MARKETING SCIENCE
Vol. 34, No. 5, September–October 2015, pp. 702–721
ISSN 0732-2399 (print) | ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2015.0939


# Short-Run Needs and Long-Term Goals: A Dynamic Model of Thirst Management

Guofang Huang
Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, gfhuang@andrew.cmu.edu

Ahmed Khwaja
Yale School of Management, New Haven, Connecticut 06520, ahmed.khwaja@yale.edu

K. Sudhir
Yale School of Management, New Haven, Connecticut 06520, k.sudhir@yale.edu

Beverage consumption occurs many times a day in response to short-run needs that fluctuate. We develop a model in which consumers are heterogeneous in self-regulating consumption by balancing short-run needs (e.g., hydration and mood) with long-term goals (e.g., health). The model has two novel features: (1) utility depends on the match between occasion-specific needs and product attributes, and (2) dynamics of consumption and stockpiling are at the level of product attributes. We estimate the model using unique intraday beverage consumption, activity, and psychological needs data. We find that only a third of individuals do not self-regulate. Of the two-thirds who self-regulate, over 40% self-regulate adaptively based on past choice, whereas 25% self-regulate both adaptively and anticipating future needs. Our attribute–need match model enables us to assess unmet demand for new products with attributes that match co-occurring occasion-specific needs. Specifically, we find that a product satisfying a combination of "health-hydrating" needs expands overall beverage consumption by as much as 5%. Our framework of modeling heterogeneity in self-regulation by balancing short-run needs with long-term goals is more broadly applicable in contexts where situational needs vary, and long-term effects are gradual and hard to discern (e.g., nutrition, smoking, and preventive health care).

*Keywords*: dynamic discrete choice; EM algorithm; self-regulation; stockpiling; health care; needs; goals; obesity; beverages; new product introductions
*History*: Received: March 19, 2012; accepted: May 26, 2015; Preyas Desai served as the editor-in-chief and Michel Wedel served as associate editor for this article.

## 1. Introduction

Individuals make choices about what to drink many times a day. This decision is driven primarily by thirst—among the most basic of human needs. Like many consumption decisions, the choice of a beverage lies on a continuum from satisfying the bare *utilitarian* need to hydrate to a *hedonic* need such as enhancing one's mood. However beverage consumption has long-term effects. For example, routine consumption of high-calorie beverages to satisfy short-run needs multiple times a day can lead to weight gain, heart disease, and diabetes (see, e.g., Malik et al. 2006, Vartanian et al. 2007, Mozaffarian et al. 2011). Individuals may therefore seek to balance short-term needs against long-term goals such as health and nutritional well-being (see, e.g., Ma et al. 2013) through self-regulation when making beverage choices.

In this paper, we introduce a stylized framework to model self-regulation by balancing short-run needs against long-term consequences within a revealed preference, dynamic choice framework. Specifically, we develop and estimate a dynamic model of thirst management, where a consumer's choice of beverage at a given consumption occasion within a day involves managing observable short-run occasion-specific needs with long-term health goals. The model allows for unobserved heterogeneity in consumer's degree of self-regulation. Two novel features of the model are that it allows for (i) the match between occasion-specific individual needs and product attributes on consumption utility, and (ii) dynamics of consumption and stockpiling at the level of product attributes. We estimate the model using unique intraday data on actual beverage consumption as well as the attendant occasion-specific activity and the psychological needs of a large, nationally representative panel of individuals and perform counterfactuals that serve to guide segmentation strategies and new product introductions in the beverage market. The framework is broadly applicable for modeling consumer choices, such as preventative healthcare, exercise, and smoking, that have long-run health consequences (e.g., cardiovascular disease and cancer) when individuals display heterogeneity in self-regulation, needs fluctuate with occasions, and long-term effects are gradual and hard to discern at a given point in time by individuals.

Beginning with the pioneering work of Guadagni and Little (1983), there is a long history of research in marketing that has focused on modeling choice at the point of purchase. These papers have studied how consumers choose stores, categories, and brands within a category, in response to the marketing mix and individual preferences or states. However, there is little empirical research on choice at the point of consumption with field data. In categories like detergents, the distinction between purchase and consumption may be moot, because individuals are very likely to use one purchased product at all points of consumption. On the other hand, in the context of consumption of food or beverages, the choice of which type of product (e.g., soda, coffee, beer, water) to consume is at least as (if not more) important as the choice of brand within a narrowly defined type. For example, would Maxwell House or Coke gain by expanding coffee's or soda's share of the overall market for beverage consumption as opposed to increasing its share of coffee or soda consumption? Given that the competition for "share of thirst" in the beverage industry is intense, a deeper understanding of the factors that drive consumption of different types of beverages at the point of consumption is critical for firms competing in this category.

There are several challenges in modeling beverage consumption. First, beverage consumption occurs multiple times, and the choice of beverage varies widely even within the day for an individual. Therefore, one needs high-frequency intraday consumption data. The traditional approach of making inferences about a consumer's utility from consumption through weekly purchase data is not very useful in modeling beverage consumption.

Second, standard approaches typically assume heterogeneous but fixed consumer preferences across time with little or no short-run variation within individuals in needs. This approach cannot rationalize the widespread variation in beverage consumption even within a day and requires us to model intraindividual heterogeneity in needs. For example, beverages are consumed in tandem with activities such as eating, work, or parties; the social environment differs across these activities and even within these activities. Some eating occasions are solitary, others happen with family, friends, or colleagues at work. Depending on these situational environments, one may have different levels of short-run physical (e.g., hydration) or psychological (e.g., mood enhancement) needs. These environments can also differentially trigger the salience of long-term needs such as health. Information about the contemporaneous needs that an individual seeks to satisfy during each potential consumption occasion is critical to accommodating the intraindividual heterogeneous needs.

Third, unlike most consumer choices, where the utility from the product is modeled as immediate, beverage (and food) consumption has long-term health consequences, and these consequences accrue very gradually. We therefore hypothesize that consumers balance their short-run needs with long-term goals, but they may differ in the degree to which they self-regulate to maintain this balance. Thus, our research is related to the psychology literature on heterogeneity in self-regulation (e.g., Tangney et al. 2004, Baumeister et al. 2011) and delay of gratification (e.g., Mischel et al. 1989). These theories provide the motivation for our modeling approach to empirically infer heterogeneity in self-regulation from naturally occurring choice data.

We address these challenges through a combination of new data and modeling framework. We address the first two challenges directly through better data. We use unique "consumption diary" data on a panel of individuals;[1] using personal digital assistants that alert consumers to record consumption eight times during the daytime (every two hours), we obtain consumption choices and contemporaneous information such as activity and psychological "needs" associated with the consumption occasion over a period of two weeks. Though it has long been recognized that situational needs can affect consumer choices (e.g., Sandell 1968; Belk 1974, 1975), there is only a small empirical literature that accounts for short-run situational needs in modeling consumption (e.g., Yang et al. 2002, Luo et al. 2013, Kim and Chintagunta 2012). Our paper extends this literature by accounting for the long-run effects of consumption choices by modeling heterogeneous self-regulation behavior.

Our model accommodates three levels of self-regulation. We call the first segment "myopic" in that their choices are entirely based on current needs and therefore exhibit no self-regulation. We call the second segment "adaptive" in that choices take into account current needs, but also past choices. Such a consumer might forego coffee at 10 A.M. because she had coffee for breakfast (past choice). Finally, we call the third segment anticipatory; these consumers take into account current situational needs and past choices, but also anticipate future needs by being forward-looking. We allow the ex ante probability of an individual belonging to the three self-regulation segments to depend on her demographic and socioeconomic characteristics.

[1] For applications of "consumption diary" data in other contexts, see, e.g., Narayan et al. (2015), Goettler and Shachar (2001), and Anand and Shachar (2011).

Next we describe how we operationalize the three types of self-regulation in our model. Based on conventional assumptions in the discrete choice literature, we model myopic behavior as a random utility logit model where current period utility is explained by contemporaneous situational needs. Without the thirst stock, this segment would be similar to the consumer model in Yang et al. (2002) or Kim and Chintagunta (2012). For adaptive behavior, we add a state dependence term that accounts for the attributes (e.g., healthy, tasty) of past choices into the current period utility. Finally, we model "anticipatory" behavior using a finite-horizon dynamic forward-looking model whose current period choice follows a random utility logit model with state dependence (as with the adaptive model). For all three types, we allow each individual's decision to drink or not in a period to also be affected by a thirst stock variable that evolves based on how long it has been since the individual drank a beverage.

Our approach may also be related to the choice heuristics literature that allows consumers to reduce effort in making decisions (e.g., Shah and Oppenheimer 2008). Although we believe all of our models are as-if models of consumer choice behavior, the myopic, adaptive, and anticipatory can be thought of as self-regulating heuristics with decreasing levels of "effort reduction," with myopic being the least complex and providing the most "effort reduction."

We highlight four novel aspects of our model. First, instead of utility just being a function of product attributes, as is typically the case, the consumption utility depends on the match between individual psychological needs and product attributes at a given occasion. Second, in the language of dynamic choice models of frequently purchased consumer goods, our model allows for dynamics in both *consumption* and *stockpiling*. We allow for the stock of "thirst" to be endogenous to past beverage consumption decisions; the thirst stock is similar to the inventory variable in dynamic structural models of stockpiling (see, e.g., Erdem et al. 2003, Hendel and Nevo 2006). Third, we model dynamics in consumption and stockpiling at the level of product attributes. By modeling products as bundles of attributes ("healthy," "unhealthy," "taste," "mood enhancing," and "hydrating") and considering dynamics at the attribute level, we are able to consider counterfactuals around the introduction of new products, defined as new attribute bundles (e.g., Petrin 2002). Fourth, changes in health in response to consumption choices are extremely gradual and not easily discernible by individuals at any given instant. Hence, it is not easy to incorporate the effects of consumption choices on future health. We introduce the idea of an end-of-day salvage value for avoiding consumption of too many unhealthy drinks in a day to account for long-term goals via a heuristic or rule of thumb (see also Gilleskie 1998).

There is a large and growing literature on examining self-regulation using a variety of approaches (e.g., Wansink et al. 2009, Dobson and Gerstner 2010, Thomas et al. 2011, Jain 2012). In particular, our framework may be related to the behavioral literature on self-regulation and goal pursuit. One prominent strand of the literature on the dynamics of self-regulation (e.g., Koo and Fishbach 2008) discusses how self-regulation can drive choices across time, where consumers either highlight or balance on characteristics that help accomplish the goal (e.g., Fishbach et al. 2009). Highlighting behavior is a byproduct of increasing "commitment" to the goal, whereas balancing behavior occurs if individuals treat past behavior as progress toward the goal, and therefore a license to do non-goal-directed behavior. We accommodate this by modeling state dependence across time in the (consumption of products with the) "healthy" attribute. If consumers have an overarching "health" goal, then a positive coefficient on lagged (consumption of products with the) healthy attribute indicates "commitment-induced highlighting" within this framework. Alternatively, a negative coefficient on lagged healthy attribute indicates "progress-induced balancing." Furthermore, Zhang et al. (2007a, b) demonstrate that intended future actions can affect current self-regulatory choices. Our model of anticipatory behavior captures this notion.

Our short-term needs and long-term goals framework also ties into the behavioral literature on goal pursuit (e.g., Shah and Kruglanski 2003). The goal pursuit literature considers the long-run "health goal" to be a "superordinate goal," whereas our short-term needs are "subordinate" goals. At different points of time, we observe the different subordinate goals that are activated (e.g., Aarts et al. 2001). For example, if the superordinate goal of health is salient, then individuals will be in the commitment frame and are more likely to highlight across time (e.g., Fishbach and Zhang 2008). On the other hand if the long-term goal (e.g., staying healthy) is not salient, then individuals are more likely to balance (e.g., Fishbach et al. 2006). In summary, our framework allows for heterogeneity with respect to whether individuals have superordinate goals, by allowing some people to have long-term goals, and we also allow for variation in whether individuals balance or highlight with respect to superordinate goals.

We estimate the model using an Expectation-Maximization (EM) algorithm (e.g., Arcidiacono and Jones 2003). The algorithm starts with an initial guess of the probability for each individual belonging to each of the three self-regulation segments. We then estimate the structural parameters of the three segments separately. At the end of each iteration of the algorithm, we use an empirical Bayes procedure to calculate the posterior probability that each individual falls into one of these three segments, and we iterate until the probabilities converge.

We use our estimated model to perform various counterfactuals relevant to consumers, health policy makers, and managers in the beverage industry. The first counterfactual examines how individuals with different degrees of self-regulation change their beverage consumption in response to shocks to situational needs (e.g., during the holiday season). From a firm's segmentation perspective, this helps reveal the type of individuals one should target to drive increased consumption during peak demand periods such as holidays. From a policy perspective, this can help assess whether there is value in potentially changing the self-regulating behavior of consumers through education and advertising strategies to encourage healthy consumption. The second counterfactual analyzes the potential for new product introductions. It sheds insight on the potential success of certain new products that satisfy different combinations of short-run needs, highlighting the role of need correlations on consumption occasions and the match of product attributes and individual needs.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 presents the model, and §4 the estimation methodology. Section 5 discusses the results, and §6 concludes.

