STATE DEPENDENCE AND ALTERNATIVE EXPLANATIONS FOR CONSUMER
INERTIA

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ABSTRACT

For many consumer packaged goods products, researchers have documented a form of state dependence whereby consumers become "loyal" to products they have consumed in the past. That is, consumers behave as though there is a utility premium from continuing to purchase the same product as they have purchased in the past or, equivalently, there is a psychological cost to switching products. However, it has not been established that this form of state dependence can be identified in the presence of consumer heterogeneity of an unknown form. Most importantly, before this inertia can be given a structural interpretation and used in policy experiments such as counterfactual pricing exercises,alternative explanations which might give rise to similar consumer behavior must be ruled out. We develop a flexible model of heterogeneity which can be given a semi-parametric interpretation and rule out alternative explanations for positive state dependence such as autocorrelated choice errors, consumer search, or consumer learning.

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1 Introduction

Researchers in both economics and marketing have documented a form of persistence in consumer choice data in which consumers have a higher probability of choosing products that they have consumed in the recent past (see, for example, Keane (1997) and Seetharaman, Ainslie, and Chintagunta (1999)). Typically, the data used to document these findings are consumer panels recording purchases of branded products. Accordingly, we will term this form of persistence, inertia in brand choice. Inertia is typically captured by a choice model specification which includes lagged choice variables. A structural interpretation of this model is that past purchases alter the utility derived from further consumption of the same goods or that consumers face some sort of psychological switching costs in changing brands. To distinguish structural interpretations from purely statistical measures, we will term the structural interpretation, state dependence in choice. The distinction between statistical and structural interpretations of persistence in choice is important from the point of view of evaluating optimal firm policies such as optimal pricing.

There are two parts to our investigation. We document that inertia in brand choice exists and is not due to a mis-specified distribution of heterogeneity in preferences or autocorrelated choice errors. We then consider if the observed inertia can be interpreted as a structural model of state dependence or is simply proxying for costly search or learning.

A standard alternative explanation for state dependence is that choice model errors are autocorrelated. Although this gives rise to inertial behavior in choice, the implications for firm policy are quite different. Firms facing consumers with auto-correlated errors have no way to influence the degree to which consumers are "loyal" to their products, while under the state dependent interpretation consumers can be induced to be loyal by price reductions and other promotional activities. We implement tests to conclude that autocorrelated errors are unlikely to be the source of observed inertia.

Another possible source of measured inertia could be mis-specification of the distribution of consumer heterogeneity in brand preferences and price sensitivity. It is well known that it is difficult to distinguish between state dependence and heterogeneity. It is particularly difficult

to do so if the entire set of taste parameters are consumer-specific. For example, there is no compeling argument to assume that consumer differences are confined to brand intercepts. The data requirements for separating hetergeneity from state dependence are formidable. Not only must moderately long panels of consumers be recorded but there must be some form of exogenous brand switching which allows for a shift in the loyalty "state." Fortunately, panel data on consumer packaged goods is captured in environments where there are frequent price discounts. These price discounts induce brand switching and should induce state dependence.

The empirical literature on state dependence assumes a normal distribution of heterogeneity[1]. There is no particular reason to assume that distributions of taste parameters should exhibit symmetric and unimodal distributions. In might be argued, for example, that the distribution of brand intercepts should be multi-modal, corresponding to different relative brand preferences for different groups of consumers. In order to establish that state dependence findings are robust to distributional assumptions, we implement a very flexible, semi-parametric specification consisting of a mixture of multivariate normal distributions. While we argue that our Bayesian methods provide extreme flexibility while retaining desirable smoothness properties, we also consider a form of model-free evidence that our heterogeneity specification is adequate.

It can be argued that persistence is not derived from state dependence but could be the result a costly search process. With high search costs, consumers may be reluctant to pay the search cost to sample other brands. We demonstrate that, while we can't eliminate the existence of search costs explanations, they do not seem to be the driving force behind the measured state dependence. To draw these conclusions, we make use of the availability of local store advertising which is determined exogeneous to individual consumer choice but changes search costs.

Others have advanced the hypothesis (see for example, Osborne (2007) and Moshkin and Shachar (2002)) that learning behavior could give rise to inertia in choices. A generic implication of learning models is that choice behavior will be non-stationary even when consumers

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[1]See, for example, Keane (1997), Seetharaman, Ainslie, and Chintagunta (1999), and Osborne (2007). Shum (2004) uses discrete distribution of heterogeneity.

face a stationary store environment. As consumers obtain more experience with any set of products, the amount of learning declines and their posterior beliefs on product quality converge to a degenerate distribution. On the other hand, a state dependence model implies that there will be a stationary distribution of consumer choice, given a stationary input process for prices. We use this key feature to distinguish learning from state dependence and see little evidence of learning.

Our goal is to document that state dependence survives a battery of tests and alternative explanations and provide support for those who wish to interpret state dependence as a structural model of utility. In a separate paper (Dubé, Hitsch, and Rossi (forthcoming)), we explore the implications of models with inertia for equilibrium prices under the assumption that the inertial terms can be given a structural interpretation.

2   Model and Econometric Specification

Our baseline model consists of households making discrete choices among J products in a category and an outside option each time they go to the supermarket. The timing and incidence of trips to the supermarket, indexed by t, are assumed to be exogenous. To capture inertia in choices, we take the standard approach, often termed "state-dependent demand," and assume that current utilities are affected by the previous product chosen in the category. For ease of exposition, we drop the household-specific index below. In the empirical specification, all the model parameters will be household specific.

The utility index from product j at time period t is

$$u_{jt} = \alpha_j + \eta p_{jt} + \gamma I\{s_t = j\} + \epsilon_{jt} \tag{2.1}$$

where p_{jt} is the product price[2] and ϵ_{jt} is the standard iid error term used in most choice models. In the model given by (2.1), the brand intercepts represent a persistent form of vertical

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[2]Other characteristics of the store environment facing the household could be entered into the "utility" model. But, then it may be problematic to interpret this as a utility specification. For example, many researchers include in-store advertising variables directly in the choice model. In Section 5, we consider a search-theoretic interpretation of the role of displays.

product differentiation that captures a household's intrinsic product (or brand) preferences. $s_t \in \{1, \ldots, J\}$ summarizes the history of past purchases from the perspective of impact on current utility. If a household buys product k in period $t-1$, then $s_t = k$. If the household chooses the outside option, then the household's state remains unchanged: $s_t = s_{t-1}$. Some term s_t the "loyalty" state of the household. If $s_t = j$, the household is said to be "loyal" to brand j. While the use of the last purchase as the summary of the past purchases is very frequently used in empirical work, it is by no means the only possible specification. For example, Seetharaman (2004) considers various distributed lags of past purchases.

If $\gamma > 0$, then the model in (2.1) will generate a form of inertia. If a household switches to brand k, the probability of a repeat purchase of brand k is higher than prior to this purchase. One possible interpretation is that γ results a form of psychological switching costs (see Farrell and Klemperer (2006)).

2.1 Econometric Specification

At the household level (indexed by h), we specify a multinomial logit model with the outside good expected utility set to zero.

$$Pr(j) = \frac{exp\left(\alpha_j^h + \eta_j^h Price_j + \gamma^h I\{s = j\}\right)}{1 + \sum_{k=1}^{J} exp\left(\alpha_k^h + \eta_k^h Price_j + \gamma^h I\{s = k\}\right)} \tag{2.2}$$

If we denote the vector of household parameters $\left(\alpha_1^h, \ldots, \alpha_J^h, \eta^h, \gamma^h\right)$ by θ^h, then heterogeneity of household types can be accommodated by assuming that the collection of $\{\theta^h\}$ are drawn from a common distribution. In the empirical literature on state dependent demand, a normal distribution is often assumed, $\theta^h \sim N\left(\bar{\theta}, V_\theta\right)$. Frequently, further restrictions are placed on V_θ such as a diagonal structure (see, for example, Osborne (2007)). Other authors restrict the heterogeneity to only a subset of the θ vector. The use of restricted normal models is due, in part, to the limitations of existing methods for estimation of random coefficient logit models.

If normal models for heterogeneity are unable to capture the full distribution of heterogeneity, then there is the potential to create a spurious finding of interia or the importance of

state dependence. For example, consider the situation in which there is a bimodal distribution of preferences for a particular brand. One mode corresponds to a sub-population of consumers who find the brand relatively superior to other brands in the choice set, while the other mode corresponds to consumers who find this brand relatively inferior. The normal approximation to a bi-modal distribution would be symmetric and centered at zero. The normal would not exhibit much in the way of differences in brand preferences (certainly not as much as the bimodal distribution). When applied to data, the model with the normal distribution would have a likelihood that puts mass on positive inertia parameter values in order to accomodate the observation that some households persistently buy (do not buy) one of the brands.

Rather than restricting the distribution of parameters across households, we want to allow for the possibility of non-normal and flexible distributions. This poses a challenging econometric problem. Even if we were to observe the $\{\theta^h\}$ without error, we would be faced with the problem of estimating a high dimensional distribution (in the applications below, we estimate models with 5-10 dimensional distributions). In practice, we have only imperfect information regarding household level parameters which adds to the econometric challenge. Even with hundreds of households, we may only have limited information for any one household given that there are typically not more than 50 observations per household. This requires a method that does not overfit the data. One approach to the problem of overfitting is to use proper prior distributions which create forms of smoothing and parameter shrinkage.

Our approach is to specify a hierarchical prior with a mixture of normals as the first stage prior (see, for example, section 5.2 of Rossi, Allenby, and McCulloch (2005)).The hierarchical prior provides one convenient way of specifying an informative prior which avoids the problem of overfitting even with a large number of normal components. The first stage is a mixture of K multivariate normals and the second stage consists of priors on the parameters of the mixture of normals.

$$p\left(\theta^h|\pi, \{\mu_k, \Sigma_k\}\right) = \sum_{k=1}^{K} \pi_k \phi\left(\theta^h|\mu_k, \Sigma_k\right) \tag{2.3}$$

$$\pi, \{\mu_k, \Sigma_k\}\,|b \tag{2.4}$$

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Here the notation $\cdot | \cdot$ indicates a conditional distribution and b represents the hyper-parameters of the priors on the mixing probabilities and the parameters governing each mixture component.

