. Second, we discuss the results of our preferred model (henceforth, CPC, for 'consumer panel conjoint') and compare it to a strong benchmark (henceforth, $BENCH$) that incorporates the innovations introduced in both Swait and Andrews (2003) and Feit et al. (2010), along with the standard scale adjustment parameter. In particular, the $BENCH$ model includes both state dependence (as suggested by Swait and Andrews (2003)) and individual-level demographics serving as observable heterogeneity (as used by Feit et al. (2010) to address sample selection bias), in addition to a constant to scale the error variance between the SP_{ss} and RP_{rs} contexts (to account for predictability differences). Third, we compare each model's predictive validity across the estimation and holdout datasets, and over the three different time periods (recall Figure 2). Finally, we explore in more detail the distinct roles of selection and contextual biases and how our approach addresses each. This last exercise leverages all three datasets, the random sample (RP_{rs}) and survey sample (RP_{ss}) purchase data, as well as the survey sample conjoint data (SP_{ss}) to assess the magnitude of the two forms of bias. In this exercise, we also empirically examine the impact of including the demographic and usage variables.

Separate Sample Estimation

To begin, we estimate using the RP_{rs} and SP_{ss} data separately following equations (1), (4), (8), and (9). The results are displayed in Table 1. We present estimates corresponding to the preferences of the average individual (the intercept-term in the Z matrix), Δ_0, and the standard deviations for the unobserved heterogeneity, σ. The full set of mean coefficients, Δ and the covariance matrix Σ, are presented in Web Appendix Tables 15 and 16. Rather than interpreting coefficients one at a time, we focus on identifying potential distortions in the Δ_0 and σ parameters as a whole.

To analyze potential preference distortions, the two panels in Figure 3 provide scatter plots of the mean and standard deviation parameters, respectively, for the common attributes, comparing the SP_{ss} and RP_{rs} models. If the parameters represent the same relative trade-offs, then points far from a line passing through zero indicate preference distortions (Swait and Louviere, 1993). As a visual aid, we include a scaling line based on the posterior mean for a single scaling λ (see the $BENCH$ model estimates below). Apparent from the first panel of figure 3 are three attributes with mean parameters that are far from this line–the coefficient on a dummy applied to all inside goods, the price sensitivity parameter, and the state dependence coefficient. Although Fage and Chobani also appear somewhat distant, we note that strong inter-brand correlations in the heterogeneity covariance matrix make addressing these means more complicated, and, as a result, we present results from a parsimonious model that does not incorporate shifters for these means. Using a similar visual inspection, in the second panel of figure 3, two attributes have variance values far away from the line: price sensitivity and Fage. We now interpret these preference distortions and one additional distortion in the conjoint estimates.

First, note that the inside options in the RP_{rs} data have a large negative intercept (mean = -10.50, se = 0.81) whereas the SP_{ss} data shows the inside options are preferred to the "None-of-These" option (mean = 1.21, se = 0.42). This sign difference is impossible to correct via a single scaling parameter. Such differences could arise from either contextual or selection biases, or both. For instance, consumers may interpret the survey outside option of "None of These" (see Web Appendix Figure 12) as no yogurt, whereas in the actual purchases we define the outside option to be any other yogurt purchase. Hence, choices could have a lower probability of "None-of-These" due to the question format (or the lack of a clear role for a budget constraint). Alternatively, the selected survey sample consumers may have a stronger preferences for Greek yogurt than the random sample. In section 4.4, we explore which explanation is more likely, but for now we abstract from this finer distinction and simply note the distortion.

The next two major differences between the two sets of estimates include the parameters on price and state dependence, which reflect magnitude differences. First, price sensitivity is significantly lower in the conjoint data (RP_{rs}: mean = -15.02, se = 1.32; SP_{ss}: mean = -3.29, se = 0.32). This is consistent with results from Horsky and Nelson (1992), who find that consumers attend more carefully to price when faced with actual choices rather than conjoint tasks. Second, state dependence plays a bigger role in the conjoint survey (mean = 3.17, se = 0.25) than in the RP_{rs} data (mean = 1.09, se = 0.33), especially relative to price. Since the state dependence dummy is triggered only for the inside options, the lower state dependence parameter indicates higher substitution with the outside good in actual purchases as compared to the survey choices.

Additionally, we identify one other mean distortion related to the fruit/flavor attribute, which is not immediately apparent in figure 3. Recall, the conjoint survey asked consumers to assume their "favorite flavor was available" when evaluating their preference for plain vs. fruit options. This aggregation in the question is potentially problematic as it might artificially reduce the preference for flavor variety. To evaluate this possibility, we examine the relative trade-offs of fruit versus other attributes. We illustrate with the comparison to the zero-fat attribute. While fruit options are more than 1.5 times preferred compared to zero-fat options in the RP_{rs} data, the preference ordering is reversed in the conjoint survey. Thus, as one might expect from the question's forced aggregation, the fruit preference is greatly understated in the conjoint preferences. Such a drastic relative preference reversal could clearly lead to distortions.

Finally, we consider the distortions in both consumer heterogeneity for price sensitivity and preference for Fage. Focusing first on the latter, the Fage taste parameter has much higher variance in the actual purchase setting (mean = 17.18, se = 2.18), corresponding to about 5 times the variance in the conjoint survey (mean = 3.83, se = 0.52). Again, these differences could arise from both contextual and selection biases. Because the survey respondents all bought Greek Yogurt in the recent past, they might have a more consistently moderate opinion of it, as compared to the more extreme preferences (positive or negative) present in the purchase data. Similarly, price sensitivities also vary around five times more in the RP_{rs} than the survey setting, indicating the presence of extreme outliers.

These documented distortions inform our modeling choices regarding which attributes to include in the mean- and variance-shift adjustment set. Based on the above analysis, we allow for additive shifters to the collection of inside goods, state dependence and fruit flavor parameters, multiplicative variance shifters for Fage, and both sets of shifters for price sensitivity in our proposed model. These shifters correspond to the attributes revealed to have the most critical distortions. As noted in the model section, the modeling choice for how many and which attributes to give shifters balances the desire to correct problematic differences between the contexts (or samples) with the need to provide a basis upon which to pool the datasets in order to forecast attributes not yet observable in the marketplace. We take a relatively parsimonious stance in our application, yet, as we show below, even including just these four mean and two variance shifters allows us to better capture the trade-offs in both datasets and improve forecasts both within and outside the training sample.

Finally, in both settings, the inside options have an intercept, and all the brand estimates represent deviations from it, with Dannon being the excluded brand. However, it should be noted that the brand intercepts in the RP_{rs} and SP_{ss} standalone estimations should be interpreted differently. In the RP_{rs} standalone estimation, attributes such as organic/all natural/rBST-free are prefectly correlated with the brand intercepts. Hence, the brand intercepts in this estimation also subsume the preferences for these attributes. These confounded attributes are incorporated in the SP_{ss} parameters in figure 3.

Revealed Preference-Stated Preference Matching

We now consider our preferred model, which integrates both the revealed preference and stated preference data across the RP_{rs} and SP_{ss} samples. Our proposed model (CPC) from equation (5) uses a single multiplicative scaling constant λ and mean shifters for the inside good, fruit flavor, price sensitivity, and state dependence, as well as variance shifters for Fage and price sensitivity heterogeneity. We note that, in our application, we use a single multiplicative scaling constant λ and additive shifters μ only for the mean preferences (intercept term) in Z and set additive shifters $\mu = 0$ for demographic/past usage variables. Similarly, we use diagonal variance shifters in the scaling matrix Φ and set any off-diagonal covariance shifters to 0.[10] We first compare our model with the strong benchmark model ($BENCH$) that is nested in our model. Recall that the $BENCH$ model has a single scaling parameter, but no other shifters. As before, we report in table 2 the mean preferences Δ_0 and unobserved heterogeneity standard deviations σ, along with the scaling constants λ, μ and Φ. Detailed results are available in Web Appendix Tables 17 and 18. On comparison, CPC fits the data much better than $BENCH$ in terms of total log marginal likelihood. Further, we note that CPC performs better in both the SP_{ss} and the RP_{rs} data. This improved performance stems from the greater flexibility of the CPC framework.

[10] We thank an anonymous reviewer who noted that the difference in outside options for the two contexts would be handled by a nested logit, where consumers first decide whether to buy Greek yogurt, and then choose between the Greek yogurt options. In this case, both SP_{ss} and RP_{rs} datasets would have different nest coefficients, indicating differences in within-nest product substitutability. We estimated a nested-logit version of the CPC model, where we allowed for nest coefficients $\rho^{SP_{ss}}$ and $\rho^{RP_{rs}}$, in addition to the full set of mean and variance shifters mentioned above. The results of this nested model are similar to the simpler version that we present. We report only the simpler version for two reasons. First, we find the nested logit appears to overfit the data: its out-of-sample forecasts are worse than the multinomial logit. Second, with an unconstrained nest coefficient, ρ, the parameter is greater than 1, a value that has limited interpretability under standard nested logit interpretations. If constrained to be within the interpretable interval [0, 1], the coefficient is estimated to be 1, a value implying no within-nest correlation (no IIA violation). These results suggest that our multinomial logit approach already captures the context differences sufficiently.

Since the parameters reported in table 2 are in SP_{ss} scale, they can be directly compared with the standalone SP_{ss} results in table 1. On the whole, the CPC estimates are closer to the standalone SP_{ss} estimates than are the $BENCH$ estimates. For instance, the CPC estimate for the inside good is 0.64 (se = 0.42), while the corresponding $BENCH$ estimate is -3.27 (se = 0.39), relative to the SP_{ss} estimate of 1.21 (se = 0.42). Similarly, the CPC variance for price sensitivity (mean = 3.58, se = 0.33) is more consistent with the standalone SP_{ss} estimates (mean = 3.08, se = 0.34), compared to the corresponding $BENCH$ estimate (mean = 5.97, se = 0.35). This closer relationship arises because the distribution shifters allow more degrees of freedom in fitting the SP_{ss} data, rather than restricting these parameters to match across the two datasets. Figures 4 and 7 compare the $BENCH$ and CPC mean and standard deviation estimates to the standalone SP_{ss} ones. We can see in both plots that the CPC estimates are much closer to the 45-degree line, signifying congruency with the underlying SP_{ss} distribution.

The more informative comparison, however, is on the RP_{rs}-scale, as this is the scale used to predict actual (future) choices. Converting to the RP_{rs}-scale, the CPC parameters again perform better than those of the $BENCH$ model. Because we need to rescale these parameters, we calculate the adjusted parameter value for each posterior sample. For instance, if one sample sat at the posterior mean of all the marginals, the estimate for the mean inside good preference in the RP_{rs} scale for CPC is $(0.64-8.74)*1.33 = -10.77$, much closer to the standalone RP_{rs} estimate of -10.50. In comparison, the corresponding $BENCH$ estimate is $-3.27 * 1.69 = -5.53$. Similarly, the RP_{rs} price-sensitivity (mean = -15.02, se = 1.32) is closer to the CPC estimate (mean = -10.40, se = 0.81) than the $BENCH$ estimate (mean = -6.72, se = 0.53). Figure 5 depicts scatterplots of mean estimates for the full set of common parameters for the $BENCH$ and CPC models, respectively. The CPC model parameters generally track the diagonal more closely, although this is largely driven by the price sensitivity and inside good parameters. Similarly, the CPC variance estimates lie closer to the diagonal in Figure 6.

To further illustrate, Figures 8 and 9 present marginal densities for the distribution of individual-level posterior means for the coefficients on Inside Good, Fruit, Price, and

State Dependence. The figures depict the densities for the full CPC model, as well as for models estimated separately on the RP_{rs} and SP_{ss} data. The densities in Figure 8 show that the model can closely match the distribution of preferences in the RP_{rs} data using only a small set of shifters. For example, in the left panel, while the SP_{ss} data alone result in an Inside Good parameter distribution that is much more positive than that from the RP_{rs} data alone, the CPC model that incorporates both datasets is able to recover closely the RP_{rs} density, including the location and size of the central mode and the location and size of the secondary lump in the distribution. Figure 9 reveals that, although our model adjustments improve the match to the RP_{rs} data, the match is not exact. The CPC parameter distributions for the Price and State Dependence parameters shift toward the RP_{rs} data, but this shift is not complete. Nonetheless, important features of the RP_{rs} data like secondary modes and skewness are picked up, albeit not perfectly. This is reflective of our parsimonious use of shifters.

Thus, while the CPC model matches the preferences revealed by the RP_{rs} data more closely and more accurately than the $BENCH$ model, it is still not perfect. The imperfect match to the RP_{rs} data can be thought of as a cost of integrating the conjoint data and incorporating the NTMA and confounded attributes into novel predictions, at the expense of sacrificing some fit for the standalone actual choice data. As mentioned, we take a relatively parsimonious stance on the number of shifters to incorporate, but conceptually, one can include many more to improve the match on common attributes. Such increased flexibility, however, could weaken the foundation linking the datasets.

Predictive Validity

In this section, we show that mapping the tradeoffs more accurately also yields better predictions. We include validation on the estimation (RP_{rs}) sample as well as the remaining random sample individuals (which form the holdout sample) for three different periods depicted in Figure 2, namely the estimation period and two forecast periods.

Table 3 shows the model fit for the different samples and time periods for each model. For the RP_{rs} individuals, we directly use their posterior draws ($R = 3200$) to generate log marginal likelihoods (as in equation 6) for each draw r and purchase occasion t for individual i. To evaluate model fit for the holdout sample, we use the log posterior predictive likelihood of an observed choice j in dataset D using the parameter set Θ -

$$
\begin{aligned}
(12) \qquad LPPL_{it}^{D} &= \log(\int_{\theta_i} \mathcal{L}(y_{ijt}^{D}|X_{ijt}^{D}, \theta_i)\mathcal{L}(\theta_i|\Theta)d\theta_i) \\
&\sim \log(\sum_{r=1}^{R} \mathcal{L}(y_{ijt}^{D}|X_{ijt}^{D}, \theta_i^{r})) \\
LPPL^{D} &= \sum_{i \in D} \sum_{i=1}^{T_i^D} LPPL_{it}^{D}
\end{aligned}
$$

The predictive log-likelihoods are calculated using $R = 10000$ draws following equation (11)[11]. Note that the standalone SP_{ss} model cannot predict in the estimation period, since the conjoint survey did not have an attribute level for the Brown Cow brand. Similarly, the standalone RP_{rs} model cannot predict for forecast period 2, as there is no estimate for the private label brand preference.

We first focus on the periods when the CPC can predict on the RP_{rs} data and compare its performance to the standalone RP_{rs} model, as this is the (gold) standard choice model for recovering revealed preferences (i.e. actual choices used to predict actual choices). By construction, in the estimation period and considering within sample fit, the RP_{rs} data must perform best (as it is not required to fit the conjoint data too). Notably, both the $BENCH$ and CPC model perform similarly to the RP_{rs} model within sample, whereas the CPC model performs better in the hold-out sample, while the $BENCH$ model performs considerably worse.

After Brown Cow exits (forecast period 1), the CPC model again predicts better than the RP_{rs} model in both within and holdout sample fit. Again, the CPC and RP_{rs} models outperform the $BENCH$ model. But in the period with Brown Cow absent, when the SP_{ss} model can predict actual choices, we can also see that, as one might expect, the conjoint alone predicts worse than either the $BENCH$ or CPC model, due to its

[11]To be precise, we randomly sample 1000 of the 3200 draws of the aggregate parameters in Θ (and repeat each 10 times), along with 10000 random draws from the standard normal distribution, and combine these to get 10000 draws of θ_i^r.

preference distortion and selection bias issues[12].

We next consider forecast period 2, after the private label brand was launched. This is the critical forecast period for evaluating the model's ability to guide managerial decision-making. In this period, the CPC model has the best predictive likelihood both within sample and in the holdout, outperforming both the choice-based conjoint model and the $BENCH$ model. Overall, the predictive likelihoods suggest that the CPC model performs similar to the RP_{rs}-only model when that model can predict and performs the best outside of that setting.