## 2. Data

Our data are from a nationally representative panel of individuals whose beverage consumption decisions were tracked for two weeks. Individuals were given a handheld device that prompted them eight times a day for two weeks to answer questions related to their beverage consumption in the previous two hours, e.g., the beverage consumed, the time, the location, the activity involved, the psychological needs and reasons for choosing the beverage, etc. We first describe how various state variables for the model related to activities, needs, and beverage attributes are defined and constructed given the data, and then provide descriptive statistics for these variables.

### 2.1. Variable Definition and Construction

**2.1.1. Needs.** At each consumption occasion, a consumer was asked why the drink was chosen. The consumer could respond with one or more of 18 possible reasons. Using factor analysis on the 18 reasons, we summarize consumer needs into four factors.[2] We interpret the factor loadings to name the resulting four factors as the "health," "taste," "mood," and "hydrate" needs. We will model consumer choice as a function of these four contemporaneous needs.

A consumer practicing anticipatory self-regulation would form expectations over future needs. The standard approach to model future needs is to treat this as a draw from the probability distribution of needs. In our setting, the conditional distribution of needs differs significantly across different activities that the consumer is involved in. We therefore model future need as a draw from a distribution conditional on the activity that the consumer is involved in. To that extent, we model the exogenous evolution of activities over the work day.[3]

**Table 1 Categories of Occasions/Activities**

| Abbreviations | Occasions | Percent |
|---|---|---|
| Eat | Eat | 29.0 |
| Work | Work, study, deskwork | 14.2 |
| Relax | Relaxing, break from work, hangout, watching TV | 46.0 |
| Exercise | Exercise, physical activity | 2.0 |
| Meeting | Meeting, traveling, shopping | 5.6 |
| Party | Party, view shows | 3.2 |

**2.1.2. Activities.** Our data contain information about 15 activities. To aid parsimony and reduce the computation challenges in estimation, we combine related activities in the survey into six broad groups using a $k$-median cluster analysis: "eat," "work," "relax," "exercise," "meeting," and "party." Table 1 shows the activities in each group. For example, the "work" category includes the activities "work," "study," and "deskwork." Similarly, the "relax" category includes "relaxing," "break from work," and "watching TV." Although both "meeting" and "party" relate to occasions in which consumption happens in the presence of company, we distinguish them in the sense that "meeting activities" tend to be more task

[2] The 18 reasons are (1) change of pace, (2) cool off, (3) warm up, (4) mood enhancer, (5) filling, (6), fortified with vitamins, (7) fruit flavored, (8) fun to drink, (9) goes well with food, (10) good for physical activity, (11) good for social situations, (12) indulgent/treat, (13) nutritional/healthy, (14) portable, (15) purifying, (16) quick energy/pick-me-up, (17) rehydrating, and (18) nearest/closest. We use the iterated principle factor analysis method on these 18 needs. Based on the eigenvalues, we keep four factors in the analysis. Then, we use the Equamax criterion to rotate the factor scores generated by the factor analysis with Horst normalization.

[3] This is also consistent with the behavioral literature that peoples' needs are dependent on their current activities, e.g., Belk (1975), Fishbach et al. (2009), and Kruglanski et al. (2002). Moreover, we focus on weekday data in our estimation to make the exogenous activity assumption reasonable for our empirical application. Activity transitions across different periods of the day evolve exogenously due to the nature of routines that people have during a work day. The exogeneity assumption seems a good first-order approximation given that we are focusing on weekdays for an estimation sample of people who work full time, and workday routines are reasonably exogenous for people within a weekday. However, we also perform a statistical test of this assumption (see §4).

oriented, whereas "party" activities tend to be more entertainment oriented.

**2.1.3. Beverage Attributes.** To explain beverage choice as a function of underlying individual needs, we define beverage attributes in terms of the four needs (obtained from the factor analysis) it can satisfy. Products are defined in terms of four binary attributes related to needs: "healthy," "tasty," "mood boosting," and "hydrating." In addition, given our interest in understanding unhealthy consumption, we define a fifth attribute, "unhealthy."

As stated earlier, we define the attributes using the beverage choice and needs data from the *first two weekdays* of the two-week sample. The broad idea is to define a drink as having a particular attribute if it is often chosen when the corresponding need is high. We implement this idea as follows. For every drink, we compute the average levels of the four needs (health, taste, mood, and hydration), conditioning on that drink being chosen. Then, using an indicator variable, we define a particular attribute of that drink to be one if its corresponding conditional average need is (statistically significantly) higher than the mean conditional average need across all drinks. If not, we set the indicator variable for that attribute to zero. For example, let $g_j$ indicate the health attribute of drink $j$. Let the average health need conditional on drink $j$ being chosen be denoted as $\bar{e}_{1j}$. Define $\bar{e}_1 = (1/J)\sum_{j=1}^{J} \bar{e}_{1j}$. Then, we set $g_j$ to one if $\bar{e}_{1j}$ is statistically significantly higher than $\bar{e}_1$ and zero otherwise. Similarly, we define the taste, mood, and hydration attributes.

We define the unhealthy attribute of a drink to be one if its conditional average health need is (statistically significantly) *lower* than the mean conditional average health need across all drinks, and otherwise we set the indicator for the unhealthy attribute to zero.[4] We define these attributes for 11 drinks in the data, such as coffee, tea, milk, etc.[5]

[4] We define the four attributes (healthy, taste, mood boosting, and hydrating) of a drink to be one if and only if its conditional average needs are above the respective mean conditional average needs plus 1.81 (95% confidence level) times the standard deviation of the average. We define the unhealthy attribute of a drink to be one if and only if the conditional average health need is below the mean conditional average health need minus 2.65 (99% confidence level) times the standard deviation of the conditional average health need. We use a more conservative threshold (99% confidence level) in defining the unhealthy attribute to ensure that we pick out the unhealthy drinks in most peoples' opinion. This prevents overstatement of the number of unhealthy drinks consumed each day by individuals in our data, which could lead to an overestimation of the effect of self-regulation through forward-looking behavior. Harris and Keane (1999) and Ching and Hayashi (2010) also use subjective perception data to account for consumer heterogeneity.

[5] There were originally 16 types of drinks in the data. We combined drinks with very small market shares (less than 1%) into the "other" drink category to reduce the computational burden in estimating the model. In any case, as is well recognized, it is almost impossible for a discrete choice differentiated products model like ours to fit the very small shares of these drinks.

**Table 2 Activity Shares (%) by Time**

| | Activity | | | | | |
|---|---|---|---|---|---|---|
| Time | Eat | Work | Relax | Exercise | Meeting | Party |
| Breakfast | 53.1 | 10.7 | 30.1 | 0.6 | 5.0 | 0.5 |
| Morning | 5.9 | 34.6 | 45.5 | 3.3 | 9.9 | 0.8 |
| Lunch | 54.4 | 6.8 | 33.5 | 0.6 | 3.6 | 1.2 |
| Afternoon | 3.9 | 27.2 | 51.3 | 4.9 | 10.7 | 2.0 |
| Dinner | 58.0 | 1.9 | 35.2 | 0.3 | 1.3 | 3.4 |
| Evening | 6.8 | 6.8 | 73.8 | 2.8 | 3.0 | 6.7 |

## 2.2. Descriptive Statistics

Our survey data have information on the choices of 2,683 individuals. Because self-regulation requires consumers to anticipate needs over the day, we focus on the beverage consumption of *full-time workers* for whom weekday activities are likely more exogenous and the needs accompanying the activities more predictable. We use the *first two weekdays* of the full-time worker data to calibrate the beverage attributes and the remaining eight weekdays for estimation. Given our focus on balancing short-run needs and long-term health goals, we dropped all individuals who did not drink a healthy or unhealthy drink during the estimation period. Because there is little consumption of beverages in the early morning and late night, we drop these periods from estimation. This leaves us with data on 1,641 individuals and their beverage choices in six consumption periods over eight weekdays. As a caveat, given our focus on the subsample of people with full-time jobs, our findings may not fully generalize to the entire population. Also, note that our grouping of activities described earlier (§2.1.2) helps alleviate the problem that individuals may have somewhat different routines even within the relatively homogenous sample of people with full-time jobs. Table 2 shows the share of activities during different times of the day. Eating is prominent during breakfast, lunch, and dinner. The high proportion of people in the "relax" category is due to "break from work" being the largest component of the relax category during the morning and afternoon.

Table 3 shows the binary attributes for the 11 drinks based on the beverage attribute definition procedure we described above. The attributes associated with the beverages based on aggregate consumer opinions appear reasonable. One concern might be whether our definitions based on aggregate consumer opinions might be appropriate for a particular individual. For example, although our definition based on aggregate opinion treats wine as unhealthy, a particular individual may not view wine as unhealthy.

**Table 3 The Five Binary Attributes of Drinks**

| Drinks | Healthy | Unhealthy | Taste | Mood boosting | Hydrating |
|---|---|---|---|---|---|
| Coffee | 0 | 1 | 0 | 1 | 0 |
| Tea | 0 | 0 | 0 | 0 | 0 |
| Milk | 1 | 0 | 0 | 0 | 0 |
| Hot chocolate | 0 | 1 | 0 | 1 | 0 |
| Juice | 1 | 0 | 1 | 0 | 0 |
| Soda | 0 | 1 | 1 | 0 | 0 |
| Beer/wine/alcohol | 0 | 1 | 1 | 1 | 0 |
| Water | 0 | 0 | 0 | 0 | 1 |
| Bottled water | 0 | 0 | 0 | 0 | 1 |
| Nutritional drink | 1 | 0 | 0 | 0 | 0 |
| Other | 0 | 0 | 1 | 0 | 0 |

*Note*. The unhealthy attribute for beer/wine/alcohol, soda, and coffee is further refined using each individual's data.

Given the focus in our paper on the regulatory behavior involving unhealthy drinks, we were particularly interested in assessing the impact of individuals deviating from the definition of the unhealthy attribute based on aggregate consumer opinions as described above. Only 68 out of 1,641 (4.1%) consumers indicated one of the two health motivations in the survey ("nutritional/healthy" or "fortified with vitamins") *whenever* they drank an unhealthy (as per our definitions above) drink (coffee, hot chocolate, soda, beer, wine, or alcohol).

We considered the possibility of revising the unhealthy attributes for a type of drink for a consumer from one to zero if the consumer *ever* indicated the type of drink as healthy. Doing so would require us to estimate separate dynamic discrete choice models for each subset of people with common attribute definitions, which would make the model computationally intractable and also create problems with statistical power for subsets with very few individuals. Furthermore, the use of common attributes is conceptually appealing to perform counterfactuals on new product introductions. So, to avoid any potential biases from the individual deviations, we drop the small number of individuals who deviate from the aggregate opinion from our analysis.[6]

Table 4 shows a large variation in people's propensity to drink. First, consumers differ in the maximum number of consecutive periods where they do not drink anything. The median number of drinks in a day is four, and the 25%–75% interquartile range is from three to five. The maximum daily consumption of unhealthy (and healthy) drinks across individuals also varies substantially. The median numbers for the maximum number of healthy and unhealthy drinks are one and two, respectively. The 25%–75% interquartile range for healthy drinks is from one to two. The corresponding numbers for unhealthy drinks are two and four. Overall, we see much greater variation in the number of unhealthy drinks across individuals. To control for such *observed* heterogeneity in consumption, we use the maximum daily consumption of all drinks and unhealthy drinks as control variables in a consumer's per-period utility function (as described in §3).

**Table 4 Descriptive Statistics of Daily Consumption**

| Variables | Obs. | 25th percentile | Median | 75th percentile | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|---|---|---|---|
| *All categories* | 9,720 | 3 | 4 | 5 | 3.7 | 1.3 | 0 | 6 |
| *Healthy drinks* | 9,720 | 0 | 1 | 1 | 0.7 | 0.8 | 0 | 5 |
| *Unhealthy drinks* | 9,720 | 1 | 1 | 2 | 1.4 | 1.2 | 0 | 6 |
| *Tasty drinks* | 9,720 | 1 | 1 | 2 | 1.5 | 1.1 | 0 | 6 |
| *Mood drinks* | 9,720 | 0 | 0 | 1 | 0.5 | 0.8 | 0 | 5 |
| *Hydration drinks* | 9,720 | 0 | 1 | 2 | 1.1 | 1.1 | 0 | 6 |
| Individual-level maximum daily total consumption | | | | | | | | |
| *Healthy drinks* | 1,215 | 1 | 1 | 2 | 1.4 | 0.6 | 1 | 6 |
| *Unhealthy drinks* | 1,215 | 2 | 2 | 4 | 2.3 | 1.1 | 1 | 5 |

We also see more variation within individuals for unhealthy drinks. Relatively few people drink more than one healthy drink a day, most of which is consumed during breakfast. By contrast, it is common for an individual to have multiple unhealthy drinks. The variation in unhealthy drink consumption even within individuals is large. Across the sample, individuals drank only one unhealthy drink on 36% of the days, and at least three unhealthy drinks on 14% of the days. Such a large variation can have important implications for consumers' long-term health.

