

# Testing a Theory of Shopping and Consumption: Are Multi-Product Choices Rational?

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## **Abstract**

This paper presents empirical evidence from three longitudinal experiments and multi-market panel data that supports a normative theory of multi-product choice. In multi-product choice, consumers select a set of substitutable hedonic products where the term “set” captures both the alternatives included (“variety”) and the number of units (“inventory”) of each alternative. Assuming that consumers are forward-looking, the theory’s closed-form value function determines the maximum expected utility available from any given set and so allows the *optimal* set to be determined. Across the three experiments, we found that the theory’s value function correctly predicted nearly half of the sets participants chose. Additionally, observed consumption patterns mimicked the theory’s dynamic, state-based decision rule, suggesting that consumers are forward looking in their consumption choices. Evidence from the final experiment showed that the normative theory explained consumption choices well; variety seeking did not. Finally, the normative theory predicts that the variety in a consumer’s multi-product set will increase as their consumption rate decreases. Evidence from panel data of yogurt purchases supports this proposition. Taken in its entirety, the empirical evidence presented in this paper supports the normative theory of multi-product choice and suggests that rational utility maximization explains the diversification commonly observed in these choices.

## **Keywords**

multi-product choice, shopping and consumption, diversification bias, rational decision-making, variety pack

## **Statement of Intended Contribution**

The topic of this paper is how consumers choose a set of substitutable hedonic products, where the term “set” captures both the alternatives included ("variety") and the number of units ("inventory") of each alternative. This "multi-product choice" has been the subject of considerable research. The primary finding from this research is that consumers usually select more variety when choosing a set for future consumption than when choosing a product on each consumption occasion. This finding, known as diversification bias, has generally been attributed to variety seeking or to poor forecasting of future preferences.

This paper tests a normative theory of shopping and consumption that frames multi-product choice as the rational response of forward-looking consumers to uncertainty in their future consumption preferences. The theory implies three propositions. To test these propositions, we gathered empirical evidence from three longitudinal experiments and from yogurt purchases recorded in multi-market panel data. The evidence uniformly supports the normative theory. It also shows that the high frequency of diversification observed in multi-product choices is optimal, based on the theory, and that observed consumption patterns are not explained by variety seeking.

This paper makes significant theoretical contributions: it provides a rational explanation of a phenomenon generally attributed to irrational causes and it provides a means of explicitly valuing variety in a common decision context. Of importance to practitioners, the normative theory’s value function accurately predicts actual multi-product choices. This provides firms that manufacture and sell multi-product packs with an objective approach to the design and pricing such packs—both fixed “variety packs” and customizable options such as “build your own 6-pack.”

## Introduction

For over 25 years, researchers have studied the choice of multiple products for future consumption. This involves selecting a set of substitutable hedonic products to be consumed one-at-a-time on future consumption occasions. For expositional simplicity, we will refer to this as “multi-product choice.”

Within and across categories, a consumer purchases enough products to justify the fixed cost of shopping (cf. Bell, Ho, and Tang, 1998).<sup>1</sup> Products are then inventoried in the consumer’s pantry, refrigerator, or freezer for future consumption. Within a category, the consumer’s inventory may include multiple product alternatives and multiple units of each alternative. Each subsequent consumption choice removes one unit from inventory. A consumption choice may exhaust the consumer’s inventory of a product alternative, thus eliminating it as an option for future consumption. In this way, buying a set of products and then consuming them one-at-a-time involves a dynamic sequence of interrelated choices.

The primary finding in multi-product choice research is that consumers usually select more variety (i.e., more different product alternatives) when choosing several products for future consumption than when choosing a single product on each consumption occasion. This finding, called *diversification bias*, has been attributed to variety seeking and to poor forecasting of future preferences. Simonson (1990) and Read and Loewenstein (1995) both described diversification bias as variety seeking and concluded that consumers usually choose too much variety when making multi-product choices. More recently, Kim, Allenby, and Rossi (2002, 2007), Dube (2004), and Richards, Gomez, and Pofahl (2012) developed econometric models for the simultaneous purchase of multiple product alternatives in varying quantities, which they called *multiple discreteness*. What these econometric models have in common is a decreasing marginal utility specification so that every unit of a product alternative purchased decreases the utility of buying another unit of that alternative on the same trip. Kim, Allenby, and Rossi (2002, p. 231) justified this specification in terms of satiation—which underlies variety seeking—by explaining that “It is important for

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<sup>1</sup>Perishability or other holding costs may limit purchase quantities.

the utility function to have diminishing marginal returns to capture satiation as we model demand situations where more than one unit is purchased and consumed.” Kahneman and Snell (1990, p. 304) took the position that diversification in multi-product choice is evidence of a systematic forecasting error, “... a mistake, which they [*consumers*] could perhaps avoid by a serious attempt to predict their tastes on each of these weeks [*consumption occasions*] separately.” It is important to note that many experimental studies of multi-product choice required participants to precommit to the sequence in which products will be consumed. In practice, consumers can choose any product from their pantry, refrigerator, or freezer, and so may never actually forecast consumption sequences when buying substitutable products. The theory we will test, and the experiments we conducted for that purpose, allow for consumption of any product in inventory at the time of consumption. This flexibility in the consumption sequence is a fundamental, yet complicating aspect of our investigation.

Some other studies have proposed that diversification in multi-product choice is actually a rational response to future preference uncertainty. However, tests of this proposition have yielded mixed evidence. Walsh (1995) and Salisbury and Feinberg (2008) found diversification in multi-product choice to be rational, but Read and Lowenstein (1995) did not. In this paper, we will present empirical evidence to test a normative theory of multi-product choice due to Fox, Norman, and Semple (2018), a theory consistent with diversification as a rational response to future preference uncertainty. For expositional simplicity, we will refer to this theory and the underlying models as “*FNS*.” This theory posits that the optimal multi-product choice set is the one that maximizes expected utility over the future consumption horizon. The purpose of our study is to provide empirical evidence that the normative model, and hence rational decision making, explains product diversification.

To develop an intuition for this theory, consider a consumer choosing a set of three products for future consumption from an assortment of three lettered product alternatives  $\{A,B,C\}$ . Assume that the consumer is indifferent between the product alternatives in the long run; that is, each alternative offers that consumer the same expected utility. If the consumer’s future preferences are at

all uncertain, the optimal choice set is one unit of each alternative  $[A,B,C]$ . The optimality of this set (in a utility-maximizing sense) will be shown later. However, stated simply, this set maximizes future consumption flexibility without sacrificing the total expected utility of products in the set. Now imagine that the same consumer is given a different task—to choose a single product on three different consumption occasions, each a multinomial choice from the full assortment of three product alternatives.<sup>2</sup> This task would most likely result in the choice of only two product alternatives because, of the  $27 = 3^3$  equally probable ordered consumption sequences, 18 include exactly two product alternatives (e.g.,  $[B,A,B]$ ,  $[A,B,B]$ ,  $[B,C,C]$ ). In other words, if consumers could forecast their future consumption preferences with perfect accuracy, their multi-product choice set would probably include two product alternatives rather than the three alternatives in the optimal set.

*FNS* proposed and analyzed two models, each with a *shopping stage* in which a set of  $n$  products is chosen for future consumption and a *consumption stage* in which products are consumed one-at-a-time from the set chosen in the shopping stage. The first model, the canonical n-pack model [*CNPM*], assumes that (i) a product is chosen on each of  $n$  consecutive consumption occasions, (ii) the future utility of each remaining product in the set is uncertain due to a stochastic error component, and (iii) the consumer's goal at each consumption stage is to maximize the total expected utility of the products remaining in the set. The second model, the generalized n-pack model [*GNPM*], relaxes the assumption that a product is selected from the set on every consumption occasion by introducing an outside option. This second model is applicable when different categories of products compete for the consumer's attention and when consumers have different usage rates. As noted previously, the sequence in which products are chosen in the consumption stage is not fixed, so consumers are free to choose whichever product maximizes their current and expected future utility.

The two models imply three testable propositions (propositions are modified here so as to be understandable without notation):

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<sup>2</sup>This illustrative example assumes that consumption choices are serially independent. Violations of independence, in particular variety-seeking, will be tested in the analysis of our experimental evidence.

1. The consumer's multi-product choices are consistent with a value function that balances the expected utility of products in the choice set and the consumption flexibility afforded by the variety of products in that set
2. The consumer's optimal consumption policy is a dynamic decision rule based on the inventory of available product alternatives and preference uncertainty
3. When an outside option is available, the optimal amount of variety in the product set is decreasing in the consumer's consumption rate of that category

The first proposition refers to the value function of the *CNPM*. This is a value function in closed-form, unique to each consumer, which can be used to predict their utility from consuming any given set. It is based on the conception of consumers as rational utility maximizers. Demonstrating the predictive accuracy of this value function would support a utility-based explanation for diversification in multi-product choice and justify using the value function in the design and pricing of multi-product packs (both fixed “variety packs” and customizable options such as “build your own 6-pack”). That is an important contribution of this paper. The value function also offers a precise, utility-based means of valuing variety in multi-product choice. The second proposition relates specifically to individual consumption choices and tests whether consumers actually maximize the utility of products in a set. More generally, this proposition tests whether consumers are forward looking when consuming the products in that set. The consumption policy of the *CNPM* is a state-based decision rule that depends on the current inventory and current utility of each product alternative (a proof of the precise rule is provided in Appendix A). This dynamic decision rule accommodates uncertainty in future preferences by allowing consumers the flexibility to choose a product when they see fit, in contrast to the consumption precommitment common in prior research. The optimality of the value function in the first proposition depends on consumers applying this consumption policy. The third proposition relates consumption rate for the product category to variety in multi-product choice sets. This proposition comes from an analysis of the *GNPM* which shows that greater variety in the choice set is necessary to compete with a more attractive outside

option (implied by a lower consumption rate). We formalize this intuition in the theory section. To our knowledge, no other theory addresses the relationship between usage rate and choice set variety nor has it ever been investigated. Empirical evidence of the second and third propositions is important to test the normative theory and its applicability to multi-product choice.