Table 4 presents the root mean squared error (RMSE) calculated as the difference between the percentage of individual product choices in the sample period and the forecasted shares for the same period. In this table, the aggregation of shares is at the individual level, with the average taken over individuals. Similar to the predictive likelihoods, the conjoint model performs worst, and here we can see that that leads to approximately twice the error as the other models. Thus, incorporating the actual choice data leads to meaningful improvements in prediction. This finding is consistent with past findings regarding data fusion (e.g., Swait and Andrews 2003). For the estimation sample and period, the RMSE for all three models is very low, since we are predicting error in individuals' product shares using their posterior draws. For the holdout sample, the CPC model slightly outperforms the RP_{rs} model for both the estimation period and forecast period 1. Thus again, the CPC model appears able to reproduce the actual trade-offs with a similar accuracy to established revealed preference methods. In contrast, the $BENCH$ model has more than 40% more error, suggesting our model performs demonstrably better. Consistent with the added difficulty of more distant forecasts, the error rates rise slightly in forecast period 1 as compared to the estimation period, and then again in forecast period 2. However, CPC still performs better than both the conjoint and the $BENCH$ models, achieving an RMSE of around 0.43. For RMSE on individual purchase shares, the CPC model performs best on the critical prediction tasks and can reproduce

[12]We note that SP_{ss} market shares can be "adjusted" following Manski and Lerman (1977), Orme and Johnson (2006) and Gilbride et al. (2008). However, we require target market shares to make these corrections, which in our context would require prior knowledge of the new product market share before that product is introduced.

closely the RP_{rs} model on forecasts where new to market attributes are not required.

We next consider the predictions needed for the store-level pricing exercise we conduct in section 5, i.e., store-level share predictions. These prediction RMSE are calculated analogously to Table 4, but here the aggregation is first at the store (instead of individual) level and then averaged across stores. Table 5 presents the results, which follow the same pattern as the individual-level RMSE results. The model differences are more stark, and we compare the store-level and individual-level results. First, for the RP_{rs} and CPC models, error rates decrease sharply by 50-60% across all samples. In comparison, the $BENCH$ error rates decrease by 40-50% for the estimation sample in forecast periods 1 and 2. On the other hand, they decrease by only 25% for the holdout sample individuals across all periods. These decreasing errors rates can be seen as arising from non-systematic errors in the CPC and RP_{rs} predictions. Whereas in the $BENCH$ and conjoint-only models, the error rates do not decrease as sharply, suggesting more bias than non-systematic error. This bias is more pronounced for out-of-sample predictions, where we use the aggregate estimates to compute average shares. The results for the hold-out sample in forecast period 2, on which the managerial decisions rely most heavily, are particularly striking: the CPC model generates less than half the level of error of the strong benchmark model, $BENCH$, and less than one fourth the error of the conjoint-only model. This is strong evidence for the predictive benefits of the CPC model, especially for informing managerial decisions related to store-level pricing.

Finally, we analyze how well each model is able to predict the actual revenue received by the firm. For this analysis, we employ the actual prices set by the retailer and use the model to simulate market shares. We compare these predicted revenues to the actual revenues. This prediction validation reflects the size of the financial risk involved in the model. Table 6 presents the relative distance from actual revenues for each of the six predictive tasks and models. The proposed CPC model achieves the closest revenue predictions–around 5-6% within sample and 9-10% in the holdouts. This performance is far superior to the comparison set. For example, in the holdout samples, the distances are 40% for the BENCH model and 70-80% for the conjoint.

To summarize, our predictive validations indicate that the proposed CPC model far outperforms the existing models in terms of predictive likelihoods, RMSE at the individual and store level, and predicted revenues. The predictions from conjoint analysis benefit greatly from the proposed model that fuses conjoint data with individual-level purchase data while also adjusting for potential bias in the conjoint estimates. Further, as noted above, our approach to selecting the set of shifters did not leverage a cross-validation based selection procedure. Such a procedure could allow even greater gains. The gains we demonstrate in this section arise from the use of a set of shifters to accommodate potential selection and contextual biases. In the next section, we evaluate the relative magnitude of these biases.

Exploring The Roles Of Selection And Contextual Biases

A key strength of our empirical context is that we observe actual purchases for both the survey and random samples of customers. This information allows a unique opportunity to quantify the extent of contextual versus selection biases and the degree to which observable RFM variables can correct for the selection component. The significance of the multiplicative scaling constant λ and the distribution shifters μ and Φ in our estimation and forecasting already suggests that there are some distortions in the preferences obtained from the conjoint survey as compared to those from actual purchases. We now explore whether these distortions arise from differences in the two choice contexts (contextual biases), or due to the differences in the consumer types that comprise the RP_{rs} and SP_{ss} datasets (selection biases).

For this investigation, we extend our model formulation by including a third dataset, RP_{ss}. We use the data for before the release of the conjoint survey (13 weeks from Feb 6-May 19, 2011), to guard against the possibility that preferences change systematically post-survey. Since survey sample individuals are, on average, more frequent shoppers, using only 13 weeks for the RP_{ss} data produces an average number of choice occasions per individual that is similar to the RP_{rs} data (56.34 vs. 58.81). In total, the RP_{ss} estimation sample has $29,640$ purchase occasions.

Since the RP_{ss} and SP_{ss} data are the actual and conjoint responses, respectively, for the *exact same* individuals, preference distortions in this data reflect contextual bias alone, as there is no selection here (though this sample is a selected subset of the full population). Thus, the distribution shifters for distortions between SP_{ss}-RP_{ss} reflect pure contextual bias in this subpopulation. As such, by comparing the SP_{ss}-RP_{ss} shifters to those for SP_{ss}-RP_{rs}, we obtain an estimate of the size of the selection bias compared to the contextual bias. If there is no selection bias on unobservables, there should be no difference between the SP_{ss}-RP_{rs} and SP_{ss}-RP_{ss} shifters.

Extending the formulation of Equation (5), we re-estimate our model with the three datasets $SP_{ss}, RP_{ss}, RP_{rs}$ to obtain separate survey sample scaling and shift parameters $\mu^{RP_{ss}}$, $\Phi^{RP_{ss}}$ and $\lambda^{RP_{ss}}$ between RP_{ss} and SP_{ss}, and $\mu^{RP_{rs}}$, $\Phi^{RP_{rs}}$ and $\lambda^{RP_{rs}}$ between RP_{rs} and SP_{ss} datasets. Since $\mu^{RP_{ss}}$, $\Phi^{RP_{ss}}$ and $\lambda^{RP_{ss}}$ are estimated between the revealed preference and stated preference data for the *same set of individuals*, they represent the bias between the actual and survey *contexts*, as opposed to *(sub)populations*. Accordingly, differences between, for example, $\mu^{RP_{ss}}$ and $\mu^{RP_{rs}}$ would then reflect the amount of selection bias (after controlling for the observable RFM heterogeneity) between the random and survey samples.

The focal results of this combined analysis are shown in table 7.[13] Note that the RP_{ss} results (and SP_{ss}-RP_{rs} comparison) involves a new estimation, as we have not yet used the RP_{ss} sample in estimation. To assess the impact of different demographic controls, we present results from models where Z_i contains the demographics-only variables and where Z_i contains the full set of variables including the RFM-related ones. We first discuss the results where Z_i contains both demographics and RFM variables (which is similar to our main specification), and then discuss the differences between that model and the demographics-only case. Detailed results are included in Web Appendix Tables 19(a)-(b) and 20(a)-(b).

To start, the significance of the $\lambda^{RP_{ss}}, \mu^{RP_{ss}}$ and $\Phi^{RP_{ss}}$ estimates clearly points to the presence of contextual bias for the same set of survey respondents. We see contextual

[13]We report the results of the most probable mode in the posterior draws for both models.

bias in each of the attributes that we include as shifters. As noted earlier, the largest distortions relate to the mean shifters ($\mu^{RP_{ss}}$) for the inside good (-5.27), price sensitivity (-3.01), and state dependence (-1.69), and variance shifters $\Phi^{RP_{ss}}$ for price sensitivity (3.12). This is strong evidence that the preference distortions documented earlier are not simply about who is selected into the survey sample.

Moreover, for the Dem & RFM model, the SP_{ss}-RP_{ss} and SP_{ss}-RP_{rs} shifters are significantly different from each other only in certain dimensions. The additive shifters for price sensitivity $\mu^{RP_{ss}}$ (mean = -3.01, se = 0.53) and $\mu^{RP_{rs}}$ (mean = -5.50, se = 0.68) have the largest difference (mean = -2.49, se = 0.68, p-value for t-test < 0.01), followed by that for the inside good (mean = -1.98, se = 0.42, p-value < 0.01). The multiplicative scaling constants $\lambda^{RP_{ss}}$ and $\lambda^{RP_{rs}}$ also have a significant difference (mean = 0.15, se = 0.05, p-value < 0.05). This indicates that there is significant selection on unobservables even after accounting for the RFM variables. However, in each case, the size of the selection effect is relatively small compared to the total bias. For price sensitivity, the selection-related part is -2.49 out of a total -5.50 or 45% of the effect size. The effect sizes for the others are all less than 30%. Thus, after controlling for the Demographics and RFM observable heterogeneity, a relatively low level of selection bias persists.[14]

The model results discussed so far include both the RFM and demographics variables. Comparing the shifters for this full set of Z_i's to the shifters for a model with only demographics can inform the kind of selection that the RFM variables are able to capture. The second set of results present the demographics-only model and the last column compares the two. We find that including RFM variables does not change the selection-related differences in the shifters. The magnitude of the SP_{ss}-RP_{ss} and SP_{ss}-RP_{rs} differences across models (with and without RFM) remain stable. This indicates that selection is predominantly along unobservable dimensions that are captured by our method. Second, on comparing the log marginal likelihoods, we see that adding in the RFM variables provides a significantly better fit for the SP_{ss} data (Bayes factor $= exp(-2164.09{+}2279.74) >> 1$),

[14]Because state dependence is captured in X_{ijt} (as suggested by Swait and Andrews (2003)), the base utility differs across consumers through their past purchases. Since past purchases are related to the selection process, including these state dependence variables may already adjust for some degree of selection.

and slightly worse fits for the RP_{ss} (Bayes factor = $exp(-18.35) << 1$) and RP_{rs} (Bayes factor = $exp(-4.05) << 1$). The total log marginal likelihood improves significantly (Bayes factor = $exp(-32784.49 + 32877.74) >> 1$) with the inclusion of RFM variables, validating their use.

To summarize, after controlling for the RFM variables, the bulk of the remaining bias is context related. In particular, less than a third of the remaining bias appears to arise from selection. We also see that RFM variables, while providing a superior model fit, do not fully correct for selection biases in our context. This suggests that simply incorporating the RFM variables in the Z_i is not enough to obtain accurate preference estimates, and that both the inclusion of the RFM variables and the distortion shifters are important for addressing the full bias.

MODEL-BASED MANAGERIAL DECISIONS

We now present an illustrative application of the CPC model to managerial decisions aimed at optimizing a new product's attributes and setting prices across locations. For the purposes of this illustration, we focus on decisions to optimize profits for the private label product only (extending this analysis to more products is conceptually straightforward, but requires knowledge of, or more assumptions related to, the costs). For the product decision, we ignore cost differences in ingredients. For the pricing problem, we use the same characteristics as the private label line the retailer ultimately launched, 0% fat yogurt products that include both fruit (e.g., blueberry) and non-fruit (e.g., plain) options and without organic or other added ingredients. The marginal cost is set at $0.40 (communications with the retailer suggested this would be a reasonable approximation). In what follows, we describe the forecasting process, objective function, and data setting, and in separate sections discuss the optimal product and store-level pricing problems.

To forecast demand, we use the aggregate parameters Θ from our estimation procedure to predict product shares. Using the predicted probabilities, we then simulate total demand for potential purchase occasions, as given by

$$Q_j(\Theta, X, p, Z) = \sum_{i=1}^{N} \sum_{t=1}^{T_i} P_{ijt}(\Theta, X, Z, p) \tag{13}$$
$$= \sum_{i=1}^{N} \sum_{t=1}^{T_i} \int_{\theta_i} P_{ijt}(y_{ijt}|X, Z, p, \theta_i)\pi(\theta_i|\Theta)d\theta_i$$

where P_{ijt} corresponds to equation (6), $\pi(\cdot)$ to equation (11), so that total predicted demand for product j, Q_j, is a function of the parameters Θ, attributes X, prices p and demographics Z. We assume a marginal cost c_{PL} for the private label and compute the expected profits from the sale of private label products as

$$\Pi_{PL}(\Theta, X, p, Z) = (p_{PL} - c_{PL})Q_{PL}(\Theta, X, p, Z) \tag{14}$$

For data, we consider the 1539 individuals from the random sample who visited at least one of the observed stores following the introduction of the private label brand (forecast period 2, see Figure 2). Following Meza and Sudhir (2010), we dropped the first four weeks after private label introduction to ensure that product roll-out, stock-outs, and limited initial product awareness do not adversely affect demand. We assume that the retailer does not change availability or prices of the other products/brands in its stores. In calculating shares, we only consider the first store visit involving yogurt category purchase for these individuals, ensuring that their level of state dependence (of previous brand purchased) is already known. All profit calculations are for this first visit by these customers. Since the same store visit may entail multiple choice occasions, we include 7957 total choices in our counterfactuals.

The manager first needs to decide which attributes to introduce in the new product line for the private label brand. To address this problem, we compare products adjusting one attribute at a time from a baseline product (low fat, rBST-free, with no additional probiotics/vitamins/omega-3/fiber content and normal single-cup packaging). In this first analysis, we do not adjust the costs based on adding potentially more expensive attributes (e.g., additional ingredients), so for these cases the profits are likely overstated.

In the three scenarios regarding packaging styles, we match Fage's policy, so that the plain flavor has the normal cup style and the fruit flavors have the special packaging, intended to isolate the extra ingredients. Table 8 shows the maximum expected profits and corresponding prices at cost level $c_{PL} = \$0.40$ for unconstrained prices.

Table 8 reveals that the expected profit for the baseline private label product at $c_{PL} = \$0.40$ is \$747.08 at an optimal price of \$0.84. Switching from low-fat to zero-fat improves the profits to \$957.55, the highest increment of any single attribute shift. This profit is achieved at a per cup price of \$0.88, implying that a \$0.04 price mark-up is acceptable for introducing the zero-fat attribute. Making the product-line all-natural (expected profits of \$798.01) is preferable to organic (\$759.47) or rBST-free (the baseline, \$747.08). Similarly, adding probiotics, omega-3 and fiber is preferable. Finally, changing the packaging style reduces the expected profits from the baseline. From Table 8, we conclude that the retailer should consider introducing a zero-fat, all-natural Greek yogurt, potentially with additional ingredients, depending on their costs. We note that we also also examined what product-price combination the SP_{ss} only model would recommend. Interestingly, we find the product combination for the SP_{ss} model matches that of the CPC model, but that the prices are unrealistically high, above \$1.40. In forecast period 2, the retailer chose to launch a similar zero-fat, rBST-free product priced in the range the CPC model suggested, which gives face validity to these product predictions.

Turning to the geographic pricing problem, we assume that the private label product is a 0% fat, rBST-free Greek yogurt with both plain and fruit options. Therefore, the only change to the individual's choice set is their prices, p_{PL}. We examine pricing under various constraints that retailers often employ. Based on communications with our focal retailer, three dominant constraints are of interest. First, brands should be line priced with all flavors and fruit varieties priced the same, which we always enforce. Second, the retailer rarely prices the private label more than \$0.10 below the comparable national brand (in the same store).[15] This constraint is also consistent with findings in the literature

[15] For the actual private label launch, which was aimed at matching Chobani's line, only 4 stores have prices above this constraint, the median price difference from Chobani is \$0.11 and the minimum other than those 4 stores is \$0.10.

(Geyskens et al. 2010; Ailawadi et al. 2008; Chintagunta et al. 2002). In practice, we find our prices always meet this constraint (so we need not impose it). The third constraint involves zone pricing. This retailer, like many others, sets prices in broad geographic zones. Our counterfactual exercise is geared toward exploring the implications of this constraint.

Although many retailers would like to exploit cross-store differences in demand conditions, they are often concerned with consumer and PR backlash over targeted pricing. If consumers cross-shop stores in the same chain and observe significant price differences across outlets, this could negatively impact the chain's reputation and threaten profits. Retailers may seek to mitigate this risk by limiting the scope for cross-shopping consumers to face different prices for the same product (across the chain's own outlets). In particular, stores that are geographically close, with more consumers having cross-shopping trips, should be constrained to have similar prices, whereas more isolated stores should have the flexibility to set different prices.

To illustrate how cross-shopping can impact pricing and profitability, we impose the following constraints: For each store, less than 10% of its cross-shopping customers should face a price difference of more than 5 cents and less than 5% of these customers should face a price difference of more than 10 cents (for the private label product). These constraints impose a regression-to-the-mean effect, where the highest-priced store within a region (or cluster of cross-shopped stores) might need to price closer to the other stores, or the lowest-priced store might need to price higher.

To implement the cross-shopping constraints, we use the actual stores visited by our random sample of consumers in forecast period 2 to estimate the extent of cross-shopping, and, as a result, the distribution of price differentials across customers. Since these cross-shopping estimates are constructed from a random sample, this measure of cross-shopping is also representative of the actual correlation of shopping trips across stores.