## 3. Model of Intraday Decisions and Self-Regulation

Our model of intraday beverage consumption decisions seeks to incorporate three features of beverage consumption. First, it accounts for contemporaneous needs in the utility function, allowing for diversity in choices across different occasions. Second, it accounts for (endogenous) accumulation of thirst similar to endogenous modeling of inventory in forward-looking stockpiling models. We model the thirst stock as the number of consecutive periods that a consumer has gone without drinking until the current period. Third, it incorporates heterogeneity in self-regulating behavior to allow consumers to balance short-run needs and long-term goals to different degrees.

[6] One possibility was to drop all individuals who do not explicitly agree with any of the attribute definitions adopted by us. However, this approach is not without its own problems because individuals may only express the most important and salient reasons for consumption in surveys. Such individuals would be classified as not explicitly agreeing with our attribute definition, even if they did not disagree. The gain from potentially erroneously dropping all individuals not explicitly agreeing with the definition of the other attributes could be overwhelmed by the cost of losing information about these individuals from our sample. Our procedure is a compromise between these trade-offs.

Each consumer is potentially one of the three self-regulatory types, which we label as myopic (no self-regulation), adaptive (backward looking), and anticipatory (backward and forward looking). Consumers' types are constant over time. Since there are no data available to us that could be used to infer or proxy for an individual's type, we treat each consumer's behavioral type as unobserved heterogeneity conditional on their demographics and model the data as a mixture of the three types of consumers (see, e.g., Kamakura et al. 1996).[7]

In the following, we first spell out the important elements in our model, and then describe our models for the three behavioral types. We model beverage consumption choice over six periods ($T = 6$) during the day, i.e., (i) at breakfast, (ii) between breakfast and lunch, (iii) at lunch, (iv) between lunch and dinner, (v) at dinner, and (vi) after dinner. Let $c_{it} \in \{0, 1, 2, \ldots, J\}$ denote a consumer $i$'s choice in period $t$, which can be either one out of the set of beverages $\{1, 2, \ldots, J\}$ or the outside option, 0, of drinking nothing.[8] Empirically, we have $J = 11$ beverage choices and an outside option of drinking nothing ($j = 0$) in each period. Although there are many attributes that may characterize a beverage, based on our data, we treat each beverage $j$ as being characterized by five binary attributes, i.e., (i) healthy, for notational convenience denoted $g_j$ ("good," for healthy); (ii) unhealthy, $b_j$ ("bad," for unhealthy); (iii) taste, $l_j$ ("likable," for tasty); (iv) mood boosting, $m_j$; and (v) hydrating, $h_j$, where $g_j, b_j, l_j, m_j, h_j \in \{0, 1\}$ (see Table 3 for the attributes of each beverage). We define the values of the five attributes to be zero for the outside option. In related work, Chan (2006) also uses an attribute approach to model demand for beverages in a static framework. The sequence of choices made by an individual $i$ over $T$ periods in a day is denoted by $c_i \equiv (c_{it})_{t=1}^{T}$.

Denoted as $g_{it}, b_{it}, l_{it}$, and $m_{it}$ are the healthy, unhealthy, taste, and mood-boosting attributes of consumer $i$'s choice in period $t$, respectively. Define the accumulated stocks of these attributes to be $G_{it} \equiv \sum_{s=1}^{t} g_{is}$, $B_{it} \equiv \sum_{s=1}^{t} b_{is}$, $L_{it} \equiv \sum_{s=1}^{t} l_{is}$, and $M_{it} \equiv \sum_{s=1}^{t} m_{is}$ for the healthy, unhealthy, taste, and mood-boosting attributes, respectively.[9] The stocks represent how many drinks of a particular type, say, healthy or unhealthy, an individual has had until the end of period $t$ on that day.

We denote the activity that consumer $i$ engages in in period $t$ by $a_{it} \in A$, where $A$ is the set of all activities. At any time $t$, consumer $i$ can be engaged in one of the following six mutually exclusive (categories of) activities: (1) eat, (2) work, (3) relax, (4) exercise, (5) meeting, or (6) party. See Table 1 for the specific activities included in each category. For example, study is in the work category; watching TV is in the relax category. We assume that $a_{it}$ follows a first-order Markov process. The transition process is described in nonparametric form by the conditional probability for each activity in the next period given the current activity and is specific to each period $t$. For example, suppose the period $t$ activity is $a_t$. (We suppress the index $i$ since this transition matrix is estimated at the sample level.) Then, the transition probability will be specified as $\widehat{\Pr}[a_t \mid a_{t-1}, t]$, where $a_t$ and $a_{t-1} \in \{1, 2, 3, 4, 5, 6\}$. Activities only play a role in forming expectations of future needs for the anticipatory self-regulation segment and are not used in modeling the myopic or adaptive consumers. Also, activities do not affect utility directly, but only indirectly through the needs associated with them.

Conditional on the activity, the consumer experiences a psychological or physical need state that enhances the utility from beverage consumption. These contemporaneous need states are the following four kinds: health ($e_{it,1}$), taste ($e_{it,2}$), mood ($e_{it,3}$), and hydration ($e_{it,4}$). These needs determine the match between the attributes of the beverage chosen and the psychological and physical state of the individual, which changes from one occasion to the next. For example, during a lunch break, an individual's needs may be best met by a bottle of water because the person is high on the health and hydration needs, but low on the mood need. On the other hand, at a party the individual may be high on the mood need but low on the health and hydration needs. More specifically, we model these needs to be dependent on each period's activity in the following way:

$$\begin{aligned} e_{it,1} &= \delta_1(a_{it}) + \eta_{it,1}, \\ e_{it,2} &= \delta_2(a_{it}) + \eta_{it,2}, \\ e_{it,3} &= \delta_3(a_{it}) + \eta_{it,3}, \\ e_{it,4} &= \delta_4(a_{it}) + \eta_{it,4}, \end{aligned} \tag{1}$$

[7] This formulation also helps us avoid the well-recognized problem associated with estimating discount factors (see, e.g., Rust 1994, Magnac and Thesmar 2002). See, e.g., Khwaja et al. (2007), Chevalier and Goolsbee (2009), and Chung et al. (2014) for alternative approaches to estimate discount factors when analyzing intertemporal decision making and forward-looking behavior.

[8] We do not observe product availability for each individual at the time of consumption; therefore, we assume that the choice set is the same across individuals and across time. The problem is not unlike the "unobservability" of consideration sets across time and across individuals in brand choice at stores. The potential bias due to this assumption is likely limited in our setting. Only in 9% of occasions in the data is "nearest" or "closest" chosen as a reason for a beverage choice.

[9] The notion of an accumulated attribute stock is related to the concept of consumption capital or stock developed in the pioneering work of Becker and Murphy (1988). See, e.g., Hartmann (2006) for another application of this concept.

where $\delta_k(a_{it})$ are activity-specific constants, and $\eta_{it,k}$ are normal random variables with zero mean. We define the vector $e_{it} \equiv (e_{it,1}, e_{it,2}, e_{it,3}, e_{it,4})$. These need states summarize the psychological and physical needs accompanying the current activity. We construct these four need states $e_{it}$ using factor analysis on stated consumer data from the 18 questions (see Footnote 2) about the psychological and physical needs that motivated the consumption decision in each period. The four need states are the four factors that explained the most variation in the individual responses to the 18 questions.

Another contemporaneous factor that affects consumption of a beverage in the short run is the stock of thirst. We use $Q_{it}$ to denote the thirst stock, that is, the total number of consecutive periods a consumer did not drink anything immediately before period $t$.[10] We model the evolution of the thirst stock to be endogenously determined as in stockpiling models (see, e.g., Erdem et al. 2003, Hendel and Nevo 2006) as follows:

$$\begin{aligned} Q_{it} &= Q_{i,t-1} + 1 \quad \text{if } j = 0 \text{ chosen in period } t-1, \\ &= 0 \quad \text{otherwise.} \end{aligned} \tag{2}$$

sum Let $B_{iT} = \sum_{t=1}^{T} b_{it}$ denote the sum of unhealthy attributes of all of the choices made by a consumer in a day. Some consumers may attach a value to $B_{iT}$ at the end of each day, reflecting their intention to regulate their daily intake of unhealthy beverages. As an empirical model of beverage consumption, it is also important to account for the fact that some people simply drink more frequently than others. For this purpose, we use $B_{i,\max} = \max B_{iT}$ and $G_{i,\max} = \max G_{iT}$ to control for a consumer's propensity to drink something, where the maximum is taken over the days in the sample that we use for calibration (as opposed to estimation), i.e., the first two days of the first week of the sample.

Next, we specify the beverage consumption model separately for each of the three types of consumers based on their degree of self-regulation. We drop the subscript $i$ to simplify notation.

[10] We conceptually distinguish hydration and thirst needs. The thirst stock, measured as the number of consecutive periods without drinking anything, captures an individual's periodic need to drink and is independent of activities. The hydration need is directly driven by the current activity and is especially high for physical activities and exercise. This is reflected in our data. For the six major activity categories, (1) eat, (2) work, (3) relax, (4) exercise, (5) meeting, and (6) party, the mean hydrating needs are, respectively, $-0.292, 0.422, -0.003, 0.833, 0.224$, and $0.124$. On the other hand, the mean thirst stock conditional on needs is roughly constant across the six activities at 1.396, 1.407, 1.434, 1.361, 1.378, and 1.426. Distinguishing the thirst and hydration needs allows us to capture, for example, the urgent need to drink water after exercise even if an individual had drank something in the last period.

### 3.1. Anticipatory Self-Regulators

We begin by describing the model for the anticipatory segment, which exhibits the most general form of self-regulatory behavior. We allow this segment to consume beverages in response to (1) contemporaneous need states and thirst stock, (2) past consumption, and (3) future anticipated consumption. We describe the current-period utility of consuming beverage $j$ as

$$U_{jt} + \varepsilon_{jt}, \tag{3}$$

where, $U_{jt}$, is the deterministic component that is specified as follows:

$$\begin{aligned} U_{jt} = {} & \mathbf{1}\{j \neq 0\}(\alpha_0 + \alpha_{01} G_{\max} + \alpha_{02} B_{\max}) + \alpha_j \\ & + g_j(\alpha_{11} e_{t,1} + \alpha_{12} e_{t,2} + \alpha_{13} e_{t,3} + \alpha_{14} e_{t,4} + \alpha_{15} G_{t-1}) \\ & + l_j(\alpha_{21} e_{t,1} + \alpha_{22} e_{t,2} + \alpha_{23} e_{t,3} + \alpha_{24} e_{t,4} + \alpha_{25} L_{t-1}) \\ & + m_j(\alpha_{31} e_{t,1} + \alpha_{32} e_{t,2} + \alpha_{33} e_{t,3} + \alpha_{34} e_{t,4} + \alpha_{35} M_{t-1}) \\ & + h_j(\alpha_{41} e_{t,1} + \alpha_{42} e_{t,2} + \alpha_{43} e_{t,3} + \alpha_{44} e_{t,4}) + \psi b_j B_{t-1} \\ & + Q_t \cdot \mathbf{1}\{j \neq 0\}(\beta_1 + \beta_2 G_{\max} + \beta_3 B_{\max}), \end{aligned} \tag{4}$$

and $\varepsilon_{jt}$ is a choice-specific random variable capturing other unobserved factors affecting a consumer's preference for choice $j$.

In the above specification, the interactions between the attributes of the product $(g_j, l_j, m_j, h_j)$ and the need states $(e_{t,1}, e_{t,2}, e_{t,3}, e_{t,4})$ capture the match values of the beverage attributes for the current need states (which depend on activity). For example, a mood-enhancing drink, such as beer, might have a high match value for needs that are high during parties. The thirst stock term, $Q_t$, captures the need to quench thirst, when a consumer has not drank anything for $Q_t$ consecutive periods. We allow $U_{jt}$ to depend on the stock of health, taste, and mood-boosting attributes $(G_{t-1}, L_{t-1}, M_{t-1})$ and the unhealthy attribute $B_{t-1}$ accumulated until the end of period $t-1$. The dependence of a consumer's preference on these accumulated stocks can be the result of either variety-seeking behavior or inertia in tastes (see, e.g., Lattin and McAlister 1985). Hence, we model habit persistence in consumption choices through accumulated product characteristics as opposed to the conventional one-period lag values of product choices. For example, the interaction term $\alpha_{15} g_j G_{t-1}$ captures the impact of the accumulated healthy attribute till the previous period on the current period's preference for a beverage with a healthy attribute. The coefficient of the interaction terms can be either positive, in the case of inertia, or negative, in the case of variety seeking in preferences. The conventional product or brand choice model uses information on purchases to make inferences about the utility consumers attach to various attributes of a product.