Evidence from three time-series experiments and multi-market panel data supports all three propositions. We tested the predictive accuracy of the normative value function (with a single parameter) against individual consumers' long-run product preferences (also with a single parameter) in multi-product choices, and found the value function to be vastly superior. Even multi-intercept models incorporating both product preferences and variety (with 4 to 8 parameters) did not offer better predictions than the more parsimonious value function model. We also found, conditional on the long-run preferences of our experimental participants, that most sets of three snack products actually chosen for future consumption were diversified (i.e., included more than one product alternative) and that diversification was usually *optimal*. The optimality of diversification is perhaps surprising given the small set size. We also tested the inventory-based consumption policy that is necessary for the value function to be optimal. Across the three experiments, we found that actual consumption choices were consistent with this policy. Interestingly, we tested variety seeking as an alternative explanation for observed consumption choices but did not find support. Finally, statistical analysis of yogurt purchases made by single-person panel households showed a negative relationship between their consumption rate and the relative variety of their multi-product choices—as predicted by the theory. In summary, we found broad, consistent empirical support for *FNS*'s normative theory of multi-product choice. This leads us to conclude, in the words of Assuncao and Meyer (1993, p. 530), that “...although it is unlikely that consumers will behave as optimal inventory theorists when making routine purchase decisions, the normative model may nevertheless provide a useful first approximation of this behavior.”

## Literature Review

Three literature streams have addressed consumers' choices of multiple substitutable products. Research in consumer psychology has compared the product variety of a set chosen for future consumption (termed "simultaneous choice") with the variety of products chosen on successive consumption occasions (termed "sequential choices"). Observe that simultaneous choice constrains subsequent consumption to the product alternatives remaining in the chosen set as it is depleted. Sequential choices are not so constrained; each consumption choice is made from the full assortment of product alternatives. The primary finding in this literature is that simultaneous choice of a given set generally includes more varied product alternatives than the same number of sequential choices (e.g., Simonson, 1990; Simonson and Winer, 1992; Read and Loewenstein, 1995). Researchers argued that this "diversification bias" (cf. Read and Loewenstein 1995) was due to poor forecasting; specifically, overestimating the probability of satiating on one's favorite products over time (Simonson 1990, Read and Loewenstein 1995, Kahn and Ratner 2005).

Simonson (1990) was the first to document the diversification bias, finding that people systematically choose a greater variety of product alternatives in simultaneous choices for future consumption than when choosing sequentially at the time of consumption. Diversification bias implies that, as the shopper purchases for more future consumption occasions, the variety of product alternatives selected will also increase. Simonson and Winer (1992) tested this implication using scanner panel data for the yogurt category, finding a positive relationship between the number of products and the variety of flavors purchased. Read and Loewenstein (1995) investigated whether diversification is actually a bias, or is consistent with rational utility maximization. They identified two sources of bias: (i) the tendency to overestimate the time between consumption occasions which causes people to overestimate satiation, and (ii) mental bracketing induced by simultaneous choice (combining multiple choices into one), which causes people to mistakenly choose a portfolio of products. Other studies of diversification bias also used the portfolio metaphor, comparing simultaneous choice to the selection of a stock portfolio to hedge against future uncertainty (Simonson 1990, Kahn and Ratner 2005). Though Read and Loewenstein (1995) did not find diver-

sification to be a rational hedge against uncertainty, others did. Notably, Salisbury and Feinberg (2008) used simulation studies to show that the extent of diversification should depend on the level of future preference uncertainty, along with the relative attractiveness of product alternatives and uncertainty about their attractiveness.

Recent econometric studies have considered the purchase of multiple products in the same category, which may vary by brand, flavor, etc. These studies modified existing discrete choice models to accommodate multiple products, with the objective of investigating price and promotion response in a multi-product context. Dube (2004) assumed that shoppers' purchases would be consumed over an unknown number of future consumption occasions. To accommodate diverse multi-product purchases, he assumed that the consumption utility for each product is concave and monotonically increasing in quantity. The resulting model was applied to carbonated soft drink purchase data. Kim, Allenby and Rossi (2002) developed a demand model based on an additive utility structure with a mixed distribution of continuous density and probability mass points. They then used this econometric approach to address retailers' assortment/pricing tradeoffs. Richards, Gomez and Pofahl (2012) applied a slightly different model that accommodated diverse multi-product purchases with a satiation parameter, implying that consumers prefer variety when buying for future consumption. They applied this model to fresh produce, specifically different varieties of apples. Lee and Allenby (2014) derived a model that incorporated differences in package size, in addition to brand and flavor variety. To investigate issues with the estimation of this model, they applied it to simulated data and to yogurt purchase data. They found that ignoring the complexity of diverse multi-product purchases leads to biased parameter estimates and improper attribution of many zero purchase quantities.

Walsh (1995) proposed and analyzed the first dynamic model of shopping and spending. In that model, the consumer chooses  $n$  total products for future consumption from two product alternatives. Walsh showed that it may not be optimal for consumers to select exclusively their favorite alternative. They may be better off also choosing a smaller quantity of the less preferred alternative, even in the absence of variety-seeking. He also showed that adding a unit to a set added

more than the unit's expected utility to the value of that set. Further, Walsh found that it is optimal to consume strategically, with consumption choice probabilities depending on the consumer's inventories of the two product alternatives.

What the relevant literatures for this study have in common is that they address the contemporaneous choice of multiple product alternatives for future consumption. Of course, there are vast and varied literatures addressing the choice of a single product; some of those focus on choices over time (e.g., variety-seeking, habit persistence). While we will consider variety seeking as an alternative explanation for one of the testable propositions, it does not play a prominent role in our in this paper's theory testing.

## **Evidence of Multi-Product Choice**

While researchers have shown considerable interest in multi-product choice, we now offer evidence of multi-product choice in grocery shopping. We used syndicated panel data from two major metropolitan markets (one in the midwestern US totalling 1707 households, the other in the southeastern US totalling 1031 households) with consumer packaged goods purchases made during a 24-month period between September 2004 and September 2006. We limited the data to single-member households to avoid confounding multi-product choice, as it applies to an individual, with intra-household preference heterogeneity. This screen yielded  $445 = 308 + 137$  single-person households from the two markets. We further screened infrequent category users and non-users by requiring households to have made a minimum of 12 purchases during the 24-month duration of the data.

Table 1 summarizes multi-product choice evidence from the top 15 categories, ranked by units purchased. We focus on the hedonic product categories, excluding cat food and dog food. The number of category users ranges from 117 for yogurt up to 345 for fresh bread and rolls. The mean number of annual trips on which households purchased in the category ranges from 11.6 for natural cheese up to 23.1 for carbonated beverages. Turning to the evidence of multi-product choice, observe that the percentage of multi-product purchases per household per trip (i) exceeded 20% for

**Table 1**  
**Panel Data Evidence of Multi-Product Choice**

Unit Purchase Ranking	Product Category	Single-Person HHs	Annual Trips per HH	Units per Trip	% multi-product purchases per HH per Trip		UPCs per HH per Trip	
					Mean	Max	Mean	Max
					1	Carbonated Beverages	292	23.1
2	Salty Snacks	310	17.2	1.94	27.1%	95.8%	1.39	3.34
3	Fresh Bread and Rolls	345	19.4	1.51	17.9%	89.0%	1.24	2.61
4	Cat Food	104	25.4	8.14	55.6%	97.1%	3.21	9.78
5	Soup	201	12.3	3.22	41.1%	99.0%	1.78	4.63
6	Chocolate Candy	250	16.9	2.65	32.1%	97.6%	1.57	4.57
7	Milk	345	20.7	1.19	6.4%	61.2%	1.07	1.77
8	Yogurt	117	14.0	4.36	56.1%	97.4%	2.40	5.21
9	Frozen Dinners/Entrees	215	15.8	3.50	58.6%	99.5%	2.51	6.47
10	Vegetables	160	12.0	3.09	35.1%	97.5%	1.62	3.94
11	Dog Food	81	21.7	4.66	42.3%	93.8%	2.26	5.96
12	Cold Cereal	189	12.9	1.69	24.6%	89.4%	1.31	2.55
13	Non-Chocolate Candy	174	13.7	2.18	23.8%	93.7%	1.35	3.17
14	Cookies	210	13.3	1.66	21.4%	90.5%	1.29	2.78
15	Natural Cheese	183	11.6	1.76	25.9%	90.2%	1.37	3.01

 Non-hedonic product category

11 of the 13 hedonic categories, (ii) exceeded 30% for 5 of the 13 hedonic categories, and (iii) exceeded 40% for 3 of the 13 hedonic categories. For the yogurt and frozen dinners/entrees categories (the 8th and 9th most frequently purchased grocery categories), *most* trips involved multi-product purchases. The reported maxima demonstrate that, in nearly every hedonic category, at least some single-person households bought multiple Universal Product Codes [UPCs] the vast majority of times that they purchased in the category. Similarly, the mean number of different UPCs per household per trip (i) exceeded 1.25 for 11 of the 13 hedonic categories, (ii) exceeded 1.50 for 5 of the 13 hedonic categories, and (iii) exceeded 1.75 for 5 of the 13 hedonic categories. Among the top 15 categories, yogurt purchases averaged 2.40 different UPCs while frozen dinners/entrees purchases averaged 2.51 different UPCs. The reported maxima again show that, in almost every hedonic category, at least some single-person household(s) bought more than 2.5 different UPCs per category purchase. In summary, the data demonstrate that multi-product choice is a material, managerially relevant behavior in the most frequently-purchased hedonic categories. Further, in some categories—yogurt and frozen dinners/entrees in our data—multi-product choices are more common than not.

## Theory

We test a normative theory of shopping and consumption based on the two models analyzed in *FNS*: (i) *CNPM*, which defines consumption occasions based on actual consumption of an item from the chosen set, and (ii) *GNPM*, which includes an outside option that allows for variation in usage rates. We borrow their notation as follows. In the shopping phase,  $n$  units are chosen from the store's full assortment of  $M$  product alternatives in the category. The  $n$  products chosen in a set can be represented by the integer vector  $(k_1, k_2, \dots, k_M)$  with  $k_i \geq 0$  and  $\sum_{i=1}^M k_i = n$ . Note that multiple units of a product alternative may be selected. We omit consumer and category subscripts for expositional clarity.

The normative theory is based on a simple random utility formulation. The utility of any product alternative  $i$  ( $i = 1, 2, \dots, M$ ) is assumed to be the sum of a consumer-specific deterministic component ( $U_i$ ) and a random component ( $\varepsilon_{it}$ ) for alternative  $i$  on the  $t^{\text{th}}$  consumption occasion. The deterministic component reflects the consumer's long-run preference for that product and so is time invariant. We assume without loss of generality that alternatives have been ordered and subscripted so that  $U_1 \geq U_2 \dots \geq U_M$ . The random component captures uncertainty about the consumer's preference for the product; it changes with each consumption occasion and is revealed immediately before consumption. The  $\varepsilon_{it}$  are assumed to be independent across product alternatives and time. After a suitable translation of the  $\varepsilon_{it}$  and  $U_i$ , one can assume each  $\varepsilon_{it}$  has zero mean and each  $U_i$  represents the expected utility of alternative  $i$ .