As is well-known, a mixture of normals models is very flexible and can accommodate deviations from normality such as thick tails, skewness, and multi-modality. A priori, we might expect that brand preference parameters (intercepts) might have a multi-modal distribution. The modes might correspond to sub-groups of consumers who very much like, very much dislike, or who are indifferent to the brand. In addition, we might expect the distribution of price coefficients to be skewed left since consumers should behave in accordance with a negative price coefficient and there may be some extremely price sensitive consumers. At the same time, we do not expect preference parameters to be independent. Thus, we are faced with the task of fitting a multivariate mixture of normals.

A useful alternative representation of the model in (2.3) and (2.4) can be obtained by introducing a latent set of variables which indicate which component each consumer is drawn from.

$$\theta^h | \pi, \{\mu_k, \Sigma_k\} \sim \phi \left(\theta^h | \mu_{ind_h}, \Sigma_{ind_h} \right)$$
$$ind_h \sim MN\left(\pi \right) \tag{2.5}$$
$$\pi, \{\mu_k, \Sigma_k\} | b$$

ind_h is a multinomial variable with probability vector, π. This representation is precisely that which would be used to simulate data from a mixture of normals, but it is also the same idea used in the MCMC method for Bayesian inference in this model, as detailed in the appendix. Viewed as a prior, (2.5) puts positive prior probability on mixtures with different numbers of components, including mixtures with a smaller number of components than K. For example, consider a model that is specified with a large number of components, $K = 10$. A priori, there is a positive probability that $ind_h \in \{1, \ldots, 5\}$. This is also possible a posteriori. This property of the posterior is important for parsimony. A posteriori, it is possible that some mixture components are "shut down" in the sense that they have very low probability and are never visited during the navigation of the posterior.

While the mixture of normals model (2.3) is notoriously difficult to fit via maximization methods, Bayesian MCMC methods are well-suited to conducting inference to this problem. The proper priors that form the second stage of the hierarchical model insure that the poles and other singularities that plague a maximization approach are avoided. Rossi, Allenby, and McCulloch (2005) define a special customized hybrid Metropolis MCMC algorithm for this model which is automatically tuned to each of the household level likelihoods (see pp. 135-136). This is particularly important for application to consumer choice data as some households will not be observed to choose from among all possible choice alternatives and a household-level MLE will be undefined for these households. Standard hybrid MCMC methods for hierarchical logit models (see the excellent survey on MCMC methods by Chib (2001)) are simply infeasible for data that include incomplete purchase histories. The Appendix provides details of the MCMC algorithm and prior settings.

Our MCMC algorithm provides draws of the mixture probabilities as well as the normal component parameters. Thus, each MCMC draw of the mixture parameters provides a draw of the entire multivariate density of household parameters. We can average these densities to provide a Bayes estimate of the household parameter density. We can also construct Bayesian Highest Posterior Density (HPD) regions[3] for any given density ordinate to gauge the level of uncertainty in the estimation of the household distribution using the simulation draws. That is, for any given ordinate, we can estimate the density of the distribution of either all or a subset of the parameters. In particular, marginals distributions can be calculated by exploiting the fact that the marginal distribution of a sub vector of a mixture of multivariate normals is the same mixture of the appropriate marginals for each component. A single draw of the original of the marginal density for the ith element of θ can be constructed as follows:

$$p_{\theta_i}^r(t) = \sum_{k=1}^{K} \pi_k^r \phi_i(t|\mu_k^r, \Sigma_k^r) \tag{2.6}$$

$\phi_i(t|\mu_k, \Sigma_k)$ is the univariate marginal density for the ith component of the multivariate

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[3]The Bayesian Highest Posterior Density region is the Bayesian analogue of the confidence interval. The 95 percent HPD is an interval which has .95 probability under the posterior. We can compute estimates of the HPD by using quantiles from the MCMC draws.

normal distribution, $\phi\left(\mu_k, \Sigma_k\right)$.

Some might argue that you do not have a truly non-parametric method unless you can claim that your procedure consistently recovers the true density of parameters in the population of all possible households. In the mixture of normals model, this requires that the number of mixture components (K) increases with the sample size. Our approach is to fit models with successively larger numbers of components and gauge the adequacy of the number of components by examining the fitted density as well as the Bayes factor (see model selection discussion below) associated with each number of components. What is important to note is that our improved MCMC algorithm is capable of fitting models with a large number of components at relatively low computational cost.

2.2 Posterior Model Probabilities

In order to establish that the inertia we observe in the data can be interpreted as a true state dependent utility, we will compare a variety of different specifications. Most of the specifications we will consider will be heterogeneous in that a prior distribution or random coefficient specification will be assumed for all utility parameters. This poses a problem in model comparison as we are comparing different and heterogeneous models. As a simple example, consider a model with and without the lagged choice term. This is not simply a hypothesis about a given fixed dimensional parameter, $H_0 : \gamma{=}0$, but a hypothesis about a set of household level parameters. The Bayesian solution to this problem is to compute posterior model probabilities and compare models on this basis. A posterior model probability is computed by integrating out the set of model parameters to form what is termed the marginal likelihood of the data. Consider the computation of the posterior probability of model M_i:

$$p\left(M_i|D\right) = \int p\left(D|\Theta, M_i\right) p\left(\Theta|M_i\right) d\Theta \times p\left(M_i\right) \tag{2.7}$$

where D denotes the observed data, Θ represents the set of model parameters, $p\left(D|\Theta, M_1\right)$ is the likelihood of the data for M_1, and $p\left(M_i\right)$ is the prior probability of model i. The first

term in (2.7) is the marginal likelihood for M_i.

$$p\left(D|M_i\right) = \int p\left(D|\Theta, M_i\right) p\left(\Theta|M_i\right) d\Theta \tag{2.8}$$

The marginal likelihood can be computed by reusing the simulation draws for all model parameters that are generated by the MCMC algorithm using the method of Newton and Raftery (1994).

$$\hat{p}\left(D|M_i\right) = \left(\frac{1}{R}\sum_{r=1}^{R}\frac{1}{p\left(D|\Theta, M_i\right)}\right)^{-1} \tag{2.9}$$

$p\left(D|\Theta, M_i\right)$ is the likelihood of the entire panel for model i. In order to minimize overflow problems, we report the log of the trimmed Newton-Raftery MCMC estimate of the marginal likelihood. Bayesian Model comparison can be done on the basis of the marginal likelihood (assuming equal prior model probabilities).

Posterior model probabilities can be shown to have an automatic adjustment for the effective parameter dimension. That is, larger models do not automatically have higher marginal likelihood as the dimension of the problem is one aspect of the prior that always matters. While we do not use asymptotic approximations to the posterior model probabilities, the asymptotic approximation to the marginal likelihood illustrates the implicit penalty for larger models (see, for example, Rossi, McCulloch, and Allenby (1996)).

$$log\left(p\left(D|M_i\right)\right) \approx log\left(p\left(D|\hat{\Theta}_{MLE}, M_i\right)\right) - \frac{p_i}{2}log\left(n\right) \tag{2.10}$$

p_i is the effective parameter size for M_i and n is the sample size. Thus, a model with the same fit or likelihood value but a larger number of parameters will be "penalized" in marginal likelihood terms. Choosing models on the basis of marginal likelihood can be shown to be consistent in model selection in the sense that the true model will be selected with higher and higher probability as the sample size becomes infinite.

3 Data

For our empirical analysis, we estimate the logit demand model described above using household panel data containing all purchase behavior for the refrigerated orange juice and the 16 oz tub margarine categories. The panel data were collected by AC Nielsen for 2,100 households in a large Midwestern city between 1993 and 1995. In each category, we focus only on those households that purchase a brand at least twice during our sample period. Hence we use 355 households to estimate orange juice, and 429 households to estimate margarine demand.

Table 1 lists the products considered in each category as well as the purchase incidence, product shares and average prices. We define the outside good in each category as follows. In the refrigerated orange juice category, we define the outside good as any fresh or canned juice product purchase other than the brands of orange juice considered. In the tub margarine category, we define the outside good as any spreadable product i.e. jams, jellies, margarine, butter, peanut butter etc). In Table 1, we see a no-purchase share of roughly 24%, in refrigerated juice, and 46% in tub margarine. We use this definition of the outside good to model only those shopping trips where purchases in the product category are considered.

In our econometric specification, we will be careful to control for heterogeneity as flexibly as possible to avoid confounding loyalty with unobserved heterogeneity. Even with these controls in place, it is still important to ask which patterns in our consumer shopping panel give rise to the identification of inertial or state dependent effects. The marginal purchase probability is considerably smaller than the re-purchase probability for all products considered. While this evidence is consistent with inertia, it could also be a reflection of heterogeneity in consumer tastes for brands. The identification of inertia in our context relies on the frequent temporary price changes typically observed in supermarket scanner data. If there is sufficient price variation, we will observe consumers switching away from their preferred products. The detection of state dependence relies on spells during which the consumer purchases these less-preferred alternatives on successive visits, even after prices return to their "typical" levels.