By contrast, the notable distinction in our framework is that it uses information about actual consumption decisions and contemporaneous needs that vary across time for a given consumer to make inferences about the match utility of product attributes at a given occasion.

We next explain the interpretation of the coefficients in the utility function. The parameter $\alpha_0$ represents the base level utility of consuming any beverage. The variables $G_{i,\max} = \max G_{iT}$ and $B_{i,\max} = \max B_{iT}$ are included to capture the fact that some people simply drink more frequently. So, the parameters $(\alpha_{01}, \alpha_{02})$, the coefficients of $G_{i,\max}$ and $B_{i,\max}$, represent the higher base utility enjoyed by those who drink more frequently from consuming any beverage. The beverage fixed effect parameter $(\alpha_j)$ captures the utility from a beverage $j$ that is not explained by the observed product attributes, need states, thirst level, etc. As is standard in the literature (e.g., Berry et al. 1995), we assume that the beverage fixed effect is mean-independent of other beverage attributes, and we normalize the mean of the beverage fixed effect to be zero. The parameters $(\beta_1, \beta_2, \beta_3)$ account for the effect of (endogenous) thirst on utility. The first parameter accounts for the base level effect of thirst on utility, whereas the second and third parameters reflect the effect of thirst accounting for the heterogeneity in frequency of beverage consumption as described above.

The utility from a beverage also depends on the interaction of its attributes with the contemporaneous need states. The coefficients of these interaction terms reflect how well a beverage's attributes match the consumer's time-varying need states. The parameters $(\alpha_{11}, \alpha_{21}, \alpha_{31}, \alpha_{41})$ represent the utility of the four attributes interacted with the level of health need $(e_{t,1})$. Similarly, the parameters $(\alpha_{12}, \alpha_{22}, \alpha_{32}, \alpha_{42})$ represent the utility of the four attributes interacted with the level of taste need $(e_{t,2})$. The parameters $(\alpha_{13}, \alpha_{23}, \alpha_{33}, \alpha_{43})$ represent the utility of the four attributes interacted with the level of mood need $(e_{t,3})$, and the parameters $(\alpha_{14}, \alpha_{24}, \alpha_{34}, \alpha_{44})$ represent the utility of the four attributes interacted with the level of hydrating need $(e_{t,4})$.

Last, the parameters $(\alpha_{15}, \alpha_{25}, \alpha_{35})$ and $\psi$ reflect the response of the current consumption to past consumption. Depending on their signs, these parameters may capture either consumption persistence or variety seeking for the health, taste, and mood-boosting attributes. We do not incorporate such persistence for the hydration attribute $(h_j)$ because that is already incorporated through the thirst stock $Q_t$.

**3.1.1. Heuristic for Long-Term Health Goals: End-of-Day Salvage Value.** Regulating the daily intake of healthy and unhealthy drinks is important for staying healthy in the long run. Health changes in response to nutritional choices such as beverage consumption occur extremely gradually over time. Thus, it is hard for consumers to monitor their current health status in detail, and so it is not feasible for them to condition their beverage consumption on their current health status. In such a context, we propose an end-of-day salvage value function based on the current day's overall consumption (that we describe below) as a reasonable way to model how forward-looking consumers can use a simple heuristic or rule of thumb to achieve long-term health goals.

In general, such a salvage value function would be a flexible function of the total number of healthy and unhealthy drinks consumed over the day $\bar{V}_{T+1}(G_T, B_T)$. However, in our application, the healthy drinks have little empirical bite in the salvage value function. This is because the total number of healthy drinks is equal to or less than one in most cases, and consumers most often consume the healthy drink during the first period of the day (breakfast). Hence, it does not affect forward-looking behavior at all. We therefore construct the salvage value function based only on the consumption of unhealthy drinks. Specifically, we assume that the end-of-day salvage value function has the following form:

$$\bar{V}_{T+1}(B_T) = \delta_1(B_T - B_{\max}) + \delta_2(B_T - B_{\max})^2, \qquad (5)$$

where $B_T$ is the end-of-day total consumption of unhealthy drinks. There may be heterogeneity among consumers about what they think is the number of unhealthy drinks that may be appropriate to drink in a day. The above specification uses $B_{\max}$ as a benchmark to capture such heterogeneity in consumers' "rule of thumb" with regard to staying healthy. The salvage value function contains the parameters $(\delta_1, \delta_2)$. The second parameter $(\delta_2)$ reflects the potential nonlinear effect of $B_T$ on the salvage value, such as increasing marginal negative impact of $B_T$ on $\bar{V}_{T+1}$.

**3.1.2. Dynamic Model.** If consumers are anticipatory (forward looking), then their utility from beverage consumption is also affected by the anticipated effect of the current choice on the future expected utility. Hence, the current choices are determined not just by the effects of past choices and contemporaneous needs but also by the expectations about their future choices. So we model the anticipatory consumer's preference by the following value function with the associated state variables $(Q_t, G_{t-1}, B_{t-1}, L_{t-1}, M_{t-1}, G_{\max}, B_{\max}, a_t)$ (note we suppress the $i$ subscript and static state variables, i.e.,

$e_t$ and $\varepsilon_t$, as arguments of the $V_{jt}$ function in the equations):

$$\begin{aligned} &V_{jt}(Q_t, G_{t-1}, B_{t-1}, L_{t-1}, M_{t-1}, G_{\max}, B_{\max}, a_t)\\ &\quad = U_{jt} + \rho E_{a_{t+1}\mid a_t} V_{t+1}(Q_{t+1}, G_t, B_t, L_t, M_t,\\ &\qquad\qquad G_{\max}, B_{\max}, a_{t+1}) + \varepsilon_{jt}\\ &\qquad \text{s.t. } Q_{t+1} = 1\{j=0\}\cdot(Q_t+1)\\ &\quad G_t = G_{t-1} + g_j, \quad B_t = B_{t-1} + b_j,\\ &\quad M_t = M_{t-1} + m_j, \quad L_t = L_{t-1} + l_j, \end{aligned} \tag{6}$$

where $\rho$ is the intertemporal discount factor, and $V_{t+1}$ is the continuation value defined as follows:

$$\begin{aligned} &V_{t+1}(Q_{t+1}, G_t, B_t, L_t, M_t, G_{\max}, B_{\max}, a_{t+1})\\ &\quad = E_{e_{t+1}} E_{\varepsilon_{t+1}} \Big( \max_j \{V_{j,t+1}(Q_{t+1}, G_t, B_t, L_t, M_t,\\ &\qquad\qquad G_{\max}, B_{\max}, a_{t+1})\}\Big), \quad \text{if } t < T, \end{aligned} \tag{7}$$

with the expectations taken over the joint distribution of $e_{t+1} \equiv (e_{t+1,1}, e_{t+1,2}, e_{t+1,3}, e_{t+1,4})$ and distribution of $\varepsilon_{t+1} \equiv (\varepsilon_{j,t+1})_{j=0}^{J}$, and

$$V_{t+1}(Q_{t+1}, G_t, B_t, L_t, M_t, G_{\max}, B_{\max}, a_{t+1}) = \bar{V}_{T+1}(B_T), \quad \text{if } t = T. \tag{8}$$

In our application, decisions are made daily, every two hours, where the total number of periods, $T$, is six. Hence, we set the discount factor $\rho = 1$. In this daily finite-horizon dynamic programming problem, consumers choose beverages to maximize the value each period, that is,

$$c_t = \operatorname*{arg\,max}_{j\in\{0,1,2,\dots,J\}} \{V_{jt}\}. \tag{9}$$

### 3.2. Adaptive Self-Regulators

We define adaptive consumers as those who respond not only to their contemporaneous needs but also respond adaptively to their past consumption decisions. Backward-looking behavior can either appear as variety seeking or inertia in tastes, and can vary by attribute. We assume that the preference of these consumers are defined by the utility function described above in (3)–(4). By contrast with the forward-looking type, the main difference is that the adaptive type's utility function excludes the continuation value (Equation (7)). The adaptive consumers also make a choice to maximize their utility every period, given by an appropriately modified version of Equation (9).

### 3.3. Myopic Self-Regulators

We define myopic consumers as those who consume beverages in response solely to contemporaneous need states and the thirst stock. These consumers are myopic because they ignore the effects of their past or future choices. For these consumers, we assume that their preferences are captured by the utility function $U_{jt} + \varepsilon_{jt}$, with the deterministic component $U_{jt}$ modified as follows:

$$\begin{aligned} U_{jt} = {} & \mathbf{1}\{j \neq 0\}(\alpha_0 + \alpha_{01} G_{\max} + \alpha_{02} B_{\max}) + \alpha_j\\ & + g_j(\alpha_{11} e_{t,1} + \alpha_{12} e_{t,2} + \alpha_{13} e_{t,3} + \alpha_{14} e_{t,4})\\ & + l_j(\alpha_{21} e_{t,1} + \alpha_{22} e_{t,2} + \alpha_{23} e_{t,3} + \alpha_{24} e_{t,4})\\ & + m_j(\alpha_{31} e_{t,1} + \alpha_{32} e_{t,2} + \alpha_{33} e_{t,3} + \alpha_{34} e_{t,4})\\ & + h_j(\alpha_{41} e_{t,1} + \alpha_{42} e_{t,2} + \alpha_{43} e_{t,3} + \alpha_{44} e_{t,4})\\ & + Q_t \cdot \mathbf{1}\{j \neq 0\}(\beta_1 + \beta_2 G_{\max} + \beta_3 B_{\max}). \end{aligned}$$

The utility function of the myopic consumers differs from that of the backward-looking types because it excludes lag stock of attributes, i.e., $(G_{t-1}, L_{t-1}, M_{t-1}, B_{t-1})$. It further differs from that of the forward-looking type because it excludes continuation value. Hence, this type of individual can only self-regulate at each consumption occasion, and their current choices are not directly affected by either their previous choices or in anticipation of future choices. The myopic consumers make a choice to maximize their utility every period as in a random utility (logit) model.

To close the model, we assume that each consumer belongs to one of the three self-regulatory types. We allow the ex ante probabilities of a consumer belonging to the three types to depend on her demographic variables $X_i$. Let $p_k(X_i \mid \phi)$ denote the ex ante probability of belonging to type $k$ for a consumer $i$ with demographic variables $X_i$, where $\phi \equiv (\phi_1, \phi_2, \phi_3)$. We assume that $p_k(X_i \mid \phi)$ has the following functional form:

$$p_k(X_i \mid \phi) = \frac{\exp(X_i \phi_k)}{\sum_{k'=1}^{3} \exp(X_i \phi_{k'})}.$$

As is conventional, we need to normalize one of three parameter vectors, $(\phi_1, \phi_2, \phi_3)$, for identification. In our estimation, we normalize $\phi_1$ to be zero. Finally, let $p_{i1}$, $p_{i2}$, and $p_{i3}$ denote the posterior probability that a consumer $i$ belongs to the myopic, backward-looking, and forward-looking types, respectively. Therefore, the unconditional share of each segment $k$ is given by $p_k = \sum_{i=1}^{N} p_{ik}/N$. We define $p \equiv (p_1, p_2, p_3)$.

## 4. Estimation

Our estimation procedure is as follows. We first estimate the activity transition matrix nonparametrically. Next, we estimate the needs–activity regressions specified in Equation (1). With these estimates in hand, we estimate the utility parameters and parameters in the segment probability function in the structural model.[11]

Denote the structural parameters in the models of the three types of consumers as $\gamma_1$, $\gamma_2$, and $\gamma_3$, respectively, and define $\gamma \equiv (\gamma_1, \gamma_2, \gamma_3)$. Following the convention in the literature (see, e.g., Rust 1987), we also assume that the choice-specific random shocks, $\varepsilon_{jt}$, are independent and identically distributed type I extreme value random variables. Thus, the conditional choice probabilities predicted by the model will have the logit functional forms (McFadden 1974, Rust 1987). For the myopic and backward-looking consumers, we can easily compute their conditional choice probabilities respectively as

$$\Pr(c_{it} = j \mid Q_{it}, e_{it}; \gamma_1) = \frac{\exp(U_{jt}(Q_{it}, e_{it}; \gamma_1))}{1 + \sum_{j'} \exp(U_{j't}(Q_{it}, e_{it}; \gamma_1))},$$

and

$$\begin{aligned}&\Pr(c_{it}=j \mid Q_{it}, e_{it}, G_{i,t-1}, L_{i,t-1}, M_{i,t-1}, B_{i,t-1}; \gamma_2)\\ &= \frac{\exp(U_{jt}(Q_{it}, e_{it}, G_{i,t-1}, L_{i,t-1}, M_{i,t-1}, B_{i,t-1}; \gamma_2))}{1+\sum_{j'} \exp(U_{j't}(Q_{it}, e_{it}, G_{i,t-1}, L_{i,t-1}, M_{i,t-1}, B_{i,t-1}; \gamma_2))}.\end{aligned}$$

For the anticipatory consumers, we use backward recursion to compute the expected continuation value functions, $V_{t+1}$, starting from the last period using Equations (6)–(9) (see, e.g., Rust 1987) with the last period value function being the end-of-day scrap-value function. Thus, the model's predicted conditional choice probabilities have the following logit functional form:

$$\begin{aligned}&\Pr(c_{it} = j \mid Q_{it}, e_{it}, G_{i,t-1}, L_{i,t-1}, M_{i,t-1}, B_{i,t-1}, a_{it}; \gamma_3)\\ &\quad = \frac{\exp(V_{ijt} - \varepsilon_{ijt})}{1 + \sum_{j'} \exp(V_{ij't} - \varepsilon_{ij't})},\end{aligned}$$

where $V_{jt}$ is as given in Equations (6)–(8).