The results for the various pricing policies are depicted in Table 10. The first line is the profit from a uniform pricing scheme that earns a profit of $957.55. We treat this as the baseline profit for comparing the store-level pricing policies that tailor the private label price to the demand conditions of each individual store. With no cross-shopping considerations, profits increase by 1.1% to \$968.11. We can further explore this lift in profits at the store-level. Figure 10 shows the lift in profits as a percentage of the store-level profits at the optimizing uniform price of \$0.88. We find that profits at the store-level vary from 0% (stores where optimal price was \$0.88, same as uniform pricing) to 11.93%. Adding in the cross-shopping constraints, the pricing policy still achieves up to 60% of the unconstrained profit increase to13 \$962.65. Thus, even with the cross-shopping constraints, customizing prices still allows the retailer to exploit demand heterogeneity to a meaningful degree. These constrained targeted prices resemble in many respects the idea of zone pricing (Meza and Sudhir 2010; Hruschka 2007).

In the final columns of Table 10, we present results where we treat the retailer as making decisions under the SP_{ss}-only model, but the actual consumer behavior is consistent with the estimates from the CPC model. These results suggest that prices would be dramatically higher and profits as much as 45% lower under decisions based only on the conjoint data. This suggests that using conjoint alone can have significant limitations for setting such prices.

CONCLUSION

This paper introduces a new approach to forecasting sales of products with new-to-market attributes that integrates choice-based conjoint data with repeated purchase data for a dense consumer panel. We show that our model improves predictions over both standard conjoint and a strong benchmark model in a series of in-sample and hold-out predictive validity tests on actual purchases made months later, after the new product was launched. Our data also allow us to evaluate the biases that limit the predictive validity of the competing models, and we find while both selection and context biases exist, after controlling for observable heterogeneity, the contextual biases are much larger. We then apply our model to inform decisions about the optimal product and store-level prices to charge. These exercises demonstrate the potential value of the approach.

We believe our method can be applied quite broadly. Any retailer can use this approach to price new product launches in their own stores by integrating the conjoint data with loyalty card data. Because our method does not require purchases for the same individuals, brand managers can apply this to household scanner data (e.g. Nielsen or IRI). This opens the method to virtually any grocery product launch. Further, although we focus on an application were the i subscript is for individuals, one can recast our problem at the micro-segment level. In this context, our approach can be applied to launches for online retailers like Amazon or Sephora, who can obtain panels of individuals with similar characteristics. In fact, any setting where purchase histories are available for a representative sample of individuals, businesses, or micro-segments, would be ripe for this approach. Moreover, since the focus of our method is on recovering the *distribution* of preferences, our method does not require repeat purchases per individual. This further opens applications to obtaining preference distributions in settings like cars and electronics where purchase frequencies may be too low to observe repeat purchases.

This research comes with some limitations that point to potential avenues for future research. First, we illustrate our approach with a single application, and we caution against overly generalizing from a single application. However, noting that it has not been historically easy to obtain repeated actual purchase settings for predictive validation, as evidenced by the limited demonstrations in the literature, our predictive validation is encouraging evidence. Second, as is often the case for customer surveys, we were not able to use the kind of incentives that have been shown to further improve the validity of conjoint estimates (Ding et al., 2005). Future research could evaluate the degree to which such incentives reduce the preference distortions arising from context effects (e.g., Yang et al. 2018). Third, for our sample sizes, models, and available computational resources, we were limited in how precisely we could identify which preference shifters would improve the linking between actual and conjoint choices. Ideally, one would apply systematic model selection with cross-validation to empirically select the preference shifters. Future research could extend the ideas here to identify a computationally efficient way to do so. Finally, given the specific setting we face in our application, we assume that conditional on the model design, the true parameters can be recovered from actual purchases, e.g., no price endogeneity. Future work could consider settings where endogeneity is a central concern and extend the method to address this concern.

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TABLES

Attributes	RP_{rs} Data		SP_{ss} Data	
	Δ_0 (S.E.)	σ (S.E.)	Δ_0 (S.E.)	σ (S.E.)
Inside Good	**-10.50 (0.81)**	**8.12 (0.62)**	**1.21 (0.42)**	**5.98 (0.44)**
Brown Cow	**1.79 (0.84)**	**4.20 (0.47)**		
Chobani	**8.37 (0.83)**	**8.42 (0.59)**	**1.94 (0.23)**	**2.52 (0.25)**
Fage	-5.74 (4.48)	**17.18 (2.18)**	0.96 (0.58)	**3.83 (0.52)**
Oikos	-0.55 (1.90)	**10.20 (0.95)**	**1.14 (0.31)**	**3.13 (0.36)**
Private Label			**2.82 (0.52)**	**3.15 (0.49)**
Zerofat	**1.30 (0.21)**	**1.64 (0.13)**	**1.34 (0.15)**	**2.58 (0.16)**
Fruit	**2.33 (0.33)**	**2.93 (0.22)**	**0.53 (0.17)**	**3.26 (0.21)**
Organic			0.03 (0.17)	**1.30 (0.25)**
All Natural			**-0.26 (0.09)**	**0.38 (0.21)**
Probiotic			**0.21 (0.07)**	**0.23 (0.13)**
Vitamins			0.11 (0.11)	**0.56 (0.21)**
Omega3			0.03 (0.11)	**0.89 (0.19)**
Fiber			0.02 (0.12)	**1.08 (0.17)**
SBS Cup	-1.51 (3.55)	**7.79 (2.34)**	**-1.50 (0.51)**	**2.20 (0.55)**
SBS Cup Incl.			**-2.13 (0.19)**	**2.95 (0.20)**
Normal Cup Incl.Top			**-1.63 (0.50)**	**2.16 (0.46)**
Price	**-15.02 (1.32)**	**17.13 (1.10)**	**-3.29 (0.32)**	**3.08 (0.34)**
State Dep.	**1.09 (0.33)**	**2.66 (0.25)**	**3.17 (0.25)**	**2.05 (0.35)**
No. of individuals	510		510	
No. of alternatives	15		5	
No. of choice occasions	28731		6120	
Log Marginal Likelihood	-7504.05		-2168.48	

Values in bold exclude zero in the 95% credible interval of the posterior draws

Table 1: Standalone estimation of RP_{rs} and SP_{ss} data

Attributes	BENCH Estimation		CPC Estimation	
	$\Delta_0^{SP_{ss}}$ (S.E.)	$\sigma^{SP_{ss}}$ (S.E.)	$\Delta_0^{SP_{ss}}$ (S.E.)	$\sigma^{SP_{ss}}$ (S.E.)
Inside Good	**-3.27 (0.39)**	**8.26 (0.50)**	0.64 (0.42)	**5.57 (0.35)**
Brown Cow	0.31 (0.36)	**2.28 (0.35)**	0.16 (0.45)	**2.65 (0.37)**
Chobani	**3.38 (0.25)**	**3.11 (0.22)**	**3.32 (0.26)**	**3.83 (0.26)**
Fage	0.67 (0.53)	**4.87 (0.42)**	**1.28 (0.55)**	**5.00 (0.50)**
Oikos	**0.83 (0.36)**	**3.62 (0.32)**	**1.54 (0.34)**	**4.35 (0.35)**
Private Label	**2.66 (0.55)**	**4.28 (0.43)**	**3.17 (0.51)**	**4.14 (0.44)**
Zerofat	**1.17 (0.11)**	**1.95 (0.13)**	**1.38 (0.12)**	**2.12 (0.13)**
Fruit	**1.06 (0.14)**	**2.79 (0.17)**	**0.72 (0.17)**	**3.03 (0.18)**
Organic	0.06 (0.23)	**1.30 (0.28)**	0.03 (0.18)	**1.36 (0.26)**
All Natural	**-0.38 (0.13)**	**0.76 (0.18)**	-0.05 (0.11)	**0.96 (0.17)**
Probiotic	**0.34 (0.08)**	**0.19 (0.13)**	**0.19 (0.07)**	**0.22 (0.14)**
Vitamins	0.21 (0.14)	**0.56 (0.23)**	0.05 (0.11)	**0.69 (0.19)**
Omega3	0.35 (0.19)	**1.19 (0.20)**	0.00 (0.12)	**0.90 (0.18)**
Fiber	0.28 (0.18)	**1.20 (0.20)**	-0.03 (0.12)	**1.16 (0.17)**
SBS Cup	-0.79 (0.42)	**2.12 (0.35)**	**-1.29 (0.45)**	**2.28 (0.37)**
SBS Cup Incl.	**-1.55 (0.29)**	**3.04 (0.23)**	**-2.27 (0.21)**	**3.09 (0.22)**
Normal Cup Incl.Top	-0.65 (0.44)	**1.62 (0.54)**	**-1.28 (0.45)**	**1.63 (0.59)**
Price	**-3.99 (0.34)**	**5.97 (0.35)**	**-3.27 (0.33)**	**3.58 (0.33)**
State Dep.	**1.54 (0.18)**	**2.38 (0.20)**	**3.00 (0.25)**	**2.06 (0.20)**
Scale Parameter $\lambda^{RP_{rs}}$	**1.69 (0.09)**		**1.33 (0.08)**	
Mean Shifter $\mu^{RP_{rs}}$ for Inside Good			**-8.74 (0.67)**	
Mean Shifter $\mu^{RP_{rs}}$ for Fruit			**1.24 (0.31)**	
Mean Shifter $\mu^{RP_{rs}}$ for Price			**-4.56 (0.69)**	
Mean Shifter $\mu^{RP_{rs}}$ for State Dep.			**-1.83 (0.35)**	
Variance Shifter $\Phi^{RP_{rs}}$ for Fage			**1.40 (0.16)**	
Variance Shifter $\Phi^{RP_{rs}}$ for Price			**2.56 (0.21)**	
No. of RP_{rs} Choice occasions	28731		28731	
No. of SP_{ss} Choice occasions	6120		6120	
RP_{rs} Log Marginal Likelihood	-7566.81		-7561.62	
SP_{ss} Log Marginal Likelihood	-2136.84		-2110.68	
Total Log Marginal Likelihood	-9703.65		-9672.30	

Values in bold exclude zero in the 95% credible interval of the posterior draws

Table 2: Comparison of $BENCH$ and CPC Estimation

Model	Estimation Period		Forecast Period 1 After Brown Cow Exit		Forecast Period 2 After Store Label Entry	
	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.
# Indiv.	510	3622	510	2223	510	2263
# Choices	28731	134693	7717	28766	7389	28145
SP_{ss} Only	NA	NA	-19016.44	-73409.07	-19414.48	-78541.27
RP_{rs} Only	-7477.89	-110346.47	-7855.60	-22255.27	NA	NA
$BENCH$	-7566.81	-158086.64	-7879.80	-31869.03	-8296.82	-35518.43
CPC	-7561.62	-107974.15	-6617.79	-21339.17	-6627.81	-24719.78

Table 3: Comparison of predictive log-likelihoods on actual purchases for estimation and holdout samples across models and time periods

Model	Estimation Period		Forecast Period 1 After Brown Cow Exit		Forecast Period 2 After Store Label Entry	
	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.
# Indiv.	510	3622	510	2223	510	2263
# Choices	28731	134693	7717	28766	7389	28145
SP_{ss} Only	NA	NA	0.8569	0.8788	0.8810	0.8883
RP_{rs} Only	0.0324	0.3789	0.4200	0.4014	NA	NA
$BENCH$	0.0297	0.5701	0.4148	0.5781	0.5037	0.6120
CPC	0.0306	0.3710	0.3618	0.3959	0.4277	0.4320

Table 4: Comparison of RMSE in individual demand predictions versus actual purchases for estimation and holdout samples across models and time periods

Model	Estimation Period		Forecast Period 1 After Brown Cow Exit		Forecast Period 2 After Store Label Entry	
	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.
# Indiv.	510	3622	510	2223	510	2263
# Choices	28731	134693	7717	28766	7389	28145
SP_{ss} Only	NA	NA	0.7658	0.7612	0.7715	0.7625
RP_{rs} Only	0.0217	0.1261	0.2113	0.1416	NA	NA
$BENCH$	0.0213	0.4391	0.1996	0.4210	0.2706	0.4488
CPC	0.0216	0.1070	0.1641	0.1121	0.2055	0.1700

Table 5: Comparison of RMSE in store demand predictions on actual purchases for estimation and holdout samples across models and time periods

Model	Estimation Period		Forecast Period 1 After Brown Cow Exit		Forecast Period 2 After Store Label Entry	
	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.	RP_{rs} Est.	RP_{rs} Hold.
Actual Revenue ($)	19319.03	91161.09	5524.80	20949.96	5360.52	20867.06
Percent Deviations from Actual Revenue						
SP_{ss} Only	NA	NA	78.3%	81.2%	70.6%	72.1%
RP_{rs} Only	0.0%	12.0%	13.5%	14.3%	NA	NA
$BENCH$	0.1%	43.2%	8.9%	43.6%	10.5%	40.2%
CPC	0.0%	9.1%	5.4%	9.1%	5.7%	10.8%

Table 6: Percentage deviations of revenue predictions from actual revenues for estimation and holdout samples across models and time periods

Attributes	CPC Estimation with Dem.[1] & RFM		CPC Estimation with Dem.[2] Only		Diff[4] in-Diff
	Mean (S.E.)	Diff. (S.E.)[3]	Mean (S.E.)	Diff. (S.E.)[3]	
Scaling Factor $\lambda^{RP_{ss}}$	**1.22 (0.06)**	**0.15 (0.05)**	**1.32 (0.06)**	**0.16 (0.05)**	0.01 (0.08)
Scaling Factor $\lambda^{RP_{rs}}$	**1.37 (0.08)**		**1.47 (0.08)**		
$\mu^{RP_{ss}}$ for Inside Good	**-5.27 (0.49)**	**-1.98 (0.42)**	**-4.96 (0.45)**	**-1.80 (0.39)**	0.18 (0.57)
$\mu^{RP_{rs}}$ for Inside Good	**-7.25 (0.56)**		**-6.76 (0.53)**		
$\mu^{RP_{ss}}$ for Fruit	**0.72 (0.22)**	0.23 (0.24)	**0.65 (0.20)**	0.21 (0.21)	-0.02 (0.32)
$\mu^{RP_{rs}}$ for Fruit	**0.95 (0.26)**		**0.86 (0.24)**		
$\mu^{RP_{ss}}$ for Price	**-3.01 (0.53)**	**-2.49 (0.68)**	**-2.80 (0.50)**	**-2.44 (0.65)**	0.05 (0.94)
$\mu^{RP_{rs}}$ for Price	**-5.50 (0.68)**		**-5.24 (0.62)**		
$\mu^{RP_{ss}}$ for State Dep.	**-1.69 (0.26)**	0.06 (0.18)	**-1.69 (0.23)**	0.01 (0.17)	-0.05 (0.25)
$\mu^{RP_{rs}}$ for State Dep.	**-1.63 (0.29)**		**-1.68 (0.26)**		
$\Phi^{RP_{ss}}$ for Fage	**1.76 (0.22)**	-0.15 (0.12)	**1.85 (0.29)**	-0.14 (0.12)	-0.01 (0.17)
$\Phi^{RP_{rs}}$ for Fage.	**1.61 (0.21)**		**1.71 (0.28)**		
$\Phi^{RP_{ss}}$ for Price	**3.12 (0.23)**	-0.22 (0.11)	**3.19 (0.24)**	-0.19 (0.12)	0.03 (0.16)
$\Phi^{RP_{rs}}$ for Price	**2.90 (0.23)**		**3.00 (0.24)**		
SP_{ss} Log Marg. Lik.	-2164.09		-2279.74		
RP_{ss} Log Marg. Lik.	-23099.86		-23081.51		
RP_{rs} Log Marg. Lik.	-7520.54		-7516.49		
Total Log Marg. Lik.	-32784.49		-32877.74		
# SP_{ss} Choice occasions		6120			
# RP_{ss} Choice occasions		29640			
# RP_{rs} Choice occasions		28731			

Values in bold exclude zero in the 95% credible interval of the posterior draws
[1] Results reported from 2032 HMC STAN draws converged at the predominant posterior mode
[2] Results reported from 1886 HMC STAN draws converged at the predominant posterior mode
[3] Differences in λ, μ and Φ between RP_{rs} and RP_{ss} datasets. Standard errors calculated from posterior draws of the differences.
[4] Comparing (RP_{rs}-RP_{ss}) differences across models via unpaired t-test.