We use the orange juice category to illustrate the source of identification of inertia or state dependence in our data. First, we observe spells during which a household repeat-purchases

the same product. Conditional on a purchase, we observe 1889 such repeat-purchases out of our total 3328 purchases in the category. Second, we observe numerous instances during which a spell is initiated by a discount price. We classify each product's weekly prices as either "regular" or "discount," where the latter implies a temporary price decrease of at least 5%. Focusing on non-favorite products, i.e. products that are not the most frequently purchased by a household, nearly 60% of the purchases are for products offering a temporary price discount. We compare the repeat-purchase rate for spells initiated by a price discount (i.e. a household repeat-buys a product that was on discount when they previously purchased it) to the marginal probability of a purchase in Table 2. For all brands of Minute Maid orange juice, the sample repurchase probability conditional on a purchase initiated by a discount is .74, which exceeds the marginal purchase probability of .43. The same is true for Tropicana brand products with the conditional repurchase probability of .83 compared to the marginal purchase probability of .57. This is suggestive that observed high repurchase rates are not simply the result of strong brand preferences but are caused by some sort of inertia.

Inertia or persistence in brand choices can be viewed as one possible source of dependence in choices over time even for the same consumer. Another frequently cited source of non-zero order purchase behavior is household inventory holdings (see, for example, Erdem, Imai, and Keane (2003)). If households have some sort of storage technology, then they may amass a household inventory either to reduce shopping costs (assuming there is a category-specific fixed cost of shopping) or to exploit a sale or price discount of short duration. It should be emphasized that household stock-piling has implications for the quantity of purchases as well as the timing of purchases. Our state dependence formulation suggests that the specific brand purchased on the last shopping trip should influence the current brand choice. A model of stock-piling simply suggests that as the time between purchases increases the hazard rate of purchase should increase. We neither use the quantity of purchase nor the timing of purchase incidence in our analysis. Finally, we should note that the possibilities for household inventory of the products (especially, refrigerated orange juice) appear to be limited. In our data, over 80 per cent of all purchases are for one unit of the product, suggesting that stock-piling is not

pervasive.

4 Inertia, Heterogeneity, and Robustness

Heterogeneity and State Dependence

It is well-known that state dependence and heterogeneity can be confounded (Heckman (1981)). We have argued that frequent price discounts or sales provide a source of brand switching that can identify inertia or state dependence in choices separately from heterogeneity in household preferences. However, it is an empirical question as to whether or not inertia is an important force in our data. With a normal distribution of heterogeneity, a number of authors have documented that positive state dependence or inertia is present in CPG panel data (see, for example, Seetharaman, Ainslie, and Chintagunta (1999)). Frank (1962) and Massy (1966) document state dependence at the panelist level using older diary data. However, there is still the possibility that these results confirming inertia are not robust to controls for heterogeneity using a flexible or non-parametric distribution of preferences. Our approach is to fit models with and without an inertia term and with and without various forms of heterogeneity. It is particularly convenient that our mixture of normals approach nests the normal model in the literature.

Table 3 provides log marginal likelihood results that facilitate assessment of the statistical importance of heterogeneity and inertia. All log marginal likelihoods are estimated using a Newton-Raftery style estimator that has been trimmed of the top and bottom 1 per cent of likelihood values as is recommended in the literature. We compare models without heterogeneity to a normal model (a one component mixture) and to five and ten mixture component models.

As is often the case with consumer panel data (Allenby and Rossi (1999)), there is pronounced heterogeneity. In a model with an inertia or state dependence term included, the introduction of normal heterogeneity improves the model fit dramatically. The log marginal likelihood improves by more 20 percent when normal heterogeneity is introduced. If two

models have equal prior probability, the difference in log marginal likelihood is related to the ratio of posterior model probabilities:

$$log\left(\frac{p\left(M_1|D\right)}{p\left(M_2|D\right)}\right) = log\left(p\left(D|M_1\right)\right) - log\left(p\left(D|M_2\right)\right) \tag{4.1}$$

Introduction of normal heterogeneity improves the log marginal likelihood by more than 100 points, such that the ratio of posterior probabilities is more than $\exp\left(100\right)$, providing overwhelming evidence in favor of a model with heterogeneity in both product categories.

The normal model of heterogeneity does not appear to be adequate for our data as the log marginal likelihood improves substantially (by at least 50 points) when a five component mixture model is used. For example, for margarine products in a model with an inertia term, moving from one to five normal components increases the log marginal likelihood from -5613 to -5550. Remember that the Bayesian approach automatically adjusts for effective parameter size (see section 2.2) and the increase in log marginal density observed in Table 3 represents a meaningful improvement in fit.

Figures 1-4 provide direct evidence on the importance of a flexible distribution of heterogeneity. Each figure plots the estimated marginal distribution of intercept, price, and inertia or "state dependence" coefficients from the five component mixture in blue (here we use the posterior mean as the Bayes estimate of each density value. The yellow envelope enclosing the five component marginal densities is a 90 percent pointwise HPD region. The one component fitted density is drawn in red. A number of the parameters exhibit a dramatic departure from normality. For example, the Shedd's brand of margarine has a noticeably bimodal marginal distribution across households. One mode is centered on a positive value (all intercepts should be interpreted as relative to the "outside" good which is defined as other products in the category) indicating strong brand preference for Shedd. The other mode is centered on a value closer to zero, reflecting consumers who view Shedd's as comparable to other products in the category. One could argue that distributions with multiple modes are more likely to be the norm rather than the exception with any set of branded products. The price coefficient (Figures 2 and 4) is also non-normal, exhibiting pronounced left skewness. Again, this might

be expected that there is a left tail of extremely price sensitive consumers. We note that the prior distribution for the price coefficient is symmetric and centered at zero.

Thus, there is good reason to doubt the appropriateness of the standard normal assumption for many choice model parameters. This opens the possibility that the findings documenting the importance of state dependence or inertia in choices are influenced, at least in part, by arbitrary distributional assumptions. However, the importance of the inertia or "state dependence" remains even when a flexible five component normal is specified. The log marginal likelihood increases from -5575 to -5501 when inertia terms are added to a five component model for margarine and from -4528 to -4434 in refrigerated orange juice. Figures 2 and 4 show that the marginal distribution of the inertia parameter is well approximated by a normal distribution for these two product categories. While this is not definitive evidence, it does suggest that the findings of inertia or state dependence in the literature are not artifacts of the normality assumption commonly used.

The five component normal mixture is a very flexible model for the joint density of choice model parameters. However, before we can make a more generic "semi-parametric" claim that our results are not dependent on the form of the distribution, we must provide evidence of the adequacy of the five component distributional model. Our approach to this is to fit a ten component model. Many would consider this to be an absurdly highly parametrized model. For the margarine category, the ten component model would have a "nominal" number of 449 parameters (the coefficient vector is 8 dimensional[4]). The log marginal likelihood declines from five to ten components; from -5551 to -5559 for margarine and -4434 to -4435 for orange juice. These results marginally favor the 5 component model over the 10 component, but, more importantly, indicate no value from increasing the model flexibility beyond five components. We feel that the posterior model probability results in conjunction with the high flexibility of the models under consideration justify the conclusion that we have accommodated heterogeneity of an unknown form.

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[4]There are 36 x 10 = 360 unique variance-covariance parameters plus 10 x 8 mean parameters plus 9 mixture probabilites = 449.

Robustness Checks

State Dependence or a Mis-Specified Distribution of Heterogeneity? Some may still doubt if we have indeed found inertia or if the lagged choice coefficient simply proxies for a mis-specification of the distribution of heterogeneity. We perform a simple check to test for this possibility. Suppose there is no state dependence and that the coefficient on the lagged choice picks up taste differences across households that are not accounted for by the assumed functional form of heterogeneity. Then, if we randomly reshuffle the order of shopping trips, the coefficient on the lagged choice will not change and still provide misleading evidence for inertia. In Table 3 we show the log marginal likelihood for a five component model with an inertia term, which we fitted to our data with randomly reshuffled purchase sequences. The log marginal likelihood for the randomized sequence data is approximately the same as for the model without the inertia terms, and much lower than the log marginal density of the model with properly ordered data and the inertia term. We thus find strong evidence against the possibility that the lagged choice proxies for a mis-specified heterogeneity distribution.

State Dependence or Autocorrelation? While the randomized sequence test gives us confidence that we have found convincing evidence of a non-zero order choice process, it does not help distinguish between an inertia or state dependence model and a model with auto-correlated choice errors. Using normal models and a different estimation method, Keane (1997) finds that state dependent and auto-correlated error models produce very similar results. However, the economic implications of the two models are markedly different. With a structural interpretation for inertia as a form of state dependent utility, firms can influence the loyalty state of the customer and this has, for example, long-run pricing implications, while the autocorrelated errors model does not allow for interventions to induce inertia or loyalty to specific brands.

In order to distinguish between a model with a lagged choice or state dependent regressor and a model with autocorrelated errors, we implement the suggestion of Chamberlain (1985). We consider a model with a five component normal mixture for heterogeneity, no lagged

choice or state dependent term, but including the lagged prices defined as the prices at the last purchase occasion. In a model with state dependence, price can influence the loyalty (or state) variable and this will influence subsequent choices. In contrast, in a model with auto correlated errors, it is not possible to influence persistence in choices using exogenous variables. In Table 3, we compare the log marginal likelihood of the model without state dependence and a five component normal mixture with the log marginal likelihood of the same model including lagged prices. For margarine, the addition of lagged prices improves the log marginal likelihood by more than 50 points and by more than 100 points for refrigerated orange juice. This is strong evidence in favor of a "state dependence" specification with lagged choices.

A limitation of the Chamberlain suggestion (as noted by both Chamberlain himself and Erdem and Sun (2001)) is that consumer expectations regarding prices (and other right hand side variables) might influence current choice decisions. Lagged prices might simply proxy for expectations even though there is no state dependence at all. Thus, the importance of lagged prices as measured by the log marginal likelihood is suggestive but not definitive.