To simplify notation, we suppress the dependence on the state variables for the conditional choice probabilities in the following discussion. One way to proceed is to estimate the structural parameters by using the brute force full information maximum likelihood estimation method. More specifically, the unconditional likelihood of observing a sequence of choices for a consumer can be expressed as follows:

$$L(\gamma, \phi \mid c_i) = \sum_{k=1}^{3} p_k(X_i \mid \phi_k) \Pr(c_i \mid \gamma_k),$$

[11] Estimating the activity transition matrix and the needs regressions before estimating the utility parameters requires making the assumption that the activity transition matrix and needs regressions are homogeneous across the different self-regulatory types of individuals. After estimating the heterogeneous self-regulation model, we test and do not reject the homogeneity assumption for the activity transition matrix and needs regressions across the estimated segments.

which is a mixture of the type-specific conditional choice probabilities. So we can find the maximum likelihood estimate of the structural parameters by solving the following optimization problem:

$$(\gamma^*, \phi^*) = \arg\max_{(\gamma, \phi)} \sum_{i=1}^{N} \ln(L(\gamma, \phi \mid c_i)).$$

The above problem is difficult to solve directly, because the optimization is taken over the space of all of the parameters (107 parameters in our case), and the objective function is highly nonlinear in the parameters. We use the EM algorithm to compute the above maximum likelihood estimator. Details of the algorithm are provided in the appendix.

We do not discuss identification in detail because it relies on assumptions that are conventional in the literature based on variation in choices over time within and across individuals. Briefly, the identification of the model comes from the different properties of the conditional choice probabilities for the three prototypical behavior models. For example, the choice probability of the myopic type is independent of the previous choices, whereas that of the adaptive type is not. The choice probabilities of the adaptive and myopic types are independent of the probability of transitioning into any particular activity (for example, party) in the next period (or in any future period) conditional on the current activity, whereas that of the anticipatory type is not.

## 5. Results and Discussion

### 5.1. The Activity Transition Matrix

We report the activity transition matrix in Table 5 for each period. The activity matrices are intuitive once we take into account the different time periods. Period 1 is around breakfast, and most people then transition to the work or relax category. There is substantial transition into eating during period 3 (lunchtime). In the fourth period, most people again transition back to the work or relax category. In period 5, i.e., early evening, people transition into "eat" or "relax." There is a substantial transition into the relax category due to "break from work" being the largest component of the "relax" category in the morning and afternoon. In period 6, late evening, individuals mostly transition into "relax" (watching TV, etc.).

### 5.2. Activity–Need Linkage Equations

Table 6 reports the results of Equation (1), the link between needs and activities. The health need is most strongly associated with exercise and work, and least associated with party. We note that lunch is classified as eating, even if one is at work. Hence, work

**Table 5 Activity Transition Matrices by Period**

| | Eat | Work | Relax | Exercise | Meeting | Party |
|---|---|---|---|---|---|---|
| Breakfast ($t = 1$) | | | Morning ($t = 2$) | | | |
| Eat | 0.078 | 0.318 | 0.457 | 0.040 | 0.101 | 0.006 |
| Work | 0.025 | 0.586 | 0.276 | 0.020 | 0.082 | 0.012 |
| Relax | 0.042 | 0.304 | 0.520 | 0.028 | 0.097 | 0.010 |
| Exercise | 0.000 | 0.323 | 0.484 | 0.129 | 0.065 | 0.000 |
| Meeting | 0.057 | 0.394 | 0.415 | 0.011 | 0.121 | 0.004 |
| Party | 0.000 | 0.286 | 0.500 | 0.000 | 0.179 | 0.036 |
| Morning ($t = 2$) | | | Lunch ($t = 3$) | | | |
| Eat | 0.640 | 0.060 | 0.255 | 0.003 | 0.039 | 0.003 |
| Work | 0.516 | 0.113 | 0.317 | 0.003 | 0.034 | 0.017 |
| Relax | 0.551 | 0.039 | 0.370 | 0.005 | 0.026 | 0.009 |
| Exercise | 0.546 | 0.032 | 0.341 | 0.054 | 0.027 | 0.000 |
| Meeting | 0.557 | 0.058 | 0.287 | 0.004 | 0.083 | 0.013 |
| Party | 0.400 | 0.111 | 0.289 | 0.022 | 0.089 | 0.089 |
| Lunch ($t = 3$) | | | Afternoon ($t = 4$) | | | |
| Eat | 0.051 | 0.246 | 0.526 | 0.051 | 0.103 | 0.023 |
| Work | 0.013 | 0.514 | 0.298 | 0.050 | 0.118 | 0.008 |
| Relax | 0.027 | 0.265 | 0.555 | 0.046 | 0.094 | 0.014 |
| Exercise | 0.030 | 0.364 | 0.424 | 0.091 | 0.091 | 0.000 |
| Meeting | 0.015 | 0.280 | 0.370 | 0.025 | 0.265 | 0.045 |
| Party | 0.076 | 0.242 | 0.470 | 0.046 | 0.121 | 0.046 |
| Afternoon ($t = 4$) | | | Dinner ($t = 5$) | | | |
| Eat | 0.741 | 0.009 | 0.218 | 0.009 | 0.009 | 0.014 |
| Work | 0.525 | 0.033 | 0.384 | 0.002 | 0.020 | 0.036 |
| Relax | 0.598 | 0.013 | 0.348 | 0.002 | 0.008 | 0.031 |
| Exercise | 0.552 | 0.022 | 0.371 | 0.007 | 0.011 | 0.037 |
| Meeting | 0.569 | 0.020 | 0.349 | 0.000 | 0.023 | 0.038 |
| Party | 0.667 | 0.009 | 0.234 | 0.000 | 0.009 | 0.081 |
| Dinner ($t = 5$) | | | Late evening ($t = 6$) | | | |
| Eat | 0.087 | 0.057 | 0.732 | 0.031 | 0.033 | 0.061 |
| Work | 0.074 | 0.361 | 0.417 | 0.037 | 0.046 | 0.065 |
| Relax | 0.038 | 0.065 | 0.787 | 0.025 | 0.022 | 0.064 |
| Exercise | 0.071 | 0.000 | 0.786 | 0.143 | 0.000 | 0.000 |
| Meeting | 0.055 | 0.247 | 0.521 | 0.000 | 0.151 | 0.027 |
| Party | 0.063 | 0.063 | 0.611 | 0.011 | 0.021 | 0.232 |

**Table 6 Regressions of Needs on Activity Dummies**

| Activity dummies | Dependent variables | | | |
|---|---|---|---|---|
| | Health need | Taste need | Mood need | Hydrate need |
| Eat | $-0.029^{**}$ | $0.058^{**}$ | $-0.202^{**}$ | $-0.268^{**}$ |
| | (0.004) | (0.004) | (0.003) | (0.004) |
| Work | $0.063^{**}$ | $-0.174^{**}$ | $0.071^{**}$ | $0.225^{**}$ |
| | (0.006) | (0.005) | (0.005) | (0.005) |
| Relax | $-0.031^{**}$ | $0.054^{**}$ | $-0.003$ | $-0.006$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Exercise | $0.332^{**}$ | $-0.131^{**}$ | $0.071^{**}$ | $0.733^{**}$ |
| | (0.015) | (0.014) | (0.013) | (0.014) |
| Meeting | $-0.020^{*}$ | $0.077^{**}$ | $0.215^{**}$ | $0.199^{**}$ |
| | (0.009) | (0.009) | (0.008) | (0.008) |
| Party | $-0.175^{**}$ | $0.385^{**}$ | $0.270^{**}$ | $0.026^{*}$ |
| | (0.012) | (0.011) | (0.010) | (0.011) |

*Note*. Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$.

includes only purely work times, when eating is not dominant. The taste need is most strongly related to party, and least associated with work and exercise. The mood need is most strongly associated with party and meetings, and least associated with eating. The hydrate need is most strongly associated with exercise and work; it is least associated with eating. All of the activity–need linkage parameters have plausible face value.

### 5.3. Model Estimates

We estimated models with alternative combinations of self-regulatory behavior. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) measures of the alternative one-, two-, and three-segment models are reported in Table 7. Our proposed three-segment model with all three forms of self-regulatory behavior (myopic, adaptive, and anticipatory) outperforms alternative one-segment and

**Table 7 Model Fit Comparison**

| Model | AIC | BIC |
|---|---|---|
| 1 Segment | | |
| Myopic | 191,122 | 191,352 |
| Adaptive | 190,951 | 191,209 |
| Anticipatory | 192,078 | 192,350 |
| 2 Segments | | |
| Myopic + adaptive | 186,447 | 187,022 |
| Myopic + anticipatory | 187,171 | 187,760 |
| Adaptive + anticipatory | 186,602 | 187,219 |
| 3 Segments | | |
| Myopic + adaptive + anticipatory | 183,810 | 184,744 |

**Table 8 Model Estimates, Type Distribution**

| Consumer types | Probability mass |
|---|---|
| Myopic | 0.33 |
| Adaptive | 0.41 |
| Anticipatory | 0.25 |

**Table 9 Estimates of Logit Segment Probability Function**

| | Adaptive | | Anticipatory | |
|---|---|---|---|---|
| Parameters | Coeff. | SE | Coeff. | SE |
| Constant | −0.131 | 0.244 | −0.939*** | 0.298 |
| Male | −0.030 | 0.156 | −0.298* | 0.181 |
| Education | | | | |
| Some college | 0.160 | 0.248 | 0.275 | 0.295 |
| College | 0.344 | 0.258 | 0.453 | 0.304 |
| Postgraduate | 0.236 | 0.282 | 0.222 | 0.336 |
| Income ranges | | | | |
| \$35K–\$50K | 0.210 | 0.216 | 0.676*** | 0.250 |
| \$50K–\$75K | 0.190 | 0.213 | 0.817*** | 0.246 |
| \$75K–\$100K | 0.112 | 0.239 | 0.272 | 0.297 |
| \$100K+ | 0.085 | 0.279 | 0.653** | 0.318 |
| Race | | | | |
| African American | 0.172 | 0.325 | 0.431 | 0.359 |
| Asian | 0.104 | 0.349 | 0.198 | 0.397 |
| Hispanic | 0.295 | 0.297 | 0.517 | 0.339 |

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

two-segment models both on the AIC and BIC. In what follows, we focus on the results of the three-segment model.

The shares of the myopic, adaptive, and adaptive-anticipatory segments are 0.33, 0.41, and 0.25 respectively (Table 8). Interestingly, only one-third of individuals do not practice any form of self-regulation. Around two-thirds of the sample self-regulate (adaptive and anticipatory) their beverage consumption beyond responding to current needs. In fact, 25% of consumers are anticipatory, justifying the dynamic self-regulatory framework used in this paper. Table 9 presents information about the characteristics of people belonging to the three segments. Although there are no gender distinctions for the adaptive and myopic segments, women are more likely to be anticipatory. Higher incomes are correlated with anticipatory behavior, and education is positive but not significant, perhaps due to education's correlation with income.

Table 10 reports parameters associated with the product attributes. Overall, the attributes and the corresponding need interactions have face validity across all three segments. The match values of each attribute and its corresponding need are all positive. For example, the health attribute–health need match value is positive across all three segments. As expected, the cross-match (mismatched attribute and need) values are mostly (29 out of 36) negative. Of note are the negative cross-match values for mood attribute–health need and mood attribute–hydrating need; i.e., people's utility for mood-enhancing drinks is very low when their health and hydrating needs are high. By contrast, the cross match value of mood attribute–taste need is either positive or only slightly negative, suggesting that mood and taste are either complementary or close to independent. These estimates have implications for predicted shares of new beverages, as we will see in our counterfactual experiments.

In terms of attribute-level state dependence (captured through attribute interactions with corresponding lagged accumulated stocks of $G_{t-1}, L_{t-1}$, and $M_{t-1}$), we find that the adaptive segment has inertia for all three attributes. However, the anticipatory segment has inertia for only the taste attribute, but is variety seeking for the health and mood attributes. For the self-regulation of unhealthy attribute consumption, the adaptive segment shows a strong preference to cut back on unhealthy drinks in response to past unhealthy drink consumption, $B_{t-1}$, as evidenced by the large significantly negative coefficient of the unhealthy attribute interaction with the corresponding stock. The anticipatory segment achieves self-regulation through the state dependence effect (i.e., interactions of $b_t$ with $B_{T-1}$) embedded in the current period utility function *and* the salvage value function. For example, in period $T$ (the last period), it is straightforward to check that the anticipatory consumer's payoff for an unhealthy drink is reduced by 0.081 ($\psi + 2\delta_2$) as a result of the state dependence effect. The effect of state dependence is similar for earlier periods (though less straightforward to calculate).