Table 7: Comparing Contextual and Selection Biases

	Unconstrained Maximization	
	Expected Profit	Price ($)
Cheap Attributes:		
Baseline	$747.08	$0.84
Zero-Fat	$957.55	$0.88
Expensive Attributes:		
Organic	$759.47	$0.84
All-Natural	$798.01	$0.87
Probiotic	$791.73	$0.86
Vitamins	$743.53	$0.83
Omega-3	$767.38	$0.85
Fiber	$778.81	$0.86
SBS Cup	$647.83	$0.81
SBS Cup Inclusions	$686.21	$0.85
Normal Cup Inclusions Top	$641.55	$0.80

* Expected profits computed by integrating over 10000 random normal draws

Table 8: Expected profits for different potential products at $c_{PL} = \$0.40$

No. of stores visited	1	2	3	4
No. of individuals	2505	317	42	5

Table 9: Distribution of individuals and no. of stores visited

Pricing Strategy	Brand pricing constraints[!]	Cross-Shopping constraints	CPC Max.* Profit ($)	CPC + Maximizing Price(s) ($)	SP_{ss} Max. Profit**	SP_{ss} maximizing Price(s) ($)
Unconstrained Uniform Pricing		✓	957.55	0.88	529.65	1.49
Constrained Uniform Pricing	✓	✓	957.55	0.88	908.34	1.00
Unconstrained Store Pricing			968.18	min = 0.75, med = 0.88, max = 1.04	595.04	min = 0.98, med = 1.44 max = 1.79
Constrained Store Pricing	✓		968.18	min = 0.75, med = 0.88, max = 1.04	688.72	min = 0.98, med = 1.28 max = 1.29
Store Pricing with brand and cross-shopping constraints	✓	✓	962.65	min = 0.84, med = 0.88, max = 0.93	848.95	min = 0.99, med = 1.07, max = 1.21

! The within store brand pricing constraints are always met, so are not enforced
* Expected profits by integrating over 10000 random normal draws
+ For store-level prices, min, max and median of optimized prices across stores are reported
** SP_{ss} max profit computed with adjusted CPC parameters at SP_{ss}-model recommended maximizing prices. Note that the SP_{ss} max profits can be higher under constrained than unconstrained pricing.

Table 10: Constrained Pricing profits

FIGURES

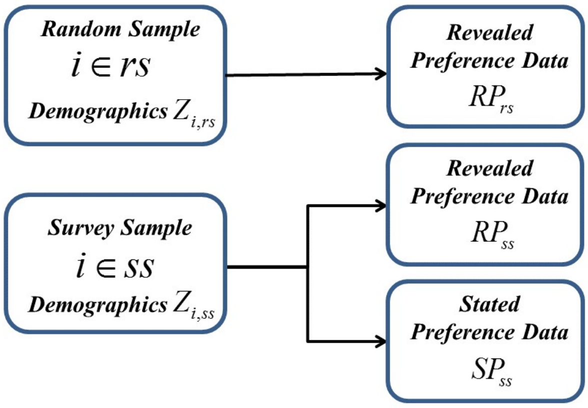

Figure 1: Relationship between Samples and Datasets

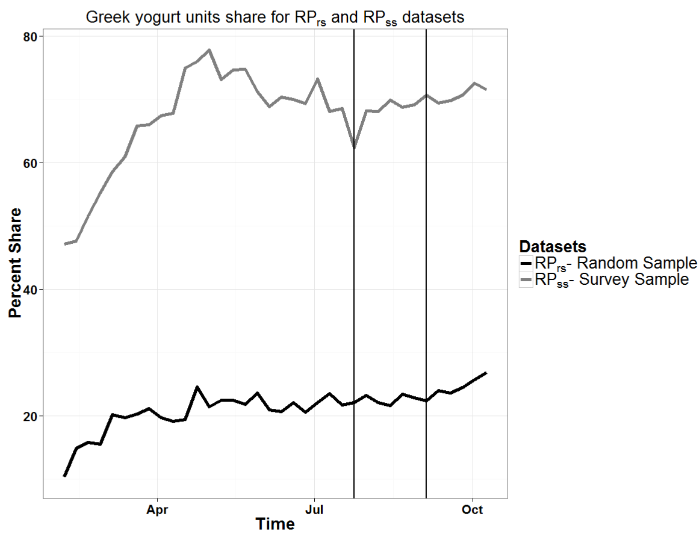

Figure 2: Evolution of Greek yogurt shares across RP_{rs} and RP_{ss} datasets

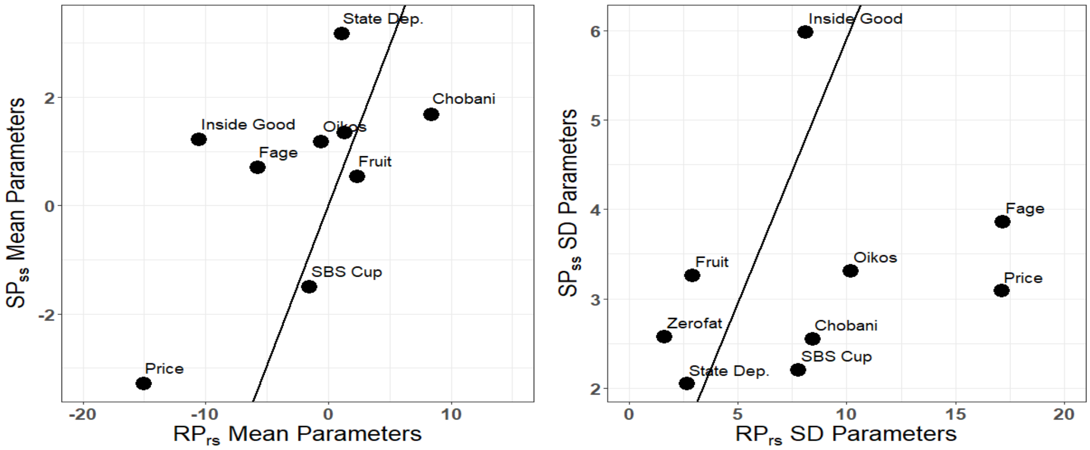

Figure 3: Comparing common Δ_0 and σ coefficients across models

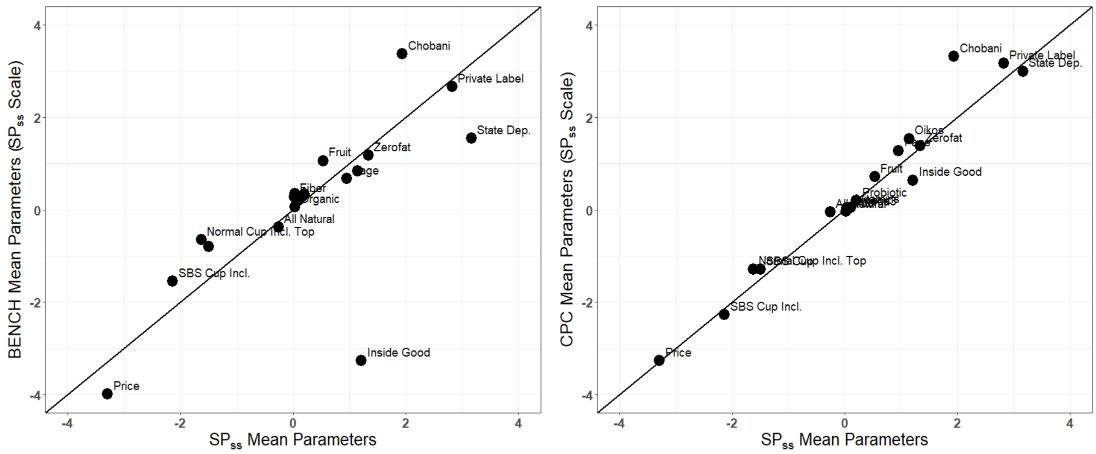

Figure 4: Comparing common Δ_0 coefficients for $BENCH$ and CPC models in the SP_{ss} scale

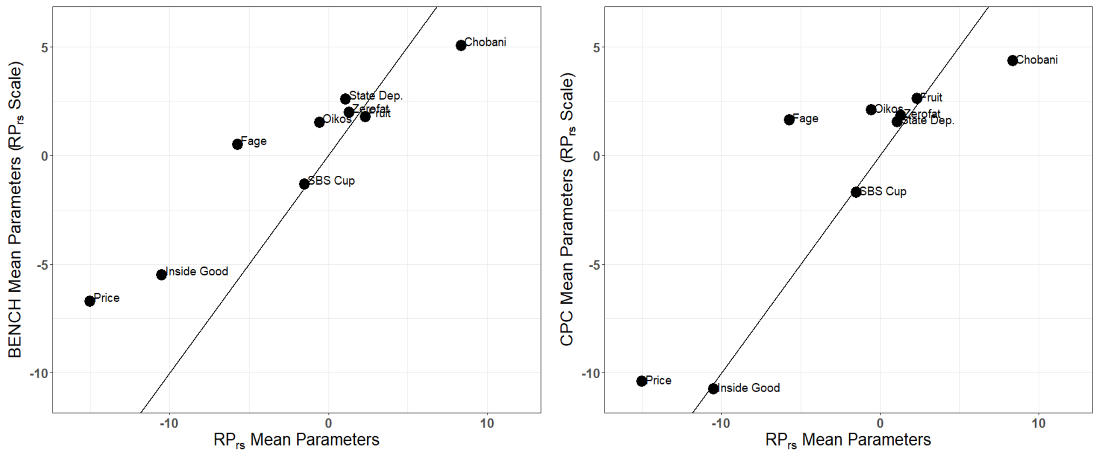

Figure 5: Comparing common Δ_0 coefficients for $BENCH$ and CPC models in the RP_{rs} scale

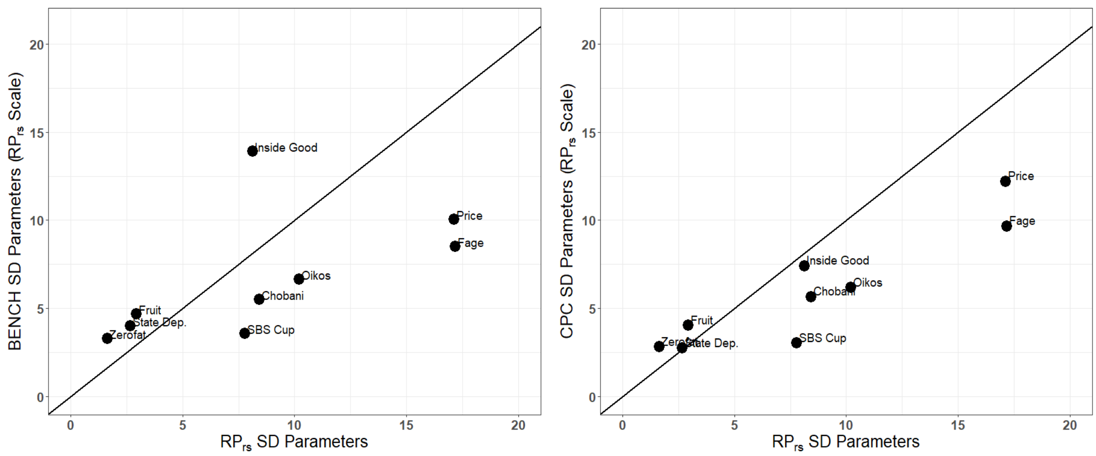

Figure 6: Comparing common σ coefficients for $BENCH$ and CPC models in the RP_{rs} scale

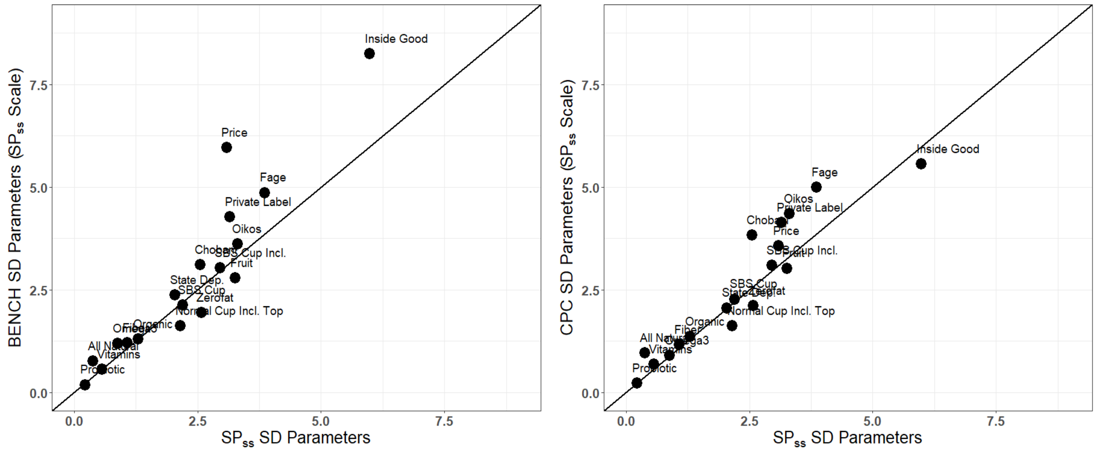

Figure 7: Comparing common σ coefficients for $BENCH$ and CPC models in the SP_{ss} scale

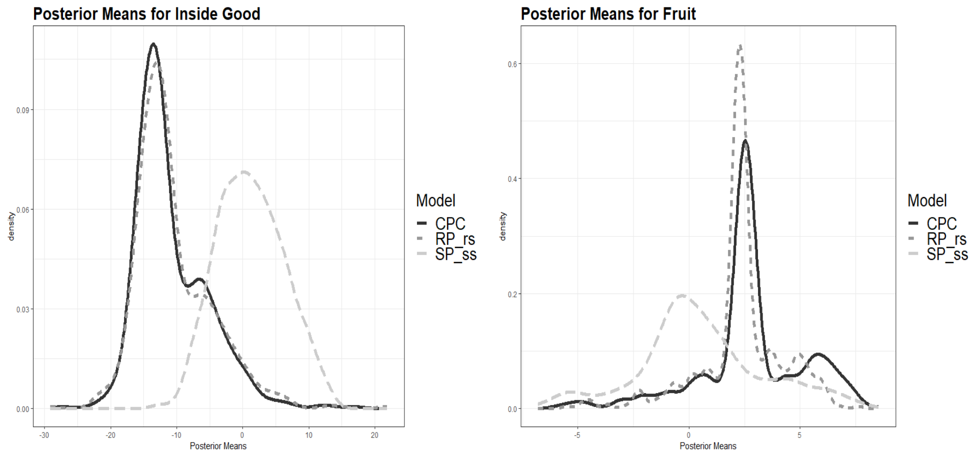

Figure 8: Comparing posterior means for Inside Good and Fruit variables across RP_{rs}, SP_{ss} and CPC Models

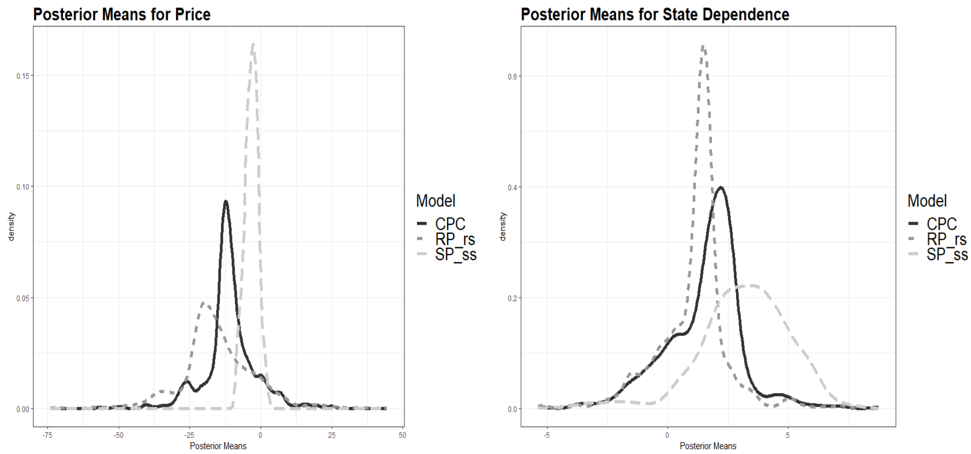

Figure 9: Comparing posterior means for Price and State Dependence variables across RP_{rs}, SP_{ss} and CPC Models

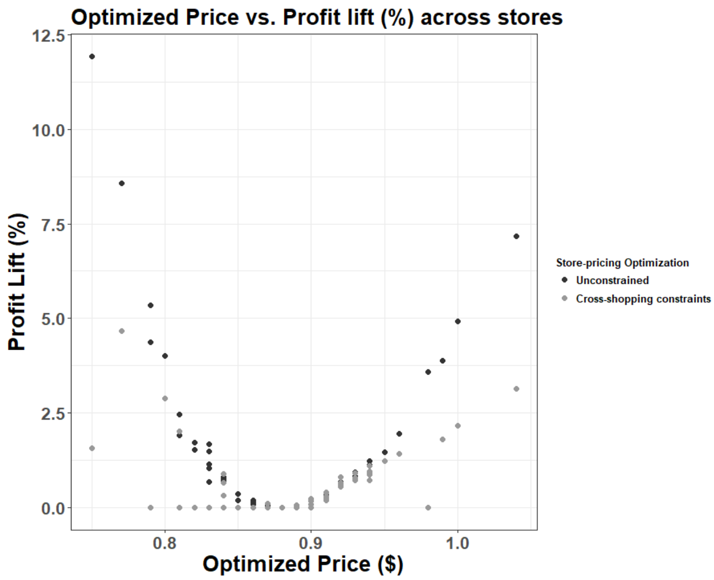

Figure 10: Store-level profit lift relative to uniform pricing for unconstrained and constrained store-pricing

WEB APPENDIX

Web Appendix A: Details Related To Data

Table 11 compares the revealed preference brand shares (of sold units) for the random sample (RP_{rs}) and survey sample (RP_{ss}) in the estimation period. During these 24 weeks, we can see that survey sample individuals are three times more likely to purchase Greek yogurt than random sample individuals (67.28% vs 20.14%). However, conditional on purchase, the survey sample individuals have similar brand shares to the random sample (cannot reject null with a Chi-Square Goodness-of-Fit Test; test-statistic = 1.50).