### Canonical $n$ -Pack Model

The canonical  $n$ -pack model [*CNPM*] assumes that a product from the choice set is selected on each consumption occasion. To illustrate the dynamics, let us suppose that there are  $M = 4$  alternatives and that a consumer has selected the set of  $n = 3$  products  $(2, 1, 0, 0)$ ; that is, two units of their favorite alternative and one unit of their second-favorite. On the first consumption occasion, the consumer can select a unit of alternative 1 (favorite) or a unit of alternative 2 (second-favorite). The current utility associated with each choice is  $U_1 + \varepsilon_{11}$  versus  $U_2 + \varepsilon_{21}$  respectively (recall

the current period errors are observed immediately before consumption). A myopic consumer would select alternative 1 if  $U_1 + \varepsilon_{11} > U_2 + \varepsilon_{21}$  and select alternative 2 if  $U_2 + \varepsilon_{21} > U_1 + \varepsilon_{11}$  (ties can be broken arbitrarily). However, a strategic consumer would consider both the current utility and the expected *future* utility. Letting  $V(q)$  represent the value of expected total future utility for a vector of quantities  $q$ , the strategic consumer chooses the alternative that maximizes  $U_1 + \varepsilon_{11} + V(1, 1, 0, 0)$  vs.  $U_2 + \varepsilon_{21} + V(2, 0, 0, 0)$ . Note that the future values are different because they incorporate different reductions in future inventory. The same “current utility” plus “expected future utility” comparison is done at each subsequent consumption occasion. In general, the hard part is determining a manageable expression for the expected future utility, or “value,” function  $V$ .

This framework necessarily abstracts shopping and consumption behavior. For example, the total number of products,  $n$ , is assumed to be exogenous. Clearly, factors such as trip type (major versus fill-in, cf. Kollat and Willet, 1967) and multiple-purchase incentives could affect  $n$ . Also, the consumer’s deterministic component of utility could be a function of store-specific factors such as price, or time-varying factors such as satiation. Introducing these complexities would not only greatly complicate the mathematical analysis, but would also obscure the basic insights on which our propositions are based.

If one assumes that the random errors follow a standard (zero-mean) Gumbel distribution—as one does in the classical logit choice framework—then it is possible to obtain some compact structural results for  $V$ . Assuming that the consumer follows an optimal consumption strategy (described shortly), then the value  $V(k_1, k_2, \dots, k_M)$  that consumer obtains from an arbitrary  $n$ -pack  $(k_1, k_2, \dots, k_M)$  is given by the formula

$$V(k_1, k_2, \dots, k_M) = \left[ \sum_{i=1}^M k_i U_i \right] + \left[ \ln(n!) - \sum_{i=1}^M \ln(k_i!) \right] \quad (0.1)$$

Our proof is in Appendix A. The value function consists of two distinct components, shown in square brackets in (0.1). The first is a linear function of quantities ( $k_i$ ) and expected utilities ( $U_i$ ). This component is increased by choosing alternatives that have higher expected utility; i.e., the

consumer's favorites. If the consumer had to pre-commit to a consumption sequence or if the random component was vanishingly small, the linear component would represent the consumer's expected utility for the set. One can think of this component as capturing the *intrinsic utility* of products in the set. However, if the consumer is free to choose an alternative at the time of consumption in the presence of future preference uncertainty, then the logarithmic second component in (0.1) must also be present. This component captures the incremental value of making consumption choices from a set using all available information at the time of consumption. Observe that the logarithmic component does not depend on the  $U_i$  but rather on the distributional properties of the quantities  $(k_1, k_2, \dots, k_M)$ . In contrast to the linear component in (0.1), the logarithmic component favors *variety*. The logarithmic component is maximized by selecting a single unit of  $n$  different alternatives, which represents the most possible variety. The two components in (0.1) capture the tension between opposing objectives: one favoring intrinsic utility, the other favoring variety. A consumer's utility-maximizing set—the optimal hedge—must balance these two objectives.

Notes: (i) Adding a unit of alternative  $j$  to a set with  $n$  units increases the expected utility of that set by an amount  $U_j + \ln(n+1) + \ln(k_j) - \ln(k_j+1)$ . Thus, the incremental benefit of adding a unit exceeds the expected utility of the choice made from those alternatives (McFadden, 1978; Ben-Akiva and Lerman, 1979). The same property was demonstrated by Walsh (1995) for the two-alternative case. (ii) Even for non-Gumbel errors, the value function can be shown to consist of a linear component  $\sum_{i=1}^M k_i U_i$  plus a nonlinear component  $f_n(k_1, k_2, \dots, k_M)$  that does not depend on the  $U_i$  and favors variety. Like the logarithmic component, the function  $f_n(k_1, k_2, \dots, k_M)$  is minimized by any set having  $n$  units of a single alternative and maximized by any set having  $n$  distinct alternatives. Unfortunately, the nonlinear component cannot typically be expressed in closed-form for general error distributions (see Alptekinoglu and Semple, 2018).

Our first proposition states that consumers will evaluate sets for purchase consistent with (0.1).

**Proposition 1.** *Consumers' choice of a set of substitutable products is consistent with the value function (0.1).*

The optimal consumption strategy is instructive as well. Suppose, on the  $t^{\text{th}}$  consumption occa-

sion, the set currently has  $q_{it}$  units of alternative  $i$  remaining. Then the utility maximizing strategy is to select the alternative that maximizes  $\ln(q_{it}) + \varepsilon_{it}$ . Observe that the optimal consumption strategy incorporates each product's current inventory,  $\ln(q_{it})$ , and random component,  $\varepsilon_{it}$ , but not its deterministic component,  $U_i$ . The result is that consumption choices are biased toward alternatives with higher inventory levels, implicitly preserving variety throughout the consumption sequence. This is the basis for our second proposition.

**Proposition 2.** (The Inventory Effect) *Let  $q_{it}$  represent the quantity of alternative  $i$  available on the  $t^{\text{th}}$  consumption occasion. Then the consumer's decision rule for selecting alternative  $i$  is a linear function of  $\ln(q_{it})$ .*

The decision rule in Proposition 2 implies that the probability of selecting an alternative is increasing in its inventory. It can be shown that this probability property generalizes to any error distribution (see Alptekinoglu and Semple 2018).

While different specifications of the value function might lead to similar propositions, the value function in (0.1) was derived from first principles. We test it without modification. A more *ad hoc* approach, such as allowing the data to determine weights for the bracketed terms in (0.1), would certainly improve fit, but we leave such exercises to future research.

## Generalized $n$ -Pack Model

The generalized  $n$ -pack model [GNPM] incorporates an outside option into the framework developed in the previous subsection, which complicates the value function. Suppose that the outside option is "product 0," with expected utility  $U_0$  and error term  $\varepsilon_{0t}$ . If  $U_0$  is large relative to the expected utilities of product alternatives in the set, then the outside option is attractive and the consumption rate (of products in the set) will be lower. Conversely, if  $U_0$  is small relative to the expected utilities of product alternatives in the set, then the outside option is unattractive and the consumption rate (of products in the set) will be higher. Note that the consumption horizon  $T$  is no longer defined to be  $n$  periods, because the outside option is inexhaustible and may be consumed in any or all periods.

As before, let the chosen set be represented by the vector of integer quantities  $(k_1, k_2, \dots, k_M)$  where  $k_i \geq 0$ ,  $\sum_{i=1}^M k_i = n$ . Now define a new set  $S_T$  of all possible consumption possibilities  $(x_0, x_1, \dots, x_M)$  over a horizon of  $T$  periods by

$$S_T(k_1, k_2, \dots, k_M) = \left\{ (x_0, x_1, \dots, x_M) : \sum_{i=0}^M x_i = T; 0 \leq x_0 \leq T; 0 \leq x_i \leq k_i \right\}.$$

Observe that consumption occasions can be decomposed into two subsets: (i) the number of times that products from the chosen set are consumed, represented by the  $(x_1, \dots, x_M)$  and necessarily satisfying  $x_i \leq k_i$  and (ii) the number of times that the outside option is consumed,  $x_0$ , which must satisfy  $x_0 = T - \sum_{i=1}^M x_i$ . Then

$$V_T(k_1, k_2, \dots, k_M) = \ln \left[ \sum_{(x_0, x_1, \dots, x_M) \in S_T(k_1, k_2, \dots, k_M)} \frac{T!}{x_0! x_1! \dots x_M!} e^{\sum_{j=0}^M x_j U_j} \right] \quad (0.2)$$

This is an unwieldy value function, but *FNS* showed that the set that optimizes (0.2) has at least as much variety as the set optimizing (0.1). Observe also that equation (0.2) nests (0.1); (0.1) is obtained by fixing the value of the outside option  $U_0 = -\infty$ .

*FNS* noted that lower consumption rates promote greater variety in the set that optimizes (0.2). A simple thought experiment provides the intuition. Imagine that a consumer has  $r$  units in inventory on the final consumption occasion of their horizon. If  $r > 1$ , then some units must go to waste (only one unit may be consumed on that final occasion). This can happen because utility could have been maximized on any prior consumption occasion by choosing the outside option rather than consuming a unit from the set. On the other hand, if  $r > 1$  and only one consumption occasion remains, then the optimal set would have  $r$  different alternatives. Maximizing the consumer's options is necessary to maximize their expected utility on this final consumption occasion. This "end of horizon" effect, as it is known in dynamic programming, would encourage consumers with low consumption rates to include greater variety in their chosen sets. We would therefore expect consumers with low consumption rates to choose sets with more variety than sets of the same size chosen by consumers with high consumption rates. This is the focus of Proposition 3.

**Proposition 3.** *For a given  $n$ , the variety included in a consumer’s optimal choice set is decreasing in consumption rate.*

## **Experimental Evidence**

In this section, we present results from three longitudinal experiments. The first was conducted to determine whether participants’ multi-product choices and consumption choices were consistent with Propositions 1 and 2, respectively. The second experiment was conducted to learn why some multi-product choices included products other than participants’ long-run favorites, and to test the robustness of Propositions 1 and 2 to a revised procedure for eliciting long-run preferences. The second experiment was also used to assess a possible boundary condition for Proposition 2. Finally, a third experiment was conducted to test the robustness of Proposition 2 across a variety of inventory levels and to test for variety seeking in consumption choices.