For the anticipatory segment, the end-of-day salvage value function contains the parameters ($\delta_1, \delta_2$), which are estimated to be −0.44 and −0.21, respectively. These estimates show that the salvage value function is concave, with decreasing marginal salvage value (i.e., increasing disutility) for unhealthy drinks. More specifically, it implies that there is disutility in consuming unhealthy drinks to an individual if it causes the end-of-day total consumption of the

**Table 10 Model Estimates, Type-Specific Models**

| | Myopic | | Adaptive | | Anticipatory | |
|---|---|---|---|---|---|---|
| Parameters | Coeff. | SE | Coeff. | SE | Coeff. | SE |
| Healthy attribute | | | | | | |
| × Health need: $\alpha_{11}$ | 1.242*** | 0.021 | 1.242*** | 0.022 | 1.106*** | 0.026 |
| × Taste need: $\alpha_{12}$ | 0.111*** | 0.028 | −0.033 | 0.028 | −0.121*** | 0.038 |
| × Mood need: $\alpha_{13}$ | −1.037*** | 0.044 | −1.052*** | 0.047 | −0.960*** | 0.061 |
| × Hydrate need: $\alpha_{14}$ | −0.708*** | 0.030 | −1.338*** | 0.044 | −1.003*** | 0.053 |
| × $G_{t-1}$: $\alpha_{15}$ | | | 0.133*** | 0.032 | −0.179*** | 0.056 |
| Taste attribute | | | | | | |
| × Health need: $\alpha_{21}$ | −0.724*** | 0.023 | −0.540*** | 0.027 | −0.539*** | 0.026 |
| × Taste need: $\alpha_{22}$ | 0.620*** | 0.018 | 1.134*** | 0.019 | 0.957*** | 0.023 |
| × Mood need: $\alpha_{23}$ | −0.281*** | 0.018 | −0.378*** | 0.024 | −0.340*** | 0.028 |
| × Hydrate need: $\alpha_{24}$ | 0.332*** | 0.020 | −0.268*** | 0.028 | 0.013 | 0.030 |
| × $L_{t-1}$: $\alpha_{25}$ | | | 0.200*** | 0.021 | 0.118*** | 0.019 |
| Mood attribute | | | | | | |
| × Health need: $\alpha_{31}$ | −2.268*** | 0.134 | −1.882*** | 0.089 | −1.951*** | 0.114 |
| × Taste need: $\alpha_{32}$ | 0.423*** | 0.051 | −0.036 | 0.024 | −0.109*** | 0.035 |
| × Mood need: $\alpha_{33}$ | 1.390*** | 0.036 | 1.312*** | 0.020 | 1.231*** | 0.026 |
| × Hydrate need: $\alpha_{34}$ | −1.539*** | 0.093 | −1.061*** | 0.034 | −1.230*** | 0.055 |
| × $M_{t-1}$: $\alpha_{35}$ | | | 0.068*** | 0.023 | −0.423*** | 0.026 |
| Hydrate attribute | | | | | | |
| × Health need: $\alpha_{41}$ | 0.215*** | 0.030 | 0.131*** | 0.019 | 0.177*** | 0.020 |
| × Taste need: $\alpha_{42}$ | −1.490*** | 0.072 | −0.995*** | 0.028 | −0.543*** | 0.029 |
| × Mood need: $\alpha_{43}$ | −1.205*** | 0.052 | −1.601*** | 0.038 | −1.379*** | 0.048 |
| × Hydrate need: $\alpha_{44}$ | 0.753*** | 0.030 | 0.809*** | 0.018 | 0.952*** | 0.023 |
| Intercept for all beverage products: $\alpha_0$ | −5.029*** | 0.057 | −4.747*** | 0.047 | −4.232*** | 0.052 |
| Main effects | | | | | | |
| $G_{\max}$: $\alpha_1$ | 0.285*** | 0.011 | 0.317*** | 0.010 | 0.246*** | 0.010 |
| $B_{\max}$: $\alpha_2$ | 0.286*** | 0.012 | 0.328*** | 0.010 | 0.192*** | 0.014 |
| Unhealthy attribute × $B_{t-1}$: $\psi$ | | | −0.193*** | 0.019 | 0.347*** | 0.021 |
| Thirst stock | | | | | | |
| Intercept: $\beta_1$ | 0.575*** | 0.061 | 0.816*** | 0.061 | −0.112 | 0.073 |
| × $G_{\max}$: $\beta_2$ | −0.117*** | 0.016 | −0.120*** | 0.014 | −0.048*** | 0.016 |
| × $B_{\max}$: $\beta_3$ | −0.067*** | 0.015 | −0.162*** | 0.016 | 0.013 | 0.018 |
| Salvage value | | | | | | |
| Linear term: $\delta_1$ | | | | | −0.441*** | 0.038 |
| Quadratic term: $\delta_2$ | | | | | −0.214*** | 0.014 |
| Product intercepts | | | | | | |
| Coffee: $\alpha_{01}$ | −0.921*** | 0.061 | 1.049*** | 0.034 | 0.188*** | 0.041 |
| Tea: $\alpha_{02}$ | 1.690*** | 0.026 | 0.917*** | 0.024 | 0.865*** | 0.033 |
| Milk: $\alpha_{03}$ | −0.018 | 0.036 | 0.195*** | 0.032 | −0.271*** | 0.046 |
| Hot chocolate: $\alpha_{04}$ | −2.269*** | 0.072 | −2.148*** | 0.069 | −2.821*** | 0.098 |
| Juice: $\alpha_{05}$ | 0.878*** | 0.034 | −0.277*** | 0.033 | 0.105** | 0.045 |
| Soda: $\alpha_{06}$ | 2.800*** | 0.025 | 1.878*** | 0.029 | 1.381*** | 0.039 |
| Beer/wine/alcohol: $\alpha_{07}$ | −1.297*** | 0.072 | −0.420*** | 0.043 | −0.915*** | 0.060 |
| Water: $\alpha_{08}$ | 0.965*** | 0.037 | 1.784*** | 0.021 | 0.752*** | 0.032 |
| Bottled water: $\alpha_{09}$ | 0.001 | 0.044 | −0.779*** | 0.039 | 1.769*** | 0.028 |
| Nutritional drink: $\alpha_{10}$ | −2.214*** | 0.072 | −1.765*** | 0.044 | −1.319*** | 0.062 |
| Other drinks: $\alpha_{11}$ | 0.385*** | 0.038 | −0.435*** | 0.043 | 0.268*** | 0.038 |

**$p < 0.05$; ***$p < 0.01$.

unhealthy attribute to hit or exceed $B_{\max}$ (the individual's threshold of daily amount of the unhealthy attribute). The *marginal* salvage value decreases by 0.43 (i.e., $2\delta_2$) for each additional unhealthy drink consumed in past periods (or each additional unhealthy drink expected to be consumed in the future periods). Taken together, the estimated salvage value function suggests that (1) the consumer would consume fewer unhealthy drinks in the current period if she expected that she would consume more unhealthy drinks in the future, and (2) the consumer would also reduce unhealthy drink consumption in response to more unhealthy consumption in the past periods. It should be noted that if these coefficients were not significantly different from zero, then anticipatory behavior would have no significant effect on consumption patterns (and would be like that of the adaptive segment).

Finally, we discuss consumers' responses to stock of thirst in terms of whether individuals consume

**Table 11 Holiday Shock: The Self-Regulation Effect of Forward-Looking Behavior**

| | Attributes | | | | |
|---|---|---|---|---|---|
| | Good | Bad | Taste | Mood | Hydration |
| | | | Myopic | | |
| Original | 19.24 | 70.78 | 80.37 | 14.44 | 23.28 |
| With mood-enhancing need shock in the last period | 16.64 | 73.94 | 77.29 | 20.74 | 20.32 |
| Total absolute change | −2.60 | 3.15 | −3.08 | 6.30 | −2.96 |
| Total percentage change | −13.51 | 4.46 | −3.84 | 43.63 | −12.73 |
| | | | Adaptive | | |
| Original | 24.17 | 63.20 | 54.00 | 33.96 | 46.65 |
| With mood-enhancing need shock in the last period | 20.96 | 72.37 | 51.29 | 45.60 | 39.87 |
| Total absolute change | −3.22 | 9.18 | −2.71 | 11.64 | −6.78 |
| Total percentage change | −13.31 | 14.52 | −5.02 | 34.26 | −14.54 |
| | | | Anticipatory | | |
| Original | 16.23 | 64.21 | 59.70 | 29.76 | 49.39 |
| With mood-enhancing need shock in the last period | 13.82 | 69.71 | 56.08 | 38.61 | 43.56 |
| Total absolute change | −2.41 | 5.50 | −3.62 | 8.85 | −5.83 |
| Total percentage change | −14.83 | 8.57 | −6.07 | 29.73 | −11.81 |
| Total absolute change in periods 1–5 | −0.43 | −1.30 | −1.24 | −0.52 | 0.49 |
| Total absolute change in period 6 | −1.97 | 6.80 | −2.39 | 9.37 | −6.32 |
| | | | Anticipatory, without salvage value | | |
| Original | 16.48 | 66.05 | 60.46 | 30.97 | 45.86 |
| With mood-enhancing need shock in the last period | 14.60 | 72.95 | 57.75 | 40.94 | 39.85 |
| Total absolute change | −1.88 | 6.90 | −2.70 | 9.97 | −6.01 |
| Total percentage change | −11.40 | 10.45 | −4.47 | 32.20 | −13.11 |
| The impact reduced due to forward-looking (in percentage) | | 20.3% | | | |

beverages (the "inside good"). The estimates of the parameters ($\beta_1, \beta_2, \beta_3$) are all statistically significant for the myopic and adaptive individuals, but only $\beta_2$ is statistically significant for the anticipatory individuals. Thus, we see that individuals in the myopic and adaptive segments are more likely to drink something when their thirst stocks are higher, though the response is weaker for those who drink more frequently. The result seems intuitive as the desire to drink in response to the immediate thirst stock can be less intense for those who drink more frequently in general (and thus likely also drank more prior to the accumulation of the thirst stock). For the anticipatory segment, the benchmark response to thirst stock is insignificant. This could be due to the fact that the anticipatory segment consumes the most hydrating drinks, offsetting the effect of the thirst stock. Similar to the other two segments, anticipatory individuals' responses to thirst stock are weaker if they drink more frequently in general.

### 5.4. Counterfactual Experiments

We perform two kinds of counterfactual experiments of relevance for managers in the beverage industry and health policy makers. The first focuses on how changes in situational needs affect beverage consumption across the three self-regulation types and its implications for targeting. It is also motivated from a policy perspective about encouraging healthy beverage consumption and combating the obesity epidemic. In particular, we consider the "holiday effect" of changes in consumption during the holidays when one is constantly tempted by a larger than usual number of parties. The second set of counterfactuals explores the potential for new product introductions designed to satisfy alternative combinations of needs.

Our simulation procedure for the benchmark and counterfactual environment is as follows. For each consumer, we first simulate the beverage consumption under the three different self-regulatory decision modes in the benchmark case (i.e., with the original activity transition matrix, needs distribution, and available product choices) over four weeks (20 weekdays in total). Then, for each consumer, we simulate the consumption in the counterfactual environment (e.g., with the introduction of a new product or with need shock in the last period) for 20 days. We compute the average total consumption for a self-regulatory type by taking the average of individual consumers' total consumption weighted by their posterior probability of belonging to the particular type. Following this, we compute the unconditional average total consumption as the sum of the average total consumption of the three types.

We operationalize the holiday effect by assuming that individuals experience a high mood-enhancing need in the last period of the day.[12] We also assume that activities prior to the last period are not affected,

[12] We implement this by replacing the mood-enhancing need in the last period with the mean mood-enhancing need during party plus

which seems reasonable given our focus on weekdays. This assumption, however, would be stretched if it were applied to weekends and should be kept in mind when interpreting our results. As reported in Table 11, with the holiday shock, all three types reduce their daily average consumption of the healthy and hydration attributes with an accompanying increase in the consumption of unhealthy and mood-boosting drinks.

Because the shock happens in the last period, the only impact for the myopic and adaptive consumers will be on their consumption in the last period. We decompose the total impact on the anticipatory segment into the effects in the first five periods and the last period. As shown in the third panel of Table 11, the consumption of unhealthy drinks decreases by 1.3 in the first five periods, whereas it increases by 6.8 in the last period. It is seen that the forward-looking behavior mitigates unhealthy consumption by reducing consumption of unhealthy drinks in earlier periods in anticipation of unhealthy consumption in the last period.[13]

To isolate the effects of forward looking on changes in aggregate consumption of unhealthy beverages due to the "holiday shock," we compare the consumption of the anticipatory segment relative to an identical (in terms of current payoffs) "as-if" segment for whom salvage value is set to zero. The unhealthy consumption goes up by 5.5 for the anticipatory segment (third panel of Table 11) and 6.9 (bottom panel of Table 11) for the as-if segment. Thus, forward looking lowers the impact of the holiday shock by 20.3%—a very significant effect.