Table 12 contains descriptive statistics for the RFM and demographic variables for the RP_{rs} and RP_{ss} data at the start of February, 2011. By the time the conjoint survey was launched in May 2011, the RFM variables for the survey sample individuals had evolved further, as is shown in the last column. Table 12 reveals that the mild selection due to requiring at least one category purchase in the estimation and two forecast periods poses little threat to the representativeness of the sub-sample of individuals. Table 13 contains descriptive statistics for the RP_{rs} and RP_{ss} choice sets.

Figure 11 presents histograms of the RFM variables for the ss and rs samples. The data indeed have sufficient coverage across the range of values, but, as expected, the survey sample is clearly slanted toward higher RFM values. We note that this is typical in conjoint surveys where participation is usually selected on past purchases to ensure participants can meaningfully assess the desired trade-offs (Ben-Akiva et al., 2015). This thinner sample could influence the effectiveness of the use of the RFM variables.

We also include an example question and a table listing the attributes available both in the marketplace and for the conjoint survey.

Brand	Total Brand Shares (%)		Inside Good Shares (%)	
	RP_{rs}	RP_{ss}	RP_{rs}	RP_{ss}
Brown Cow	1.68	6.89	8.34	10.24
Chobani	12.62	43.15	62.66	64.13
Dannon	2.78	7.06	13.80	10.49
Fage	1.70	6.31	8.44	9.38
Oikos	1.35	3.88	6.70	5.77
Outside Good	79.86	32.72		

Table 11: Brand Shares for RP_{rs} and RP_{ss} during the estimation period

Summary Stats	Random Sample (RP_{rs})	Random Estimation Sample	Survey Sample (RP_{ss})	Survey Sample (SP_{ss})
No. of individuals	4132	510	504*	510
Period Starting	Feb 6, 2011	Feb 6, 2011	Feb 6, 2011	May 20, 2011
Mean # of days since last Greek yogurt purchase	386.6	364.6	165.7	25.9
Mean # of visits with Greek yogurt purchase in past 90 days	0.4	0.5	3.2	8.0
Mean sales in Greek yogurt per category purchase in past 90 days ($)	0.4	0.4	2.0	3.9
% Households $< 75k$	51.5	52.4	38.0	38.0
% Households ≤ 3 Members	59.2	58.8	58.3	58.3

* RP_{ss} sample sizes differs from SP_{ss} due to six individuals not visiting any store during a period.

Table 12: Demographics and RFM variables for random and survey samples

Summary Stats	Random Estimation Sample (RP_{rs})	Survey Estimation Sample (RP_{ss})
No. of individuals	510	504
No. of choice occasions	28731	29640
No. of products	15	15
% product availability	97.75	97.26
Mean (S.E.)		
Price	\$1.22 (0.41)	\$1.20 (0.42)
State dependence	0.05 (0.21)	0.17 (0.21)

Table 13: Descriptive Statistics for RP_{rs} and RP_{ss} choice sets

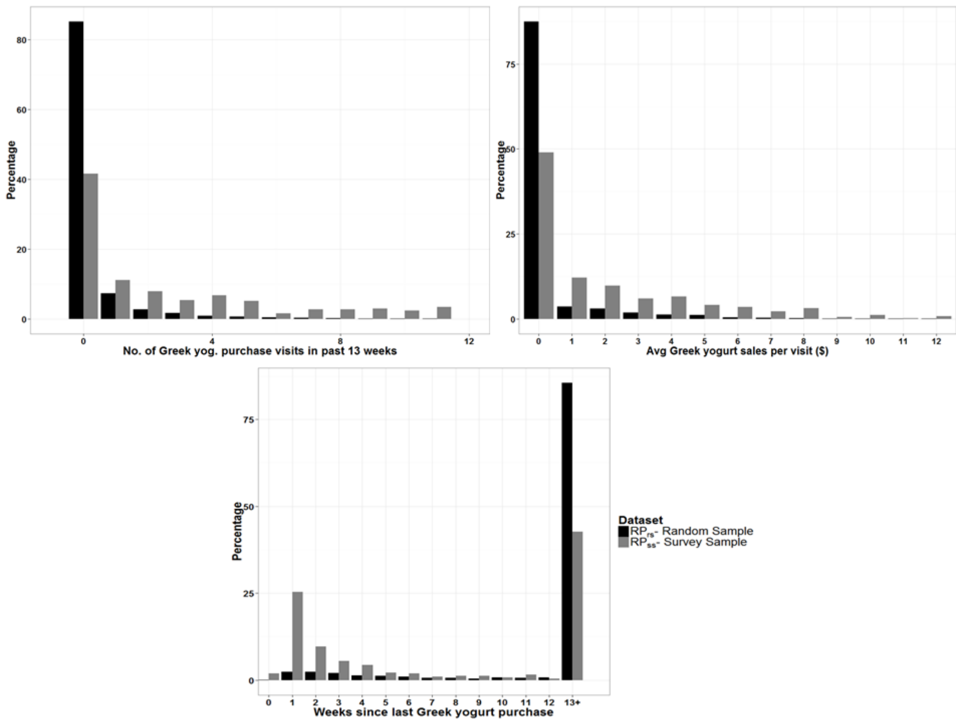

Figure 11: Comparing RFM variables across RP_{rs} and RP_{ss} datasets

Figure 12: Sample Choice-based Conjoint Question

Attributes	Marketplace Levels	Conjoint Levels	Attribute Type
Cup-Style	Normal Side-by-Side (SBS) Cup	Normal Side-by-Side (SBS) Cup	Common
		SBS Cup with Inclusions Normal Cup with Inc. on Top	NTMA
Probiotic		Yes/No	
Vitamins		Yes/No	
Fiber		Yes/No	
Omega-3		Yes/No	
Brand		Private Label	
	Brown Cow[1]		RP-Only
	Chobani[1] Dannon Fage[1] Oikos[2]	Chobani Dannon Fage Oikos	Common
0% fat content	Yes/No	Yes/No	
Flavor	Plain/Fruit	Plain/Fruit	
Price	Continuous	$0.89, $0.99, $1.29, $1.49, $1.79 (Treated as continuous)	
Organic Content	Organic All-Natural rBst-Free	Organic All-Natural rBst-Free	Confounded

[1] Brand coefficient represents Brand + All Natural
[2] Brand coefficient represents Brand + Organic

Table 14: Comparison of characteristics between Marketplace and Conjoint Survey

Web Appendix B: Prior And Estimation Details

In section, 2.3 we present the likelihood and mixing distribution for the model. To complete the model, we use the following prior distributions:

$$\mathrm{vec}(\Delta^{SP_{ss}}), \mu^{RP_{rs}} \sim \mathbb{N}(0, 100)$$
$$\lambda^{RP_{rs}}, \mathrm{diag}(\Phi^{RP_{rs}}), \sim \mathbb{N}(0, 100), \text{ s.t.}$$
$$\lambda^{RP_{rs}}, \mathrm{diag}(\Phi^{RP_{rs}}) \geq 0$$
$$\Sigma^{SP_{ss}} = \mathrm{diag}(\tau) L_\Omega L'_\Omega \mathrm{diag}(\tau); \quad L_\Omega \sim LKJ(2) \propto det(L_\Omega)$$

We estimate the joint posterior parameter distribution using Hybrid Monte Carlo techniques (STAN). We initialize four over-dispersed parallel chains and draw 5000 posterior simulations for each initialization point. We drop the first 1000 draws of each chain as burn-in and thin the remaining simulations to every fifth draw. To assess convergence, we compare the four chains. All parameters achieved Gelman-Rubin potential scale reduction factors below 1.1 (Brooks and Gelman, 1998) and visual inspection of trace plots comparing the log-likelihoods of the chains also indicated that the chains had converged.

Web Appendix C: Identification Details

While linking the survey and revealed preference datasets, we note that the two datasets record different number of variables with some overlap. These overlapping set of variables are called "common" variables, with cardinality K_{Common}. Further, there may be variables in both datasets that are perfectly collinear in the actual context but can be varied independently in the survey. These we call "Confounded" variables with cardinality $K_{Confounded}$. Finally, both conjoint and actual purchase data hold variables that are unique to those datasets. These are the new-to-market attributes (cardinality K_{NTMA}) for the conjoint, and the "RP-Only" attributes (cardinality $K_{RP-Only}$).

Therefore, in standalone estimations of the two datasets, we can identify $K_{Common} + K_{Confounded} + K_{NTMA}$ attributes for the conjoint data and $K_{Common} + K_{RP-Only}$ for the actual purchase data.

Turning to identification, given equations (1), (4), and (5), we can identify shifters only for the K_{Common} dimensions. This yields up to $N_z * K_{Common} + K_{Common} * (K_{Common} + 1)/2$ scaling constants (additive or multiplicative) for the common attributes between the RP_{rs} and SP_{ss} datasets. Going back to equation (5), take attribute k that is present in both RP_{rs} and SP_{ss} data. Then, for k,

$$\beta_{ik}^{RP_{rs}} = Z_{i,rs}\Delta_k^{RP_{rs}} + \nu_{i,k}^{RP_{rs}}, \quad \nu_{i,k}^{RP_{rs}} \sim \mathbb{N}(0, \Sigma_{k,k}^{RP_{rs}})$$
$$\beta_{ik}^{SP_{ss}} = Z_{i,ss}\Delta_k^{SP_{ss}} + \nu_{i,k}^{SP_{ss}}, \quad \nu_{i,k}^{SP_{ss}} \sim \mathbb{N}(0, \Sigma_{k,k}^{SP_{ss}})$$

We can therefore match the N_z parameters $\Delta_k^{RP_{rs}}, \Delta_k^{SP_{ss}}$ relating observable heterogeneity Z with attribute k. Similarly, we can match the unobserved heterogeneity variances $\Sigma_{k,k}^{RP_{rs}}, \Sigma_{k,k}^{SP_{ss}}$, as well as any correlations k has with other common attributes k'. This brings us to a total of $N_z * K_{Common} + K_{Common} * (K_{Common} + 1)/2$ separate scaling constants. To fully saturate the matching requires all scaling parameters and distribution shifters, but doing so would not allow pooling. To allow pooling, we take the approach of forcing a subset to be fixed across the two datasets.

The identification in this model assumes the typical scale and additive constant normalizations that are standard in discrete choice settings. One dataset will have its scale normalized (in our case, the actual data)[16].

Web Appendix D: Detailed Results

In this section, we report the full parameter estimates for our estimated models. These include the aggregate parameters Δ and Σ signifying the characteristics of the individual-specific estimates for each model. For simplicity, we only report the lower diagonal for the covariance matrix Σ. All models were estimated via Hybrid Monte Carlo (STAN) techniques with 4 parallel chains of 5000 draws each.

[16]Note that the distribution shifters are identified only for common parameters that exist in both datasets. For attributes that exist in only one dataset, including new-to-market attributes, mean $\mu^{RP_{rs}}$ and variance shifters $\Phi^{RP_{rs}}$ are assumed to be zero and identity matrix respectively. This requirement exists for all conjoint techniques.

Attributes	$\Delta^{SP_{ss}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. \$ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size $leq3$
Inside Good	**1.21 (0.42)**	-0.36 (0.72)	**-0.44 (0.15)**	1.18 (0.86)	1.17 (0.80)	**1.58 (0.78)**
Brown Cow						
Chobani	**1.94 (0.23)**	-0.30 (0.34)	0.11 (0.08)	-0.26 (0.43)	-0.10 (0.39)	-0.65 (0.41)
Fage	0.96 (0.58)	-0.19 (0.88)	0.24 (0.20)	-1.19 (1.15)	-0.30 (1.03)	-0.05 (1.03)
Oikos	**1.14 (0.31)**	-0.67 (0.49)	-0.02 (0.11)	0.02 (0.59)	0.47 (0.55)	-0.82 (0.56)
Private Label	**2.82 (0.52)**	-1.47 (0.80)	0.14 (0.18)	-0.99 (1.05)	0.67 (0.94)	-0.22 (0.94)
Zerofat	**1.34 (0.15)**	**0.82 (0.27)**	-0.02 (0.05)	0.49 (0.31)	0.19 (0.29)	-0.05 (0.29)
Fruit	**0.53 (0.17)**	**-1.00 (0.33)**	0.06 (0.07)	-0.30 (0.39)	0.29 (0.37)	-0.56 (0.36)
Organic	0.03 (0.17)	0.16 (0.28)	0.05 (0.06)	-0.16 (0.34)	0.13 (0.32)	0.28 (0.31)
All Natural	**-0.26 (0.09)**	**-0.46 (0.17)**	-0.01 (0.04)	-0.33 (0.20)	-0.27 (0.18)	0.10 (0.18)
Probiotic	**0.21 (0.07)**	-0.13 (0.13)	0.02 (0.03)	-0.02 (0.15)	0.04 (0.14)	0.01 (0.14)
Vitamins	0.11 (0.11)	0.14 (0.19)	0.01 (0.04)	-0.05 (0.22)	0.09 (0.21)	-0.21 (0.21)
Omega3	0.03 (0.11)	-0.30 (0.20)	0.03 (0.04)	-0.40 (0.24)	0.04 (0.22)	0.28 (0.21)
Fiber	0.02 (0.12)	-0.21 (0.20)	0.02 (0.04)	-0.06 (0.25)	0.26 (0.23)	-0.33 (0.22)
SBS Cup	**-1.50 (0.51)**	0.62 (0.76)	0.11 (0.17)	0.13 (1.00)	-0.26 (0.91)	0.59 (0.90)
SBS Cup Incl.	**-2.13 (0.19)**	-0.27 (0.32)	0.07 (0.07)	**-0.88 (0.39)**	-0.06 (0.35)	**0.72 (0.36)**
Normal Cup Incl. Top	**-1.63 (0.50)**	0.35 (0.75)	0.00 (0.17)	-0.26 (1.00)	-0.08 (0.90)	0.31 (0.90)
Price	**-3.29 (0.32)**	0.48 (0.51)	0.15 (0.11)	-0.53 (0.61)	-0.84 (0.56)	-1.06 (0.56)
State Dep.	**3.17 (0.25)**	**-1.47 (0.49)**	**0.25 (0.08)**	-0.22 (0.45)	-0.07 (0.43)	0.61 (0.43)
SP_{ss} Log Marginal Likelihood			-2150.63			

No. of SP_{ss} Choice occasions - 6120
Values in bold exclude zero in the 95% credible interval of the posterior draws
Results reported from 3200 converged HMC STAN draws