## **Experimental Design**

Following Simonson (1990), these experiments involved students consuming snack products once or twice per week over a series of consumption occasions. The three experiments share a common design.<sup>3</sup> Each experiment was conducted in two phases. In the first (i.e., shopping) phase, participants completed an online questionnaire by first selecting a snack sub-category—either salty snacks or candies. Participants were then offered an assortment from their selected subcategory of 15 single-serve products found in local vending machines. We then elicited participants’ long-run choice probabilities for their three favorite products in that assortment. To do this, we used a hypothetical scenario in which participants imagined that they were choosing snacks from a local vending machine. “If you purchase twice a week for a full year, what percent of the time would you choose each product? Please assign a choice percentage to each product, so that they add up to 100 (it’s OK to assign a choice percentage of 0 to a product).” We interpreted the assigned

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<sup>3</sup>The experimental design was approved for human participants by the University Institutional Review Board.

percentages as participants' long-run choice probabilities for products in the assortment.

In Experiment 1, participants identified their three most preferred snacks (unordered) from the full assortment *before* assigning long-run choice probabilities. In this experiment, the vending machine in the preference elicitation scenario offered only the participant's three most preferred snacks; hence, these were the only snacks assigned a choice probability. The assigned choice probabilities were used to identify participants' favorite, second-favorite, and third-favorite snacks. Ties in long-run choice probabilities were broken based on quantities that participants included in their multi-product choice sets later in this first (i.e., shopping) phase of the experiment. In Experiments 2 and 3, we modified the preference elicitation procedure. In these experiments, participants identified their favorites *after* first assigning long-run choice probabilities to all 15 snacks in the assortment. Unlike Experiment 1, the vending machine in Experiment 2 and 3's hypothetical preference elicitation scenario offered the full 15-product assortment. After assigning those choice probabilities, participants then separately identified their favorite, second-favorite, and third-favorite snacks (in rank order; no ties).<sup>4</sup> In all three experiments, long-run choice probabilities were used to calculate the intrinsic utilities specified in the *FNS* value function. To complete the first (i.e., shopping) phase of all three experiments, participants selected a set of three snacks for future consumption—the multi-product choice. This set could include one or more units of any product alternative in the full 15-product assortment (because participants were able to choose multiple units of the same snack product, we will proceed to use the term “product alternative” rather than “product” for clarity). Our experimental design effectively replicated Simonson's “simultaneous choice for sequential consumption,” although participants in our experiments did not pre-commit to a consumption order. Finally, participants provided minimal demographic information.

The second (i.e., consumption) phase of each experiment was longitudinal. We filled a box with a set of five snacks for each student participant to consume at class meetings over multiple weeks. The box contained a combination of the participant's favorite and second-favorite product

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<sup>4</sup>We included a time lag between preference elicitation and the ordered identification of participants' three favorite products so we could assess reliability.

alternatives.<sup>5</sup> Boxes containing all participants' snacks were wheeled into the classroom on a cart before each class meeting. At the beginning of class, participants chose one snack from their box for personal consumption that day. Participants were instructed not to trade snacks or to select a snack for someone else to consume. At the end of class, researchers removed the cart and recorded which product alternative each participant had chosen to consume. Each consumption choice reduced the participant's inventory of either their favorite or second-favorite alternative, thus affecting subsequent consumption choices. This procedure was repeated until all snacks were consumed.

## Experiment 1

In Experiment 1, 69 graduate student participants completed the first phase questionnaire, 61 of whom then completed the second phase. Of the participants who completed the first phase, 11 chose three-product sets that included a product alternative that was not one of their three favorites. We could not analyze the choice sets of those 11 participants because they chose a product alternative for which we had not elicited their long-run preference (though we were able to evaluate the consumption choices of most of these participants). *FNS* implies that the optimal multi-product choice set of  $n$  products would include only the  $n$  most preferred product alternatives. We considered several possible explanations for participants choosing less-preferred products, including indifference between alternatives (i.e., ties) and trying unfamiliar alternatives (i.e., exploration). These explanations will be assessed in the Experiment 2.

Proposition 1 states that multi-product choices are consistent with the normative value function (0.1). To test this proposition, we analyzed the three-product choice sets generated in the first phase questionnaire with three multinomial logit [*MNL*] choice models. In the first model, which we call the "normative value function model," the value function is the only predictor. Ordering favorites

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<sup>5</sup>The two most preferred snacks were used to ensure, to the extent possible, that participants were able to choose between products they like. In a pilot study, some participants had received sets with a combination of their favorite product alternative and their second-favorite; others had received a combination of their favorite alternative and their third-favorite. This design manipulated the relative preference between product alternatives in the set. We found that relative preference for products did not have a significant effect on consumption choices, so this manipulation was not included in the three experiments reported here.

by preference ( $i = 1, 2, 3$ ), we determined intrinsic utilities using long-run choice probabilities,  $U_i = \ln(p_i/p_1)$ , where  $p_i$  is the participant's long-run choice probability for their  $i$ th favorite.<sup>6</sup> These intrinsic utilities, together with the quantities of each favorite alternative, were entered into (0.1) to compute valuations  $V_j$  of the  $j = 1, 2, \dots, J$  ordered sets. Valuations were then used to compute choice probabilities of the ordered sets with a multinomial logit [MNL] choice model  $\exp(\beta V_j) / \sum_{j=1}^J \exp(\beta V_j)$ . In the second model, which we call the "intrinsic utility model," the only choice set predictor is the quantity-weighted sum of individual-specific expected utilities for product alternatives in the set,  $\sum_{i=1}^M k_i U_i$ , where  $k_i$  is the quantity of their  $i$ th favorite. Comparing the normative value function model to the intrinsic utility model (which lacks the choice flexibility component in (0.1)'s second set of square brackets) permits us to assess the contribution of choice flexibility to the normative value function's predictions.<sup>7</sup> The third model, which we call the "choice set intercepts model," specifies intercepts for each ordered set of the three favorite product alternatives. The possible sets are (3,0,0), (0,3,0), (0,0,3), (2,1,0), (2,0,1), (1,2,0), (0,2,1), (1,0,2), (0,1,2), and (1,1,1). In none of our studies were all of these sets chosen, so each experiment's choice set intercepts model specifies fewer than the maximum nine intercepts, with (3,0,0) set as the baseline. Observe that the multi-intercept specification accommodates both choice flexibility (via variety in the set) and relative utility ordering, so we would expect it to provide a strong test of the single-parameter normative value function model.

Because the three models are non-nested, we compute hit rates as well as *AIC* and *BIC* to enable comparison.

Table 2 shows fit statistics for the normative value function model, the intrinsic utility model, and the choice set intercepts model for Studies 1, 2, and 3. Focusing on Experiment 1 in the table's first column, we find that the single-parameter normative value function model dominates the single-parameter intrinsic utility model. It has a much higher hit rate (48.3% vs. 17.2%) and a higher log likelihood (-82.5 vs. -100.5). Interestingly, the normative value function and intrinsic

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<sup>6</sup>Note that the utility of the favorite is set to  $0 = \ln(p_1/p_1)$

<sup>7</sup>It is worth noting that the quantity-weighted sum of individual-specific expected utilities for product alternatives in the set,  $\sum_{i=1}^M k_i U_i$ , is also the expected utility of the choice set *if the consumption sequence is determined (or forecasted) in advance*.

**Table 2**  
**Multi-Product Choice Models**

	Experiment 1	Experiment 2	Experiment 3
n =	58	49	126
<b>Normative Value Function Model</b>			
Hit Rate	48.3%	44.9%	48.4%
Log Likelihood	-82.5	-72.9	-247.9
AIC	167.1	147.7	497.9
BIC	169.1	149.6	500.7
Coefficient:			
Normative Value Function	2.049 ***	0.445 *	0.762 ***
<b>Intrinsic Utility Model</b>			
Hit Rate	17.2%	22.4%	24.6%
Log Likelihood	-100.9	-76.9	-277.7
AIC	203.9	155.8	557.5
BIC	205.9	157.7	560.3
Coefficient:			
Intrinsic Utility	0.373 *	0.172	0.286 ***
<b>Choice Set Intercepts Model</b>			
Hit Rate	41.4%	40.8%	50.0%
Log Likelihood	-79.6	-64.8	-185.3
AIC	169.3	137.5	386.6
BIC	179.6	145.1	409.3
Intercept Coefficients:			
Intercept (0,3,0)			-1.945 *
Intercept (0,0,3)			-2.636 *
Intercept (2,1,0)	1.050 *	0.827	1.074 ***
Intercept (2,0,1)	-0.847	-0.336	-1.542 *
Intercept (1,2,0)	-1.253		-1.252 *
Intercept (0,2,1)	-1.253	-1.946	-1.945 *
Intercept (1,0,2)			-1.542 *
Intercept (0,1,2)			
Intercept (1,1,1)	1.232 **	1.050 *	1.504 ***

\* Significant at  $\alpha = 0.05$

\*\* Significant at  $\alpha = 0.01$

\*\*\* Significant at  $\alpha = 0.001$

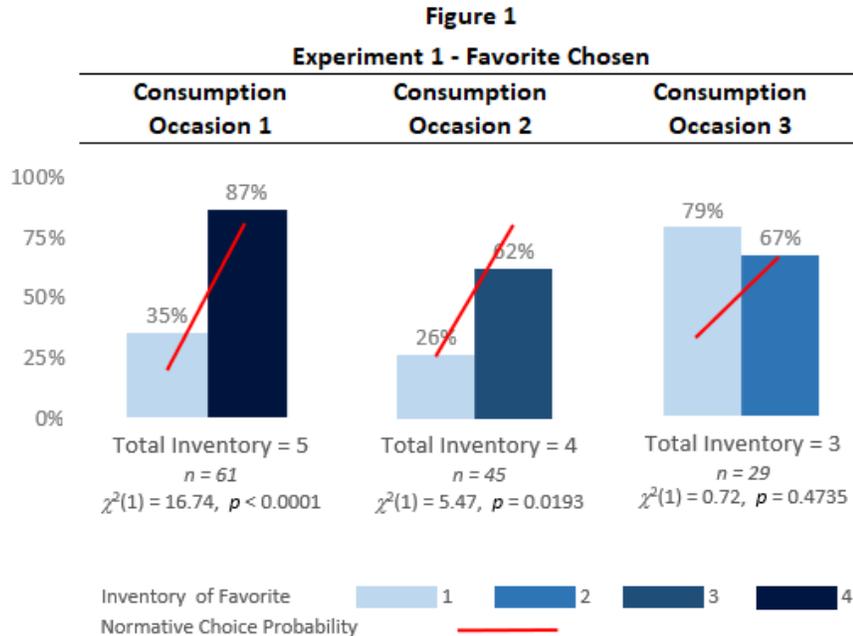
utility variables are highly correlated ( $r = 0.899$ ). Yet adding choice flexibility to intrinsic utility increases the normative value function's hit rate by more than 2.8 times without additional parameters. The normative value function model also offers better predictions than the five-parameter choice sets intercept model. It has a higher hit rate (48.3% vs. 41.4%) and lower *AIC* and *BIC* values. The normative value function model's superior predictive accuracy provides support for Proposition 1—evidence that multi-product choices are consistent with the normative value function.