As another comparison between a model with auto correlated errors and a state dependent model, we exploit the price discounts or sales in our data. Since auto correlated errors are not synchronized across households nor with price discounting by the retailer, we can differentiate between state dependent and auto-correlated error models by examining the impact of price discounts on measured state dependence. The intuition for this test is as follows. In a world of serially correlated errors, households that are induced by price discounts to switch to a new product will not exhibit inertia or persistence in choice. However, in a world with state dependence, brand switching induced by any reason should create persistence. To implement this idea, we interact the loyalty variable with an indicator for whether the loyalty state was initiated by a discount or not (i.e. whether the last product purchased was purchased on discount).

$$u_{jt} = \alpha_j + \eta_j p_{jt} + \gamma_1 I\{s_t = j\} + \gamma_2 I\{s_t = j\} \cdot I\{discount_{s_t} = j\} + \epsilon_{jt} \qquad (4.2)$$

The term, $discount_t$, indicates whether the brand to which the consumer is currently loyal was on discount when it was last purchased. In a model with auto-correlated errors, the loyalty effect should dissipate for loyalty states generated by discounts, i.e. $\gamma_1 + \gamma_2 = 0$.

Table 3 provides a comparison of the log marginal likelihoods for the specification in (4.2); the log marginal likelihood values for the discount interaction term are in the last row of the table. The interaction term does improve model fit but by a modest 15-20 log density points. It remains an open question as to whether measured state dependence changes materially when we compare the distribution of the state dependence conditional on a past purchase that was or was not on discount. Recall that we allow for an entire distribution of parameters across the population of consumers so that we cannot provide the Bayesian analogue of a point estimate and a confidence interval. Instead, we plot the fitted marginal distribution of γ_1 and $\gamma_1 + \gamma_2$ in figure 5. The blue density curve is from our baseline model without any interaction term (2.1), the red is the inertial or state dependence effect conditional on a discount on the focal brand during the previous purchase occasion (labelled "lagged sale") (denoted γ_1 in 4.2), and the green is the effect conditional on no discount (labelled "no lagged sale") (denoted $\gamma_1 + \gamma_2$ in 4.2). There is little difference between the three densities for the orange juice category and a slight shift toward zero with a lagged sale in the margarine category. We conclude that there is scant evidence to support the claim that auto correlated errors are the source of measured inertia.

Brand-Specific State Dependence

In the basic utility specification (2.1), the inertia effects are governed by one parameter that is constrained to be the same across brands for the same household. There is no particular reason to impose this constraint other than parsimony. Several authors have found the measurement of inertial effects to be difficult (see, for example, Keane (1997), Seetharaman, Ainslie, and Chintagunta (1999), and Erdem and Sun (2001)) even with a one component normal model for heterogeneity. The reason for imposing one "state dependence" or inertia parameter could simply be a need for greater efficiency in estimation. However, it would be misleading to

report state dependent effects if these are limited to, for example, only one brand in a set of products. It also might be expected that some brands with unique packaging or trade-marks might display greater inertia than others. It is also possible that the formulation of some products may induce more inertia via some mild form of "addiction" in that some tastes are more habit-forming than others. For these reasons, we consider an alternative formulation of the state dependence model with brand-specific loyalty parameters. Our Bayesian methods have a natural advantage for more highly parametrized models in the sense that if a model is weakly identified from the data, the prior keeps the posterior well-defined and regular.

A five component mixture of normals with brand specific inertia fits the data with a higher log marginal likelihood for both categories. For margarine, the log marginal likelihood increases from -5551 to -5505 when brand specific effects are introduced into state dependence. There is an even more dramatic increase for the orange juice products, from -4436 to -4364. However, there is a difference between substantive and statistical significance. For this reason, we plot the fitted marginal densities for the inertia or "state dependence" parameters for each brand in figures 6 and 7. The distributions displayed in figure 6 compare the baseline model with models that allow for different inertia distributions for each brand. Interestingly, all four distributions are centered close to the baseline, constrained specification. In the orange juice category, figure 7 plots the distributions of inertia parameters for the four highest share brands. In this category, the 96oz brands have higher inertia than the 64oz brands. We should note that the prior distribution[5] on the inertia parameters is centered at zero and very diffuse. This means that data has moved us to a posterior which is much tighter than the prior and moved the center of mass away from zero. Thus, our results are not simply due to the prior specification but are the result of evidence in our data.

The main conclusion is that allowing for brand-specific inertia does not reduce the importance of inertial effects nor restrict these effects to a small subset of brands.

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[5]It should be noted that, as detailed in the appendix, our "prior" is a prior on the parameters of the mixture of normals – the mixing probabilities and each component mean vector and covariance matrix. This induces a prior on the distribution over parameters and the resultant marginal densities. While this is of no known analytic form, the fact that our priors on each component parameters are diffuse mean that the prior on the distributions is also diffuse.

5 Alternative Sources of Inertia: Search and Learning

We have established that inertial effects remain even with a very flexible distribution of heterogeneity, are robust to mis-specification of heterogeneity and are unlikely to be the result of auto correlated taste shocks. This holds out the possibility that changes in the exogenous variables such as price can change the brands for which households exhibit inertia and, thus, may have implications for firm policy. However, to evaluate these firm policy implications requires a structural interpretation that the inertia term represents a form of state dependence in which the utility for brands that have been recently purchased is altered. In this section, we consider the role of consumer search and product learning as possible alternative explanations.

We assess the extent to which our findings of inertia in brand purchase might be explained, not by state dependent utility, but by search or learning behavior. We do not postulate specific structural models of search or learning which would involve some strong structural assumptions on consumer behavior. Rather, we focus on aspects of consumer behavior that differentiate search or learning explanations from state dependence and that can be directly observed in our data.

Search

There can be no doubt that consumers face search costs in the recall of identities and location of products in a store. Hoyer (1984) found that consumers spent, on average, only 13 seconds "from the time they entered the aisle to complete their in-store decision." Furthermore, only 11% of consumers examined 2 or more products before making a choice in a given product category. Facing high search costs, consumers may purchase the products that they can easily recall or locate in the store. These products are likely to be the products which the consumer has purchased most recently. In this situation, consumers would display persistence or inertia in product choice as they may not be willing to pay the implicit search costs for investigating products other than those recently purchased.

In order to distinguish between inertia due to state dependence and inertia due to high search costs, we exploit data on in-store advertising, sometimes termed "display" advertising.

Retailers frequently add signage and even rearrange the products in the aisle so as to call attention to specific products. In the refrigerated orange juice category, 17.5% of the chosen items had an in-store display during the shopping trip (in the margarine category displays are seldom present)[6]. A display can be thought of as an intervention that reduces a consumer's search cost.

In the marketing literature, it is often assumed that consumers only choose among a subset of products in any given category. This subset is called the *consideration set*. Mehta, Rajiv, and Srinivasan (2003) construct a model for consideration set formation based on a fixed sample size search process. Using data for ketchup and laundry detergent products, they find that promotional activity, such as in-store displays, increase the likelihood that a product enters a consideration set. This work affirms the idea that in-store displays can reduce search costs.

If displays affect demand via search costs, we should expect that a display increases the probability of a purchase. In addition, if a consumer has purchased a specific product in the past $(s_t = j)$, then displays on *other* products should reduce the inertial effect or the tendency for the consumer to continue to purchase product j. This can be implemented by adding a specific interaction term to the baseline utility model:

$$u_{jt} = \alpha_j + \eta p_{jt} + \gamma_1 I\left\{s_t = j\right\} + \gamma_2 I\left\{s_t \neq j\right\} \cdot I\left\{display_{jt} = 1\right\} + \lambda I\left\{display_{jt} = 1\right\} + \epsilon_{jt} \quad (5.1)$$

To illustrate the coding of the interaction term in (5.1), consider the case of two brands and various display and inertia state conditions. If the consumer has purchased brand 1 in the past $(s_t = 1)$ and neither brand is on display, then utility for brand 1 relative to brand 2 is increased by γ_1. If brand 1 is on display, the utility difference increases by λ. If brand 2 is also on display, the main effect of display, λ, cancels out, but the interaction term turns on with the potential to offset the inertia effect. The difference between the utility for brand 1 and brand 2 due to state dependence and displays will be $\gamma_1 - \gamma_2$. Thus, γ_2 measures the

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[6]There is a good deal of independent variation between displays and price discounts. No correlation between the display dummy variable and the level of prices exceeds 0.4 in magnitude.

extent to which displays moderate the inertial effect of past purchases. If state dependence entirely proxies for search costs and if search costs disappear in the presence of a display, then we expect that $\gamma_1 - \gamma_2 = 0$.

Figure 8 plots the estimated marginal distribution of the inertia effect with and without a display on alternative products. We can see that the two distributions are nearly identical. There is virtually no evidence that displays affect persistence in choice. This leads us to conclude that the measured state dependence is not merely a reduced-form effect that proxies for in-store search costs.

The addition of a display main effect and interaction terms to the model improves the model fit. The log marginal likelihood increases from -4434 to -4339 with the addition of the display variables. However, most of this improvement in fit is due to the main effect terms (-4434 to -4360). We interpret the finding that display has a main effect on the purchase probability but does not change the measured degree of state dependence as evidence for a direct utility-enhancing advertising effect of displays. Whatever the interpretation of the main effect of displays, it is clear that that state dependence we estimate does not result from search behavior.

Learning

It has often been argued that consumers have imperfect knowledge of the quality of products and that the consumption of a product provides information about its true quality. This may create persistence in choices over time. For example, suppose a consumer prefers brand B to brand A under perfect information. However, initially the consumer has only imperfect knowledge of the product's quality, and expects that the utility from consuming A is larger than the utility from consuming B. We then observe the consumer buying brand A until she gains experience with brand B, for example if she tries B when the product is on promotion.

If learning is important in driving our state dependence findings, we would expect that experienced consumers in the category would exhibit less inertia than inexperience consumers. To proxy for shopping experience, we introduce a dummy for whether the primary shopper in

the household is over 35 years old. Let θ_h be the vector of household parameters (including brand intercepts, price, and the inertia term). We then partition θ_h into a part associated with the experienced shopper dummy and into residual unobserved heterogeneity that follows the mixture of normals distribution:

$$\theta_h = \delta z_h + u_h$$

$$u_h \sim N\left(\mu_{ind}, \Sigma_{ind}\right); ind \sim MN\left(\pi\right)$$

(5.2)

δ is a vector which allows the means of all model coefficients to be altered by the experienced shopped dummy, z_h.