Table 15: (a) SP_{ss} Only Estimation: $\Delta^{SP_{ss}}$ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**36.00**																		
	(5.35)																		
2																			
3	-2.11		**6.42**																
	(1.52)		**(1.28)**																
4	**-7.93**		**2.45**	**14.94**															
	(2.62)		**(1.32)**	**(4.02)**															
5	-2.69		**2.86**	2.41	**9.92**														
	(1.89)		**(1.06)**	(1.68)	**(2.29)**														
6	-3.85		**3.35**	**6.50**	2.18	**10.18**													
	(2.21)		**(1.19)**	**(2.95)**	(1.42)	**(3.10)**													
7	**-3.19**		-0.21	0.73	0.12	0.58	**6.66**												
	(1.14)		(0.53)	(0.97)	(0.72)	(0.85)	**(0.85)**												
8	**-4.30**		0.02	-0.70	-1.10	1.68	**-1.59**	**10.67**											
	(1.50)		(0.70)	(1.23)	(0.89)	(1.10)	**(0.56)**	**(1.35)**											
9	-0.30		0.01	0.44	-0.31	-0.23	-0.30	-0.16	**1.75**										
	(0.98)		(0.48)	(0.73)	(0.70)	(0.60)	(0.40)	(0.48)	**(0.65)**										
10	0.34		-0.02	0.01	0.04	-0.03	0.15	-0.06	0.03	**0.19**									
	(0.47)		(0.19)	(0.30)	(0.25)	(0.24)	(0.20)	(0.23)	(0.12)	**(0.18)**									
11	0.15		-0.04	0.01	-0.04	-0.02	-0.02	-0.06	0.04	0.00	**0.07**								
	(0.30)		(0.13)	(0.19)	(0.15)	(0.16)	(0.12)	(0.15)	(0.07)	(0.02)	**(0.07)**								
12	-0.34		0.02	-0.02	0.35	-0.05	0.12	0.33	-0.09	-0.01	0.00	**0.36**							
	(0.54)		(0.26)	(0.37)	(0.35)	(0.31)	(0.23)	(0.31)	(0.15)	(0.05)	(0.03)	**(0.23)**							
13	0.18		0.39	0.14	0.36	0.14	0.03	0.43	-0.16	-0.01	0.00	0.10	**0.82**						
	(0.70)		(0.33)	(0.49)	(0.42)	(0.42)	(0.28)	(0.35)	(0.20)	(0.07)	(0.05)	(0.10)	**(0.33)**						
14	-0.04		-0.05	-0.26	0.47	0.26	-0.04	-0.06	-0.01	0.06	0.01	0.00	0.19	**1.20**					
	(0.74)		(0.36)	(0.56)	(0.47)	(0.47)	(0.30)	(0.37)	(0.24)	(0.11)	(0.06)	(0.12)	(0.16)	**(0.38)**					
15	-2.06		0.57	2.09	0.89	1.51	0.65	-0.25	-0.06	0.03	-0.05	-0.07	-0.13	-0.09	**5.14**				
	(1.91)		(0.88)	(1.23)	(1.09)	(0.99)	(0.75)	(0.96)	(0.49)	(0.19)	(0.12)	(0.24)	(0.34)	(0.38)	**(2.38)**				
16	-0.83		0.52	**4.01**	0.04	**4.52**	**1.48**	0.90	-0.32	0.15	-0.07	-0.12	-0.08	-0.26	**2.52**	**8.76**			
	(1.38)		(0.65)	**(1.59)**	(0.87)	**(1.45)**	**(0.54)**	(0.65)	(0.48)	(0.23)	(0.15)	(0.27)	(0.33)	(0.38)	**(1.36)**	**(1.22)**			
17	0.37		0.68	0.33	0.32	0.78	0.33	0.06	-0.06	0.07	0.04	-0.15	0.13	0.07	1.90	**3.40**	**4.86**		
	(1.78)		(0.86)	(1.41)	(1.02)	(1.13)	(0.73)	(0.94)	(0.45)	(0.19)	(0.12)	(0.24)	(0.32)	(0.37)	(1.71)	**(1.37)**	**(2.04)**		
18	**-12.41**		-0.68	1.84	0.34	-0.88	-0.45	-1.27	0.24	-0.29	0.03	0.14	-0.44	0.14	0.09	-1.75	-1.27	**9.64**	
	(2.86)		(0.95)	(1.40)	(1.21)	(1.27)	(0.73)	(0.94)	(0.58)	(0.31)	(0.16)	(0.31)	(0.45)	(0.44)	(1.04)	(0.95)	(1.01)	**(2.14)**	
19	**-5.68**		0.90	**2.68**	0.80	**1.97**	-0.46	-0.19	0.06	-0.04	-0.07	0.01	0.15	0.28	1.13	0.53	0.20	1.31	**4.31**
	(1.69)		(0.68)	**(1.18)**	(0.91)	**(1.04)**	(0.58)	(0.77)	(0.45)	(0.17)	(0.12)	(0.22)	(0.30)	(0.37)	(0.87)	(0.72)	(0.79)	(0.88)	**(1.45)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 3200 converged HMC STAN draws

Table 15: (b) SP_{ss} Only Estimation: $\Sigma^{SP_{ss}}$ Estimates

Attributes	$\Delta^{RP_{rs}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. $ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size ≤ 3
Inside Good	**-10.50 (0.81)**	-0.73 (0.85)	1.00 (0.56)	-2.59 (1.91)	1.77 (1.12)	-0.48 (1.07)
Brown Cow	**1.79 (0.84)**	0.68 (0.63)	0.40 (0.35)	2.34 (1.28)	-0.78 (0.85)	0.91 (0.83)
Chobani	**8.37 (0.83)**	0.02 (0.87)	0.38 (0.53)	-1.42 (1.96)	-1.69 (1.12)	-0.95 (1.12)
Fage	-5.74 (4.48)	0.50 (2.27)	**2.61 (1.14)**	-2.66 (4.38)	-5.19 (3.08)	1.39 (3.16)
Oikos	-0.55 (1.90)	-0.87 (1.29)	0.63 (0.79)	-1.61 (2.68)	**-3.65 (1.80)**	0.20 (1.77)
Private Label						
Zerofat	**1.30 (0.21)**	-0.14 (0.20)	0.00 (0.08)	0.03 (0.39)	0.41 (0.26)	0.15 (0.26)
Fruit	**2.33 (0.33)**	-0.05 (0.34)	0.10 (0.15)	-0.97 (0.69)	0.30 (0.43)	-0.20 (0.43)
Organic						
All Natural						
Probiotic						
Vitamins						
Omega3						
Fiber						
SBS Cup	-1.51 (3.55)	-0.67 (2.00)	-1.52 (0.83)	1.08 (3.52)	-0.92 (2.63)	0.03 (2.70)
SBS Cup Inclusions						
Normal Cup Inclusions Top						
Price	**-15.02 (1.32)**	-1.85 (1.61)	-1.29 (1.08)	6.98 (3.65)	-0.65 (2.11)	2.10 (2.12)
State Dependence	**1.09 (0.33)**	0.33 (0.34)	0.00 (0.19)	0.80 (0.69)	-0.13 (0.45)	0.33 (0.46)
RP_{rs} Log Marginal Likelihood			-7477.89			

No. of RP_{rs} Choice occasions - 28731
Values in bold exclude zero in the 95% credible interval of the posterior draws
Results reported from 3200 converged HMC STAN draws

Table 16: (a) RP_{rs} Only Estimation: $\Delta^{RP_{rs}}$ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**66.28**																		
	(10.14)																		
2	**-11.43**	**17.82**																	
	(4.57)	**(4.02)**																	
3	-5.44	**16.79**	**71.29**																
	(5.97)	**(5.17)**	**(10.08)**																
4	11.41	20.67	**76.15**	**300.06**															
	(16.58)	(11.46)	**(20.30)**	**(77.23)**															
5	**19.16**	**10.70**	**40.96**	**93.21**	**104.86**														
	(8.66)	**(5.81)**	**(11.05)**	**(25.44)**	**(19.59)**														
6																			
7	**-3.89**	0.52	**2.83**	-2.41	0.96		**2.69**												
	(1.49)	(0.85)	**(1.16)**	(3.11)	(1.87)		**(0.43)**												
8	**-8.87**	0.24	**8.10**	0.89	0.95		0.74	**8.64**											
	(2.46)	(1.23)	**(2.01)**	(6.11)	(2.86)		(0.56)	**(1.32)**											
9																			
10																			
11																			
12																			
13																			
14																			
15	-12.52	8.36	12.59	-2.91	13.91		-3.20	2.47							**66.19**				
	(13.09)	(8.11)	(14.09)	(29.71)	(15.80)		(2.21)	(4.77)							**(41.46)**				
16																			
17																			
18	**-60.06**	-10.74	**-98.40**	**-173.68**	**-109.81**		-1.06	-3.16							-10.58			**294.50**	
	(12.47)	(7.79)	**(15.65)**	**(38.36)**	**(20.67)**		(2.25)	(3.92)							(23.71)			**(37.84)**	
19	-2.89	0.25	0.93	-2.21	0.00		-0.11	0.77							-1.85			-2.87	**7.16**
	(2.26)	(1.25)	(1.87)	(5.39)	(2.88)		(0.43)	(0.70)							(4.21)			(3.73)	**(1.34)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 3200 converged HMC STAN draws

Table 16: (b) RP_{rs} Only Estimation: $\Sigma^{RP_{rs}}$ Estimates

Attributes	$\Delta^{SP_{ss}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. $ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size ≤ 3
Inside Good	**-3.27 (0.39)**	**-1.22 (0.52)**	-0.18 (0.18)	0.08 (0.90)	0.98 (0.67)	0.86 (0.67)
Brown Cow	0.31 (0.36)	0.52 (0.35)	0.22 (0.16)	1.07 (0.64)	0.20 (0.45)	0.15 (0.45)
Chobani	**3.38 (0.25)**	-0.03 (0.26)	0.14 (0.08)	-0.24 (0.40)	-0.36 (0.34)	-0.57 (0.33)
Fage	0.67 (0.53)	-0.21 (0.55)	**0.65 (0.16)**	**-1.81 (0.91)**	-0.99 (0.72)	0.15 (0.74)
Oikos	**0.83 (0.36)**	-0.76 (0.40)	0.07 (0.11)	-0.34 (0.57)	-0.37 (0.50)	-0.58 (0.50)
Private Label	**2.66 (0.55)**	-1.00 (0.58)	**0.48 (0.15)**	-1.48 (0.87)	0.24 (0.72)	-0.17 (0.73)
Zerofat	**1.17 (0.11)**	0.15 (0.14)	0.00 (0.04)	0.15 (0.21)	0.17 (0.18)	0.01 (0.18)
Fruit	**1.06 (0.14)**	-0.15 (0.18)	0.06 (0.06)	-0.10 (0.30)	0.25 (0.25)	-0.34 (0.25)
Organic	0.06 (0.23)	0.23 (0.26)	0.06 (0.06)	-0.27 (0.32)	0.18 (0.31)	0.19 (0.30)
All Natural	**-0.38 (0.13)**	**-0.40 (0.17)**	0.00 (0.04)	-0.27 (0.21)	-0.29 (0.19)	0.15 (0.19)
Probiotic	**0.34 (0.08)**	-0.10 (0.13)	0.02 (0.03)	0.00 (0.15)	0.07 (0.14)	0.01 (0.14)
Vitamins	0.21 (0.14)	0.17 (0.18)	0.02 (0.04)	-0.16 (0.22)	0.01 (0.21)	-0.24 (0.21)
Omega3	0.35 (0.19)	-0.14 (0.19)	0.04 (0.04)	**-0.48 (0.24)**	0.06 (0.22)	0.14 (0.22)
Fiber	0.28 (0.18)	-0.15 (0.20)	0.03 (0.04)	-0.15 (0.25)	0.24 (0.23)	**-0.45 (0.23)**
SBS Cup	-0.79 (0.42)	0.55 (0.47)	-0.20 (0.13)	0.47 (0.76)	-0.15 (0.60)	0.38 (0.62)
SBS Cup Inclusions	**-1.55 (0.29)**	-0.14 (0.31)	0.08 (0.07)	**-0.95 (0.38)**	-0.05 (0.34)	**0.71 (0.34)**
Normal Cup Inclusions Top	-0.65 (0.44)	0.50 (0.50)	**-0.30 (0.13)**	0.13 (0.77)	0.03 (0.63)	0.17 (0.65)
Price	**-3.99 (0.34)**	-0.13 (0.42)	-0.01 (0.13)	0.40 (0.69)	-0.62 (0.57)	-0.24 (0.57)
State Dependence	**1.54 (0.18)**	0.03 (0.20)	**0.21 (0.07)**	0.14 (0.36)	-0.05 (0.27)	0.27 (0.28)
Scale Parameter λ^{RP_rs}			**1.69 (0.09)**			
SP_{ss} Log Marginal Likelihood			-2136.84			
RP_{rs} Log Marginal Likelihood			-7566.81			

No. of SP_{ss} Choice occasions - 6120, No. of RP_{rs} Choice occasions - 28731
Values in bold exclude zero in the 95% credible interval of the posterior draws
Results reported from 3200 converged HMC STAN draws

Table 17: (a) $BENCH$ Estimation: $\Delta^{SP_{ss}}$, $\lambda^{RP_{rs}}$ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**68.43**																		
	(8.31)																		
2	**-6.41**	**5.32**																	
	(3.18)	**(1.62)**																	
3	**-8.01**	**2.03**	**9.72**																
	(2.15)	**(1.06)**	**(1.38)**																
4	-4.24	1.09	**6.81**	**23.88**															
	(3.51)	(1.52)	**(1.67)**	**(4.11)**															
5	3.23	1.04	**4.59**	**7.60**	**13.22**														
	(2.70)	(1.13)	**(1.19)**	**(1.97)**	**(2.36)**														
6	-1.47	0.32	**7.73**	**14.80**	**6.61**	**18.47**													
	(3.42)	(1.53)	**(1.64)**	**(3.29)**	**(1.79)**	**(3.64)**													
7	**-2.18**	0.00	0.21	0.56	0.47	0.69	**3.80**												
	(1.13)	(0.62)	(0.36)	(0.63)	(0.52)	(0.61)	**(0.49)**												
8	**-7.01**	-1.01	**2.27**	0.44	-0.58	**2.47**	**-0.85**	**7.81**											
	(1.66)	(0.71)	**(0.56)**	(1.02)	(0.72)	**(0.95)**	**(0.32)**	**(0.92)**											
9	-0.17	0.08	0.22	1.28	0.34	0.61	-0.28	0.01	**1.77**										
	(1.57)	(0.58)	(0.59)	(0.95)	(0.70)	(0.82)	(0.29)	(0.41)	**(0.70)**										
10	1.60	-0.29	0.18	0.59	0.69	0.65	0.19	0.08	0.14	**0.61**									
	(0.98)	(0.36)	(0.33)	(0.58)	(0.45)	(0.50)	(0.18)	(0.10)	(0.20)	**(0.27)**									
11	-0.11	0.02	0.03	0.08	-0.02	0.04	-0.01	-0.01	0.03	-0.01	**0.05**								
	(0.40)	(0.11)	(0.14)	(0.22)	(0.16)	(0.19)	(0.08)	(0.11)	(0.07)	(0.04)	**(0.07)**								
12	-0.46	-0.03	0.40	0.51	0.60	0.44	0.11	0.37	-0.04	0.02	0.00	**0.37**							
	(0.84)	(0.27)	(0.38)	(0.55)	(0.48)	(0.49)	(0.17)	(0.28)	(0.15)	(0.09)	(0.03)	**(0.26)**							
13	-0.68	-0.12	**1.36**	**1.82**	**1.41**	**1.64**	-0.07	**0.75**	0.03	0.12	0.01	0.21	**1.45**						
	(1.25)	(0.49)	**(0.53)**	**(0.80)**	**(0.61)**	**(0.75)**	(0.21)	**(0.34)**	(0.25)	(0.16)	(0.06)	(0.16)	**(0.49)**						
14	-0.58	-0.09	0.49	1.02	**1.19**	**1.40**	-0.04	0.21	0.12	0.26	0.01	0.07	**0.48**	**1.49**					
	(1.24)	(0.54)	(0.50)	(0.78)	**(0.61)**	**(0.73)**	(0.22)	(0.33)	(0.26)	(0.18)	(0.06)	(0.13)	**(0.25)**	**(0.47)**					
15	-1.91	0.32	0.42	1.66	0.58	0.79	0.05	0.26	0.08	-0.05	-0.03	0.02	-0.05	0.00	**4.64**				
	(2.31)	(0.88)	(0.90)	(1.31)	(1.04)	(1.27)	(0.45)	(0.73)	(0.45)	(0.28)	(0.10)	(0.23)	(0.39)	(0.40)	**(1.52)**				
16	-1.67	-0.26	**1.98**	**7.56**	1.81	**7.73**	**0.86**	1.03	0.23	0.56	-0.02	0.14	0.48	0.27	1.39	**9.30**			
	(2.25)	(1.25)	**(0.85)**	**(1.81)**	(1.03)	**(1.71)**	**(0.38)**	(0.57)	(0.53)	(0.35)	(0.13)	(0.29)	(0.46)	(0.44)	(1.17)	**(1.39)**			
17	-0.81	0.06	0.67	0.95	0.31	0.79	0.09	0.10	0.04	0.16	0.03	-0.01	0.26	0.19	0.90	**2.30**	**2.93**		
	(2.29)	(0.80)	(0.91)	(1.30)	(0.98)	(1.16)	(0.44)	(0.68)	(0.38)	(0.25)	(0.09)	(0.20)	(0.36)	(0.36)	(1.08)	**(1.28)**	**(1.75)**		
18	**-14.26**	**2.95**	**-6.96**	**-12.52**	**-9.25**	**-13.77**	0.11	**-1.82**	-1.44	**-2.12**	-0.07	-0.85	**-3.63**	**-2.47**	-0.30	**-6.72**	-1.69	**35.71**	
	(3.31)	**(1.40)**	**(1.46)**	**(2.79)**	**(2.10)**	**(2.93)**	(0.63)	**(0.88)**	(1.27)	**(0.86)**	(0.28)	(0.80)	**(1.24)**	**(1.11)**	(1.61)	**(1.89)**	(1.67)	**(4.19)**	
19	**5.96**	-0.38	-0.33	1.31	1.31	1.14	-0.31	**-1.03**	0.09	0.11	-0.06	0.01	-0.02	0.25	0.67	-0.23	-0.09	0.44	**5.70**
	(1.81)	(0.71)	(0.58)	(1.00)	(0.86)	(1.10)	(0.37)	**(0.57)**	(0.52)	(0.30)	(0.13)	(0.27)	(0.42)	(0.44)	(0.69)	(0.85)	(0.70)	(0.90)	**(0.97)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 3200 converged HMC STAN draws