Now we consider choice set composition. Of the 58 multi-product choice sets analyzed, only 12.1% were non-diversified (i.e., included only a single product alternative), while 46.6% were partially diversified (i.e., included two alternatives) and 41.4% were fully diversified (i.e., included all three of their favorite alternatives). That participants included variety in their three-product sets so consistently is perhaps not surprising considering prior literature. However, comparing *FNS* normative valuations shows that a partially-diversified set offered higher value than a non-diversified set with probability 0.765 and that a fully-diversified set offered more value than a non-diversified set with probability 0.679; probabilities that are roughly consistent with observed diversification frequencies. Overall, diversification in multi-product choice (partial or full) was generally optimal for participants in Experiment 1.

In the second phase of Experiment 1, participants sequentially consumed a set of five snacks. Figure 1 shows, from left to right, the sample proportion of participants that chose their favorite on the first, second, and third consumption occasions. We did not test the two final consumption occasions because they offered no information about the effects of inventory on consumption. The red line shows the normative probability of choosing their favorite, based on the inventory product alternatives in their boxes. On the first consumption occasion, 61 participants chose from a set that included either one or four units of their favorite product alternative with the remainder being their second-favorite.<sup>8</sup> A test of independence ( $\chi^2(1) = 16.74, p < 0.0001$ ) shows strong evidence of a relationship between inventory and consumption choice of the favorite. Observe that

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<sup>8</sup>61 of the 69 participants who completed the first phase went on to complete the second phase; this was the sample whose consumption choices were evaluated.



participants were far more likely to choose their favorite if they had four units in inventory than just one. On the second consumption occasion, the 45 participants who still had a choice (and completed the task) chose from a set that included either one or three units of their favorite with the remainder being their second-favorite. The test of independence for this consumption occasion ( $\chi^2(1) = 5.47, p < 0.0193$ ) again shows a relationship between inventory and consumption choice. Participants were twice as likely to choose their favorite when they had three units in inventory than only one. On the third consumption occasion, the 29 participants who still had a choice (and completed the task) chose from a set with either one or two units of their favorite product alternative with the remainder being their second-favorite. The test of independence for this consumption occasion ( $\chi^2(1) = 0.72, p < 0.4735$ ) offers insufficient evidence of a relationship between inventory and consumption choice. Interestingly, most participants chose their favorite product on the third consumption occasion, regardless of whether they had one or two units in inventory. This raised the possibility of a boundary condition for the optimal consumption policy, which we addressed in the next two experiments. Except for the third consumption occasion, which was limited to only 29 choices, Experiment 1 provided support for Proposition 2's inventory-based consumption rule.

## Experiment 2

In Experiment 2, we modified and expanded Experiment 1’s preference elicitation approach to learn why some participants’ multi-product choice sets included snacks that were not among their favorites. The key modifications were to: (i) elicit long-run choice probabilities for all 15 products in the assortment—not just the participant’s three most preferred, (ii) then require participants to specifically identify their favorite, second-favorite, and third-favorite product alternatives to break ties in long-run choice probability. Further, we asked participants “Are there any snacks you like as much as your three favorites?” Nearly half (47.8% = 33/69) responded “yes.” Most identified one or more snacks *not in* the 15-product assortment; only 10.3% (= 7/69) identified snacks *in* the assortment that they liked as much as their self-reported favorites. We also asked participants “Did your set of three snacks include any that wasn’t one of your favorites? If so, why?” For the 16.2% (= 11/68) who responded “yes,” their reasons are reported in Appendix B. Those reasons include four expressions of dissatisfaction with the product alternatives in the assortment, two of which mentioned a preference for healthier snacks.<sup>9</sup> The number of participants who preferred snacks not in the vending machine assortments, together with the participants who reported that they had simply changed their minds, motivated us to ensure that preferences were reliable. We screened participants for test-retest reliability by requiring that (i) their self-reported favorite product alternative to have a long-run choice probability at least as high as all other alternatives, (ii) their second-favorite alternative to have a long-run choice probability at least as high as all other alternatives besides their favorite, and (iii) their third-favorite alternative to have a long-run choice probability at least as high as all other alternatives besides their favorite and second-favorite.<sup>10</sup>

Experiment 2’s first phase incorporated the modified preference elicitation approach detailed

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<sup>9</sup>Two participants reported that they were motivated to explore unfamiliar products. Exploration implies gathering information to learn one’s own preferences, suggesting a different model than *FNS*. Though only these two participants reported using their multi-product choices for exploration, we conjecture that exploration might be more prevalent in categories with large or seasonal assortments—beer, for example. We address exploration as a motivation in our concluding remarks.

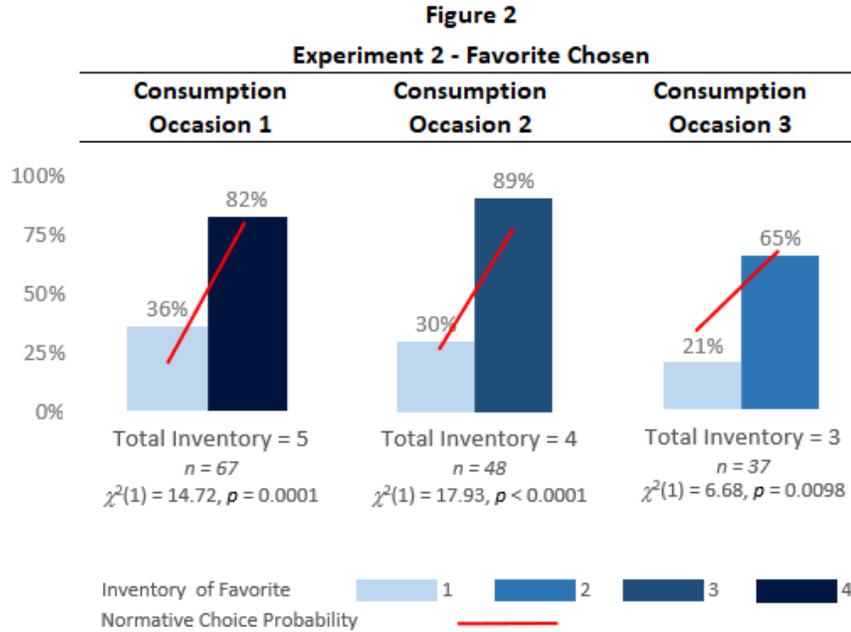
<sup>10</sup>We acknowledge that Experiment 2’s (and Experiment 3’s) requirement to allocate 100% across 15 products in a hypothetical scenario could be cognitively taxing, and that some participants may have failed the test-retest reliability screen because of task difficulty. Nevertheless, reliable information about long-run preferences was important for our investigation so we assessed the rigor to be worthwhile.

above; the second phase replicated Experiment 1 exactly. Participants received a set of five snacks including either: (i) four units of their favorite product alternative and one unit of their second-favorite, or (ii) one unit of their favorite and four units of their second favorite. Sixty-nine graduate student participants completed the first phase of Experiment 2 and 67 participants provided data for the second phase. After screening for test-retest reliability, 49 choice sets were evaluated.

Returning to Table 1, fit statistics for Experiment 2 can be found in the second column. The normative value function model once again dominates the intrinsic utility model—more than double the hit rate (44.9% vs. 22.4%) and a higher log likelihood (-72.9 vs. -76.9). The normative value function and intrinsic utility variables are even more highly correlated than in the previous experiment ( $r = 0.977$ ) yet, by adding choice flexibility to intrinsic utility, the value function more than doubles the hit rate of intrinsic utility alone. The one-parameter normative value function model also offers a higher hit rate than the four-parameter choice sets intercept model (44.9% vs. 40.8%), though the choice set intercepts model offers lower *AIC* and *BIC* values. The superior hit rate of the normative value function model provides additional support for Proposition 1 and affirms the consistency of actual multi-product choices with *FNS*'s normative value function.

Analysis of choice set variety reveals that only 14.3% were non-diversified (i.e., included only a single product alternative), 45.0% were partially diversified (i.e., included two alternatives) and 40.8% were fully diversified (i.e., included all three of their favorite alternatives). As in Experiment 1, the vast majority of participants included variety in their three-product sets. Comparing *FNS* normative valuations shows that a partially diversified set offered more value than a non-diversified set with probability 0.796 and that a fully diversified set offered more value than a non-diversified set with probability 0.592. In sum, most participants in Experiment 2 diversified their three-product choice sets by including multiple product alternatives—which was optimal based on the normative value function.

In the second phase of Experiment 2, participants sequentially consumed a set of five snacks. Figure 2 shows the sample proportion of participants who chose their favorite on the first, second, and third consumption occasions. On the first consumption occasion, 67 participants chose from



a set that included either one or four units of their favorite product alternative with the remainder being their second-favorite. A test of independence ( $\chi^2(1) = 14.72, p = 0.0001$ ) shows strong evidence of a relationship between inventory and consumption choice of the favorite. On the second consumption occasion, the 48 participants who still had a choice (and completed the task) chose from a set that included either one or three units of their favorite with the remainder being their second-favorite. A test of independence ( $\chi^2(1) = 17.93, p < 0.0001$ ) again shows strong evidence of a relationship between inventory and consumption choice. On the third consumption occasion, the 37 participants who still had a choice (and completed the task) chose from a set with either one or two units of their favorite alternative with the remainder being their second-favorite. A test of independence ( $\chi^2(1) = 6.68, p = 0.0098$ ) again shows evidence of a relationship between inventory and consumption choice. Thus, inventory was predictive of participants' decision to consume their favorite product on all three consumption occasions. Further, participants were more than twice as likely to choose their favorite if they had multiple units in inventory (vs. a single unit) on all three consumption occasions, as predicted by the optimal consumption policy. Overall then, Experiment 2's consumption choices provide strong support for Proposition 2's inventory-based decision rule.