We find that the model fit is changed only slightly by the addition of the experienced shopper dummy. The element of δ that allows for the possibility of shifting the distribution of the inertia or state dependence coefficient is imprecisely estimated with a HPD that covers 0. For margarine, the posterior mean of this element is .17 with a 95 percent Bayesian credibility region of $(-.25, .60)$. For orange juice the mean is .12 with a 95 percent Bayesian credibility region of $(-1.9, 1.75)$. We conclude that there is no evidence that experienced shoppers exhibit a different distribution of the inertia coefficient than less experienced shoppers.

A more powerful test of the learning hypothesis involves exploiting the fundamental difference between state dependence and learning models in terms of the implications for the behavior of the choice process. Under state dependence, as long as the exogenous variables (price, in our case) follow a stationary process, the choice process will also be stationary. However, in any model where learning is achieved through purchase and consumption, the choice process will be non-stationary. The consumers' posterior distributions of product quality will tighten as more consumption experience is obtained and consumers will exhibit less inertia. Eventually, consumers will behave in accordance with a standard choice model with no parameter uncertainty.

We will exploit this difference in behavior to construct a comparison of state dependence and learning model implications. Our panel is reasonably long and we might expect that consumers will learn as they obtain more consumption experience with a brand. We define

brand level consumption experience as the cumulative number of purchases of the brand, E_{jt}. We can interact the inertia or "state dependence" variable with this new experience variable to provide a means of comparing the learning and pure state dependence models.

$$u_{jt} = \alpha_j + \eta_j p_{jt} + \gamma_1 I\left\{s_t = j\right\} + \gamma_2 I\left\{s_t = j\right\} \cdot E_{jt} + \lambda E_{jt} + \epsilon_{jt} \tag{5.3}$$

Since the experience variable adds additional information to the choice model, we should not directly compare the log marginal likelihood values of the interaction model (5.3) and the baseline model (2.1). The hypothesis that state dependence proxies for learning has implications for the interaction term in equation (5.3). Under learning, the interaction term should reduce state dependence as brand experience accumulates. Table 4 provides the likelihood values for each category for a comparison of the model with the interaction term as in (5.3) with a model containing only a main effect of brand experience:

$$u_{jt} = \alpha_j + \eta_j p_{jt} + \gamma_1 I\left\{s_t = j\right\} + \lambda E_{jt} + \epsilon_{jt} \tag{5.4}$$

The marginal likelihood values increase by only 6 points when the interaction is added to (5.4) in the margarine category. In the orange juice category, the addition of the interaction term reduces the marginal likelihood. Figure 9 verifies that the interaction terms are centered at 0 and contribute little to the model. The red line in the figure plots the estimated marginal distribution of γ_2 in (5.3), while the blue line plots the estimated marginal distribution of γ_1.

It might be argued that learning models only apply to products for which consumers have little consumption experience. Substantial evidence for learning has been found for new products by Ackerberg (2003), and Osborne (2007). Moshkin and Shachar (2002) find that learning explains findings of state dependence for televisions programs, a product category with a very large and frequent number of new products. In our case, the same products have been in the market place for a considerable period of time. The households in the data might be expected to show little evidence of learning given their experience with the brands prior to their involvement in the panel. This underscores the importance of a flexible

model of heterogeneity. As a number of authors have noted, it is hard to distinguish learning models with heterogeneous initial priors from a standard choice model with brand preference heterogeneity. Indeed, Shin, Misra, and Horsky (2007) fit a learning model to a product category populated by well-established products. Once they supplement their data with survey data on household priors over product qualities, they measure very little learning.

6 The Dollar Value of State Dependence

The inclusion of the outside option in the model enables us to assign money-metric values to our model parameters simply by re-scaling them by the price parameter (i.e. the marginal utility of income), $\frac{\gamma}{\eta}$. The ratio represents the dollar equivalent of the utility premium induced by state dependence. The state dependence demand model has the same implications for consumer behavior as a model where consumers pay a specific amount of money when switching products.[7] Thus, the dollar equivalent ratio can be interpreted as a switching cost.

Table 5 displays selected quantiles from the distribution of the dollar state dependence premium across the population of households. Some of the values on which this distribution puts substantial mass are rather large values, others are small. To provide some sense of the magnitudes of these values, we also compute the ratio of the dollar loyalty premium to the average price of the products. For margarine products, the median dollar value of state dependence is 28 per cent of the average product price; for orange juice, the ratio is slightly lower at 21 per cent. However, there is a good deal of dispersion in the dollar value of state dependence. At the 75th percentile of the dollar value distribution, the dollar value of state dependence is 75 per cent of the purchase price for margarine and 41 per cent for orange juice. These are large values and of the order of many examples of standard economic (as opposed to psychologically derived) switching costs. For example, a cell phone termination penalty of $150 might be much less than total cell phone expenditures over the expected length of the contract. Another example of switching costs among packaged goods is razors and razor blades; a consumer needs to purchase a new razor when switching the type of razor blades.

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[7]See Dubé, Hitsch, and Rossi (forthcoming) for a detailed discussion.

Here the monetary switching cost is small relative to razor blade prices (**?**).

7   Conclusions

Inertia in consumer purchases has been documented in a variety of studies that use frequently purchased consumer packaged goods. Typically, the lagged brand choice is found to influence current brand choice positively and the results are interpreted as evidence in favor of state dependent demand. It is well known, however, that state dependence can be confounded with heterogeneity. Households that simply prefer one brand over the others in a product category exhibit, what appears to be, persistence. In package goods panel data, there are frequent sales which can induce brand switching and which can, in principle, differentiate state dependence from heterogeneity.

Most empirical studies of state dependence use a normal distribution of heterogeneity. There is good reason to believe that a normal distribution may be inadequate to capture heterogeneity in many choice model parameters. It remains to be seen if the findings of state dependence are robust to a more flexible heterogeneity distribution. We use a mixture of a large number of multivariate normal distributions and exploit recent innovations in estimation technology to implement a Bayesian MCMC procedure for this problem.

When applied to data on choices among brands of tub margarine and refrigerated orange juice, we do, indeed, find very substantial evidence of non-normality. Findings of inertia in brand choice are robust to a flexible distribution of preferences. It might be argued, however, that our findings of inertia stem from auto-correlated choice error terms. As Keane (1997) has pointed out, "state dependence" and auto-correlated error specifications can produce similar patterns in the data. The key difference between state dependence and auto correlation is that state dependence can be changed by external variables that alter the state and, therefore, the pattern of persistence in the future. On the other hand, the persistence stemming from auto-correlated errors cannot be altered. We exploit this difference between the models to create a test for auto correlation based on whether the past purchase was initiated by a price discount or not. We find evidence in favor of the state dependent model and against the

auto-correlated error specification.

The structural interpretation of the state dependence model is that, when a brand is purchased, there is a utility premium accorded that brand in future choices. Equivalently, we could interpret the state dependence model as a model of switching costs in which a cost is paid (in utility terms) from switching to brands not bought on the last purchase occasion. The switching cost interpretation of brand inertia or brand loyalty is based on the existence of psychological switching costs rather than explicit monetary or product adoption costs.

Alternative structural models which could give rise to inertia in choices are models with important brand search or learning effects. In search models, consumers may persist in purchasing one brand if the costs of exploring other options are high. In learning models, what appears to be inertia can arise because of imperfect information about product quality. Products which a consumer has consumed have less uncertainty in quality evaluation and this may make consumers reluctant to switch to alternative products for which there is greater quality uncertainty.

Comparison of the state dependent model to a model with learning or search effects could be done conditional on a specific implementation of the search or learning model. Learning models, for example, make explicit and restrictive distributional assumption regarding the likelihood of signal information and priors. Typically, a normal prior and likelihood are assumed for tractability. This poses a problem for a clean comparison of state dependence and learning as the comparison is between state dependence and a specific parametric learning model. Our approach is to examine those empirical implications of search and learning models which are different than those of a state dependence model.

For search models, we exploit the fact that we have in-store advertising data which can alter the cost of search. Our findings are that there is little evidence consistent with a generic implication of search models for choice under a regime of reduced search costs. For learning models, we use the non-stationary implications of the learning model for choice behavior. A state dependent model implies a stationary choice process (controlling for exogenous variables) while the learning model implies lower persistence in choices as consumers acquire

more information about a particular brand. The evidence in the data is consistent with the stationary state dependence framework.

We have established a firmer basis for the structural interpretation of the state dependent choice model for demand. This model implies that variables under firm control, such as prices, can influence the future choice behavior of consumers. This opens a number of possibilities for work on firm policy. In the companion pieces, Dubé, Hitsch, Rossi, and Vitorino (2008) and Dubé, Hitsch, and Rossi (forthcoming), we explore the implications of the estimates switching costs for dynamic pricing under multi-product monopoly and dynamic oligopoly respectively.

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Appendix: MCMC and Prior Settings

The MCMC method applied here is a hybrid method with a customized Metropolis chain for the draw of the household level parameters coupled with a standard Gibbs sampler for a mixture of normals conditional on the draws of household level parameters. That is, once the collection of household parameters are drawn, the MCMC algorithm treats these as "data" and conducts Bayesian inference for a mixture of normals. Thus, there are "two" stages in the algorithm.

$$\theta_h | y_h, X_h, ind_h, \mu_{ind_h}, \Sigma_{ind_h} \quad h = 1, \ldots, H \tag{7.1}$$

$$ind, \pi, \{\mu_k, \Sigma_k\} | \Theta \tag{7.2}$$

Θ is matrix consisting of H rows, each with the θ_h parameters for each household, y_h is the vector choice observations for household h, and X_h is the matrix of covariates. The first stage of the MCMC in (7.1) is a set of H Metropolis algorithms tuned to each household MNL likelihood. The tuning is done automatically without any "pre-sampling" of draws and is done on the basis of a fractional likelihood that combines the household likelihood fractionally with the pooled MNL likelihood (for further details, see Rossi, Allenby, and McCulloch (2005), chapter 5). It should be noted that this tuning is just for the Metropolis proposal distribution. This procedure avoids the problem of undefined likelihoods for tuning purposes. The household likelihood used in the posterior computations is not altered.