Table 17: (b) $BENCH$ Estimation: $\Sigma^{SP_{ss}}$ Estimates

Attributes	$\Delta^{SP_{ss}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. $ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size ≤ 3
Inside Good	0.16 (0.45)	0.61 (0.41)	0.32 (0.17)	1.26 (0.76)	0.26 (0.50)	0.16 (0.51)
Brown Cow	**3.32 (0.26)**	-0.42 (0.29)	0.16 (0.10)	-0.32 (0.46)	-0.36 (0.38)	-0.58 (0.37)
Chobani	**1.28 (0.55)**	-0.57 (0.61)	**0.69 (0.17)**	**-1.90 (0.97)**	-1.30 (0.81)	0.36 (0.79)
Fage	0.64 (0.42)	-0.70 (0.38)	-0.21 (0.14)	0.40 (0.66)	0.75 (0.51)	0.91 (0.52)
Oikos	**1.54 (0.34)**	**-0.98 (0.43)**	0.08 (0.12)	-0.39 (0.63)	-0.55 (0.54)	-0.54 (0.55)
Private Label	**3.17 (0.51)**	**-1.29 (0.61)**	**0.52 (0.16)**	-1.49 (0.90)	0.03 (0.75)	0.08 (0.75)
Zerofat	**1.38 (0.12)**	0.18 (0.15)	0.00 (0.04)	0.20 (0.24)	0.22 (0.20)	0.01 (0.20)
Fruit	**0.72 (0.17)**	-0.11 (0.20)	0.06 (0.06)	-0.07 (0.31)	0.24 (0.27)	-0.39 (0.27)
Organic	0.03 (0.18)	0.24 (0.28)	0.07 (0.06)	-0.19 (0.34)	0.12 (0.32)	0.27 (0.31)
All Natural	-0.05 (0.11)	**-0.52 (0.18)**	0.00 (0.04)	-0.33 (0.22)	-0.34 (0.20)	0.18 (0.19)
Probiotic	**0.19 (0.07)**	-0.13 (0.13)	0.02 (0.03)	-0.03 (0.15)	0.05 (0.14)	0.00 (0.14)
Vitamins	0.05 (0.11)	0.20 (0.19)	0.01 (0.04)	-0.10 (0.23)	-0.01 (0.21)	-0.28 (0.21)
Omega3	0.00 (0.12)	-0.19 (0.19)	0.05 (0.04)	-0.43 (0.23)	0.04 (0.22)	0.22 (0.21)
Fiber	-0.03 (0.12)	-0.20 (0.21)	0.04 (0.04)	-0.13 (0.25)	0.19 (0.23)	-0.39 (0.22)
SBS Cup	**-1.29 (0.45)**	0.62 (0.50)	-0.25 (0.14)	0.65 (0.81)	-0.02 (0.66)	0.31 (0.67)
SBS Cup Incl.	**-2.27 (0.21)**	-0.25 (0.33)	0.07 (0.07)	**-0.94 (0.40)**	-0.09 (0.36)	**0.77 (0.36)**
Normal Cup Incl.Top	**-1.28 (0.45)**	0.51 (0.52)	**-0.34 (0.14)**	0.28 (0.81)	0.16 (0.68)	0.07 (0.68)
Price	**-3.27 (0.33)**	0.13 (0.37)	-0.04 (0.11)	-0.05 (0.55)	-0.28 (0.46)	-0.67 (0.46)
State Dep.	**3.00 (0.25)**	0.23 (0.20)	**0.18 (0.08)**	0.34 (0.36)	-0.09 (0.26)	0.46 (0.27)
Scale Parameter $\lambda^{RP_{rs}}$			**1.33 (0.08)**			
Mean Shifter $\mu^{RP_{rs}}$ for Inside Good			**-8.74 (0.67)**			
Mean Shifter $\mu^{RP_{rs}}$ for Fruit			**1.24 (0.31)**			
Mean Shifter $\mu^{RP_{rs}}$ for Price			**-4.56 (0.69)**			
Mean Shifter $\mu^{RP_{rs}}$ for State Dep.			**-1.83 (0.35)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Fage			**1.40 (0.16)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Price			**2.56 (0.21)**			
SP_{ss} Log Marginal Likelihood			-2110.68			
RP_{rs} Log Marginal Likelihood			-7561.62			

No. of SP_{ss} Choice occasions - 6120, No. of RP_{rs} Choice occasions - 28731
Values in bold exclude zero in the 95% credible interval of the posterior draws
Results reported from 3200 converged HMC STAN draws

Table 18: (a) CPC Estimation: $\Delta^{SP_{ss}}$, $\lambda^{RP_{rs}}$, $\mu^{RP_{rs}}$ and $\Phi^{RP_{rs}}$ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**31.16**																		
	(3.86)																		
2	**-4.33**	**7.15**																	
	(1.77)	**(2.00)**																	
3	-1.93	1.87	**14.71**																
	(1.36)	(1.20)	**(1.97)**																
4	-2.20	1.22	**8.60**	**25.27**															
	(2.16)	(1.65)	**(1.95)**	**(4.99)**															
5	2.00	0.95	**7.60**	**11.48**	**19.07**														
	(1.81)	(1.42)	**(1.61)**	**(2.49)**	**(3.08)**														
6	-0.80	0.29	**9.28**	**14.76**	**8.50**	**17.30**													
	(2.00)	(1.71)	**(1.90)**	**(3.65)**	**(2.14)**	**(3.66)**													
7	**-2.95**	-0.38	0.48	0.47	0.46	0.68	**4.50**												
	(0.76)	(0.70)	(0.44)	(0.70)	(0.60)	(0.67)	**(0.57)**												
8	**-5.72**	-1.53	**2.34**	0.36	-0.21	**2.57**	**-0.98**	**9.20**											
	(1.13)	(0.86)	**(0.68)**	(1.06)	(0.87)	**(0.99)**	**(0.37)**	**(1.08)**											
9	0.07	0.23	0.35	1.36	0.35	0.49	-0.21	-0.15	**1.93**										
	(0.95)	(0.75)	(0.74)	(0.99)	(0.85)	(0.80)	(0.32)	(0.46)	**(0.70)**										
10	1.05	-0.31	**1.30**	**1.38**	**1.47**	**1.08**	0.31	0.19	0.19	**0.96**									
	(0.61)	(0.47)	**(0.49)**	**(0.71)**	**(0.63)**	**(0.56)**	(0.21)	(0.31)	(0.24)	**(0.33)**									
11	0.14	0.00	-0.05	0.02	-0.04	-0.01	-0.01	-0.08	0.03	-0.01	**0.07**								
	(0.27)	(0.15)	(0.20)	(0.25)	(0.22)	(0.20)	(0.09)	(0.14)	(0.07)	(0.05)	**(0.07)**								
12	-0.43	0.00	0.16	0.52	0.93	0.19	0.17	0.33	-0.07	-0.01	0.00	**0.52**							
	(0.56)	(0.38)	(0.43)	(0.58)	(0.57)	(0.46)	(0.19)	(0.29)	(0.18)	(0.12)	(0.04)	**(0.26)**							
13	-0.26	0.01	0.85	0.97	1.07	0.70	0.01	0.43	-0.11	0.07	0.00	0.17	**0.84**						
	(0.63)	(0.49)	(0.51)	(0.66)	(0.60)	(0.55)	(0.21)	(0.33)	(0.20)	(0.15)	(0.05)	(0.12)	**(0.33)**						
14	-0.01	0.05	0.04	0.58	**1.27**	0.63	0.01	-0.05	0.09	0.25	0.01	0.07	0.22	**1.38**					
	(0.74)	(0.62)	(0.57)	(0.75)	**(0.66)**	(0.62)	(0.24)	(0.35)	(0.25)	(0.19)	(0.06)	(0.12)	(0.17)	**(0.40)**					
15	-1.69	0.45	0.40	1.58	0.79	0.67	0.25	-0.15	0.02	0.05	-0.03	0.07	-0.10	0.01	**5.31**				
	(1.55)	(1.09)	(1.16)	(1.42)	(1.28)	(1.35)	(0.53)	(0.81)	(0.50)	(0.36)	(0.12)	(0.14)	(0.34)	(0.41)	**(1.73)**				
16	0.03	-0.76	0.92	**6.60**	1.44	**6.62**	**1.07**	0.70	0.08	0.53	-0.06	0.01	-0.05	-0.17	1.55	**9.62**			
	(1.32)	(1.55)	(1.02)	**(1.88)**	(1.19)	**(1.64)**	**(0.42)**	(0.58)	(0.54)	(0.39)	(0.15)	(0.28)	(0.37)	(0.40)	(1.30)	**(1.36)**			
17	-0.08	-0.06	0.85	0.61	0.18	0.74	0.25	0.04	-0.07	0.24	0.03	-0.07	0.11	0.11	1.11	**2.25**	**3.00**		
	(1.42)	(0.92)	(1.12)	(1.37)	(1.18)	(1.16)	(0.50)	(0.77)	(0.40)	(0.32)	(0.09)	(0.32)	(0.28)	(0.34)	(1.30)	**(1.35)**	**(1.95)**		
18	**-10.08**	**2.48**	**-5.75**	**-8.74**	**-8.45**	**-7.74**	-0.21	-0.76	-0.50	**-1.86**	0.03	-0.11	-0.61	-0.38	-0.12	**-3.26**	-0.87	**12.89**	
	(1.91)	**(1.02)**	**(1.14)**	**(1.87)**	**(1.62)**	**(1.86)**	(0.45)	(0.63)	(0.71)	**(0.56)**	(0.18)	(0.23)	(0.54)	(0.55)	(1.06)	**(1.11)**	(1.04)	**(2.34)**	
19	**-2.65**	0.39	-0.10	1.09	0.65	0.81	-0.42	-0.07	0.11	-0.10	-0.05	-0.04	0.26	0.46	0.50	-0.10	-0.01	-0.01	**4.28**
	(0.98)	(0.62)	(0.63)	(0.84)	(0.85)	(1.00)	(0.37)	(0.49)	(0.50)	(0.31)	(0.12)	(0.41)	(0.34)	(0.42)	(0.66)	(0.82)	(0.62)	(0.52)	**(0.83)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 3200 converged HMC STAN draws

Table 18: (b) CPC Estimation: $\Sigma^{SP_{ss}}$ Estimates

Attributes	$\Delta^{SP_{ss}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. $ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size ≤ 3
Inside Good	-0.19 (0.35)				**1.10 (0.34)**	**0.67 (0.34)**
Brown Cow	**0.73 (0.22)**				0.01 (0.30)	-0.02 (0.31)
Chobani	**3.83 (0.23)**				-0.48 (0.29)	-0.56 (0.29)
Fage	**1.12 (0.48)**				-0.93 (0.62)	1.07 (0.61)
Oikos	**0.97 (0.31)**				-0.51 (0.47)	-0.52 (0.45)
Private Label	**2.73 (0.47)**				0.35 (0.61)	0.83 (0.61)
Zerofat	**1.19 (0.08)**				-0.06 (0.12)	0.05 (0.12)
Fruit	**0.82 (0.15)**				0.03 (0.17)	-0.34 (0.18)
Organic	-0.04 (0.17)				0.11 (0.29)	0.22 (0.28)
All Natural	0.07 (0.10)				-0.28 (0.17)	0.16 (0.18)
Probiotic	**0.17 (0.07)**				0.05 (0.13)	0.01 (0.13)
Vitamins	-0.04 (0.11)				-0.05 (0.20)	-0.28 (0.20)
Omega3	-0.03 (0.12)				0.08 (0.21)	0.18 (0.20)
Fiber	-0.10 (0.12)				0.20 (0.21)	-0.34 (0.21)
SBS Cup	-0.59 (0.41)				-0.35 (0.52)	-0.68 (0.49)
SBS Cup Incl.	**-2.11 (0.20)**				-0.13 (0.32)	0.65 (0.34)
Normal Cup Incl.Top	-0.52 (0.42)				-0.20 (0.55)	-0.80 (0.53)
Price	**-2.69 (0.29)**				-0.36 (0.38)	-0.33 (0.37)
State Dep.	**2.73 (0.22)**				0.13 (0.14)	0.27 (0.14)
Scaling Factor $\lambda^{RP_{ss}}$			**1.32 (0.06)**			
Scaling Factor $\lambda^{RP_{rs}}$			**1.47 (0.08)**			
Mean Shifter $\mu^{RP_{ss}}$ for Inside Good			**-4.96 (0.45)**			
Mean Shifter $\mu^{RP_{rs}}$ for Inside Good			**-6.76 (0.53)**			
Mean Shifter $\mu^{RP_{ss}}$ for Fruit			**0.65 (0.20)**			
Mean Shifter $\mu^{RP_{rs}}$ for Fruit			**0.86 (0.24)**			
Mean Shifter $\mu^{RP_{ss}}$ for Price			**-2.80 (0.50)**			
Mean Shifter $\mu^{RP_{rs}}$ for Price			**-5.24 (0.62)**			
Mean Shifter $\mu^{RP_{ss}}$ for State Dep.			**-1.69 (0.23)**			
Mean Shifter $\mu^{RP_{rs}}$ for State Dep.			**-1.68 (0.26)**			
Variance Shifter $\Phi^{RP_{ss}}$ for Fage			**1.85 (0.29)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Fage			**1.71 (0.28)**			
Variance Shifter $\Phi^{RP_{ss}}$ for Price			**3.19 (0.24)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Price			**3.00 (0.24)**			
SP_{ss} Log Marginal Likelihood			-2279.74			
RP_{ss} Log Marginal Likelihood			-23081.51			
RP_{rs} Log Marginal Likelihood			-7516.49			

No. of SP_{ss} Choice occasions - 6120, No. of RP_{ss} Choice occasions - 29640, No. of RP_{rs} Choice occasions -28731

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 1886 HMC STAN draws converged on the predominant posterior mode