Recall that participants were more likely than not to choose their favorite on the third consumption occasion in Experiment 1. This finding was not replicated in Experiment 2. In fact, fewer than half of participants chose their favorite on the third consumption occasion, offering no evidence of a boundary condition for Proposition 2.<sup>11</sup>

### **Experiment 3**

Recall that some previous work characterized diversification in multi-product choice as variety-seeking (Simonson 1990, Read and Loewenstein 1995). Yet satiation, the rationale for variety-seeking, applies to *consumption choices*, not to multi-product choices made prior to consumption (Raju 1980, McAlister and Pessimier 1982). For variety seeking to cause diversification in multi-product choice, consumers would have to anticipate variety seeking in downstream consumption. In Experiment 3, we tested variety-seeking as an alternative explanation for diversification in multi-product choice by determining whether consumption choices are consistent with variety-seeking. Specifically, we tested for a relationship between consecutive consumption choices. The design of the consumption (i.e., second) phase in the two previous experiments did not permit such a test. Consumption choices were made between one product alternative with multiple units in inventory and another with a single unit in inventory. If the product alternative with a single unit in inventory was chosen, it could not be chosen again. As a result, for every consumption choice in the data, the previous consumption choice was necessarily the alternative with multiple units in inventory. This confound precluded a test of consecutive consumption choices.

In Experiment 3, participants again received a set of five snacks split between the participants' favorite and second-favorite product alternatives. However, participants received either one, two, three, or four units of their favorite—not either one or four units as in previous experiments—with the remainder being their second-favorite. This design enabled us to test whether participants'

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<sup>11</sup>Comparing Experiments 1 and 2, (i) the consumption phase was identical, and (ii) similar participant profiles offered no rationale for the differing result. In Experiment 1, participants were graduate business students at a private university in the Southern US with an average age of 29 years, 31% of whom were female. In Experiment 2, participants were graduate business students at the same private university in the Southern US with an average age of 28 years, 44% of whom were female.

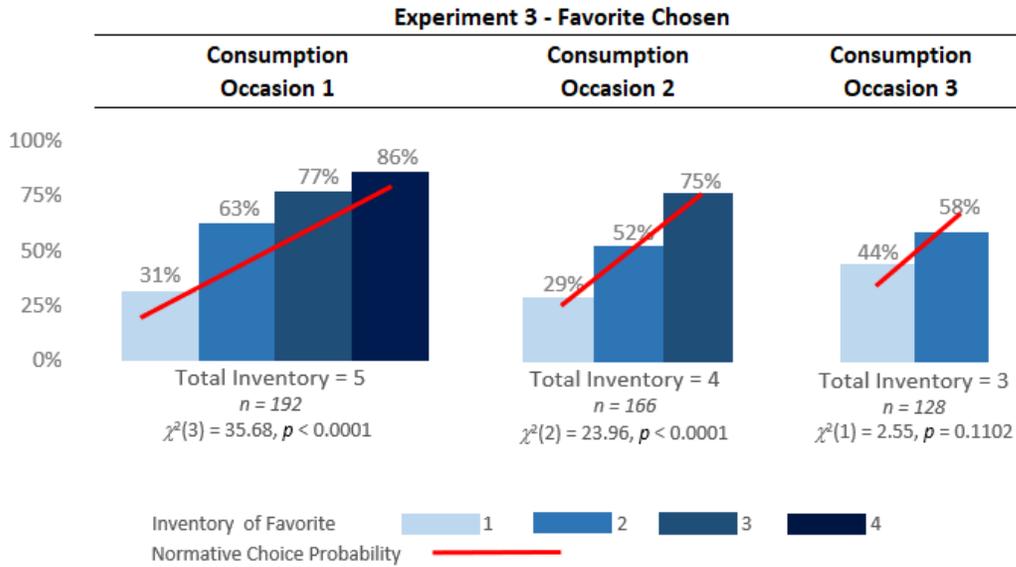
consumption choices were consistent with variety-seeking, while also evaluating the robustness of Proposition 2's inventory-based consumption rule to a wider range of inventory allocations. Note that the first (shopping) phase of Experiment 3 was unchanged from Experiment 2.

A total of 201 participants completed the first phase and 192 provided data for the second phase. After screening for test-retest reliability of their preferences, 126 participants' multi-product choices were evaluated. Returning to Table 1, the fit statistics for Experiment 3 can be found in the third column. As in previous experiments, the normative value function model dominates the intrinsic utility model as evidenced by a higher hit rate (48.4% vs. 24.6%) and a higher log likelihood (-247.9 vs. -277.7). The normative value function and intrinsic utility variables are even more highly correlated than in the previous experiments ( $r = 0.980$ ). Yet again, the *FNS* value function's addition of choice flexibility to intrinsic utility nearly doubles the hit rate without adding any parameters. Comparing the normative value function model to the choice set intercepts model is more complicated. The one-parameter normative value function model has a hit rate nearly as high as the eight-parameter choice sets intercept model (48.4% vs. 50.0%). On the other hand, the choice sets intercept model offers lower *AIC* and *BIC* values than the normative value function model. Overall, the normative value function model's predictive accuracy and parsimony provides additional support for Proposition 1. As in previous experiments, nearly half of participants' multi-product choices were made "as if" they were applying the *FNS* normative value function.

Analysis of choice set variety shows that only 11.9% were non-diversified (i.e., included only one product alternative) while 38.1% were partially diversified (i.e., included two alternatives) and 50.0% were fully diversified (i.e., included all three of their favorite alternatives). Comparing *FNS* normative valuations shows that a partially diversified set offers more value than a non-diversified set with probability 0.833 and a fully diversified set offers more value than a non-diversified set with probability 0.611. Overall, the vast majority of participants in Experiment 3 included variety in their three-product choice sets, a decision that was usually optimal based on *FNS*'s normative value function.

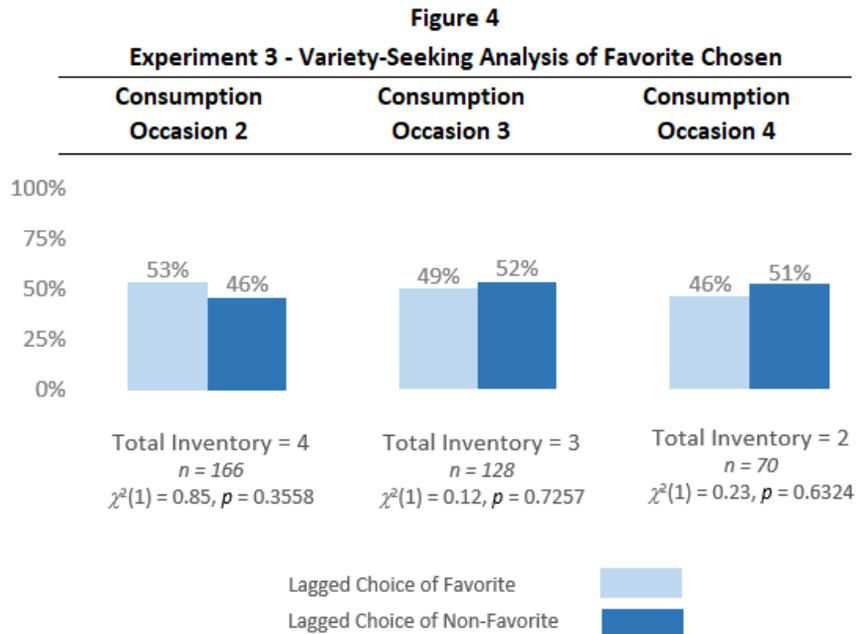
Figure 3 shows consumption choices of the favorite on Experiment 3's first, second, and third

Figure 3



consumption occasions. On the first consumption occasion, 192 participants chose from a five-product set that included one, two, three, or four units of their favorite product alternative with the remainder being their second-favorite. A test of independence ( $\chi^2(3) = 35.68, p < 0.0001$ ) shows strong evidence of a relationship between inventory and consumption choice. On the second consumption occasion, the 166 participants who still had a choice (and completed the task) chose from a set with one, two, or three units of their favorite alternative with the remainder being their second-favorite. A test of independence ( $\chi^2(2) = 23.96, p < 0.0001$ ) offers additional strong evidence of a relationship between inventory and consumption choice. On the third consumption occasion, the remaining 128 participants who still had a choice (and completed the task) chose from a set with either one or two units of their favorite with the remainder being their second-favorite. The test of independence ( $\chi^2(1) = 2.55, p = 0.1102$ ) offers insufficient evidence to confirm a relationship between inventory and consumption choice, though the pattern of choices is consistent with *FNS*'s inventory-based decision rule. Crucially, participants were more likely to choose their favorite when they had more inventory of that favorite *for every inventory configuration on all consumption occasions*, further strong support for Proposition 2 and inventory-based consumption choices.

Recall again that we found participants in Experiment 1 were more likely to choose their fa-



vorite than their second-favorite product alternative on the third consumption occasion. That was not replicated in Experiment 2 nor in Experiment 3, with a much larger sample. Overall then, we find insufficient evidence of a boundary condition where Proposition 2’s inventory-based decision rule gives way to a preference to select one’s favorite.

In Experiment 3, we introduced additional variation in starting inventory levels to test for variety seeking in consumption choices. Figure 4 shows consumption choices for the second, third, and fourth consumption occasions, together with lagged choices (i.e., the previous consumption occasion’s choice). Satiation, and so variety seeking, would imply a negative relationship between successive consumption choices as the consumer’s utility for the product and its attributes diminishes. We find no such relationship. Specifically, tests of independence for the second ( $\chi^2(1) = 0.85, p = 0.3558$ ), third ( $\chi^2(1) = 0.12, p = 0.7257$ ), and fourth ( $\chi^2(1) = 0.23, p = 0.6324$ ) consumption occasions provide scant evidence of satiation in participants’ consecutive consumption choices. The lack of variety seeking evidence stands in contrast to the compelling evidence of inventory-based consumption choices.