The above results suggest that one approach to combating obesity could be to get myopic and adaptive individuals to be more anticipatory in terms of their consumption choices. Given the estimated large size of the myopic and adaptive segments in our model, this can indeed be a productive communication tactic. Behavioral research suggests approaches to implement such communications strategies. For example, Hershfield (2011a, b) shows that communications that makes the future self closer and more vivid to the current self can make a person more forward looking in her behavior.

Next we examine the market potential for new products, defined as novel combinations of attributes (see, e.g., Petrin 2002). Specifically, we consider three new products for the counterfactuals: (i) a "healthy–hydration" beverage that is a combination of the healthy and hydration attributes, (ii) a "mood–hydration" beverage that is a combination of the mood-boosting and hydration attributes, and (iii) a taste–hydration beverage that is a combination of the taste and hydration attributes. In the simulations, we set the beverage fixed effects for the three new products at the mean beverage fixed effect, which we had normalized to zero. As discussed earlier, the assumption that the ex ante expectation of a new beverage's fixed effect is the mean beverage fixed effect is natural given the standard assumption that the beverage fixed effect is mean-independent of other beverage attributes. This counterfactual is also related to the concept of "multifinality" in the goal systems literature, whereby multiple goals may be achieved concurrently by using "multifinal" means, thus allowing one to "have one's cake and eat it too" (Kopetz et al. 2012, p. 216).

We report results in Tables 12 and 13. The new healthy–hydration drink obtains a market share of 5.2%, very similar to that of bottled water and tea. Out of the 5.2% market share for the new product, one-third (1.7%) comes from the market expansion effect of meeting unmet needs of consumers who previously chose the outside option of not consuming a beverage. The remaining 3.5% is from cannibalizing the market shares of existing products. This is a significantly better outcome than from the introduction of mood–hydration and taste–hydration drinks, which obtain market shares of 3.1% and 2.9%, respectively.

Why do we see such significant variation in the market shares of the new products? We note that these new products all combine two attributes, which makes them able to meet two types of needs simultaneously. However, how popular a new product made of two attributes will be is further affected by the following two major factors. The first is the joint distribution of the needs. Table 14 shows the correlation matrix of the four needs. Significant positive correlation implies that there are occasions when the two corresponding needs are both relatively high, suggesting potential high value for a product that combines the corresponding two attributes. For needs that are negatively correlated, products combining the two corresponding attributes offer no positive value because there are rarely occasions when the two needs are both high concurrently. From Table 14, we see that hydration and health needs are significantly positively correlated, whereas the hydration need is negatively correlated with the mood and taste needs. Therefore, we should expect, ceteris paribus, the healthy–hydration new beverage to command higher market shares than the other two new beverages.

The second important factor is the "cross-match values" that describe the utility from consuming a

2.56 (1% significance level) times the standard deviation of mood need.

[13] We also explored a counterfactual experiment in which we let individuals exercise with probability one in the last period (after dinner) and to see how total consumption changed. The main finding was that the total consumption of the hydrating attribute increased by around 13%, which is consistent with the high hydrating needs during exercise. We did not see any significant change in consumption patterns in earlier periods in this experiment.

**Table 12 Counterfactual Experiments: Introducing New Beverages**

| | | | With new beverage | | | |
|---|---|---|---|---|---|---|
| | | | Mood + hydrating | | Healthy + hydrating | |
| Products | Attributes | Baseline share | New share | Share change | New share | Share change |
| Nothing | — | 0.402 | 0.391 | −0.011 | 0.385 | −0.017 |
| Coffee | Bad + mood | 0.068 | 0.063 | −0.004 | 0.067 | −0.001 |
| Tea | Neutral | 0.051 | 0.050 | −0.001 | 0.049 | −0.002 |
| Milk | Healthy | 0.035 | 0.034 | −0.001 | 0.030 | −0.005 |
| Hot chocolate | Mood | 0.005 | 0.004 | 0.000 | 0.005 | 0.000 |
| Juice | Good + taste | 0.045 | 0.044 | −0.001 | 0.040 | −0.004 |
| Soda | Bad + taste | 0.164 | 0.161 | −0.003 | 0.160 | −0.004 |
| Beer/wine/alcohol | Bad + taste + mood | 0.037 | 0.035 | −0.003 | 0.037 | −0.001 |
| Water | Hydrating | 0.112 | 0.108 | −0.004 | 0.101 | −0.012 |
| Bottled water | Hydrating | 0.054 | 0.053 | −0.001 | 0.050 | −0.004 |
| Nutritional drink | Healthy | 0.006 | 0.006 | 0.000 | 0.005 | −0.001 |
| Other | Taste | 0.021 | 0.020 | −0.001 | 0.020 | −0.001 |
| New | — | 0 | 0.031 | 0.031 | 0.052 | 0.052 |

product with a particular attribute when a specific need is high at a consumption occasion. As can be seen from Table 10 (the model estimates), most cross-match values are negative. For a new product trying to exploit some positively correlated needs to actually be popular, one still needs to make sure that the cross-match values are not too negative such that the gains from positive needs correlation are not offset. In the case of the healthy–hydration drink, the cross-match values of hydration attribute–health need are actually positive for all three segments, though those of health attribute–hydration need are all negative. Quantitatively, these cross-match values are comparable to those of the taste–hydration drink, but significantly better than those of the mood–hydration drink. Taken together, we see that the health–hydration new drink can obtain higher market share than the other two new products we considered, because (1) the health and hydration needs are significantly positively correlated, whereas the corresponding needs of the other two new products are negatively correlated, and (2) the cross-match values related to the healthy–hydration drink also turn out to be similar to or dominate those related to the other two new products. Therefore, one can examine the potential for new products by examining the correlation in needs data and the estimated cross-match values from the empirical model.[14]

It is also noteworthy that as the (cross-)match values vary across segments, the market shares of the new products also vary across segments. So, when marketing certain selected new beverages, one may also consider the behavioral differences across consumers when allocating marketing resources. In our case, Table 15 shows that the new beverages that we considered are more popular with the adaptive segment. One implication is therefore to consider allocating more marketing resources toward the adaptive consumers.

[14] A caveat here is that our model is only appropriate for examining the market potential (in terms of gain in market shares based on category expansion or business stealing) of new products. It is beyond the scope of this paper to provide practical guidance on other relevant marketing mix strategies, e.g., pricing, positioning, or advertising, for actual new product launches.

**Table 13 Counterfactual Experiments: Introducing New Beverages**

| Baseline | | | With new beverage Taste + hydrating | |
|---|---|---|---|---|
| Products | Attributes | Share | New share | Share change |
| Nothing | — | 0.402 | 0.391 | −0.010 |
| Coffee | Bad + mood | 0.068 | 0.067 | −0.001 |
| Tea | Neutral | 0.051 | 0.050 | −0.001 |
| Milk | Healthy | 0.035 | 0.034 | −0.001 |
| Hot chocolate | Mood | 0.005 | 0.005 | 0.000 |
| Juice | Good + taste | 0.045 | 0.043 | −0.001 |
| Soda | Bad + taste | 0.164 | 0.161 | −0.003 |
| Beer/wine/alcohol | Bad + taste + mood | 0.037 | 0.036 | −0.001 |
| Water | Hydrating | 0.112 | 0.107 | −0.006 |
| Bottled water | Hydrating | 0.054 | 0.051 | −0.002 |
| Nutritional drink | Healthy | 0.006 | 0.006 | 0.000 |
| Other | Taste | 0.021 | 0.020 | −0.001 |
| New | — | 0 | 0.029 | 0.029 |

**Table 14 Needs Correlation Matrix**

| | Health | Mood | Taste | Hydration |
|---|---|---|---|---|
| Health | 1 | | | |
| Mood | 0.033 | 1 | | |
| Taste | −0.085 | 0.189 | 1 | |
| Hydration | 0.131 | −0.074 | −0.017 | 1 |

*Note.* All correlation coefficients are significant at the 1% level.

**Table 15 Market Share of the New Product by Segment**

| New product | Myopic | Adaptive | Anticipatory | Total |
|---|---|---|---|---|
| Mood + hydrating | 0.033 | 0.034 | 0.024 | 0.031 |
| Health + hydrating | 0.047 | 0.061 | 0.042 | 0.052 |
| Taste + hydrating | 0.023 | 0.033 | 0.030 | 0.029 |

## 6. Conclusion

Most models of consumer choice in the literature are estimated using purchase data, not actual consumption or usage data. When analyzing food or beverage consumption, this is a serious limitation, because individuals consume a variety of different foods or beverages during the day, in response to needs that change within the day. Using unique intraday consumption, activity, and needs data, this paper provides insight into occasion-specific individual consumption choices.

From a modeling perspective, consumption choices of food and beverages not only provide immediate utility but also have long-term health consequences such as obesity and heart disease. We provide a dynamic structural framework that accommodates consumer self-regulation balancing short-run needs and long-term goals. Furthermore, health changes in response to consumption choices manifest extremely gradually and are not easy for individuals to discern; hence, we implement long-term goals as a heuristic rule of thumb through an end-of-day salvage-value construct. The framework also allows for unobserved heterogeneity in consumers' ability to self-regulate. We find that although one-third of individuals do not self-regulate, the other two-thirds practice some form of self-regulation on beverage consumption. Over 40% of individuals self-regulate adaptively based on past choice, whereas 25% self-regulate both adaptively and anticipating future needs. The model also provides insight on the potential success of a new product based on how well its mix of attributes targets a combination of occasion-specific needs. Products with attributes that match with needs that are highly correlated and co-occur are more likely to be successful. We find that new beverages that aim to satisfy the combinations of taste–hydration and mood–hydration needs achieve less market share than ones that satisfy health–hydration needs. Moreover, the new health-hydration beverage gains a third of its market share through market expansion by meeting previously unmet needs among those who did not consume any beverages earlier at the given consumption occasion.

Our modeling approach expands the existing dynamic structural modeling literature in allowing for consumption and stockpiling dynamics at the level of the product attributes. Furthermore, our empirical modeling framework using detailed consumption, situational needs, and activity data allows us to make linkages between the structural decision-theoretic model of consumption we develop and the behavioral literature on dynamic self-regulation and goal pursuit through consumption. Our analysis provides insight on how self-regulatory behavior helps consumers regulate unhealthy consumption when faced with high short-run needs for unhealthy consumption. This has implications not just for managers but also for policy makers tackling health and nutrition issues such as the obesity epidemic.

Finally, we discuss limitations of our current work that provide opportunities for future research. We treat beverage consumption as a function of activities, but independent of other consumption during those occasions. One could potentially imagine that an individual may balance consumption across beverages and food, i.e., consume healthier drinks when eating a decadent steak or, alternatively, highlight consumption by either choosing all "healthy" or all "decadent" items to obtain a "peak" experience. Although, there is a large literature on cross-category purchase behavior (e.g., Manchanda et al. 1999, Niraj et al. 2008) there is little work on cross-category consumption. We abstract from coconsumption, but coconsumption leads to new modeling challenges and substantive questions. For example, do consumers balance consumption within occasions or across time or both? Furthermore, we only model the quantity of drinks consumed through the total number of drinks consumed over the day, but we abstract away from the quantity consumed on any particular occasion—an issue of relevance on issues related to total calorie intake.

Furthermore, our model was developed to explain "stable" consumption behavior in mature categories of products. One could study consumption dynamics in the context of a portfolio of choices in categories where consumption is in the early stages and has not stabilized, e.g., because of the relative novelty of the product category. Such activities could include new recreational activities, where consumers seek to sample a range of activities and learn about one's tastes and abilities. One would need to expand the dynamic model to incorporate learning and yet model time allocation across activities in such situations (e.g., Luo et al. 2013).

Lastly, we note that the modeling approach has broad relevance in many settings where occasion-specific needs vary, individual's display heterogeneity in self-regulation, and short-run choices have gradual and difficult to discern immediate effects but with grave long-run consequences, e.g., consumer choices about preventive medical care, food, and nutrition, and health-related decisions such as exercise and smoking. Clearly, the availability of consumption data (as opposed to purchase data) should inspire a new set of substantive research questions and development of new models and methods to handle such data. We hope this paper serves as an impetus for a focused research agenda on modeling and understanding consumption choice.


## Acknowledgments

The authors thank seminar participants at the INFORMS Marketing Science Conference 2011, Yale School of Public Health Workshop, Marketing Dynamics Conference 2011, University of Texas at Dallas Frontiers of Research in Marketing Science Conference 2012, Yale School of Management Faculty Seminar, Four School Conference at Columbia University, and Yale Industrial Organization Prospectus Workshop for helpful comments and suggestions. All remaining errors are the authors'.