The second stage (7.2) is a standard unconstrained Gibbs Sampler for a mixture of normals. The "label-switching" problem for identification in mixture of normals is not present in our application as we are interested in the posterior distribution of a quantity which is label-invariant, i.e. the mixture of normal density itself. The priors used are:

$$\pi \sim Dirichlet\,(a)$$

$$\mu_k | \Sigma_k \sim N\left(\overline{\mu}, a_\mu^{-1}\Sigma_k\right)$$

$$\Sigma_k \sim IW\,(\nu, \nu I)$$

The prior hyperparameters were assessed to provide proper but diffuse distributions. $a = (.5/K, K)$, $a_{mu} = 1/16$, $\nu = dim\,(\theta_h) + 3$. The Dirichlet prior on π warrants further comment. The Dirichlet distribution is conjugate to the multinomial. $\sum a$ can be interpreted as the size of a prior sample of data for which the classification of θ_h "observations" is known. The number of observations of each "type" or mixture component is given by the appropriate element of a. Our prior says that each type is equally likely and that there is only a very small amount of information in the prior equal to a sample "size" of .5. As the number of normal components increases, we do not want to change how informative the prior is; this is why we scale the elements of the a vector by K.

Our computer code for this model can be found in the contributed R package, `bayesm`, available on the CRAN network of mirror sites (see function `rhierMnlRwMixture`).

Table 1: Description of the Data

Margarine

Product	Average Price	%Trips
Promise	1.69	13.11
Parkay	1.63	4.98
Shedd's	1.07	12.66
ICBINB	1.55	23.51
no-purchase (% trips)	45.73	
# households	429	
# trips per household	18.25	
# purchases per household	9.90	

Refrigerated Orange Juice

Product	Average Price	% Trips
64oz MM	2.21	11.1
Premium 64oz MM	2.62	7.00
96oz MM	3.41	14.7
Premium 64oz TR	2.73	28.8
64oz TR	2.26	6.76
Premium 96 oz TR	4.27	7.99
no-purchase (% trips)	23.75	
# households	355	
# trips per household	12.3	
# purchases per household	9.37	

Table 2: Re-purchase Rates

Margarine

Brand	Purchase Frequency	Re-purchase Frequency	Re-purchase Frequency After Discount
Promise	.24	.83	.85
Parkay	.09	.90	.86
Shedd's	.23	.81	.80
ICBINB	.43	.88	.88

Orange Juice

Brand	Purchase Frequency	Re-purchase Frequency	Re-purchase Frequency After Discount
Minute Maid	.43	.78	.74
Tropicana	.57	.86	.83

Table 3: Log Marginal Likelihood for State Dependence (SD) Specifications

Model	Margarine	Orange Juice
Homogeneous Model without SD	-10755	-7612
5 Comp Normal without SD	-5575	-4528
5 Comp Normal with lagged prices, no SD	-5517	-4389
Homogeneous Model with SD	-8175	-6297
5 Comp Normal with SD	-5501	-4434
5 Comp, SD, Randomized Purchase Sequence	-5581	-4503
5 Comp, SD, Interaction with Discount	-5537	-4419

Table 4: Learning and State Dependence

Model	Margarine	Orange Juice
5-comp, SD	-5551	-4434
5-comp, SD, experienced shopper dummy	-5533	-4477
5-comp, SD, main effect of brand experience	-5302	-4264
5-comp, SD, main and interaction effect of brand exp	-5266	-4293

Table 5: Dollar Value of State Dependence

Margarine

Quantile	Dollar Value	Dollar Value/Mean Price
10%	$0.07	0.04
25%	$0.17	0.11
50%	$0.44	0.28
75%	$1.16	0.75
90%	$2.69	1.74

Orange Juice

Quantile	Dollar Value	Dollar Value/Mean Price
10%	$0.12	0.04
25%	$0.27	0.10
50%	$0.56	0.21
75%	$1.15	0.42
90%	$2.09	0.77