At the end of Experiment 3’s second (i.e., consumption) phase, we asked participants which factors had affected their consumption choices. Specifically, participants were asked: “Looking back on only those days when you could choose between your favorite and second-favorite

snacks, which of the following factors affected your choices?” Current *preference* was identified as “which snack I felt like eating the most on that day.” *Inventory* was identified as “the number of each product that was available in my box on that day,.” *Satiation* was identified as “which snack I had eaten recently and so was ’getting tired of.’” Participants evaluated all three factors using a 7-point agreement scale with 1 = “Strongly Disagree” and 7 = “Strongly Agree.” For the 177 participants who responded, the mean response for current *preference* was 5.71 (indicating agreement), the mean response for *inventory* was 5.14 (indicating somewhat lesser agreement), and the mean response for *satiation* was 4.23 (basically neither agreeing nor disagreeing). Paired *t*-tests clearly show that both current *preference* ( $t(175) = 7.75, p < 0.0001$ ) and *inventory* ( $t(175) = 5.58, p < 0.0001$ ) were more important than *satiation* when making consumption choices. It is worth noting that *FNS*’s normative theory holds that both current preference and inventory should be considered when making consumption choices. Satiation, and hence variety seeking, is an entirely different rationale for consumption choices—it is not supported by our analysis.

In summary, the three experiments provided clear and consistent support for Propositions 1 and 2. Specifically, we found that participants’ multi-product choices were better predicted by *FNS*’s normative value function than by competing models, in particular than the expected utilities of chosen products. We also found that consumption choices were made consistent with *FNS*’s inventory-based optimal consumption policy. We will now test the third proposition implied by *FNS* with multi-market panel data.

## **Panel Data Evidence**

Proposition 3 states that the variety included in a consumer’s optimal multi-product choice set decreases with consumption rate. Rather than testing this proposition by attempting to manipulate consumption rate, we chose to use observational data. Following Simonson and Winer (1992), we used panel data purchases of single-serve yogurt products. We used the same panel data from

the two US markets detailed our earlier evidence of multi-product choice. Rather than screening single-family households for yogurt purchases over the entire two-year duration, the dataset was partitioned so that the first 18 months served as a calibration period while the final six months were used for estimation. We required that households had made at least 10 yogurt purchases during the calibration period, then purchased again during the estimation period. The final dataset included 70 single-member households that purchased a total of 8,670 single-serve yogurt cups on 1,611 shopping trips during the calibration period, then purchased 2,376 cups on 443 shopping trips during the estimation period. Although this dataset is small, it was constructed purposefully to avoid intra-household heterogeneity and so provide a clean test of Proposition 3.<sup>12</sup>

Data from the calibration period were used for two purposes. The first was to determine panelists' long-run consumption preferences. Those preferences were determined by *UPC* because the variety and ambiguity of flavors (e.g., white chocolate strawberry, cherry vanilla creme, pina colada, cookies & creme, apricot mango, lemon meringue, key lime pie, mixed berry) did not allow for a parsimonious attribute decomposition. From consumption preferences, we developed household-level utilities for *UPCs*. The second use of calibration data was to calculate consumption rates. Panelists did not record their consumption—such data are rare—so we estimated consumption rates by averaging over the calibration period (assuming that all yogurt purchases were consumed). Initially, we conjectured that each day presented a consumption opportunity. Interestingly, we found that one panelist consumed 1.328 units/day, buying yogurt on 114 shopping trips during the calibration period (recall that each unit is a single serving). However, the other panelists consumed fewer than one unit/day.

Data from the calibration period were used to assess the relative variety of yogurt purchases. Consistent with *FNS*'s normative theory of shopping and consumption, we assumed that  $n$ , the number of units chosen on a given trip, was exogenous.<sup>13</sup> Variety was measured as the number of

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<sup>12</sup>Two panelists that met the screening criteria were omitted from the dataset because they consistently made exceptionally large purchases—up to 146 cups on a single trip. Given the perishable nature of yogurt, such purchases were clearly not intended for personal consumption.

<sup>13</sup>We would expect higher consumption rates to be associated with larger  $n$ ; however, the relative variety measure we used prevents this association from affecting our analysis.

product alternatives  $m$  in the chosen set. Clearly,  $m$  depends on the set size  $n$  ( $m \leq n$ ). To control for this dependency, we took advantage of the fact that the *CNPM* (with no outside option) is actually the limiting case of the *GNPM* (with utility of the outside option set to  $-\infty$ ) for a given set size  $n$ . To evaluate the observed  $m$ , we therefore compared it to the variety of the *CNPM*'s optimal set of the same size,  $m^{opt}$ , which implicitly assumes the maximum consumption rate. Using (0.1) to compute set valuations, we determined  $m^{opt}$  based on the *CNPM* for every panelist and every set size  $n$ , which we then used to determine the relative variety of observed purchases. The relative variety measure for yogurt purchases is the proportional difference between observed and optimal variety,  $D = \frac{m - m^{opt}}{m^{opt}}$ .<sup>14</sup>

Proposition 3 states that the variety included in a consumer's optimal choice set is decreasing in consumption rate; however, it does not specify a functional form for that relationship. We therefore began by estimating nonparametric correlations—Spearman's Rank Correlation and Kendall's Tau—as well as Pearson's  $R$ . An important characteristic of the data is that relative variety changed across a panelist's yogurt purchases, but the panelist's consumption rate did not. We therefore include subscripts for trip  $t$  and household  $h$  in the remaining exposition. Household consumption rate was measured in  $Units/Day_h$ , but its inverse  $Days/Unit_h$  was also analyzed. The proportional difference in variety for household  $h$  on trip  $t$ ,  $D_{ht}$ , was used to compute trip-level correlations; the household's average across trips,  $\bar{D}_h$ , was used to compute correlations at the household-level. Table 2 shows that all correlations have the expected sign: negative for  $Units/Day_h$  and positive for  $Days/Unit_h$ . All nonparametric correlations are significant at the 0.05 level, and are uniformly higher in magnitude for household-level correlations than for trip-level correlations. Interestingly, Pearson's  $R$  was higher in magnitude for  $Days/Unit_h$  than for  $Units/Day_h$ , suggesting that the relationship between relative variety and consumption rate was more linear for the former than the latter.

The combination of a time invariant household-level predictor ( $Units/Day_h$  or  $Days/Unit_h$ ) and a time varying household-level response variable ( $D_{ht}$ ) led us to model the data using a hierar-

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<sup>14</sup>Using  $\frac{m - m^{opt}}{m^{opt}}$  rather than, say,  $m - m^{opt}$  enabled us to avoid scaling issues.

**Table 3**  
**Correlations of Consumption Rate and Relative Variety**

	Trip-Level Correlations ( $D_{ht}$ )		Household-Level Correlations ( $\bar{D}_h$ )	
	Units/Day <sub>h</sub>	Days/Unit <sub>h</sub>	Units/Day <sub>h</sub>	Days/Unit <sub>h</sub>
Spearman's Rank	-0.1707 (0.0003)	0.1707 (0.0003)	-0.3303 (0.0052)	0.3303 (0.0052)
Kendall's Tau	-0.1249 (0.0003)	0.1249 (0.0003)	-0.2107 (0.0116)	0.2107 (0.0116)
Pearson's R	-0.1282 (0.0069)	0.2239 (<.0001)	-0.1625 (0.1788)	0.2632 (0.0277)

*p*-values are shown in parentheses

chical random coefficients model. The first-level equation was specified

$$D_{ht} = \theta_h + \xi_{ht} \quad (0.3)$$

and the hierarchical equation was specified

$$\theta_h = \delta + \gamma \cdot f(\text{Units}/\text{Day}_h) + \zeta_h, \quad (0.4)$$

where  $f(\cdot)$  is a monotonic transformation to allow for flexibility in functional form. The parameter of interest is  $\gamma$ , which captures the relationship between the relative variety of a choice set,  $D_{ht}$ , and the transformed consumption rate,  $f(\text{Units}/\text{Day}_h)$ . The resulting model was estimated in a hierarchical Bayesian framework with minimally informative priors so that the posterior estimates were driven by the data. For each model, the 25000 Markov Chain Monte Carlo iterations converged quickly after a short burn-in period and autocorrelation proved acceptable (we also “thinned the line”), resulting in a stable posterior distribution for  $\gamma$ .

Table 4 shows estimates for the “Random Coefficients” model specified by (6.1) and (6.2) with selected monotonic transformations of the independent variable. The table also shows estimates for two nested models: (i) “Fixed Intercept” (i.e.,  $\theta_1 = \theta_2 = \dots = \theta_H = \theta$ ), and (ii) “Random Coefficients ( $\gamma = 0$ ).” To compare models, we used the Deviance Information Criterion [*DIC*], a Bayesian analog of *AIC* (see Spiegelhalter, et al. 2002). To assess model predictions, we bootstrapped the estimation dataset, then compared actual values of  $D_{ht}$  with predicted values

**Table 4**  
**Relative Variety Models for Yogurt Purchases**

Model	Predictor	Posterior Predictions			Posterior Distribution of $\gamma$		
		DIC	MAD	MSE	Mean	Pr( $\gamma < 0$ )	(2.5% , 97.5%)
Fixed Intercept	N/A	364.26	0.267	0.132	N/A	N/A	N/A
Random Coefficient ( $\gamma=0$ )	N/A	245.33	0.267	0.133	N/A	N/A	N/A
Random Coefficient	Units/Day <sub>h</sub>	245.24	0.267	0.134	-0.2107	0.909	(-.5232,.0970)
Random Coefficient	exp(Units/Day <sub>h</sub> )	244.80	0.270	0.136	-0.1000	0.870	(-.2747,.0857)
Random Coefficient	Days/Unit <sub>h</sub>	245.55	0.258	0.127	0.0145	0.016	(.0016,.0274)
Random Coefficient	ln(Days/Unit <sub>h</sub> )	244.73	0.261	0.130	0.0923	0.024	(.0006,.1838)

using Mean Absolute Deviation [*MAD*] and Mean Squared Error [*MSE*]. Four random coefficient models are reported in the table, reflecting different transformations of *Units/Day<sub>h</sub>*. We selected *Units/Day<sub>h</sub>* (no transformation) and *Days/Unit<sub>h</sub>* (inverse transformation), along with two monotonic transformations that generally fit the data better:  $\exp(\text{Units/Day}_h)$  and  $\ln(\text{Days/Unit}_h)$ .