## Appendix. The EM Algorithm to Compute Maximum Likelihood Estimate

The maximum likelihood estimate is given by the sample analog of the following equation:

$$(\gamma^*, \phi^*) = \arg\max_{(\gamma, \phi)} E_{c_i \mid \gamma^*, \phi^*}\left[\ln\left(\sum_{k=1}^{3} p_k(X_i \mid \phi)\Pr(c_i \mid \gamma_k)\right)\right].$$

It can also be computed as follows:

$$\begin{aligned}(\gamma^*, \phi^*) &= \arg\max_{(\gamma, \phi)} E_{c_i, \kappa_i \mid \gamma^*, \phi^*}(\ln(p_{\kappa_i}(X_i \mid \phi)\Pr(c_i \mid \gamma_{\kappa_i})))\\ &= \arg\max_{(\gamma, \phi)} \sum_{k=1}^{3} E_{c_i \mid \gamma^*, \phi^*}\Big[\Pr(\kappa_i = k \mid c_i; \gamma^*, \phi^*)\\ &\qquad \cdot (\ln(p_k(X_i \mid \phi)\Pr(c_i \mid \gamma_k)))\Big],\end{aligned}$$

where $\kappa_i$ is a random variable indicating the type of consumer $i$. Thus, we have that

$$\begin{aligned}\gamma_k^* &= \arg\max_{\gamma_k} E_{c_i \mid \gamma^*, \phi^*}\left[\Pr(\kappa = k \mid c_i; \gamma^*, \phi^*)(\ln\Pr(c_i \mid \gamma_k))\right], \quad \forall k;\\ \phi^* &= \arg\max_{\phi} \sum_{k=1}^{3} E_{c_i \mid \gamma^*, \phi^*}\left[\Pr(\kappa = k \mid c_i; \gamma^*, \phi^*)\ln(p_k(X_i \mid \phi))\right].\end{aligned} \tag{10}$$

Broadly, the EM algorithm iterates over the following two steps. In Step 1, use an initial guess of $(\gamma^*, \phi^*)$ to compute segment membership probabilities $\Pr(\kappa_i = k \mid c_i; \gamma^*, \phi^*)$ in (10). In Step 2, conditional on the segment membership probabilities, maximize (10) over $(\gamma, \phi)$ to obtain $(\gamma^*, \phi^*)$. Use the $(\gamma^*, \phi^*)$ from Step 2 to revise the segment membership probabilities in Step 1, and iterate over this process until the $(\gamma^*, \phi^*)$ converge.

More specifically, let $\theta \equiv (\gamma, \phi)$, $\theta^*$ denote the true parameters, and let $\theta^{(1)}$ be the initial guess of $\theta^*$. Define

$$L(\theta^{(n)} \mid c_i) \equiv \sum_{k=1}^{3} p_k(X_i \mid \phi^{(n)})\Pr(c_i \mid \gamma_k^{(n)}) \quad \text{and}$$

$$p_{ik}^{(n)} \equiv \frac{p_k(X_i \mid \phi^{(n)})\Pr(c_i \mid \gamma_k^{(n)})}{L(\theta^{(n)} \mid c_i)}.$$

Then update the parameter estimates using the following recursive formula till the parameters converge:

$$\gamma_k^{(2)} = \arg\max_{\gamma_k} \sum_{i=1}^{N} p_{ik}^{(1)} \ln(\Pr(c_i \mid \gamma_k)), \quad \forall k,$$

$$\phi^{(2)} = \arg\max_{\phi} \sum_{k=1}^{3}\sum_{i=1}^{N} p_{ik}^{(1)} \ln(p_k(X_i \mid \phi)),$$

$$p_{ik}^{(2)} = \frac{p_k(X_i \mid \phi^{(2)})\Pr(c_i \mid \gamma_k^{(2)})}{L(\theta^{(2)} \mid c_i)}.$$

Similarly, we compute $\theta^{(3)}$ based on $\theta^{(2)}$, and so on. We stop the iteration process when $\|\theta^{(n)} - \theta^{(n-1)}\| < \varepsilon$ for some predetermined small number $\varepsilon > 0$.

## References


Aarts H, Dijksterhuis A, De Vries P (2001) On the psychology of drinking: Being thirsty and perceptually ready. *British J. Psych.* 94(2):631–642.

Anand B, Shachar R (2011) Advertising, the matchmaker. *RAND J. Econom.* 42(2):205–245.

Arcidiacono P, Jones JB (2003) Finite mixture distributions, sequential likelihood, and the EM algorithm. *Econometrica* 71(3): 933–946.

Arcidiacono P, Miller RA (2011) Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica* 7(6):1823–1868.

Baumeister RF, Masicampo EJ, Vohs KD (2011) Do conscious thoughts cause behavior? *Annual Rev. Psych.* 62:331–361.

Becker G, Murphy K (1988) A theory of rational addiction. *J. Political Econom.* 96(4):675–700.

Belk RW (1974) An exploratory assessment of situational effects in buyer behavior. *J. Marketing Res.* 11:157–164.

Belk RW (1975) Situational variables and consumer behavior. *J. Consumer Res.* 2(3):156–163.

Berry S, Levinsohn J, Pakes A (1995) Automobile prices in market equilibrium. *Econometrica* 63(4):841–890.

Chan T (2006) Estimating a continuous hedonic choice model with an application to demand for soft drinks. *RAND J. Econom.* 37(2):466–482.

Chevalier J, Goolsbee A (2009) Are durable goods consumers forward-looking? Evidence from college textbooks. *Quart. J. Econom.* 124(4):1853–1884.

Ching AT, Hayashi F (2010) Payment card rewards programs and consumer payment choice. *J. Banking Finance* 34(8):1773–1787.

Chung DJ, Steenburgh T, Sudhir K (2014) Do bonuses enhance sales productivity? A dynamic structural analysis of bonus-based compensation plans. *Marketing Sci.* 33(2):165–187.

Dobson PW, Gerstner E (2010) For a few cents more: Why supersize unhealthy food? *Marketing Sci.* 29(4):770–778.

Erdem T, Imai SS, Keane M (2003) Brand and quantity choice dynamics under price uncertainty. *Quant. Marketing Econom.* 1(1):5–64.

Fishbach A, Zhang Y (2008) Together or apart: When goals and temptations complement versus compete. *J. Personality Soc. Psych.* 94:547–559.

Fishbach A, Dhar R, Zhang Y (2006) Subgoals as substitutes or complements: The role of goal accessibility. *J. Personality Soc. Psych.* 91:232–242.

Fishbach A, Zhang Y, Koo M (2009) The dynamics of self-regulation. *Eur. Rev. Soc. Psych.* 20:315–344.

Gilleskie DB (1998) A dynamic stochastic model of medical care use and work absence. *Econometrica* 66(1):1–45.

Goettler R, Shachar R (2001) Spatial competition in the network television industry. *RAND J. Econom.* 32(4):624–656.

Guadagni PM, Little JDC (1983) A logit model of brand choice calibrated on scanner data. *Marketing Sci.* 2(3):203–238.

Harris K, Keane MP (1999) A model of health plan choice: Inferring preferences and perceptions from a combination of revealed preference and attitudinal data. *J. Econometrics* 89:131–157.

Hartmann W (2006) Intertemporal effects of consumption and their implications for demand elasticity estimates. *Quant. Marketing Econom.* 4(4):325–349.

Hendel I, Nevo A (2006) Measuring the implications of sales and consumer inventory behavior. *Econometrica* 74(6):1637–1673.

Hershfield HE (2011a) Future self-continuity: How conceptions of the future self transform intertemporal choice. *Ann. N Y Acad. Sci.* 1235:30–43.

Hershfield HE (2011b) Increasing saving behavior through age-progressed renderings of the future self. *J. Marketing Res.* 48:S23–S37.

Jain S (2012) The marketing of vice goods: A strategic analysis of the package size decision. *Marketing Sci.* 31(1):36–51.

Kamakura W, Kim B, Lee J (1996) Modeling reference and structural heterogeneity in consumer choice. *Marketing Sci.* 15(2):152–172.

Khwaja A, Silverman D, Sloan F (2007) Time preference, time discounting, and smoking decisions. *J. Health Econom.* 26(5): 927–949.

Kim M, Chintagunta P (2012) Investigating brand preferences across social groups and consumption contexts. *Quant. Marketing Econom.* 19(3):305–333.

Koo M, Fishbach A (2008) Dynamics of self-regulation: How (un)accomplished goal actions affect motivation. *J. Personality Soc. Psych.* 94:183–195.

Kopetz C, Kruglanski A, Arens Z, Etkin J, Johnson H (2012) The dynamics of consumer behavior: A goal systemic perspective. *J. Consumer Psych.* 22:208–223.

Kruglanski A, Shah J, Fishbach A, Friedman R, Chun WY, Sleeth-Keppler DD (2002) A theory of goal systems. Zanna MP, ed. *Advances in Experimental Social Psychology*, Vol. 34 (Academic Press, San Diego), 331–378.

Lattin JM, McAlister L (1985) Using a variety-seeking model to identify substitute and complementary relationships among competing products. *J. Marketing Res.* 22(3):330–339.

Luo L, Ratchford BT, Yang B (2013) Why we do what we do: A model of activity consumption. *J. Marketing Res.* 50(1):24–43.

Ma Y, Ailawadi KL, Grewal D (2013) Soda versus cereal and sugar versus fat: Drivers of healthful food intake and the impact of diabetes diagnosis. *J. Marketing* 77(3):101–120.

Magnac T, Thesmar D (2002) Identifying dynamic discrete choice models. *Econometrica* 70(2):801–816.

Malik VS, Schulze MB, Hu FB (2006) Intake of sugar-sweetened beverages and weight gain: A systematic review. *Amer. J. Clinical Nutrition* 84(2):274–288.

Manchanda P, Ansari A, Gupta S (1999) The shopping basket: A model for multicategory purchase incidence decisions. *Marketing Sci.* 18(2):95–114.

McFadden D (1974) Conditional logit analysis of qualitative choice behavior. Zarembka P, ed. *Frontiers in Econometrics* (Academic Press, New York), 105–142.

Mischel W, Shoda Y, Rodriguez ML (1989) Delay of gratification in children. *Science* 244:933–938.

Mozaffarian D, Hao T, Rimm EB, Willett WC, Hu FB (2011) Changes in diet and lifestyle and long-term weight gain in women and men. *New England J. Medicine* 364(25):2392–2404.

Narayan V, Rao V, Sudhir K (2015) Early adoption of modern grocery retail in an emerging market: Evidence from India. *Marketing Sci.* Forthcoming.

Niraj R, Padmanabhan V, Seetharaman PB (2008) A cross-category model of households' incidence and quantity decisions. *Marketing Sci.* 27(2):225–235.

Petrin A (2002) Quantifying the benefits of new products: The case of the minivan. *J. Political Econom.* 110:705–729.

Rust J (1987) Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica* 55:999–1033.

Rust J (1994) Structural estimation of Markov decision processes. Engle RF, McFadden DL, eds. *Handbook of Econometrics* (North-Holland, Amsterdam), 3081–3143.

Sandell RG (1968) Effects of attitudinal and situational factors on reported choice behavior. *J. Marketing Res.* 4:405–408.

Shah AK, Oppenheimer DM (2008) Heuristics made easy: An effort-reduction framework. *Psych. Bull.* 134(2):207–222.

Shah J, Kruglanski A (2003) When opportunity knocks: Bottom-up priming of goals by means and its effects on self-regulation. *J. Personality Soc. Psych.* 84:1109–1122.

Shah J, Friedman R, Kruglanski A (2002) Forgetting all else: On the antecedents and consequences of goal shielding. *J. Personality Soc. Psych.* 83:1261–1280.

Tangney JP, Baumeister RF, Boone AL (2004) High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J. Personality* 72(2):271–324.

Thomas M, Desai KK, Seenavasin S (2011) How credit card payments increase unhealthy food purchases: Visceral regulation of vices. *J. Consumer Res.* 38(1):126–139.

Vartanian LR, Schwartz MB, Brownell KD (2007) Effects of soft drink consumption on nutrition and health: A systematic review and meta-analysis. *Amer. J. Public Health* 97(4):667–675.

Wansink B, Just DR, Payne CR (2009) Mindless eating and healthy heuristics for the irrational. *Amer. Econom. Rev.: Papers Proc.* 99(2):165–169.

Yang S, Allenby GM, Fennell G (2002) Modeling variation in brand preference: The roles of objective environment and motivating conditions. *Marketing Sci.* 21(1):14–31.

Zhang Y, Fishbach A, Dhar R (2007a) When thinking beats doing: The role of optimistic expectations in goal-based choice. *J. Consumer Res.* 34:567–578.

Zhang Y, Fishbach A, Kruglanski A (2007b) The dilution model: How additional goals undermine the perceived instrumentality of shared path. *J. Personality Soc. Psych.* 83:389–401.