Table 19: (a) CPC Estimation with RP_{rs}, RP_{ss} and SP_{ss} data with Demographics Only - $\Delta^{SP_{ss}}$, λ, μ, Φ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**24.43**																		
	(2.53)																		
2	**-3.53**	**6.22**																	
	(1.03)	**(1.23)**																	
3	**-3.09**	**2.81**	**17.25**																
	(1.09)	**(1.02)**	**(2.01)**																
4	**3.11**	2.27	**14.11**	**29.27**															
	(1.40)	(1.28)	**(2.40)**	**(7.48)**															
5	**7.17**	0.73	**12.96**	**22.15**	**35.14**														
	(1.64)	(1.23)	**(1.88)**	**(3.67)**	**(4.17)**														
6	1.62	1.18	**13.72**	**20.32**	**16.91**	**22.07**													
	(1.62)	(1.60)	**(2.28)**	**(5.15)**	**(2.99)**	**(4.63)**													
7	**-1.35**	-0.44	0.32	0.32	0.61	0.80	**2.61**												
	(0.38)	(0.31)	(0.29)	(0.42)	(0.45)	(0.45)	**(0.29)**												
8	**-5.38**	**-0.93**	**2.95**	0.75	0.26	**2.73**	-0.33	**6.61**											
	(0.71)	**(0.44)**	**(0.52)**	(0.70)	(0.69)	**(0.80)**	(0.19)	**(0.67)**											
9	0.47	0.22	0.50	**2.00**	1.42	0.98	-0.08	-0.25	**1.49**										
	(0.76)	(0.61)	(0.74)	**(1.06)**	(0.97)	(0.89)	(0.22)	(0.35)	**(0.57)**										
10	**1.08**	-0.09	**2.09**	**2.76**	**3.14**	**2.25**	0.19	0.39	0.20	**1.14**									
	(0.52)	(0.41)	**(0.51)**	**(0.87)**	**(0.83)**	**(0.67)**	(0.15)	(0.24)	(0.23)	**(0.32)**									
11	0.12	-0.01	-0.04	0.01	-0.03	-0.01	-0.01	-0.04	0.02	-0.01	**0.05**								
	(0.21)	(0.12)	(0.18)	(0.23)	(0.25)	(0.20)	(0.06)	(0.10)	(0.05)	(0.05)	**(0.05)**								
12	0.02	-0.04	0.29	1.26	**1.92**	0.63	0.20	0.16	0.04	0.05	0.01	**0.65**							
	(0.52)	(0.37)	(0.47)	(0.76)	**(0.82)**	(0.61)	(0.14)	(0.22)	(0.16)	(0.14)	(0.04)	**(0.25)**							
13	-0.15	0.06	1.00	**1.36**	**1.55**	1.04	0.00	0.37	-0.04	0.13	0.00	**0.20**	**0.68**						
	(0.51)	(0.40)	(0.52)	**(0.74)**	**(0.75)**	(0.63)	(0.15)	(0.25)	(0.16)	(0.15)	(0.03)	**(0.11)**	**(0.26)**						
14	0.33	0.01	0.42	1.01	**2.33**	0.89	0.03	0.05	0.12	0.28	0.01	0.17	0.22	**1.12**					
	(0.61)	(0.51)	(0.55)	(0.83)	**(0.88)**	(0.73)	(0.15)	(0.26)	(0.21)	(0.18)	(0.05)	(0.13)	(0.14)	**(0.34)**					
15	-1.80	0.70	-0.36	**-3.25**	-1.79	**-4.41**	-0.64	-0.21	-0.11	-0.31	0.00	-0.12	-0.28	-0.08	**12.02**				
	(1.44)	(1.05)	(1.25)	**(1.68)**	(1.65)	**(2.00)**	(0.36)	(0.66)	(0.64)	(0.46)	(0.14)	(0.43)	(0.44)	(0.55)	**(2.53)**				
16	0.57	-0.03	1.24	**4.27**	1.23	**4.53**	0.50	0.44	0.23	0.53	-0.04	-0.11	-0.05	-0.24	2.80	**8.23**			
	(1.08)	(1.35)	(1.04)	**(2.10)**	(1.53)	**(1.83)**	(0.29)	(0.46)	(0.45)	(0.38)	(0.12)	(0.29)	(0.31)	(0.34)	(1.53)	**(1.13)**			
17	-1.40	0.47	0.00	-2.43	-2.22	-2.86	-0.22	-0.09	-0.28	-0.05	0.02	-0.31	-0.08	-0.03	**6.74**	**3.50**	**7.22**		
	(1.48)	(1.16)	(0.37)	(2.18)	(1.82)	(2.16)	(0.37)	(0.65)	(0.56)	(0.43)	(0.12)	(0.38)	(0.37)	(0.48)	**(2.49)**	**(1.48)**	**(2.82)**		
18	**-9.46**	1.30	**-7.67**	**-14.26**	**-15.92**	**-11.70**	**-0.52**	-0.43	-0.82	**-2.47**	0.02	-0.50	-0.69	-0.76	1.33	**-2.71**	0.86	**13.44**	
	(1.40)	(0.72)	**(1.19)**	**(2.45)**	**(2.13)**	**(2.13)**	**(0.24)**	(0.38)	(0.68)	**(0.59)**	(0.16)	(0.48)	(0.50)	(0.56)	(0.96)	**(1.12)**	(1.14)	**(2.32)**	
19	**-1.94**	0.09	0.27	0.36	0.01	0.23	0.03	0.09	0.01	-0.06	-0.03	0.07	0.22	0.25	-0.25	0.24	-0.14	0.13	**2.49**
	(0.46)	(0.34)	(0.40)	(0.49)	(0.59)	(0.69)	(0.14)	(0.22)	(0.34)	(0.24)	(0.08)	(0.22)	(0.23)	(0.29)	(0.49)	(0.61)	(0.56)	(0.27)	**(0.33)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 1886 HMC STAN draws converged at the predominant posterior mode

Table 19: (b) CPC Estimation with RP_{rs}, RP_{ss} and SP_{ss} data with Demographics Only - $\Sigma^{SP_{ss}}$ Estimates

Attributes	$\Delta^{SP_{ss}}$ (S.E.)					
	Constant	Log Weeks since last Greek yog. purchase	Avg. $ Sales in Greek yog. per cat. purchase in past 90 days	Log No. store visits in Greek yog. in past 90 days	Inc. $\leq 75k$	Family Size ≤ 3
Inside Good	-0.30 (0.38)	0.11 (0.26)	**-0.25 (0.09)**	0.82 (0.45)	**1.17 (0.37)**	**0.77 (0.37)**
Brown Cow	**0.83 (0.23)**	0.38 (0.24)	**0.19 (0.09)**	0.66 (0.38)	0.15 (0.33)	-0.09 (0.32)
Chobani	**4.11 (0.26)**	-0.36 (0.25)	**0.27 (0.08)**	**-0.89 (0.37)**	-0.39 (0.32)	**-0.68 (0.32)**
Fage	**1.19 (0.52)**	-0.40 (0.50)	**0.69 (0.14)**	-1.14 (0.73)	-0.62 (0.67)	0.80 (0.66)
Oikos	**0.98 (0.35)**	**-1.02 (0.39)**	**0.22 (0.11)**	-0.36 (0.55)	-0.37 (0.50)	-0.68 (0.50)
Private Label	**2.91 (0.50)**	-1.04 (0.53)	**0.49 (0.13)**	-1.32 (0.73)	0.63 (0.67)	0.56 (0.62)
Zerofat	**1.29 (0.08)**	0.11 (0.09)	0.01 (0.03)	0.08 (0.15)	-0.06 (0.13)	0.06 (0.13)
Fruit	**0.88 (0.16)**	-0.01 (0.13)	0.06 (0.04)	-0.31 (0.21)	0.03 (0.19)	**-0.38 (0.19)**
Organic	-0.04 (0.18)	0.25 (0.27)	0.06 (0.06)	-0.23 (0.33)	0.17 (0.30)	0.20 (0.30)
All Natural	0.08 (0.11)	**-0.51 (0.17)**	0.02 (0.04)	-0.35 (0.21)	-0.30 (0.18)	0.15 (0.18)
Probiotic	**0.18 (0.08)**	-0.14 (0.13)	0.01 (0.03)	-0.03 (0.15)	0.03 (0.14)	0.01 (0.14)
Vitamins	-0.05 (0.12)	0.21 (0.19)	0.01 (0.04)	-0.10 (0.23)	-0.03 (0.21)	-0.31 (0.21)
Omega3	-0.03 (0.12)	-0.20 (0.19)	0.05 (0.04)	**-0.51 (0.23)**	0.06 (0.21)	0.17 (0.21)
Fiber	-0.12 (0.13)	-0.21 (0.19)	0.04 (0.04)	-0.17 (0.24)	0.19 (0.23)	-0.37 (0.22)
SBS Cup	-0.63 (0.44)	0.28 (0.40)	-0.14 (0.11)	0.37 (0.59)	-0.56 (0.55)	-0.52 (0.53)
SBS Cup Incl.	**-2.22 (0.21)**	-0.24 (0.32)	0.08 (0.07)	-0.75 (0.40)	-0.17 (0.36)	0.68 (0.36)
Normal Cup Incl.Top	-0.57 (0.44)	0.28 (0.47)	**-0.23 (0.11)**	-0.21 (0.64)	-0.43 (0.59)	-0.62 (0.57)
Price	**-2.83 (0.32)**	-0.15 (0.31)	-0.05 (0.09)	0.15 (0.44)	-0.43 (0.39)	-0.38 (0.40)
State Dep.	**2.81 (0.25)**	**0.27 (0.10)**	**0.13 (0.04)**	0.01 (0.18)	0.12 (0.15)	0.28 (0.15)
Scaling Factor $\lambda^{RP_{ss}}$			**1.22 (0.06)**			
Scaling Factor $\lambda^{RP_{rs}}$			**1.37 (0.08)**			
Mean Shifter $\mu^{RP_{ss}}$ for Inside Good			**-5.27 (0.49)**			
Mean Shifter $\mu^{RP_{rs}}$ for Inside Good			**-7.25 (0.56)**			
Mean Shifter $\mu^{RP_{ss}}$ for Fruit			**0.72 (0.22)**			
Mean Shifter $\mu^{RP_{rs}}$ for Fruit			**0.95 (0.26)**			
Mean Shifter $\mu^{RP_{ss}}$ for Price			**-3.01 (0.53)**			
Mean Shifter $\mu^{RP_{rs}}$ for Price			**-5.50 (0.68)**			
Mean Shifter $\mu^{RP_{ss}}$ for State Dep.			**-1.69 (0.26)**			
Mean Shifter $\mu^{RP_{rs}}$ for State Dep.			**-1.63 (0.29)**			
Variance Shifter $\Phi^{RP_{ss}}$ for Fage			**1.76 (0.22)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Fage			**1.61 (0.21)**			
Variance Shifter $\Phi^{RP_{ss}}$ for Price			**3.12 (0.23)**			
Variance Shifter $\Phi^{RP_{rs}}$ for Price			**2.90 (0.23)**			
SP_{ss} Log Marginal Likelihood			-2164.09			
RP_{ss} Log Marginal Likelihood			-23099.86			
RP_{rs} Log Marginal Likelihood			-7520.54			

No. of SP_{ss} Choice occasions - 6120, No. of RP_{ss} Choice occasions - 29640, No. of RP_{rs} Choice occasions -28731
Values in bold exclude zero in the 95% credible interval of the posterior draws
Results reported from 2032 HMC STAN draws converged at the predominant posterior mode

Table 20: (a) CPC Estimation with RP_{rs}, RP_{ss} and SP_{ss} data with Demographics and RFM - $\Delta^{SP_{ss}}$, λ, μ, Φ Estimates

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	**28.29**																		
	(3.08)																		
2	**-3.94**	**6.46**																	
	(1.10)	**(1.37)**																	
3	**-3.49**	**3.19**	**19.62**																
	(1.18)	**(1.22)**	**(2.33)**																
4	**4.17**	2.48	**16.69**	**35.53**															
	(1.67)	(1.46)	**(2.64)**	**(7.84)**															
5	**8.28**	0.87	**14.59**	**26.11**	**39.87**														
	(1.86)	(1.35)	**(2.21)**	**(4.07)**	**(4.90)**														
6	2.05	1.20	**15.75**	**24.26**	**19.18**	**25.93**													
	(1.89)	(1.86)	**(2.58)**	**(5.56)**	**(3.52)**	**(5.36)**													
7	**-1.58**	-0.58	0.38	0.40	0.74	1.03	**3.08**												
	(0.46)	(0.36)	(0.33)	(0.50)	(0.53)	(0.57)	**(0.35)**												
8	**-6.32**	-0.80	**3.42**	0.97	0.18	**3.05**	-0.40	**7.69**											
	(0.87)	(0.46)	**(0.61)**	(0.82)	(0.81)	**(0.95)**	(0.23)	**(0.83)**											
9	0.61	0.20	0.82	**2.53**	1.70	1.43	-0.09	-0.19	**1.87**										
	(0.93)	(0.68)	(0.82)	**(1.24)**	(1.16)	(1.05)	(0.25)	(0.42)	**(0.65)**										
10	**1.27**	-0.06	**2.46**	**3.41**	**3.66**	**2.52**	0.26	0.41	0.32	**1.40**									
	(0.62)	(0.46)	**(0.59)**	**(1.01)**	**(0.93)**	**(0.79)**	(0.17)	(0.27)	(0.28)	**(0.39)**									
11	0.18	-0.01	-0.09	-0.01	-0.06	-0.05	-0.01	-0.09	0.03	-0.02	**0.07**								
	(0.27)	(0.15)	(0.23)	(0.29)	(0.31)	(0.26)	(0.07)	(0.14)	(0.08)	(0.06)	**(0.07)**								
12	0.08	-0.13	0.33	1.39	**2.23**	0.72	0.24	0.25	0.02	0.05	0.01	**0.79**							
	(0.60)	(0.43)	(0.54)	(0.83)	**(0.90)**	(0.69)	(0.17)	(0.28)	(0.20)	(0.17)	(0.05)	**(0.29)**							
13	-0.09	0.07	**1.24**	**1.74**	**1.94**	1.29	0.05	0.36	-0.03	0.15	0.00	0.25	**0.83**						
	(0.61)	(0.46)	**(0.60)**	**(0.89)**	**(0.91)**	(0.76)	(0.17)	(0.28)	(0.20)	(0.18)	(0.05)	(0.14)	**(0.32)**						
14	0.48	-0.10	0.32	1.19	**2.65**	0.94	0.04	-0.02	0.18	0.36	0.02	0.19	0.24	**1.42**					
	(0.69)	(0.60)	(0.65)	(1.00)	**(1.03)**	(0.86)	(0.19)	(0.30)	(0.25)	(0.22)	(0.06)	(0.16)	(0.17)	**(0.40)**					
15	-2.00	0.66	-0.65	**-3.94**	-1.85	**-5.47**	-0.75	-0.43	-0.34	-0.25	-0.01	-0.16	-0.37	-0.03	**13.94**				
	(1.62)	(1.19)	(1.41)	**(1.99)**	(1.95)	**(2.46)**	(0.46)	(0.82)	(0.78)	(0.59)	(0.20)	(0.52)	(0.53)	(0.67)	**(2.87)**				
16	0.62	-0.44	1.61	**5.04**	1.74	**5.26**	**0.64**	0.56	0.22	0.66	-0.07	-0.15	-0.07	-0.26	3.24	**9.44**			
	(1.30)	(1.51)	(1.18)	**(2.38)**	(1.72)	**(2.08)**	**(0.33)**	(0.54)	(0.53)	(0.44)	(0.15)	(0.35)	(0.35)	(0.40)	(1.79)	**(1.29)**			
17	-1.84	0.26	0.17	-2.99	-2.24	-3.57	-0.27	0.03	-0.48	0.03	0.04	-0.35	-0.12	0.06	**7.88**	**4.03**	**8.63**		
	(1.72)	(1.32)	(1.54)	(2.55)	(2.24)	(2.68)	(0.46)	(0.81)	(0.67)	(0.55)	(0.16)	(0.45)	(0.46)	(0.57)	**(2.87)**	**(1.73)**	**(3.35)**		
18	**-11.10**	1.10	**-9.11**	**-17.67**	**-18.84**	**-13.87**	**-0.62**	-0.39	-1.12	**-2.98**	0.02	-0.62	-0.94	-0.98	1.67	**-3.28**	0.97	**15.95**	
	(1.66)	(0.79)	**(1.38)**	**(2.77)**	**(2.51)**	**(2.49)**	**(0.28)**	(0.43)	(0.84)	**(0.68)**	(0.20)	(0.55)	(0.63)	(0.68)	(1.09)	**(1.30)**	(1.37)	**(2.77)**	
19	**-2.19**	0.14	0.32	0.27	0.06	0.36	0.00	0.05	0.01	-0.06	-0.03	0.04	0.23	0.35	-0.29	-0.24	0.00	0.17	**2.83**
	(0.52)	(0.38)	(0.43)	(0.57)	(0.67)	(0.85)	(0.17)	(0.24)	(0.40)	(0.28)	(0.09)	(0.26)	(0.27)	(0.35)	(0.57)	(0.72)	(0.70)	(0.31)	**(0.39)**

Index: 1 - Inside Good, 2 - Brown Cow, 3 - Chobani, 4 - Fage, 5 - Oikos, 6 - Private Label, 7 - Zero-Fat, 8 - Fruit, 9 - Organic, 10 - All Natural, 11 - Probiotic, 12 - Vitamins, 13 - Omega-3, 14 - Fiber, 15 - Side by side (SBS) cup, 16 - SBS Cup with incl., 17 - Normal cup with inclusions on top, 18 - Price, 19 - State Dependence

Values in bold exclude zero in the 95% credible interval of the posterior draws

Results reported from 2032 HMC STAN draws converged at the predominant posterior mode

Table 20: (b) CPC Estimation with RP_{rs}, RP_{ss} and SP_{ss} data with Demographics and RFM - $\Sigma^{SP_{ss}}$ Estimates