The two nested models, “Fixed Intercept” and “Random Coefficient ( $\gamma = 0$ ),” differ greatly from one another in terms of fit—“Random Coefficient ( $\gamma = 0$ )” has a far lower *DIC* than “Fixed Intercept” (lower is better)—but are very similar in predictive accuracy. In terms of fit, the “Random Coefficient ( $\gamma = 0$ )” model has only a slightly higher *DIC* than three of the four full “Random Coefficient” models, and actually has a slightly lower *DIC* than the fourth. In terms of predictive accuracy, the “Random Coefficient ( $\gamma = 0$ )” model offers posterior predictions similar to the four full “Random Coefficient” models. We therefore conclude that unmodeled individual differences explain much more variation in  $D_{ht}$  than consumption rate does. On the other hand, the functional form of the relationship between consumption rate and variety matters for predictive accuracy. The “Random Coefficient” model using  $\ln(\text{Days/Unit}_h)$  as the predictor has the lowest *DIC* and, like the “Random Coefficient” model using *Days/Unit<sub>h</sub>* as the predictor, offers more accurate predictions than the other models. The superior predictive accuracy of the two models using  $f(\text{Days/Unit}_h)$  as the predictor is consistent with the nonparametric correlations reported above, where the proportional difference in variety was more highly correlated with *Days/Unit* than with *Units/Day*. Taken together, these results suggest that the relationship between relative variety and usage rate be specified as a function of *Days/Unit*. A more extensive exploration of

functional form is left for future research.

Returning to the preferred model, the “Random Coefficient” model using  $\ln(Days/Unit_h)$  as the predictor, the parameter estimate for  $\gamma$  is positive and significant. The mean estimate is 0.092 and, based on the posterior *cdf*,  $Pr(\gamma > 0) = 0.024$ . For the “Random Coefficient” models using different predictors, the posterior estimate of  $\gamma$  is always in the expected direction—positive for  $f(Days/Unit_h)$  and negative for  $f(Units/Day_h)$ , though the posterior estimates of  $\gamma$  are only significant for models using  $f(Days/Unit_h)$  as the predictor. Taken together, the random coefficient models and nonparametric correlations provide support for Proposition 3.

## Concluding Remarks

This paper presents empirical evidence for a theory of shopping and consumption in which rational, utility-maximizing consumers make multi-product choices according to a theoretically-derived value function. The first proposition we tested deals with the predictive accuracy of this value function. We found evidence that it effectively captures the mental tradeoffs made when consumers choose a set of substitutable products. As a result, the value function could be used in a number of practical applications, including the design and pricing of variety packs for consumer markets and the pricing of customized variety packs for individual consumers. Demonstrating the predictive accuracy of this value function is therefore a primary contribution of this paper. Evidence from three experiments not only supports the predictive accuracy of the value function, but also establishes the contribution of product variety to consumers’ expected utility from a choice set. This represents an additional theoretical contribution. The three experiments also provide evidence about diversification in multi-product choice. Across those experiments, the vast majority of three-product choice sets were diversified; i.e., included multiple alternatives. More importantly, applying the value function to participants’ self-reported preferences reveals that diversification was usually *optimal*. Thus, diversification in multi-product choice, which has long been framed as a bias in decision-making, is also identifiable as a rational response to future preference uncertainty.

The second proposition we tested considers how multi-product sets should be consumed so that the value function in the first proposition maximizes consumers' utility. The normative consumption policy suggests that consumers save units of their favorite alternative for consumption occasions when it is most preferred to other available alternatives. This is particularly evident when consumers have only a single unit of the favorite alternative. Here again, we found strong evidence that consumption choices are consistent with this policy. Across three experiments, we observed a pattern that resembles inventory-based consumption, a pattern consistent with consumers matching product alternatives to consumption occasions in a way that extracts the most utility from a multi-product set. Support for this second proposition also offers additional indirect support for the first proposition inasmuch as the consumption policy underpins the optimality of the value function.

The third proposition predicts that the multi-product choices of consumers with lower usage rates include more variety than the multi-product choices of consumers with higher usage rates. This prediction can be explained in terms of competition. In cases where a category is seldom consumed, implying an attractive outside option, more variety in multi-product choices is the best strategy to overcome that outside option and 'win' a consumption occasion. For example, if one rarely drinks wine, having two bottles of red or two bottles of white is likely inferior to having one bottle of each. The set with greater variety offers a higher probability of including an alternative that one wants when the mood strikes. We found empirical support for this proposition using multi-market panel data of yogurt purchases.

In summary, we present evidence that uniformly supports a normative theory of multi-product choice based on preference for sets that maximize expected future utility. This theory represents a compelling alternative to existing theories of multi-product choice that explain observed diversification in terms of bias (i.e., diversification bias), or the expectation of satiation (i.e., variety-seeking), or forecasting error. This is not to suggest that competing theories are wrong; rather, we find substantial support for a theory of rational behavior against which competing theories could be evaluated.

This paper has the potential to generate a number of future research opportunities. Testing

this normative theory of multi-product choice, along with variety-seeking and diversification bias, is likely to find conditions under which different models of behavior apply. For example, consumption rate might moderate the effect of variety seeking in multi-product choice. Based on once- or twice-weekly consumption of snack products (cf. Simonson 1990), we found evidence of forward-looking consumption choices but not variety seeking. This might change if consumption occasions were more frequent. Exploring boundary conditions of different multi-product choice models could also be a fruitful avenue for future research. Consumption rate is logically related to constructs like involvement, familiarity, and expertise in a product category, yet might affect multi-product choices in different ways than these constructs suggest. Finally, studies of consumption have generally been limited—perhaps because consumption data are difficult to obtain. Gathering and analyzing observational data of consumption in the context of multi-product choice could be another potentially fruitful avenue for future research.

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# Appendix A: A Short Proof of the Value Function and Optimal Policy

*Proof.* The proof is by induction. The standard zero-mean Gumbel  $\varepsilon_i$  has c.d.f.  $F(x) = \exp(-\exp(-x - \gamma))$  where  $\gamma$  is the Euler-Mascheroni constant. The value formula (3.1) is trivially true for  $n = 1$ . Assume the truth of (0.1) for the case  $(n-1)$ . Let  $k^T = (k_1, \dots, k_M)$  with  $\sum_{i=1}^M k_i = n - 1$ . Then the truth of the result for  $n-1$  implies  $V(k) = \ln \left( \frac{(n-1)!}{\prod_{i=1}^M k_i!} \cdot \exp(k^T u) \right)$ . We now use the expected value formula for  $\max_{i=1,2,\dots,m} (W_i + \varepsilon_i)$  where  $W_i$  are given parameters. If there are  $m$  distinct alternatives to choose from each having expected utility  $W_i$ , then the expected value of the best (maximum) choice is

$$E \left( \text{Max}_{i=1,\dots,m} \{W_i + \varepsilon_i\} \right) = \ln \left[ \sum_{i=1}^m e^{W_i} \right]. \quad (.5)$$

For the case of  $n$  items, assume *wlog* that there are  $m$  distinct alternatives and that they are the first  $m$  alternatives of the  $M$  possible alternatives. Let  $k^T = (k_1, \dots, k_m)$  with  $\sum_{i=1}^m k_i = n$ . The expected utility of alternative  $i$  is  $u_i$ , and  $u^T = (u_1, \dots, u_m)$ . The expected value of the set is then

$$\begin{aligned} V(k) &= E \left( \text{Max}_i \{V(k - e_i) + u_i + \varepsilon_i\} \right) \\ &= \ln \left( \sum_{i=1}^m \exp(V(k - e_i) + u_i) \right) \quad (\text{by (.5) with } W_i = V(k - e_i) + u_i) \\ &= \ln \left( \sum_{i=1}^m \frac{(n-1)!(k_i)}{\prod_{j=1}^m k_j!} \cdot \exp((k - e_i)^T u + u_i) \right) \quad (\text{by the induction hypothesis}) \\ &= \ln \left( \frac{n!}{\prod_{j=1}^M k_j!} \cdot \exp(k^T u) \right). \end{aligned}$$

(Note that we use the fact that  $0! = 1$  to continue the formula to the remaining  $M - m$  alternatives in the last step; a similar continuation applies to  $k^T u$ .) Moreover, the optimal policy, to select the alternative maximizing  $\ln(k_i) + \varepsilon_i$ , is readily apparent:

$$\begin{aligned}
\text{Max}_i \{V(k - e_i) + u_i + \varepsilon_i\} &= \text{Max}_i \left\{ \ln \left( \frac{(n-1)! (k_i)}{\prod_{j=1}^m k_j!} \cdot \exp((k - e_i)^T u) \right) + u_i + \varepsilon_i \right\} \\
&= \text{Max}_i \left\{ \ln \left( \frac{(n-1)! (k_i)}{\prod_{j=1}^m k_j!} \cdot \exp(k^T u) \right) + \varepsilon_i \right\} \\
&= \ln \left( \frac{(n-1)!}{\prod_{j=1}^m k_j!} \cdot \exp(k^T u) \right) + \text{Max}_i \{ \ln(k_i) + \varepsilon_i \}
\end{aligned}$$

## Appendix B: Reasons for Including Non-Favorite Product Alternatives in Multi-Product Choice Sets

Table A1  
Reasons for Including Non-Favorite Product Alternatives in Multi-Product Choice Sets

Response Category	Response
Prefer Items Not in the Assortment	<ul style="list-style-type: none"> <li>• Gardetos because they are salty and a nice mix of pretzels crisps and little bread sticks.</li> <li>• Honey Buns they are in all the vending machines around [the university] and have the biggest mass/sugar ratio so I always used to eat them when I needed to fill my stomach and get my blood sugar high when I was a physics TA and was trapped here grading late.</li> </ul>
Prefer Healthier Items Not in the Assortment	<ul style="list-style-type: none"> <li>• Yes because I never eat candy but I prefer it to chips and I never eat those either. I eat healthy everyday I would only eat the granola bars if I was forced to.</li> <li>• No but it would include my favorites that arent listed... In all honesty I wouldnt choose any of these over not having them. They are my favorite avail but I wouldnt make any concerted effort to get any of these...</li> </ul>
Test-Retest Unreliable	<ul style="list-style-type: none"> <li>• Changed my mind.</li> <li>• I found a different choice I liked.</li> </ul>
Exploration	<ul style="list-style-type: none"> <li>• I want try it.</li> <li>• To add variety to the palette of tastes.</li> </ul>
Messy Eating in the Classroom	<ul style="list-style-type: none"> <li>• White cheddar popcorn is messy and not a good snack for the classroom.</li> <li>• Less messy to eat in class. I dont [want] to get crumbs everywhere.</li> </ul>