Shedd's

ICBINB
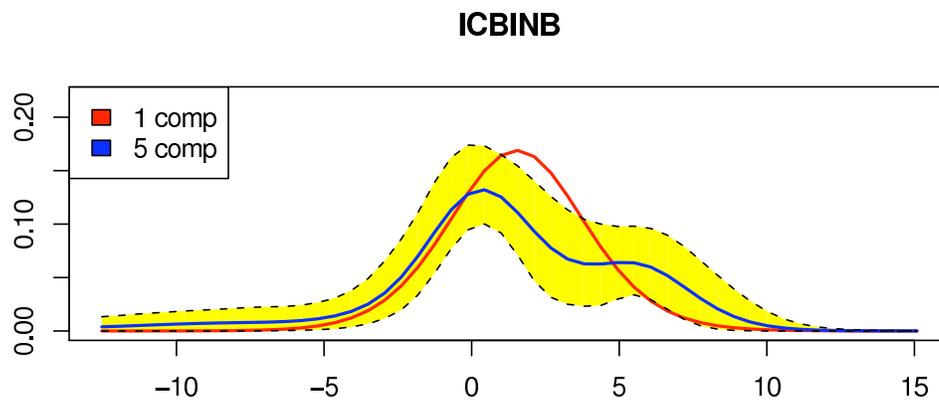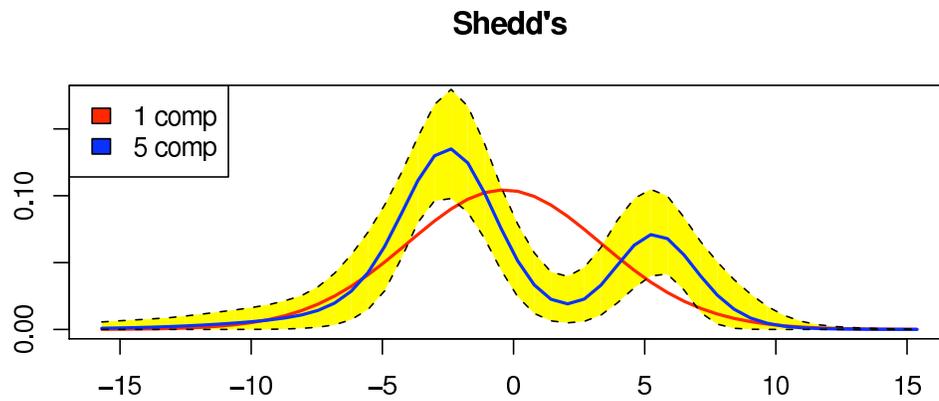
Figure 1: Margarine Intercepts
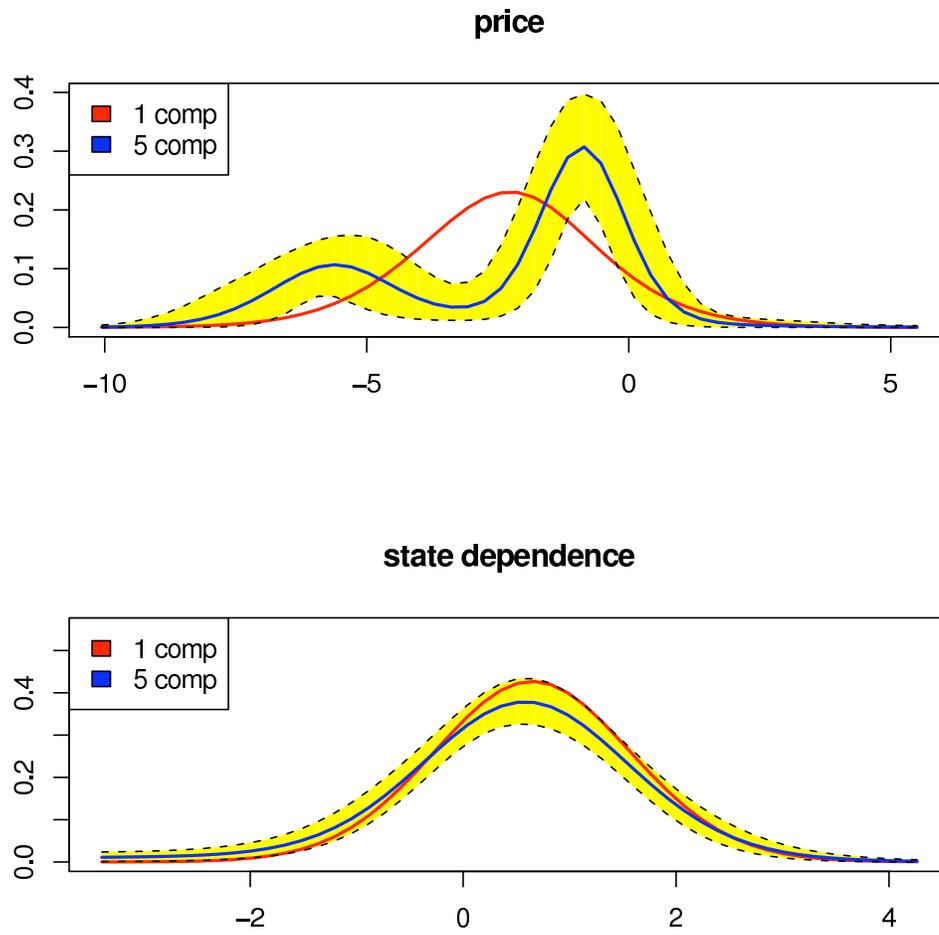
Figure 2: Price and State Dependence Coefficients: Margarine
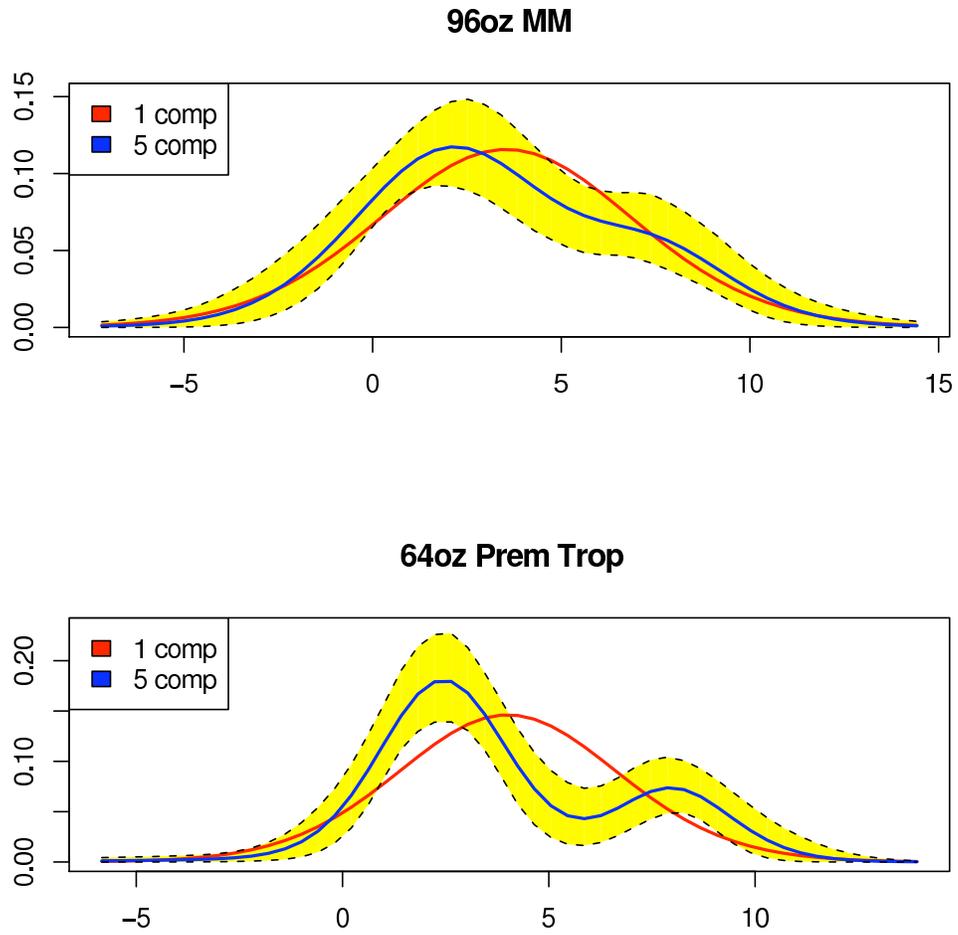
Figure 3: Refrigerated Orange Juice Brand Intercepts
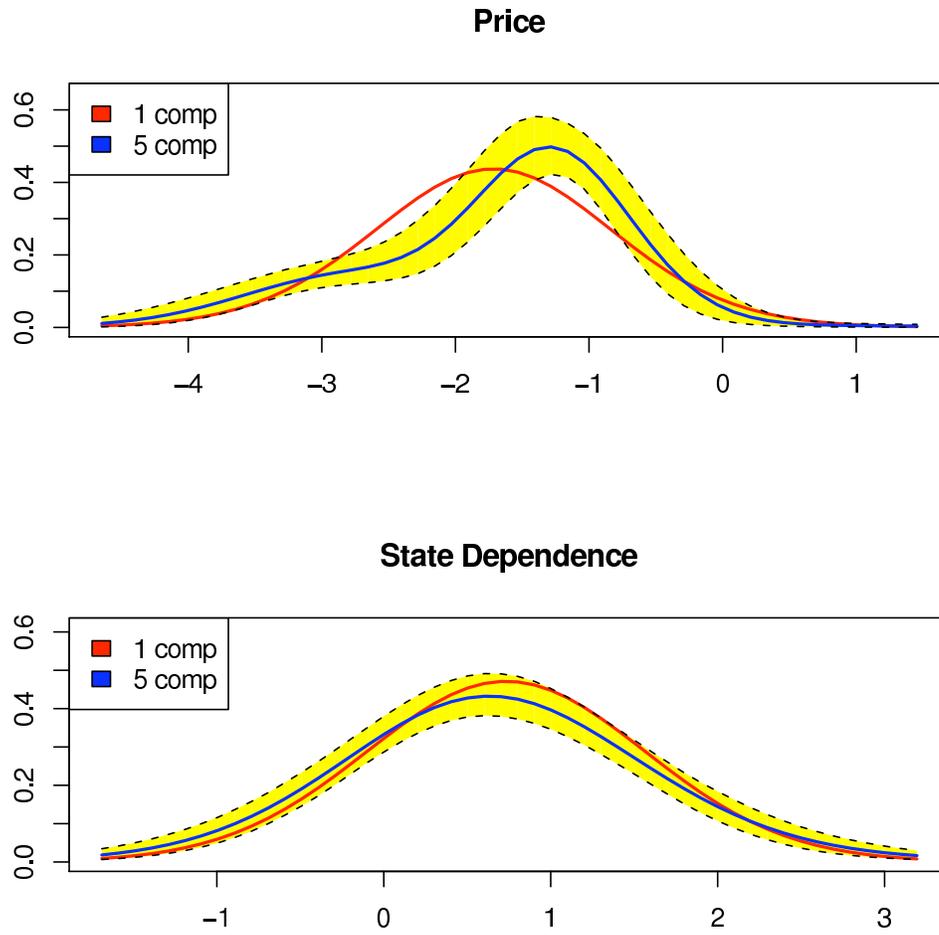
Figure 4: Price and State Dependence Coefficients for Refrigerated Orange Juice

Margarine

OJ
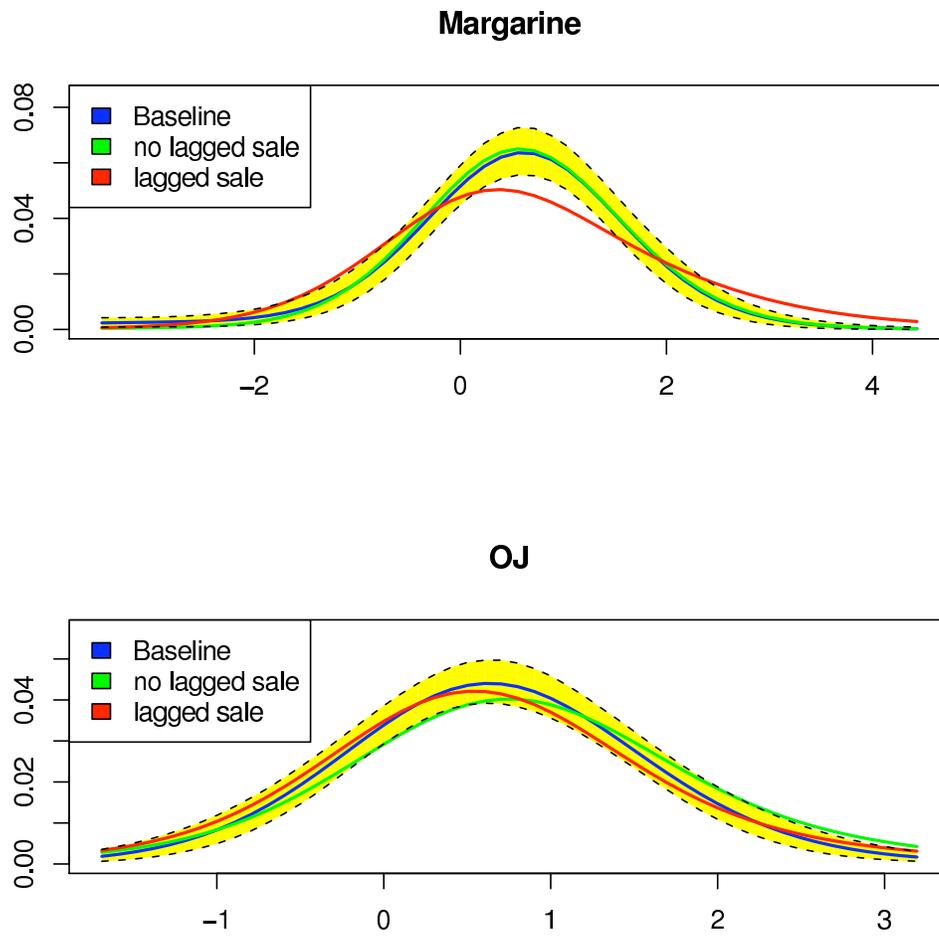
Figure 5: State Dependence and the Interaction with Price Discounts
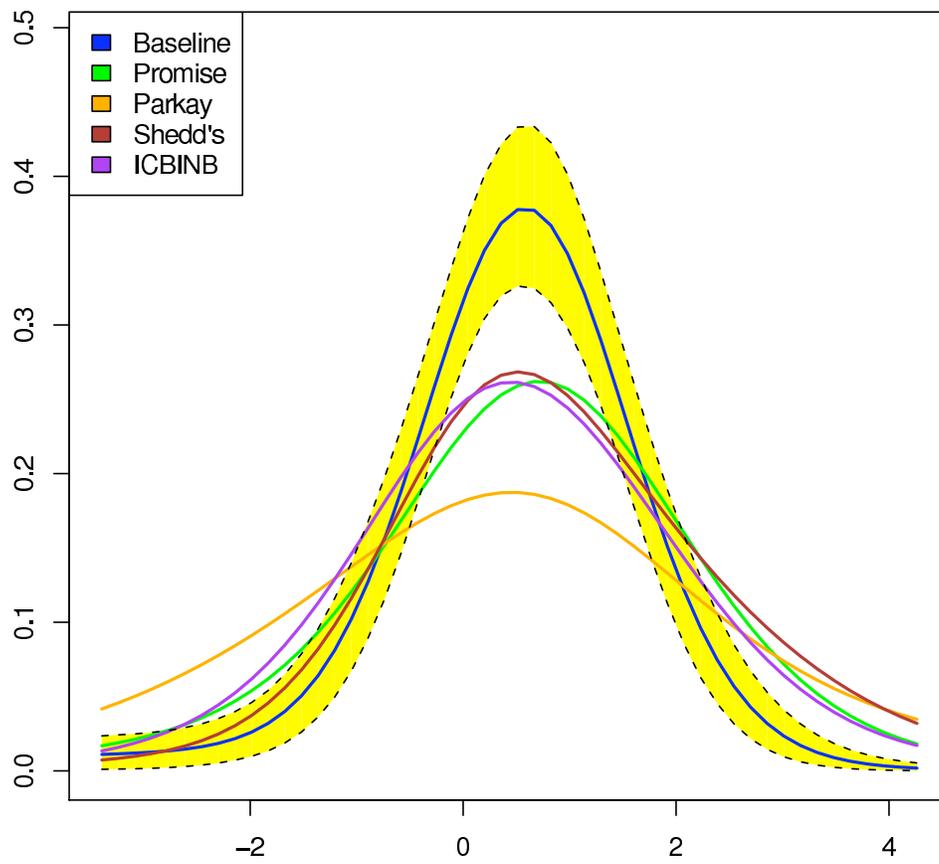
Figure 6: Brand Specific State Dependence: Margarine
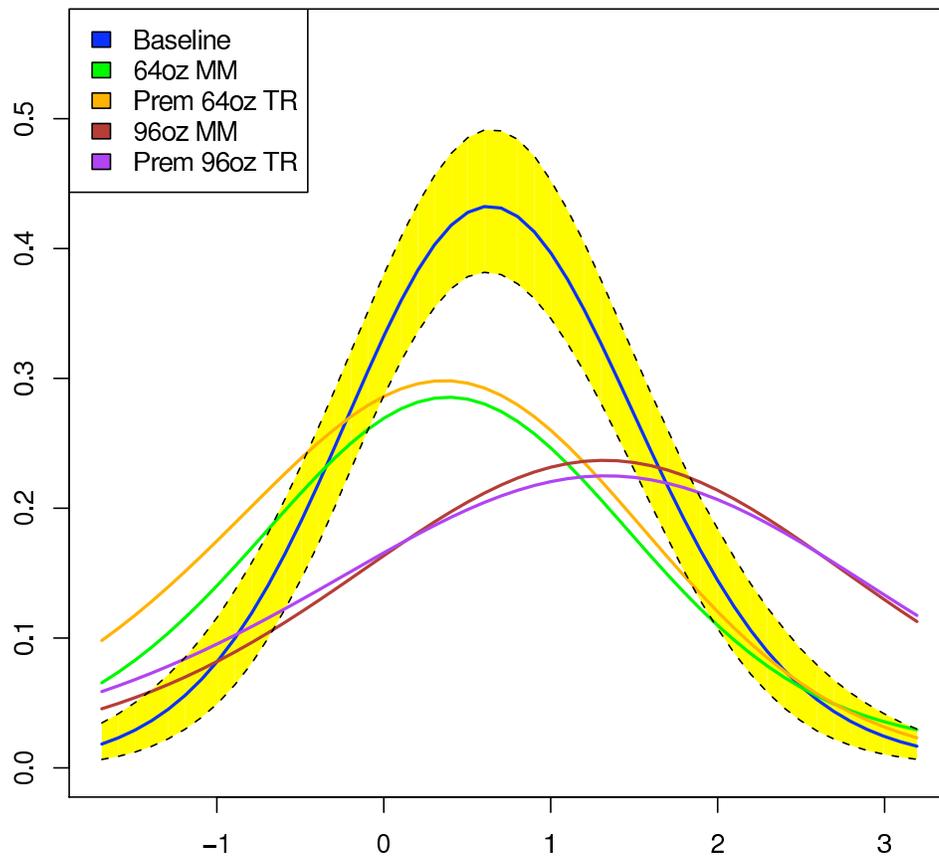
Figure 7: Brand Specific State Dependence: Orange Juice
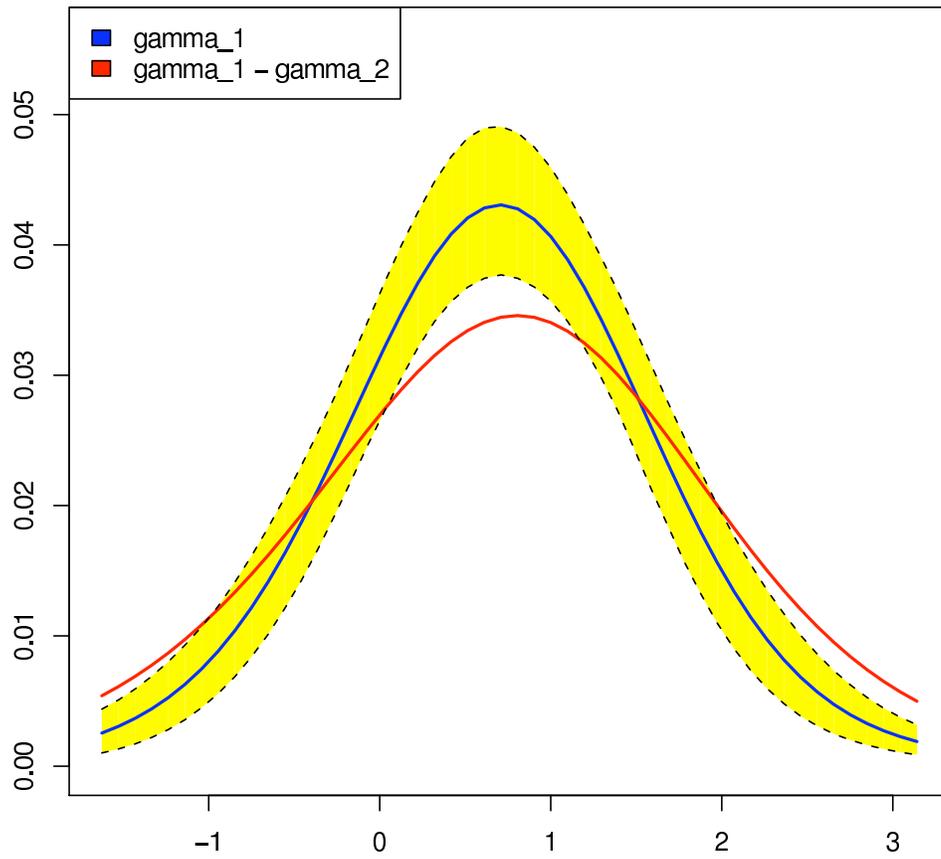
Figure 8: Interaction Between State Dependence and Display

Margarine

OJ
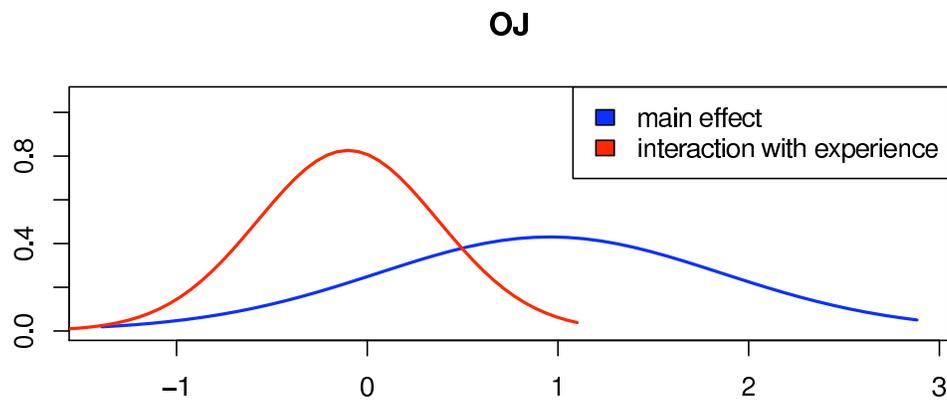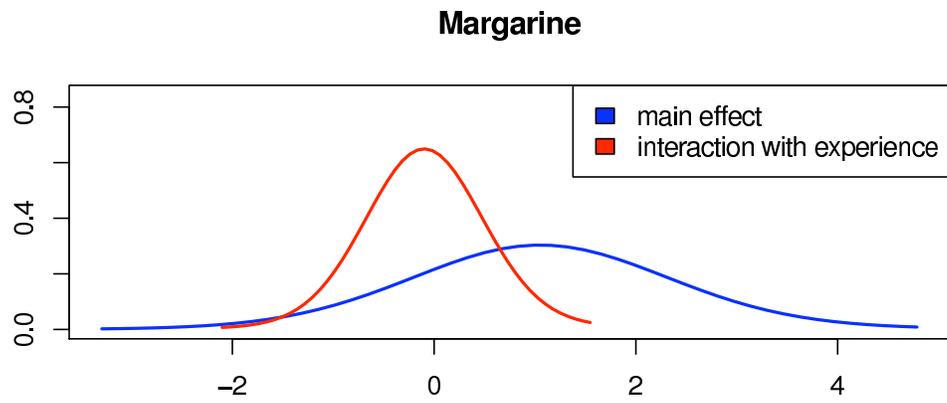
Figure 9: Interaction between State Dependence and Prior Brand Consumption